ESSAYS ON AGRICULTURAL POLICIES, PRODUCTION, AND CONSERVATION PRACTICE ADOPTION

By

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ABSTRACT

This dissertation consists of four chapters that explore the impacts of agricultural policies on production decisions and the adoption of conservation practices. The first chapter provides an overview and introduction to the dissertation. The second chapter investigates the effect of ethanol production on conservation practice adoption. The third chapter delves into moral hazard behavior in water use. The fourth chapter analyzes the effect of crop insurance premium subsidies on enrollment in wetland easement programs. This dissertation aims to provide empirical evidence on the interplay between production-related policies and their impacts on environmental stewardship, offering insights for policy evaluation and decision-making.

The first essay (Chapter 2) examines the effect of ethanol production on the adoption of on-farm conservation practices. From 2002-2019, United States ethanol production increased ten-fold. Using Renewable Fuel Standard (RFS) mandate changes to instrument for ethanol capacity, we assess whether changes in ethanol production affect the prevalence of cover cropping in corn-soy agriculture. We find that a 100 million gallon/year increase in local ethanol capacity implies a 0.35 percentage point decline in cover cropping. Considering a counterfactual where United States ethanol capacity remained at 2005 levels, our estimates imply that United States annual cover cropped area in 2015 would be 570.5 thousand acres greater, leading to additional greenhouse gas sequestration valued at $19.0 million/year based on current estimates of the social cost of carbon.

The second essay investigates the effect of crop insurance on water use. Using crop-specific water use data and unit pumping costs for groundwater extraction, we analyze moral hazard behavior in water use and the effect of pumping costs on water use responses to insurance participation. To address the potential endogeneity between water use and insurance participation, we adopt an instrumental variable approach using government-set premium subsidy levels and insurance participation from the previous year. We focus on areas overlying the High Plains Aquifer where groundwater serves as the primary source for irrigation. We find that an increase in insurance participation raises per-acre water use when pumping costs are low. When the pumping costs are high enough, we observe moral hazard behavior in water use, where per-acre water use decreases

in response to insurance coverage. For average pumping costs, a one percentage point increase in insurance participation leads to a 0.4% decrease in per-acre water use. These findings provide policy implications for both crop insurance and water regulations. Moral hazard behavior in water use may lead to higher indemnity payouts, whose costs are partially born by taxpayers. In addition, programs increasing water prices may lead to over-pricing and inefficient use of resources, if the moral hazard effect is not considered.

The third essay examines whether federal crop insurance premium subsidies discourage enrollment in wetland easement programs. Wetland conservation programs in the United States aim to restore environmentally critical lands that are often at risk of conversion for agricultural use. Using county-level panel data from the Mississippi River Basin between 1997 and 2020, we estimate a Poisson quasi-maximum likelihood model with a control function approach to address endogeneity. Our findings show that a 1% increase in premium subsidy reduces easement enrollment by approximately 3.2%. The economic magnitude of the effect is relatively modest where the average partial effect is estimated to correspond to a reduction of 2.7 enrolled acres. These results suggest that while crop insurance subsidies create some crowding-out effects, their practical impact on long-term wetland conservation commitments remains limited.

I dedicate this dissertation to my family.

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CHAPTER 1

INTRODUCTION

Understanding how farmers make on-farm management decisions in response to agricultural and environmental policies is crucial for assessing the overall cost-effectiveness of those policies and their impacts on environmental and production outcomes. Farmers make production decisions under uncertainties from both market and weather conditions, while navigating a set of incentives shaped by various programs. In some cases, these programs may pursue conflicting objectives, where the implementation of one program compromises the effectiveness of another (Smith et al., 2017). In other cases, unintended changes in production decisions in response to a program may undermine its own intended outcomes. Failing to account for these behavioral responses can lead to over- or underestimating policy effectiveness and result in inefficient resource allocation.

This dissertation aims to deepen our understanding of how agricultural or environmental policies affect farm management decisions, such as input use and adoption of conservation practices. While these policies are often designed to address market failures by subsidizing certain programs or products, they may induce some unintended behavioral responses that can lead to different environmental consequences. For example, it has been widely examined that subsidies on insurance premiums can promote riskier production decisions, such as expanding cropping acreage and reducing input use. While evaluating whether such policies achieve their primary goals is essential, it is also important to assess their unintended effects to provide a more comprehensive understanding of their overall effectiveness. This motivates the three essays in this dissertation, each of which investigates the policy impacts on farm management decisions with important environmental implications.

The first essay explores whether changes in output prices, induced by biofuel blending mandates in transportation fuels, affect cover cropping adoption. The mandates, formally known as the Renewable Fuel Standard (RFS), were established in 2005, with corn ethanol serving as the primary source of the biofuel. While the RFS was designed to reduce greenhouse gas emissions from gasoline consumption, it also works as an implicit subsidy for the agricultural sector (De Gorter

and Just, 2010; Smith and Moschini, 2024). Many studies have examined the effect of the RFS on production decisions, such as acreage effects and rotational effects (Li et al., 2019; Lark et al., 2022; Smith and Moschini, 2024).

Despite extensive literature on production effects of the RFS, there has been little research related to its effects on on-farm conservation decisions. This study attempts to fill this gap and contribute to the understanding of the relationship between an output market and conservation practice adoption by analyzing the effect of ethanol production on nearby cover cropping adoption. This study offers insight into how ethanol production may discourage the adoption of cover cropping, undermining the environmental benefits associated with this practice.

The second essay investigates the moral hazard behavior in water use from crop insurance. Moral hazard in input use suggests that farmers may change their optimal input decisions in ways that increase the likelihood of crop failure, especially when the expected marginal return to additional input is negative (Yu and Hendricks, 2020). This behavior has been widely studied, as it can distort the actuarial soundness of insurance products and lead to excessive indemnity payments. Research on moral hazard is particularly important given the high level of subsidies in the crop insurance program, as such behavior can undermine the program's cost-effectiveness. Among other farm inputs, research on moral hazard in water use has been relatively scarce. Understanding how insured farmers adjust their irrigation decisions is becoming increasingly important in light of growing water scarcity driven to over-extraction exceeding natural recharge rates.

We contribute to the literature on moral hazard of crop insurance by empirically examining how insurance uptake affects water use behavior of insured farmers. Our findings suggest that insured farmers may reduce per-acre water use under prevailing pumping costs. Another key contribution of this study is that we find moral hazard behavior in water use can depend on its water prices. Specifically, we find that in regions where water prices are high, we would observe more pronounced moral hazard (a decrease in per-acre water use) compared to regions with low water prices. This results suggest an interesting implication that under conditions of severe water scarcity and where water prices are high, moral hazard behavior may support more sustainable water use

and contribute to improved water management.

In the third essay, we examine whether premium subsidies for crop insurance discourage enrollment in wetland easement program. Insured farmers often expand their acreage, which may reduce participation in conservation programs, especially those that target non-working lands, such as the Conservation Reserve Program (CRP) (DeLay, 2019; Yu et al., 2022). If this crowding-out effect is substantial, it may suggest a potential trade-off in federal policy, where support for risk management may unintentionally undermine environmental objectives.

This study focuses on wetland easement programs, such as the Wetland Reserve Program, which offer long term or permanent contracts spanning 30 years or more. The findings of this research suggests that although there is some evidence of crowding-out effects on easement program participation, the marginal effect is relatively modest. Additional analysis using field-level cropping data and easement location information suggests that some eased lands may not be productive enough to support long-term agricultural production of the lands. This likely mitigates the marginal effect of premium subsidies on easement participation.

These essays collectively offer insights into how agricultural policies affect farm management decisions and the resulting environmental consequences of agricultural production. The findings of these essays underscore the importance of considering both intended and unintended effects to holistically assess policy effectiveness.

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CHAPTER 2

CASH CROP DEMAND AND CONSERVATION PRACTICES: THE EFFECT OF ETHANOL EXPANSION ON COVER CROPPING

2.1 Introduction

Addressing the negative environmental externalities of agriculture remains an important societal goal, with ongoing efforts to promote the adoption of agricultural conservation practices (Khanna and Ando, 2009; Claassen, 2006). Federal programs aimed at increasing the adoption of conservation practices in the United States include the Conservation Stewardship Program, Regional Conservation Partnership Program, and Environmental Quality Incentives Program (EQIP). Cover cropping, the planting of a non-harvested crop over the winter season, is one such conservation practice often encouraged through these programs. Although these programs have been shown to increase conservation practice adoption, many farmers adopt conservation practices without receiving federal incentives (Howard et al., 2023; Wallander et al., 2021). This prompts the question of how conservation adoption decisions may be affected by agricultural policies that do not explicitly target conservation practices.

Cover crops are non-harvested crops that are planted for seasonal cover and conservation purposes.[1] Cover crops are planted following the harvest of a row crop and are left over the winter until they are naturally or intentionally terminated prior to planting of the next cash crop. Cover cropping has many potential benefits. Prior research has demonstrated that cover cropping can control soil erosion and improve soil health (Snapp et al., 2005; Langdale et al., 1991; Decker et al., 2022), reduce water degradation (Blanco-Canqui, 2018; Dabney et al., 2001), and increase carbon sequestration (Hubbard et al., 2013). Some of these benefits, such as erosion control and soil health, are private benefits that accrue to the farmer. Other benefits are social goods that reduce negative externalities (e.g., reduced nutrient pollution) or provide public goods (e.g., carbon sequestration).

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[1]The definition of cover crops by the United States Department of Agriculture (USDA) allows for grazing and harvesting as hay or silage if it is not prohibited by the USDA Risk Management Agency (Wallander et al., 2021).

Despite these private and public benefits, the use of cover crops on agricultural land remains limited. In 2017, just 5.1% of agricultural land in the United States was cover cropped (Wallander et al., 2021). Government efforts to increase the prevalence of cover cropping have primarily centered on cost-sharing programs, such as the EQIP and the Maryland Agricultural and Water Quality Cost Sharing program (Wallander et al., 2021). These payments can help offset the costs of implementing cover crops that may include seed purchases, additional labor, and machinery use (Plastina et al., 2020). Prior work has found mixed evidence on the effectiveness of payment-for-environmental-services schemes for increasing cover crop use. For example, some studies find that the cost-sharing programs had considerable effects on cover cropping acreage, increasing the cover cropping acreage share by 15 to 27 percentage points (Fleming, 2017; Sawadgo and Plastina, 2021). However, other studies like Plastina et al. (2020) and DeVincentis et al. (2020) find that despite the cost-sharing programs, the annual net returns to cover cropping were negative, at least in the short run, and suggest that payments for conservation practices need to be higher than the current level.

Crop choice and management decisions are greatly affected by commodity prices (Hendricks et al., 2014b; Shapiro et al., 2008). Yet limited research exists on the effect of output prices and other market factors on the adoption of conservation practices. The willingness to plant a cover crop in the fall may depend on its expected revenue impacts, which are shaped by the market price and expected yields of the primary cash crop. Cover crops can affect farm profitability by influencing yields through two mechanisms: by enhancing soil health and improving long-term yields, and by imposing short-term yield penalties through competition for resources (e.g., water and nitrogen) and delayed planting (Sustainable Agriculture Research & Education, 2020). Delayed planting can occur when farmers fail to terminate cover crops in time to plant main cash crops at the optimal planting window. The opportunity cost of these yield changes rises with the market price of the cash crop, as the marginal value product of each additional unit of yield becomes higher. As a result, when output prices increase, the expected foregone revenue from even small yield reductions becomes larger. If the short-term yield penalties outweigh the long-term yield benefits, higher output prices can discourage cover crop adoption.

A better understanding of how commodity prices may affect cover cropping decisions can enable better-targeted policy incentives for cover crop adoption. To investigate this relationship, one could imagine looking at the association between crop prices and cover cropping acreage. However, commodity prices tend to have little spatial variation and temporal trends in prices may be confounded with other factors that also affect cover cropping decisions, such as technology and climate. In this paper, we explore the effects of ethanol plant construction, a large localized demand shock, on nearby cover cropping adoption.

There has been considerable growth in ethanol production in the United States over the past two decades. The 2005 and 2007 Renewable Fuel Standard (RFS) introduced mandates on the minimum amount of biofuel required in transportation fuel. Since the overwhelming majority of biofuels produced in the United States utilize corn feedstocks, this policy has significantly increased the demand for corn (Wallander et al., 2011; Westcott, 2010). Previous studies on the environmental effects of the RFS have largely focused on the impacts of increased corn production (Lark et al., 2022; Hendricks et al., 2014a). As the RFS increases local demand for corn, farmers may be incentivized to switch from other crops into corn production (Li et al., 2019; Wang and Ortiz-Bobea, 2019; Motamed et al., 2016; Brown et al., 2014) or convert idle land into corn production (Chen and Khanna, 2018; Ifft et al., 2019; Swinton et al., 2011). Lark et al. (2022) estimate that the RFS induced a 2.1 million hectares increase in continuous corn production and the conversion of 1.8 million hectares into cropland between 2008 and 2016 in the United States, leading to a 5.3% increase in nitrate-leaching and a 3.2% increase in phosphorus runoff. Hendricks et al. (2014a) find that a billion gallons of ethanol production leads to an increase in the size of the hypoxic zone by 32.7 square miles, including the effect of the Conservation Reserve Program. While there have been many studies analyzing the effect of the RFS on acreage, crop choice, and fertilizer applications, but other management decisions have not received similar attention. In particular, the adoption of conservation practices that may affect the environmental impacts of corn production represents an additional channel through which ethanol policy may affect environmental outcomes. In our case, if increased ethanol demand increases local demand for corn and reduces cover cropping

on nearby farms, this exacerbates the negative environmental consequences of the RFS. We find suggestive evidence that local increases in ethanol capacity decrease the adoption of cover cropping on surrounding agricultural areas.

This study investigates the effect of the expansion in ethanol capacity on cover cropping in the Midwest. To estimate this effect, we combine satellite data on cover cropping with data on ethanol production capacity. We adopt a panel with fixed effects approach to estimate the effect of ethanol production capacity on nearby cover cropping adoption, controlling for time-invariant location heterogeneity. We perform analyses at the agricultural district level[2]. Our results provide consistent evidence that market forces, such as a local demand increase for a cash crop, can affect farmers' decisions regarding cover crops.

This study makes several contributions to the conservation practice adoption literature. Our findings show that market factors, policy-driven local demand changes, can affect the adoption of conservation practices. We argue that an increase in local demand for a cash crop may amplify the potential effect of short-term yield penalties on the profitability, thereby discouraging the adoption. To the best of our knowledge, this paper is the first empirical analysis showing a shift in the local demand for crops affecting conservation practice adoption. Furthermore, our findings underscore the importance of considering the unintended effects of agricultural and environmental policies on on-farm conservation decisions, especially when we attempt to assess the environmental impacts of these policies. A relevant example is the RFS program, which has boosted the demand for corn in the United States. The induced changes in the adoption of conservation practices may either enhance or offset the initially intended environmental benefits by the program. Therefore, considering these changes is crucial for the design and assessment of these policies.

The paper is organized as follows: Section 2.2 introduces our data and provides background context on ethanol production and cover cropping trends in the Midwest. Our empirical analysis, presented in Sections 2.3 and Section 2.4, provides empirical evidence that increases in ethanol capacity decrease cover cropping adoption. In Section 2.5, we use our estimates to calculate

[2]Agricultural Statistics Districts (districts), defined by the USDA National Agricultural Statistics Service (NASS), are groupings of counties in each state, by geography, climate, and cropping practices.

counterfactual cover cropping area and provide a back-of-the-envelope calculation of the additional greenhouse gas emissions attributable to the increase in ethanol capacity since 2005. Section 2.6 concludes.

2.2 Empirical setting and data

2.2.1 The expansion of ethanol capacity in the Midwest

Established by the Energy Policy Act of 2005 and subsequently extended under the Energy Independence and Security Act of 2007, the RFS sets standards for biofuel use, requiring a minimum blend of biofuels in transportation fuel. Biofuel is categorized into four sub-categories: (1) cellulosic biofuels, (2) biomass-based diesel, (3) other advanced biofuels, and (4) conventional biofuels. Conventional biofuels, which include corn ethanol, has remained the primary focus of the program at least through 2015, when the mandated volumes for conventional biofuels accounted for approximately 75% of the total mandated volumes.

Since the implementation of the RFS mandates, the total ethanol production capacity in the United States has surged from 4.3 billion gallons per year in 2006 to 17.7 billion gallons per year by 2022 (Renewable Fuels Association, 2006, 2022). As a result of this growth, the share of corn production utilized for ethanol production has risen from 19% in 2006 to 35% in 2022 (USDA Economic Research Service, 2023). This increase in demand has subsequently led to an increase in corn prices (Lark et al., 2022; Carter et al., 2017; Roberts and Schlenker, 2013). For instance, Lark et al. (2022) estimates that the RFS contributed to a 30% increase in corn prices compared to a business-as-usual scenario. In addition to the broader changes in corn prices, prior studies have indicated that adding a new ethanol plant with a capacity of 100 million gallons per year (MGY) can increase local corn basis by 0.9 to 35.6 cents per bushel (Miller, 2015; Behnke and Fortenbery, 2011; McNew and Griffith, 2005).

The Midwest is home to a disproportionate share of the country's ethanol production facilities due to the easy and cost-effective access to corn feedstocks (Lambert et al., 2008; Stewart and Lambert, 2011). Figure 2.1 displays plots of the locations and capacities of ethanol plants in 2006 and 2015. It shows that a majority of the new plants were established after 2006, and they are

primarily concentrated in Iowa and neighboring states. The majority of ethanol plants constructed between 2006 and 2015 have capacities ranging from 50 to 200 MGY. The grey-colored districts in the maps represent our study area. We consider ethanol plants located outside of this area when calculating the effective ethanol production capacity of a particular agricultural district.

2.2.2 The unclear relationship between cover cropping and yields

Understanding the effects of cover cropping on cash crops' yields is important for understanding farmers' decision-making regarding cover crop adoption. While yield improvements may encourage adoption of the practice, large yield penalties may prompt farmers to discontinue the practice. The yield effects of cover cropping are particularly relevant to our research, as output price changes can amplify these yield effects on farm profitability and influence the decision to adopt cover cropping practices.

Previous agronomic studies often find that cover cropping has negative yield effects on cash crops (Deines et al., 2023; Abdalla et al., 2019; Malone et al., 2022). A review by Abdalla et al. (2019) finds that cover cropping leads to an average yield reduction of 4% on primary crops such as corn and wheat, with variations observed depending on regions and cover crop types. Potential reasons include that cover crops taking up water or nitrogen required by subsequent cash crops (Pantoja et al., 2015; Rosa et al., 2021), as well as incomplete termination of cover crops resulting in competition for resources (Malone et al., 2022). The yield effects may vary depending on the time frame considered, as soil health improvement resulting from cover cropping requires time. Myers et al. (2019) finds that five consecutive years of cover crop adoption enhanced the corn yields by 3%, while one year of cover cropping only led to 0.5% improvement. In sum, cover cropping is expected to have both positive long-term yield effect by enhancing soil health and negative short-term yield effect.

Prior works also find that cover cropping has heterogeneous effects based on the types of following cash crops (Deines et al., 2023; Qin et al., 2021; Myers et al., 2019). Deines et al. (2023) find that cover cropping has greater negative effects on corn yields (5.5%) than those on soy yields (3.5%). Other studies find negative yield effects on corn, but minimal effects on soy (Qin et al.,

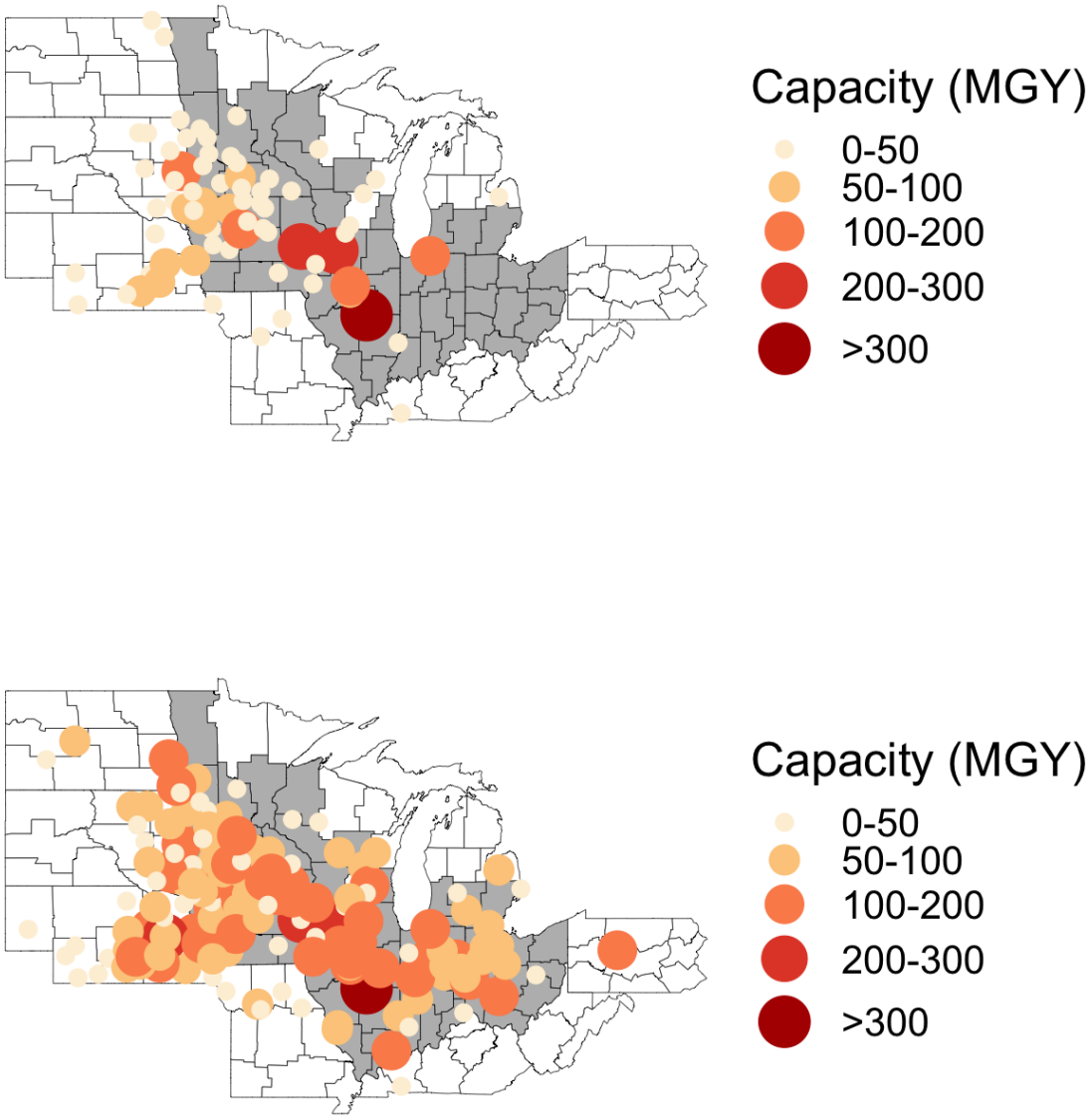

Figure 2.1 **Ethanol Plants and Production Capacity in 2006 and 2015**: The figure displays the map of our study area and adjacent states, and plots of ethanol plants. Production capacity is the nameplate capacity.

2021). Larger yield penalties for corn compared to soy are likely due to corn's greater demand for nitrogen and water, as well as differences in their production windows (Deines et al., 2023; Sustainable Agriculture Research & Education, 2020). These varied effects by crops suggest that an output price change may have heterogeneous effects on fields for different crops.

When output prices rise, farmers may evaluate whether to use cover cropping based on its expected impact on future profits. When the short-term negative yield effects are relatively large compared to the long-term positive yield effects, then an increase in an output price may reduce cover crop adoption. When short-term yield penalty is relatively small, then an increase in output price may encourage more adoption of the practice. These differing responses highlight how the direction of cover cropping response to an output price increase depends on the relative magnitudes of long-term yield benefits and short-term yield penalties. Therefore, we turn to our empirical analysis to investigate the effect of output price shocks on the propensity to cover crop.

2.2.3 Data

We examine cover crop use in the Midwest, the primary region for ethanol production in the United States (Duffield et al., 2015). Specifically, we focus on seven states for which cover crop use data are available: Illinois, Indiana, Iowa, Michigan, Minnesota, Ohio, and Wisconsin. To construct our primary dataset, we collect district-level data on cover cropping rates, effective ethanol capacity, and other covariates such as weather variables. The district-level data span 2006 to 2015. In this subsection, we provide an explanation of the data used in our study. Summary statistics for key variables are shown in Table 2.1.

Cover crop use

We utilize remotely sensed satellite data that covers seven states at the district-level, called the OpTIS data. District-level cover cropping data come from the Operational Tillage Information System (OpTIS) dataset, which is produced by Conservation Technology Information Center.[3] The OpTIS dataset provides acreage and ratio information on cover crops and winter commodity crops. For our analysis, we only include data on cover crops that are not intended for commercial sale and

[3] `https://www.ctic.org/OpTIS_tabular_query`

Table 2.1 Summary Statistics (2006-2015) for IA, IN, IL, MI, MN, OH, and WI

Variable	Mean	Std. Dev.	Min.	Max.
Cover cropping rates after corn/soy (%)	1.8	3.4	0.0	29.9
Cover cropping rates after corn (%)	1.5	2.5	0.0	17.7
Cover cropping rates after soy (%)	2.1	4.9	0.0	43.6
Effective ethanol capacity, 30-km radius (MGY)	136.0	176.4	0.0	770.5
Effective ethanol capacity, 50-km radius (MGY)	137.3	166.1	0.0	702.2
October temperature (°C)	10.9	2.3	4.1	16.6
November temperature (°C)	4.0	3.0	-6.9	10.5
October precipitation (mm)	82.2	44.3	6.8	275.9
November precipitation (mm)	57.7	39.5	0.7	191.1
Ln(Corn futures price)	1.3	0.1	1.1	1.5
EQIP Areas (million acres)	1.3	1.5	0.003	5.9
Conservation tillage after corn/soy (%)	88.5	3.7	68.9	96.2
RFS mandates (Billion Gallons per Year)	10.9	3.7	4.0	15.0
Railroad density (km)	1,664.9	708.0	642.1	4,515.2
Instrumental variable (km*BGY)	18,180.5	10,226.5	2,568.6	67,728.2

that are terminated before the next cash crop is planted. The data include 51 districts across the states.[4] Some districts in Michigan, Wisconsin, and Minnesota are not included as data on those districts are not provided.

The OpTIS data relies on remote sensing methods to detect the presence of cover crops or other ground covers during the winter months (Griffiths et al., 2020). Validation of the OpTIS data shows that this data is 87.9% accurate in identifying cover-cropped fields (Hagen et al., 2020). This accuracy rate was established by comparing OpTIS classifications with ground-truthed photo and survey data collected from 961 fields across selected representative counties.

A crop year in the OpTIS data begins on November 1 of the previous year and ends on October 31. Given that the decision to cover crop is made in the fall after harvesting, we assign the winter cover cropping acreage (potentially observed in January or February) to the previous calendar year. For example, an area documented to have cover crops in 2011 data would have had its cover crops planted in the fall of 2010 (Griffiths et al., 2020). We would assign this cover cropping acreage to 2010 in our analysis.

[4]Cover crops in these districts account for about 22% of the total cover cropping area in the United States. This estimate is based on 2015 cover cropping data from the OpTIS data and national totals reported in from Wallander et al. (2021).

The OpTIS data categorizes cover cropping acreages and rates into four groups based on the previous year's cash crops (corn, soy, small grains, and others). In this study, we focus on the cover cropping after corn and soy production. Since decisions on cover cropping may differ depending on the following cash crop, as suggested in our Section 2.2, cover cropping for corn, soy, and combined fields are separately modeled in our empirical analysis.

Our outcome variable is cover cropping rate, defined as a share of corn and/or soy acreage that is followed by cover crops. For example, when a district with 100 acres of corn and soy fields has 5 acres of cover crops, the cover cropping rate will be 5%. Cover cropping rates after corn production is defined as a share of corn acreage that is cover cropped, and the rate after soy production is similarly defined. The main reason we use cover cropping rates is that acreage information may not fully reflect spatial differences and temporal changes in overall agricultural activities in a given area. For example, planting 5 acres of cover crops on 100 acres of farmland represents a different level of intensity than planting the same 5 acres on a 1,000-acre farmland.

Figure 2.2 illustrates the annual cover cropping rates after corn and soy production from 2006 to 2015 across various states. An upward trends are noticeable in Illinois, Indiana, and Iowa since the early 2010s, despite some sharp declines for Indiana and Illinois in 2013 and 2014. Indiana has exhibited more active adoption of cover cropping compared to Iowa and Illinois, while Illinois and Iowa show similar adoption rates. The other states, other than Michigan, have experienced relatively stable and less active adoption of cover cropping. These states initially witnessed slight decreases in cover cropping until 2010, but have since turned around and shown slight upward trends.

Ethanol production capacity

Plant-level ethanol capacity data is obtained from the reports by the Renewable Fuels Association (RFA) and BBI International (BBI). We use the RFA reports for data from 2006 to 2009 and the BBI reports for data from 2010 to 2015.[5] The lists of plants in the RFA reports were updated in

[5]BBI reports provide more complete data than RFA reports in terms of capacities by plants. For example, RFA reports aggregate capacities under the same company and are missing for 2013 and 2015. However, BBI reports only start from 2010. Hence, we supplement the data with RFA reports for years between 2006 and 2009.

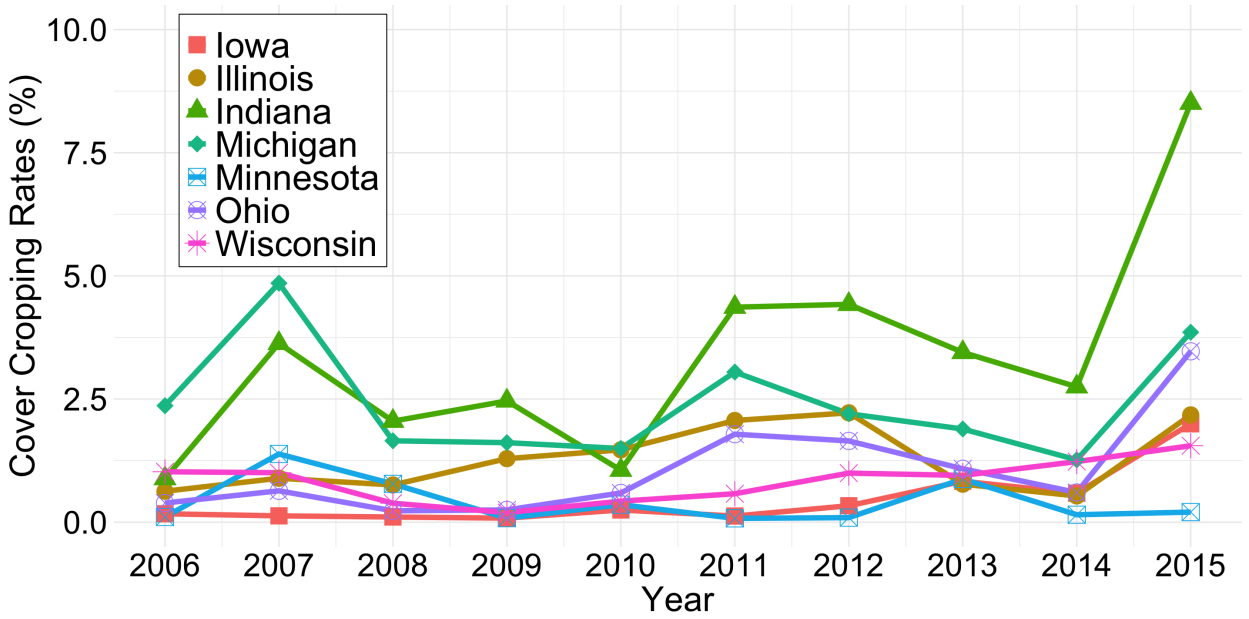

Figure 2.2 **Cover Cropping Rates by States from 2006 to 2015**: The figure shows changes in cover cropping rates across states from 2006 to 2015.

January and the ones in the BBI reports in March each year. The data includes information on the city and state where plants operate, feedstock used, and nameplate capacity in MGY. Plants that do not use any corn as their feedstock are excluded from the analysis.

For our main explanatory variable, we construct district-level effective ethanol capacities. Following the methodology of Li et al. (2019), we draw a 30-km (18.6 mile) buffer from the centroid of a city where an ethanol plant is located, which assumes that this plant is located at the center of the city rather than being at the exact location. This assumption is made because the data only provides the city name, not the exact location of each plant. Then, we calculate the share of the overlapping area between the boundary and a nearby county, relative to the total area of the buffer zone. This share is used to determine the effective ethanol capacity assigned to each county from the plant. The county's effective ethanol capacity is the sum of the plant-level effective capacities assigned to that county. We take into consideration the production capacities of ethanol plants in neighboring states when their boundaries overlap with our study area. For instance, if the boundary from an ethanol plant in Nebraska, which falls outside of our study area, overlaps with a county in Iowa, we include its capacity in our analysis. We obtain district-level effective ethanol capacity by

aggregating the county-level capacities that fall within the district.

We choose 30-km as our preferred criterion as previous research has indicated that half of the ethanol plants draw their feedstock within a 25-mile (40.2 km) radius (Li et al., 2019) and several other studies have selected similar criteria (Towe and Tra, 2013; Ifft et al., 2019; Gardner and Sampson, 2022; Sampson et al., 2021). Estimation results using the 50-km boundary as a robustness check are presented in Table 2B.1 in the appendix.

Other variables

We include average temperature and precipitation in October and November as controls in the estimation. Previous studies have illustrated that cover crop use could be affected by weather conditions (Connor et al., 2022; Yoder et al., 2021; Li and McCann, 2019; Bergtold et al., 2019; Pantoja et al., 2015). Li and McCann (2019) and Connor et al. (2022) explain that longer growing seasons can allow farmers to have a longer window for seeding cover crops and a higher probability of successful establishment. Yoder et al. (2021) find that intense precipitation and low temperature after harvest can discourage cover cropping by making fall establishment difficult for farmers. To construct district-level variables, we compute the average temperature and precipitation. County-level information on temperature and precipitation is obtained from the PRISM dataset.

The state-level EQIP enrollment data is obtained through a Freedom of Information Act request to the USDA Farm Production and Conservation Business Center. This data includes the number of acres enrolled in the cover cropping practice. Information on conservation tillage comes from the OpTIS. Conservation tillage includes no-till and reduced tillage.

For the robustness checks presented in Table 2F.1, we use corn futures price data sourced from Barchart[6]. We use the average prices in October and November for the December corn futures contract of the following year. For example, the corn futures price in 2010 is determined by averaging the closing prices of the 2011 December contract traded during October and November of 2010. We select this price, as it reflects the anticipated market price of corn at the time when cover cropping decisions for the following year are typically made.

[6]`https://www.barchart.com`. Barchart provides real-time and historical price information on stock and commodities.

We obtain data on railroad lines from the National Transportation Atlas Databases[7]. This dataset provides geospatial information on the rail network in the United States. Using the 2003 railroad line data, we construct a district-level railroad density variable by calculating the total length of railroads in each district. We choose 2003, preceding our sample period, to ensure that railroad density is exogenous to the construction of ethanol plants.

2.3 Methodology

This section introduces our empirical model and discusses the potential endogeneity between ethanol capacity and cover cropping rates. We then outline our identification strategy to address the potential bias arising from this endogeneity.

2.3.1 Empirical model

The relationship between ethanol capacity and cover cropping can potentially be affected by an array of unobserved factors. These could be geographic factors, such a soil characteristics or proximity to university extension services, or temporal factors, such as commodity or fertilizer prices or government incentives for conservation. We attempt to address these potential confounders through location and year fixed effects. An additional risk to identification is present if trends in ethanol capacity expansion is driven, in part, by time-varying factors that are correlated with the propensity of farmers to plant to cover crops. To address this concern we present results for a model that instruments for ethanol capacity with the interaction of pre-existing rail infrastructure and the RFS mandate level. In mitigating these two risks– omitted variables and reverse causality– we face a trade-off as our first-stage IV regression is insufficiently strong when year fixed effects are included. We resolve this trade-off by focusing on OLS models with district and year fixed effects, as well as state time trends, and also presenting results for an IV specification that includes only district fixed effects and state time trends.

Our estimating equation for our OLS specifications is:

$$CCR_{it} = \phi EC_{it} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2.1}$$

where CCR_{it} is the cover cropping rates and EC_{it} is the effective ethanol capacity for district i in

[7] https://geodata.bts.gov

year t. In year t, the ethanol capacity is determined in the first quarter of the year, preceding the decision of cover cropping in the fall. ϕ is the parameter of our interest. $\boldsymbol{X}_{it}$ is a $(1 \times k)$ vector of covariates including weather variables and state-specific time trends. The state-specific time trends control for linear time trends common to all districts in each state. $\boldsymbol{\beta}$ is a $(k \times 1)$ vector of parameters that are associated with $\boldsymbol{X}_{it}$. μ_i is a district fixed effect and γ_t is a year fixed effect. ε_{it} is the idiosyncratic error term. For OLS specifications, we estimate Equation 4.12 with and without year fixed effects (γ_t). For IV specifications, Equation 4.12 represents our second-stage, with EC_{it} being replaced with predicted ethanol capacity. Standard errors are clustered at the district and state-by-year levels to account for potential serial and spatial correlation in the error term. We first estimate Equation 4.12 on corn/soy fields. We then estimate the same equation on corn and soy fields, respectively, to evaluate heterogeneous responses.

2.3.2 Identification strategy

The main challenge to identify the effect of ethanol expansion on cover cropping is that decisions on the location and size of plants are endogenous to corn and soy areas (Motamed et al., 2016; Li et al., 2019). For instance, ethanol plants are more likely to be located close to regions with high corn production, as feedstock costs represent a significant portion of ethanol production expenses (Duffield et al., 2015; Lambert et al., 2008). However, we do not observe factors that affect the location and size of each plant, which may vary both spatially and temporally. These unobserved factors can lead to reverse causality and bias our estimated coefficients. If omitted variables are positively correlated with cover cropping rates and ethanol production, it would result in an upward bias in OLS estimates for ethanol capacity on cover cropping rates. While the district fixed effects and state trends included in our models control for factors that are common for each district and linear trends by states, they do not control for factors that vary at the district level over time.

To address this potential endogeneity, we use an IV exploiting exogenous variations in government-set ethanol mandates in the RFS and the district-level railroad density in 2003, based on the relevant literature (Li et al., 2019; Motamed et al., 2016). The RFS mandates provide temporal variations and railroad density provides spatial variations to our IV.

The RFS mandates are highly correlated with ethanol production capacity, as most of the mandates have been met with corn ethanol (Bracmort, 2018). Since annual changes in corn production or demand for ethanol do not affect the mandates set at the federal level, the mandates are assumed to be exogenous to farmers' on-farm decisions. The railroad density is expected to be correlated with ethanol plant locations, as 60 to 70% of ethanol is transported via rail (Association of American Railroads, 2024). We contend that the railroad density is a valid source of exogeneity to planting and cover cropping decisions, as discussed in Motamed et al. (2016) and Li et al. (2019). First, trucking has emerged as a prominent mode of grain transportation over railroads, accounting for 70% of total corn transportation in 2020 in the United States (Henderson et al., 2024). Second, as discussed in Motamed et al. (2016), there is limited evidence suggesting that railroads drove the establishment of farm regions.

Table 2A.1 presents the first-stage regression results for the effective ethanol capacity variable. Columns (1) and (2) show the results without and with year fixed effects, respectively. In a model without year fixed effects, our instrumental variable is fairly strongly correlated with the instrumented, with a first-stage F-statistic of 21.3, exceeding the conventional rule of thumb threshold of 10. However, when year fixed effects are included, the instrumental variable becomes weaker, making the model unreliable.

2.4 Results

In our main analysis, we use cover cropping rates on corn or soy fields as our dependent variable.[8] We show results for four specifications: Column (1) presents OLS estimates from a model that includes district fixed effects and state trends; Column (2) presents OLS estimates from a model that additionally includes year fixed effects; Columns (3) and (4) report IV estimates. Column (3) presents results for a model without year fixed effects, while Column (4) presents results for a model with year fixed effects. Including year fixed effects in the IV approach substantially weakens the strength of the instrument (first-stage F-statistic is 0.03), rendering these results wholly

[8]We provide estimation results using the natural logarithm of cover cropped acreage as a dependent variable in Table 2C.1 in the appendix. We find consistent results showing that ethanol production capacity leads to a 15-80% decrease in cover cropping adoption across specification, though the estimates for the IV model and the OLS model with year fixed effects are not statistically significant.

unreliable. Our preferred specification is shown in Column (2): the OLS model that includes year fixed effects, which are essential for controlling for the effects of global commodity prices, which have considerable year-to-year fluctuations which are poorly captured by state-level trends.

We find that the estimated coefficients of effective ethanol capacity are negative and statistically significant across the models shown in columns (1) through (3). The results in Column (2) imply that when effective ethanol capacity increases by 100 MGY in an agricultural district, the cover cropping rates decrease by about 0.35 percentage points. At the sample mean of corn/soy area, this translates to a reduction of 5,856 acres in cover cropping area.[9] For context, a 100 MGY increase in ethanol capacity can be considered comparable to the construction of an average-sized plant. One potential explanation for this negative effect is that a surge in demand for a cash crop may magnify the cost of yield penalties associated with cover crops, as discussed in the previous Section. Having year fixed effects leads to a smaller estimated coefficient on ethanol capacity, as year fixed effects capture price shocks including corn or soy prices. These results suggest that cover cropping adoption is negatively affected by local ethanol expansion independent of broader changes in output prices.

We find statistically significant and consistent estimates for temperature, whereas we generally do not find statistically significant results for precipitation. The results suggest that milder weather conditions in fall promote more adoption of cover cropping, given that cold and wet fall weather may impede the growth of cover crops (Malone et al., 2022; Chamberlain et al., 2020). We do not find statistically significant results for the specifications with year fixed effects, likely because the year fixed effects absorb much of the temporal variation in weather variables.

Potential mechanisms

The total effect of a change in local ethanol capacity on cover cropping rates depends on the effect of the change on the management of existing fields and its effect on marginal fields that may enter or exit production. For instance, if the construction of an ethanol plant induces farmers to allocate more land to corn production, these additional lands may exhibit different properties

[9]This calculation assumes that ethanol production affects the cover cropping area, not total crop area. Since ethanol production is likely to expand crop area, the calculated reduction of 5,856 acres should be viewed as an upper bound.

Table 2.2 Estimation Results: Cover Cropping Rates

	(1)	(2)	(3)	(4)
	OLS		IV	
Effective Ethanol Capacity (100 MGY)	−0.59***	−0.35**	−3.34***	−24.89
	(0.20)	(0.16)	(1.11)	(218.63)
October Temperature (°C)	0.238*	−0.174	0.151	−3.121
	(0.126)	(0.254)	(0.113)	(26.332)
November Temperature (°C)	0.263***	0.016	0.314***	−0.110
	(0.086)	(0.254)	(0.084)	(1.527)
October Precipitation (mm)	0.002	0.004	0.001	−0.008
	(0.003)	(0.004)	(0.003)	(0.109)
November Precipitation (mm)	−0.006	−0.007	−0.010*	−0.060
	(0.005)	(0.007)	(0.005)	(0.470)
District FE	Yes	Yes	Yes	Yes
State Trends	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	510	510	510	510
First-stage F-stat			21.3	0.03
Adjusted R-squared	0.626	0.640		

*p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the state-by-year and district level
R-squared is not provided for IV regressions, as it does not have natural interpretation as in the OLS regressions

related to cover cropping compared to existing lands. In this case, the effect may be more driven by changes in the planted acreage than by changes in cover cropping areas.

We compare the magnitude of our estimated effects to estimates of the effect of ethanol production on crop choice and cropland expansion. Studies that have directly estimated land use changes from ethanol capacity growth have found relatively modest increases in corn and cropland areas (Li et al., 2019; Wang and Ortiz-Bobea, 2019; Lark et al., 2022). For example, Li et al. (2019) find that expansion in corn ethanol capacity from 2008 to 2014 increased corn area by 3.1% and total cropland area by 0.9%. Considering the period between 2008 to 2016, Lark et al. (2022) find larger land use change effects of the RFS, with corn area increasing by 8.7%. In either case, the

effect of this additional acreage on cover cropping rates is likely to be quite small. To illustrate why, consider an extreme case where capacity growth increases corn acreage by 9% and that these additional acres are not suitable for cover cropping (i.e., the cover cropping rate on these areas is zero), while cover cropping rates on existing lands are unchanged (roughly 2% as in Table 2.1). In this scenario, the increase in corn acreage causes cover cropping rates to decline by 0.2 percentage points. Considering that average effective ethanol capacity increased by 87 MGY from 2008 to 2015 in our data, our estimates imply this resulted in a 2.3 percentage point decline in cover cropping rates. Therefore, we conclude that the majority of the estimated effects of ethanol capacity on cover cropping rates is attributable to changes in the management of existing corn and soy fields.

2.4.1 Response heterogeneity across crops

To investigate whether the response of cover cropping to ethanol capacity shocks is influenced by the preceding season's crop, we estimate separate models for after-corn and after-soy cover cropping rates. Table 2.3 reports the estimation results. The results in Columns (1) to (3) are restricted to fields previously planted to corn only, and Columns (4) to (6) present estimates for cover cropping rates previously planted to soy only. Here, we drop the IV model with year fixed effects due to the weak instrument problem.

Focusing on our preferred OLS specification which includes year fixed effects, we find that the magnitude of the estimated coefficient (-0.38) on ethanol capacity for after-soy cover cropping is similar to our full-sample estimate (-0.35), though much less precisely estimated. For after-corn cover cropping rates, we find a slightly less negative, though statistically significant, effect of -0.26. Given that Midwestern farmers typically follow a corn-soy rotation, these estimates are consistent with the idea that increases in ethanol capacity may have larger effects on farmers' propensity to cover crop in the fall prior to planting corn. This is perhaps not surprising, given that increases in local ethanol capacity are more likely to affect corn prices than soy prices (Lark et al., 2022). This finding is also consistent with results from previous studies that indicate cover cropping has greater negative effects on corn yields than soy yields (Deines et al., 2023).

Table 2.3 Estimation Results: Heterogeneity by Crops

	(1)	(2)	(3)	(4)	(5)	(6)
	After Corn			After Soy		
	OLS	OLS 2-way FE	IV	OLS	OLS 2-way FE	IV
Effective Ethanol Capacity (100 MGY)	−0.32*** (0.10)	−0.26** (0.12)	−1.73** (0.79)	−0.79*** (0.28)	−0.38 (0.23)	−4.53*** (1.53)
October Temperature (°C)	0.109 (0.081)	−0.326 (0.199)	0.065 (0.078)	0.406* (0.210)	−0.092 (0.402)	0.288 (0.191)
November Temperature (°C)	0.206*** (0.067)	−0.299 (0.197)	0.232*** (0.065)	0.312** (0.118)	0.316 (0.441)	0.381*** (0.118)
October Precipitation (mm)	−0.002 (0.003)	0.001 (0.003)	−0.003 (0.003)	0.007 (0.006)	0.007 (0.006)	0.006 (0.006)
November Precipitation (mm)	−0.008 (0.007)	−0.002 (0.005)	−0.010 (0.007)	−0.004 (0.008)	−0.012 (0.010)	−0.009 (0.008)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State Trends	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	No	Yes	No
Observations	510	510	510	510	510	510
First-stage F-stat			21.3			21.3
Adjusted R-squared	0.488	0.556		0.585	0.603	

*p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the state-by-year and district level
R-squared is not provided for IV regressions, as it does not have natural interpretation as in the OLS regressions

2.4.2 Additional analyses

In this section, we summarize the results of additional analyses and explore the robustness of our main findings. We consider the following: (1) constructing effective ethanol capacity with 50-km boundaries, (2) models that include additional controls related to enrollment in EQIP and other conservation management practices, and (3) non-linear effects.

Effective ethanol capacity with 50-km boundaries

We construct effective ethanol capacity using 50-km boundaries from ethanol plants, as ethanol

plants can draw some feedback beyond 30 km and using smaller boundaries might affect the results. The results, presented in Table 2B.1, show consistent results to our main results in Table 2.2 that an increase in effective ethanol capacity lowers the adoption of cover cropping. A 100 MGY increase in ethanol capacity lowers cover cropping rates by 0.39 percentage points in the OLS including year fixed effects in Column (2). The estimated coefficients are almost identical to the main results.

Additional controls

EQIP offers incentives to farmers for adopting conservation practices, such as cover cropping and conservation tillage. The lengths of an EQIP contract can span multiple years, potentially constraining farmers from promptly adjusting their cover cropping adoption in response to exogenous shocks. Here, we control for the state-level acreage enrolled in EQIP for cover cropping to assess the robustness of the estimated coefficients on effective ethanol capacity.

In addition, several studies have demonstrated that conservation tillage and cover cropping practices are complementary where cover cropping can enhance the beneficial effects of conservation tillage (Fleming, 2017; Balkcom et al., 2007). Conservation tillage includes both no-till and reduced-till practices. Hence, we include the adoption of conservation tillage practice, measured as a percentage, as a control variable. Including a contemporaneous conservation tillage variable could potentially lead to a "bad control" as conservation tillage adoption might also be influenced by ethanol production. To avoid this, we include a lagged conservation tillage variable.

Table 2D.1 presents the results including these additional controls. While we observe a decrease in statistical significance compared to those in Table 2.2, the estimated coefficients on effective ethanol capacity remain negative and almost identical in magnitude.

Our estimation results show that increased EQIP enrollment is positively associated with higher cover cropping rates, with a million acre increase in acreage under the EQIP program raising cover cropping rates by 0.61 percentage points. Additionally, the adoption of conservation tillage is also positively associated with cover cropping rates, aligning with findings from the existing literature (Fleming, 2017; Balkcom et al., 2007).

Non-linearity

Our main specification assumes that the marginal effects of effective ethanol capacity is constant across the ethanol capacity. We consider non-linear effects of ethanol capacity on cover cropping adoption using a quadratic model in this subsection. For the IV estimation, we additionally include the squared IV for the first-stage regression. Non-linear relationship may arise when there is a decreasing marginal return in local output price from ethanol production expansion. In addition, local competition level between ethanol factories can affect local output prices (Jung et al., 2022).

The estimation results of the quadratic model are reported in Table 2E.1. The fixed effect estimation results, presented in Columns (1) and (2), show that the marginal effects of ethanol capacity decrease as ethanol capacity increases. Focusing on the specification with year fixed effects shown in Column (2), the marginal effect of ethanol capacity turns from negative to positive when ethanol capacity exceeds 657.7 MGY, which is 2.96 standard deviations above the sample mean and higher than all but 9 district-year observations. At the sample mean of the effective ethanol capacity, the marginal effect of ethanol capacity is -0.61, with a standard error of 0.24. At the maximum value of ethanol capacity in our sample, 770.5 MGY, the marginal effect is 0.13, but this estimated effect is not statistically distinguishable from zero. Estimates from the IV estimation imply a similar marginal effect of ethanol capacity at the sample mean of 136 MGY (-3.35 in the full sample versus -3.85 in the quadratic specification), although the quadratic IV specification implies unrealistically negative and unrealistically positive marginal effects of ethanol capacity at, respectively, very small and very large values.

2.5 The impact of ethanol capacity growth on cover cropping and greenhouse gas sequestration

In this section, we compute counterfactual cover cropping areas and provide back-of-the-envelope estimates of the change in greenhouse gas (GHG) sequestration in 2015, compared to a scenario where effective ethanol capacity remains at the 2005 level. Given that the RFS was established in 2005 through the Energy Policy Act (Smith, 2017) and the mandates started from 2006, selecting the year 2005 allows us to analyze counterfactual effects in the absence of

this government intervention in ethanol production. We use the estimated coefficients on ethanol capacity for cover cropping rates across corn and soy areas, presented in Column (2) in Table 2.2. It is important to note that this counterfactual analysis is a partial analysis, focusing solely on GHG changes resulting from shifts in cover cropping adoption. For instance, our back-of-the-envelope estimates would not account for changes in yields or overall acreage attributable to the RFS.

We use the result in Column (2) in Table 2.2 for our counterfactual analysis for two reasons. First, we believe that controlling for broader year-to-year changes in commodity prices and outlook through year fixed effects is essential given our relatively short panel. Secondly, while the first stage F-statistic of the IV estimation shown in Column (3) of Table 2.2 is over 10 which is considered a common rule of thumb, recent research suggests that the F-statistic should be over 50 for a single IV (Keane and Neal, 2024). Our F-statistic is 21.3 and falls below this criteria, which raises some concerns about a potential weak instrument problem.

2.5.1 Data

Information on how much GHG are sequestered per acre of cover cropped land is required to compute the counterfactual reduction in GHG sequestration resulting from the loss in cover cropping areas. We obtain these reduction coefficients, measured in metric ton of CO_2-eq. per acre per year, from COMET-Planner 3.0[10] (Swan et al., 2022b). The reduction coefficients include carbon sequestration or loss of carbon dioxide, nitrous oxide, and methane associated with the use of cover crops. These coefficients are calculated based on the assumption that the use of nitrogen fertilizer is reduced by 25% when non-legume cover crops are planted.

The emission reduction coefficients (ERC) are based on county-rectified Major Land Resource Areas, defined by the USDA Natural Resources Conservation Service (Swan et al., 2022a). That is, these coefficients are available at the county level, but they remain constant within a Major Land Resource Area. For this reason, the ERCs exhibit spatial variations based on the criteria used to delineate Major Land Resource Areas, which include factors like geology, climate, water resources,

[10] `http://comet-planner.com`. COMET-Planner was developed by the USDA Natural Resources Conservation Service and Colorado State University for the purpose of providing generalized estimates of the GHG impacts of conservation practices during the initial planning stage of conservation projects.

soils, and land use (USDA Natural Resources Conservation Service, 2022).

The ERCs are categorized based on factors such as the use of legume/non-legume cover crops, adoption of no-tillage practice, irrigation of cropland, among others. In this study, we use the coefficients for non-legume cover crops along with tillage practice. Additionally, we calculate the irrigation-weighted average coefficients by utilizing the state-level ratio of irrigated croplands, which we obtained from the USDA's 2017 Census of Agriculture (USDA, 2019). District-level ERCs are calculated by computing weighted average of the county-level coefficients by corn and soy areas. Standard errors of the district-level coefficients are calculated assuming independent distributions of county-level coefficients.

The district-level ERCs of cover crops are mapped in Panel (a) in Figure 2.3. This map shows a general trend where the coefficients tend to be greater in southern districts, particularly in Illinois and Indiana. This general trend primarily depends on the properties of a Major Land Resource Area, such as soil and climate, in which counties within a given district are located. Therefore, the trend implies that the Major Land Resource Areas located in the southern parts of our sample states are likely to have some more suitable properties for carbon sequestration of cover crops. For instance, the Southern Mississippi Valley Loess, one of the Major Land Resource Areas, includes two counties in southern Illinois which exhibit the largest emission reduction coefficients in our sample.

2.5.2 Methodology

Counterfactual Changes in Cover Cropping Areas

Counterfactual change in cover cropping areas resulting from increased ethanol capacity across districts is calculated using the following Equation 2.2:

$$\widehat{\Delta CA_{2015}} = \sum_{i=1}^{I} [\frac{1}{100} \times \widehat{\phi} \times (EC_{i,2005} - EC_{i,2015}) \times A_{i,2015}] = \sum_{i=1}^{I} \widehat{\Delta CA_{i,2015}} \tag{2.2}$$

where $\widehat{\Delta CA_{2015}}$ denotes counterfactual changes in cover cropping areas in 2015 in the absence of the growth in effective ethanol production capacity since 2005. When the sign of $\widehat{\Delta CA_{2015}}$ is positive, it implies that there has been a loss in cover cropping areas due to ethanol expansion. $\widehat{\phi}$

is an estimated coefficient on effective ethanol capacity for cover cropping rates aggregated across corn and soy production areas presented in Column (2) in Table 2.2. $EC_{i,t}$ is the effective ethanol capacity in district i in year t. $A_{i,2015}$ denotes corn and soy acres in district i in 2015. $\Delta\widehat{CA_{i,2015}}$ is the counterfactual change in cover cropping areas on corn and soy fields in district i in 2015.

To calculate the counterfactual change in cover cropping areas, we first obtain differences in ethanol capacities in year 2015 and 2005 by districts. These differences are multiplied by the estimated coefficient on effective ethanol capacity to determine the differences in cover cropping rates between the actual and counterfactual rates by district. To convert these percentage effects into acreage effects, the coefficients are multiplied by the district-level corn and soy acreages. Finally, the calculated counterfactual changes in cover cropping acreages are summed over districts. Our estimates of counterfactual change in cover cropping areas are subject to uncertainty arising from sampling errors in estimating $\widehat{\phi}$. We present 95% confidence intervals for these estimates as shown in Table 2.4.

Counterfactual Reduction in GHG Emissions

Having calculated the counterfactual changes in cover cropping areas using Equation 2.2, we can estimate the resulting annual reduction in GHG sequestration by multiplying the changes in cover cropping areas with the amount of GHG sequestered per acre of cover crops per year. This calculation is presented in Equation 2.3 below. For this calculation, we exclude one district in Ohio due to missing data on standard errors for its emission reduction coefficients.

$$\Delta\widehat{GHG_{2015}} = \sum_{i=1}^{I} [\Delta\widehat{CA_{i,2015}} \times \overline{ERC_i}] \tag{2.3}$$

where $\Delta\widehat{GHG_t}$ denotes counterfactual reduction in GHG emissions in year t as a result of the growth in ethanol production capacity. $\overline{ERC_i}$ is an emission reduction coefficient for district i.

When calculating the counterfactual reduction in GHG emissions, there are two sources of uncertainty: $\widehat{\phi}$ and $\overline{ERC_i}$. To address these uncertainties, we calculate the overall uncertainty in the estimate of counterfactual GHG emissions reduction using a bootstrap procedure. For each bootstrap sample, we randomly sample $\widehat{\phi}$ and $\overline{ERC_i}$ from each distribution, calculate district-level

reductions in GHG emissions, and sum them over districts. We obtain the standard error of the reductions in GHG emissions, using 1,000 bootstrap replications.

2.5.3 Results

Table 2.4 presents the calculation results for counterfactual changes in cover cropping areas and the reduction in GHG emissions in 2015 under a scenario where the effective ethanol capacity remains at its 2005 level. Column (1) displays the results using the estimated coefficients from Column (1) in Table 2.2, which are estimated using the FE method. Column (2) presents the counterfactual GHG emissions reduction resulting from the counterfactual loss in cover cropping areas shown in Column (1).

Under our counterfactual scenario in the absence of ethanol capacity growth since 2005, the results show that we would have observed an additional 570.5 thousand acres of cover crops in the Midwest in 2015. To put this in context, this counterfactual loss in 2015 would have raised cover cropping rates by 0.7 percentage points, from 2.8% to 3.4% in our study area. We further conduct a back-of-the-envelope calculation of the counterfactual reduction in GHG emissions, resulting from the loss in cover cropping areas. In our study area, we would have reduced emissions by 100.1 thousand metric ton of CO_2-eq. if ethanol capacity had stayed at 2005 level. When we apply the social cost of carbon as \$190 per ton of carbon dioxide, recently proposed by the Environmental Protection Agency in 2022, the counterfactual damages amount to \$19.0 million (Environmental Protection Agency, 2022).

Table 2.4 Counterfactual Cover Cropping Area Loss and GHG Emissions Reduction in 2015

	(1) Counterfactual Increase in CC Area (thousand acres)	(2) Counterfactual GHG Sequestration Increase (thousand tCO_2-eq.)
Total	570.5 [62.1 to 1,078.9]	100.1 [9.5 to 190.8]

Intervals in brackets represent 95% confidence interval

Figure 2.3 shows the counterfactual changes in cover cropping areas in 2015 by districts. We find that these counterfactual changes are more pronounced in districts that experienced larger shifts

in ethanol capacity and with larger corn and soy areas. While the emission reduction coefficients of cover crops are larger in the southern part of Indiana and Ohio, as illustrated in Panel (a) in Figure 2.3, Panel (c) of Figure 2.3 shows that greater counterfactual reduction in GHG emissions occurs in the northern part of Illinois and Iowa showing a similar pattern to Panel (b).

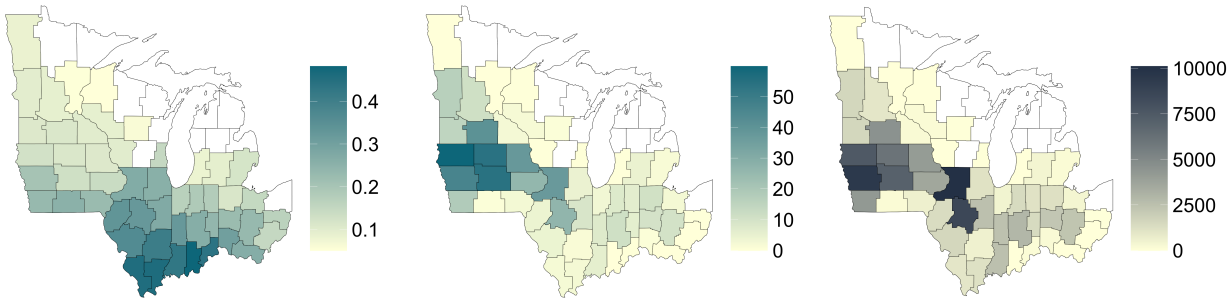

Figure 2.3 **Counterfactual Changes in Cover Cropping Areas and Reduction in GHG Emissions in 2015**: The figures show (a) the district-level emission reduction coefficients, (b) counterfactual changes in cover cropped acres based on the estimates in Table 2.2, and (c) the counterfactual reduction in GHG emissions. Panel (c) is calculated by multiplying the values in panel (a) and panel (b). The emission reduction coefficients, obtained from the COMET-Planner, represent the amount of GHG emissions reduced per acre of cover cropped land.

2.6 Conclusions

This study investigates how one major change in local output demand– increased ethanol production– has affected the adoption of cover cropping in the Midwest. We exploit changes in ethanol production capacity as local demand shocks for corn to estimate output demand's effect on cover cropping adoption. We find suggestive evidence that an increase in ethanol production capacity has negative effects on cover cropping adoption in the Midwest. Our preferred model implies that a 100 MGY increase in effective capacity reduces nearby cover cropping rates by 0.35 percentage points. The empirical results are suggestive that when output demand increases, farmers are less likely to adopt cover cropping, as they may perceive its short-term yield penalties to outweigh the long-term yield benefits.

These findings contribute to a growing body of literature examining the environmental trade-offs of biofuel policies. Prior research has demonstrated that the RFS has contributed to land-use change by increasing the incentive to plant corn, leading to higher rates of land conversion from grasslands

and other non-cropland uses (Searchinger et al., 2008; Fargione et al., 2008; Lark et al., 2022). Our results suggest that the expansion of ethanol demand may also discourage cover cropping and thus affect the carbon impact of the RFS through a reduction in carbon sequestration. One could view Lark et al. (2022) as essentially estimating the carbon impact of ethanol policy through an extensive margin channel of shifting land use. Our paper, in contrast, estimates one particular intensive channel: when demand for corn rises, farmers may prioritize short-term productivity and reduce (or forego adoption of) cover cropping practices, particularly if they perceive cover crops as imposing yield risks or additional management costs.

How large are the reductions in cover cropping due to ethanol expansion? From a carbon standpoint, quite small. Although we cannot make a perfect apples-to-apples comparison due to differences in the geographic and temporal scope, Lark et al. (2022) estimates that land use changes attributable to the RFS reduced ecosystem carbon sequestration by a total of roughly 400 million tons of CO_2-eq. versus the 100 thousand tons we estimate in foregone 2015 carbon sequestration. From a cover cropping perspective, our estimates appear somewhat larger: our estimates imply that returning to 2005 ethanol capacity levels would raise cover cropping rates in our sample from 2.8% to 3.4%, an increase of over 20%. Our estimates are also large relative to the effect on cover cropping of other government policies. For example, the USDA's EQIP enrolled 3.5 million acres of farmland in cover cropping contracts in fiscal year 2019. Thus, our estimated reduction in cover cropping acreage is over 15% of this total, a meaningful reduction in the national level of cover cropping.

Our results underscore the need for better integration of biofuel and conservation policies. The environmental benefits of biofuels depend, in part, on how they affect broader land management practices. If higher demand for biofuels suppresses conservation efforts, the net climate benefits of biofuel policies may be overstated. One potentially promising measure is to tie participation in biofuel incentive programs to adoption of conservation practices. An example of this includes the 45Z tax credit introduced by the 2022 Inflation Reduction Act, which provides differential incentives based on the adoption of conservation practices, including cover cropping.

More broadly, our results suggest that conservation adoption may be influenced by broader trends in commodity prices and supply-and-demand factors. A better understanding of how agricultural conservation goals are shaped by these forces may help to more effectively target conservation incentive resources. We hope this work prompts further investigation of how to best consider market factors when designing environmental incentive programs.

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APPENDIX 2A

FIRST-STAGE REGRESSION RESULTS

Table 2A.1 The First-stage Regression

	(1)	(2)
IV	0.00003**	0.00000
	(0.00001)	(0.00001)
October Temperature (°C)	−0.018**	−0.120***
	(0.008)	(0.030)
November Temperature (°C)	0.013	−0.005
	(0.011)	(0.036)
October Precipitation (mm)	−0.0001	−0.0005
	(0.001)	(0.001)
November Precipitation (mm)	−0.001	−0.002***
	(0.001)	(0.001)
Time Trends		
Time_{Iowa}	0.281***	0.295***
	(0.067)	(0.057)
$\text{Time}_{Illinois}$	0.068	0.109**
	(0.053)	(0.049)
$\text{Time}_{Indiana}$	0.075**	0.080***
	(0.033)	(0.027)
$\text{Time}_{Michigan}$	−0.024	
	(0.032)	
$\text{Time}_{Minnesota}$	0.080	0.098*
	(0.058)	(0.053)
Time_{Ohio}	0.018	0.037
	(0.035)	(0.030)
$\text{Time}_{Wisconsin}$	0.013	0.013
	(0.026)	(0.028)
District FE	Yes	Yes
Year FE	No	Yes
Observations	510	510
First stage F-statistic	21.3	0.03

*p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the state-by-year and district level

APPENDIX 2B

ESTIMATION RESULTS USING 50-KM RADIUS

We present estimation results using 50-km boundary to compute effective ethanol capacity, rather than the 30-km boundary used in our preferred specification. We find similar results to the main results reported in Table 2.2, suggesting negative effects of ethanol capacity on cover cropping adoption.

Table 2B.1 Estimation Results with 50-km Boundary: Cover Cropping Rates

	OLS		IV	
	(1)	(2)	(3)	(4)
Effective Ethanol	−0.67***	−0.39**	−3.32***	−25.41
Capacity (100 MGY)	(0.22)	(0.18)	(1.04)	(203.55)
October	0.236*	−0.176	0.152	−3.031
Temperature (°C)	(0.125)	(0.255)	(0.113)	(23.314)
November	0.264***	0.018	0.314***	−0.010
Temperature (°C)	(0.086)	(0.254)	(0.085)	(0.934)
October	0.002	0.004	0.001	−0.009
Precipitation (mm)	(0.003)	(0.004)	(0.003)	(0.106)
November	−0.006	−0.007	−0.010*	−0.060
Precipitation (mm)	(0.005)	(0.007)	(0.005)	(0.428)
District FE	Yes	Yes	Yes	Yes
State Trends	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	510	510	510	510
First-stage F-stat			24.9	0.04
Adjusted R-squared	0.627	0.640		

*p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the state-by-year and district level
R-squared is not provided for IV regressions, as it does not have natural interpretation as in the OLS regressions

APPENDIX 2C

ESTIMATION RESULTS ON COVER CROPPING AREAS

Table 2C.1 reports estimations results with logarithm of cover cropping acreage as an outcome variable. Columns (1) to (3) present estimation results for cover cropping adoption on corn/soy fields. Areas with no cover cropping acreage are assigned a value of ln(1). We find negative effects across all specifications. Based on Column (1), a 100 MGY increase in effective ethanol capacity decreases cover cropping areas by 20%. While this effect appears large in magnitude, given the relatively small baseline cover cropping acreage, it corresponds to a reduction of only 4,004 acres in a district at the sample mean of cover cropping acreage.

Table 2C.1 Estimation Results: Ln(Cover Cropping Areas)

	(1) OLS-FE	(2) OLS 2-Way FE	(3) IV
Effective Ethanol Capacity (100 MGY)	−0.20* (0.11)	−0.15 (0.10)	−0.80 (0.71)
October Temperature (°C)	0.112** (0.050)	−0.327** (0.161)	0.093* (0.049)
November Temperature (°C)	0.066 (0.040)	−0.130 (0.133)	0.077** (0.033)
October Precipitation (mm)	0.002 (0.002)	0.004** (0.002)	0.001 (0.002)
November Precipitation (mm)	−0.001 (0.003)	−0.004 (0.003)	−0.002 (0.003)
District FE	Yes	Yes	Yes
State Trends	Yes	Yes	Yes
Year FE	No	Yes	No
Observations	510	510	510
First-stage F-stat			21.3
Adjusted R-squared	0.587	0.640	

*p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the state-by-year and district level
R-squared is not provided for IV regressions, as it does not have natural interpretation as in the OLS regressions

APPENDIX 2D

ADDITIONAL CONTROLS

Table 2D.1 Estimation Results: Additional Controls

	(1) OLS-FE	(2) OLS 2-Way FE	(3) IV
Effective Ethanol Capacity (100 MGY)	−0.59** (0.29)	−0.36 (0.26)	−4.25** (2.02)
October Temperature (°C)	0.334* (0.172)	−0.223 (0.257)	0.216 (0.159)
November Temperature (°C)	0.266*** (0.080)	−0.125 (0.225)	0.315*** (0.088)
Total October Precipitation (mm)	0.005 (0.005)	0.006 (0.006)	0.003 (0.004)
Total November Precipitation (mm)	−0.007 (0.007)	−0.007 (0.009)	−0.011* (0.006)
EQIP Acreage (million acres)	0.606*** (0.163)	0.285 (0.236)	0.075 (0.390)
Conservation Tillage (%)	0.079** (0.033)	0.041 (0.037)	0.088* (0.045)
District FE	Yes	Yes	Yes
State Trends	Yes	Yes	Yes
Year FE	No	Yes	No
Observations	456	456	456
First stage F-stat			12.2
Adjusted R-squared	0.630	0.643	

*p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the state-by-year and district level
R-squared is not provided for IV regressions, as it does not have natural interpretation as in the OLS regressions

APPENDIX 2E

RESPONSE NON-LINEARITY

Table 2E.1 Estimation Results: Non-linearity

	(1) OLS-FE	(2) OLS 2-way FE	(3) IV
Effective Ethanol Capacity (100 MGY)	−1.240***	−0.764**	−7.204
	(0.397)	(0.311)	(7.879)
Squared Effective Ethanol Capacity	0.097**	0.058*	1.232
	(0.039)	(0.030)	(2.047)
October Temperature (°C)	0.231*	−0.185	0.197***
	(0.123)	(0.253)	(0.070)
November Temperature (°C)	0.268***	0.011	0.302***
	(0.086)	(0.253)	(0.080)
October Precipitation (mm)	0.002	0.004	0.002*
	(0.003)	(0.004)	(0.001)
November Precipitation (mm)	−0.006	−0.007	−0.004
	(0.005)	(0.007)	(0.009)
District FE	Yes	Yes	Yes
State Trends	Yes	Yes	Yes
Year FE	No	Yes	No
Observations	510	510	510
First stage F-stat			
Effective Ethanol Capacity			29.2
Sq. Effective Ethanol Capacity			6.4
F-stat (H^0: The sum of the ethanol capacity coefficients=0)	5.53	3.15	7.84
Adjusted R-squared	0.629	0.641	

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the state-by-year and district level

R-squared is not provided for IV regressions, as it does not have natural interpretation as in the OLS regressions

APPENDIX 2F

CONTROLLING FOR CORN FUTURES PRICE

This section provides estimation results controlling for corn futures price. We do not report results with year fixed effects as our corn futures price data do not have within-year spatial variation. We find consistent, albeit slightly large in magnitude, results to our preferred specification. Considering the IV approach, controlling for corn futures prices substantially weakens our instrument and generally renders the IV estimates unreliable.

Table 2F.1 Estimation Results: Controlling for Corn Futures Price

	(1)	(2)	(3)	(4)	(5)	(6)
	After Corn/Soy		After Corn		After Soy	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Ethanol Capacity (100 MGY)	−0.50***	−7.10	−0.46***	−7.66	−0.46*	−5.30
	(0.17)	(5.42)	(0.15)	(6.41)	(0.23)	(4.46)
Ln(Corn Futures Price)	−1.010	5.603	1.642	8.853	−3.694**	1.153
	(1.012)	(5.688)	(1.152)	(6.579)	(1.638)	(5.336)
October Temperature (°C)	0.252*	−0.031	0.086	−0.223	0.458**	0.251
	(0.134)	(0.304)	(0.090)	(0.311)	(0.224)	(0.341)
November Temperature (°C)	0.286***	0.247**	0.168**	0.126	0.396***	0.368***
	(0.088)	(0.104)	(0.065)	(0.083)	(0.123)	(0.131)
October Precipitation (mm)	0.002	0.002	−0.002	−0.001	0.006	0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
November Precipitation (mm)	−0.007	−0.010*	−0.007	−0.010	−0.007	−0.009
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	510	510	510	510	510	510
First stage F-stat		3.1		3.1		3.1
Adjusted R-squared	0.627		0.495		0.595	

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the state-by-year and district level

R-squared is not provided for IV regressions, as it does not have natural interpretation as in the OLS regressions

CHAPTER 3

EFFECTS OF CROP INSURANCE ON WATER USE: MITIGATING EFFECTS OF IRRIGATION COSTS

3.1 Introduction

Since the 1980's, the federal crop insurance program expanded rapidly, becoming one of the most widely adopted risk management tools for farmers in the United States (Glauber, 2013). The number of net insured acres increased from 102 million acres in 1989 to 445 million acres in 2020 (Risk Management Agency, 1994, 2024). With growing participation in crop insurance, concerns persist over potential moral hazard behavior, where insured farmers make riskier management decisions affecting the probability of receiving indemnities (e.g., Babcock and Hennessy (1996), Weber et al. (2016), Deryugina and Konar (2017), Yu and Sumner (2018), Regmi et al. (2022)).

Participation in crop insurance may lead to riskier management decisions such as a greater use of risk-increasing inputs or reduced use of risk-decreasing inputs. Inputs are considered risk-decreasing if they reduce the probability of having low yields. For instance, irrigation primarily serves as a risk-reducing input, with additional water use lowering the probability of low yields. Insurance coverage may lead to reduced input use, especially when farmers anticipate poor yields (Yu and Hendricks, 2020). In such cases, it may be more profitable for them to lower input use and receive indemnities rather than applying more inputs to possibly increase yields. While there is extensive literature on moral hazard behavior in input use, studies on examining water use remain limited.[1] In addition, input prices may affect this moral hazard behavior by altering the marginal profit of additional input use (Suchato et al., 2022). For instance, in water-stressed regions where water prices are typically higher, the reduction in water use in response to insurance coverage may be more pronounced compared to regions with abundant water resources.

Examining the impact of crop insurance enrollment on water use is particularly crucial in light of the growing concerns over groundwater depletion and water scarcity. In the United States,

[1] Another related problem is adverse selection. However, considering that crop insurance is highly subsidized, more than 60% for some coverage levels, the adverse selection problem is less of a concern in the case of crop insurance (Suchato et al., 2022; Schnitkey et al., 2023).

droughts in western states and declines in groundwater levels in major aquifers have underscored issues regarding water availability in times of potential weather shocks (McGuire, 2017; Bruno and Sexton, 2020; Hrozencik and Aillery, 2021). Various programs, including water pricing schemes and regulations, have been implemented to manage agricultural water demand. Further analysis on crop insurance and water use will offer insights into how farmers change water use decisions in response to other agricultural policies.

This study investigates how per-acre water use is affected by participation in crop insurance. We estimate the heterogeneous effects of insurance participation on water use depending on irrigation costs. We use crop-specific water use data for five major crops (corn, soybeans, wheat, cotton, and sorghum) focusing on regions overlying the High Plains Aquifer (HPA). Using crop-specific water use information allows to directly estimate moral hazard in water use, accounting for changes in acreage and crop choices.

The major challenge in identifying the effects of crop insurance on water use is the potential endogeneity between insurance participation and input use (Smith and Goodwin, 1996; Weber et al., 2016; Deryugina and Konar, 2017; Biram et al., 2024). Farmers are likely to jointly make insurance enrollment and water use decisions, which biases our estimates. To address this endogeneity problem, we adopt an instrumental variable (IV) approach. In particular, we exploit exogenous variation in government-set premium subsidy rates and insurance uptake in 2007, prior to our sample period, building on the literature (Yu et al., 2018; DeLay, 2019; Connor and Katchova, 2020; Connor et al., 2022; Biram et al., 2024). The underlying assumptions are that premium subsidy rates and the prior year's insurance uptake do not affect the current year's water use, other than by influencing the current year's insurance participation.

To estimate heterogeneous effects by irrigation costs, we use the costs of extracting a unit of groundwater as a proxy for water prices. This approach has been taken in previous studies, due to the lack of volumetric pricing of water for agricultural use (Hendricks and Peterson, 2012; Bruno and Jessoe, 2021; Burlig et al., 2021). Unit pumping costs represent marginal price of groundwater

use for irrigation.[2] Our empirical approach allows us to compare how crop insurance affects water use between counties with higher and lower unit pumping costs. To ensure that pumping costs represent relevant irrigation costs, we focus on counties overlying the HPA that primarily rely on groundwater for irrigation. We use county-crop-year observations for five major field crops over the period between 2008 and 2020.

We first find empirical evidence of moral hazard behavior in water use under prevailing pumping costs, where increased insurance participation results in a decrease in per-acre water use. This finding aligns with the theoretical predictions that insurance coverage may weaken incentives to apply risk-reducing inputs when marginal returns are uncertain or low. Second, we find consistent evidence that insurance participation increases water use per acre when pumping costs are low, contrary to the expectations of moral hazard behavior in input use. We suggest possible explanations for this positive effect with our conceptual framework and forward-looking behavior of farmers taking the effect of current year's yields on future indemnity level into account. Furthermore, our findings suggest that higher pumping costs reverse this positive water use response to insurance. When the pumping costs are high enough, the effect of crop insurance on water use eventually becomes negative. This implies that in areas where water prices are high, potentially due to policies increasing water prices or diminished supply, insured farmers are more prone to reduce water use in response to insurance coverage than ones in areas with abundant water and lower water prices.

Our contributions to the literature are two-fold. First, we contribute to the moral hazard literature by providing empirical evidence on moral hazard in water use. Prior work has focused on moral hazard in inputs such as fertilizer and pesticides (Smith and Goodwin, 1996; Goodwin et al., 2004; Regmi et al., 2022). We expand on this by empirically analyzing moral hazard in water use which has received less attention (Deryugina and Konar, 2017; Ghosh et al., 2021; Suchato et al., 2022). In addition, we find that moral hazard behavior may vary depending on input prices, with higher input prices associated with increased moral hazard.

[2]We use "unit pumping costs" and "pumping costs" interchangeably. They both refer to the costs to extract a unit of groundwater to surface.

Second, our paper is also relevant to the studies on water demand for agricultural use. There exists a large body of literature on the analysis of water demand. While existing studies have largely focused on direct factors such as water prices (Schoengold et al., 2006; Bruno and Jessoe, 2021) and water regulations (Drysdale and Hendricks, 2018), our paper adds to this body of work by exploring how other agricultural policies may indirectly influence water use decisions. Our findings suggest that higher water prices can indirectly reduce per-acre water use through moral hazard effects. This indirect effect lowers water use further, in addition to the direct price effect. Therefore, this indirect effect needs to be considered when designing and evaluating water pricing policies to ensure efficient water resource management.

This paper proceeds in the following way. Section 3.2 discusses background for crop insurance and the HPA. Then, we use a simple conceptual model to demonstrate that the effect of insurance uptake on water use is ambiguous, depending on the relative magnitudes of risk aversion and moral hazard. This finding motivates our empirical analysis in Section 3.4 to Section 3.6, which provides empirical evidence that moral hazard behavior depends on pumping costs. Section 3.7 presents counterfactual estimates of water savings resulting from reduced insurance participation. The paper concludes with Section 3.8.

3.2 Background

3.2.1 Crop Insurance Program

The United States federal crop insurance program, operated by the Risk Management Agency (RMA) and the Federal Crop Insurance Corporation, offers a wide range of insurance plans designed to support farmers. The two most common plans are yield protection (YP) and revenue protection (RP), which accounted for 5.4% and 70.6% of total liability in 2022, respectively (Risk Management Agency, 2024). Both RP and YP use average historical yields, calculated by averaging past yields over a period of four to ten years. This method of averaging past yields to determine expected yield is known as Actual Production History (APH) yields.[3]

[3]There is a separate insurance plan called "Actual Production History", which works similarly to the YP plan. The difference between the two plans is that farmers select the percentage of the predicted price to insure with the Actual Production History plan. (`https://www.rma.usda.gov/Policy-and-Procedure/Insurance-Plans/`

Crop insurance is a subsidized program, where the government subsidizes the insurance premium as well as the administrative and operational costs. If the premium rates were actuarially fair, as targeted by the RMA, the expected net profit gain of purchasing insurance policies for farmers would be equal to the premium subsidy. With the support of the premium subsidy and the subsequent expected net profit gain, insurance participation in the United States has steadily increased, reaching 86.3% in 2021 in terms of insured acreage (United States Department of Agriculture, 2023). Figure 3.1 shows the changes in subsidy rates, defined as the ratio of premium subsidies to total premiums, by coverage levels for selected crops including corn, soybeans, wheat, sorghum, and cotton. The subsidy rates for the 0.65 and 0.75 coverage levels show slight but steady increases over time, while the subsidy rates for the 0.85 coverage level have remained stable since 2011.

The RMA sets the premium rates according to the risk exposure of production, considering factors such as the riskiness of crops being insured, selected coverage levels, and farming practices. For example, as irrigated production carries less risk compared to non-irrigated production, the premium rate for irrigated production is correspondingly lower. The RMA requires farmers to have an adequate water supply for irrigation and to show that they have actually applied sufficient irrigation to receive an indemnity. These requirements are likely to discourage moral hazard behavior in input use, if they were perfectly enforced. However, enforcement is unlikely to be perfect in reality due to the high cost of monitoring (Atwood et al., 2006; Suchato et al., 2022).

3.2.2 High Plains Aquifer

The HPA, spanning 118.8 million acres and being one of the largest aquifers globally, overlies parts of eight states in the United States: Colorado, Kansas, Nebraska, New Mexico, Oklahoma, South Dakota, Texas, and Wyoming (McGuire, 2017). More than 95% of the water withdrawal from the HPA is used for irrigation and it supplies irrigation to about 27% of irrigated lands in the United States (Miller and Appel, 1997; Dennehy, 2000). The principal crops cultivated on the regions overlying the HPA are corn, wheat, sorghum, cotton, and alfalfa. Geographically, the HPA is divided into three regions: northern, central, and southern.

Actual-Production-History)

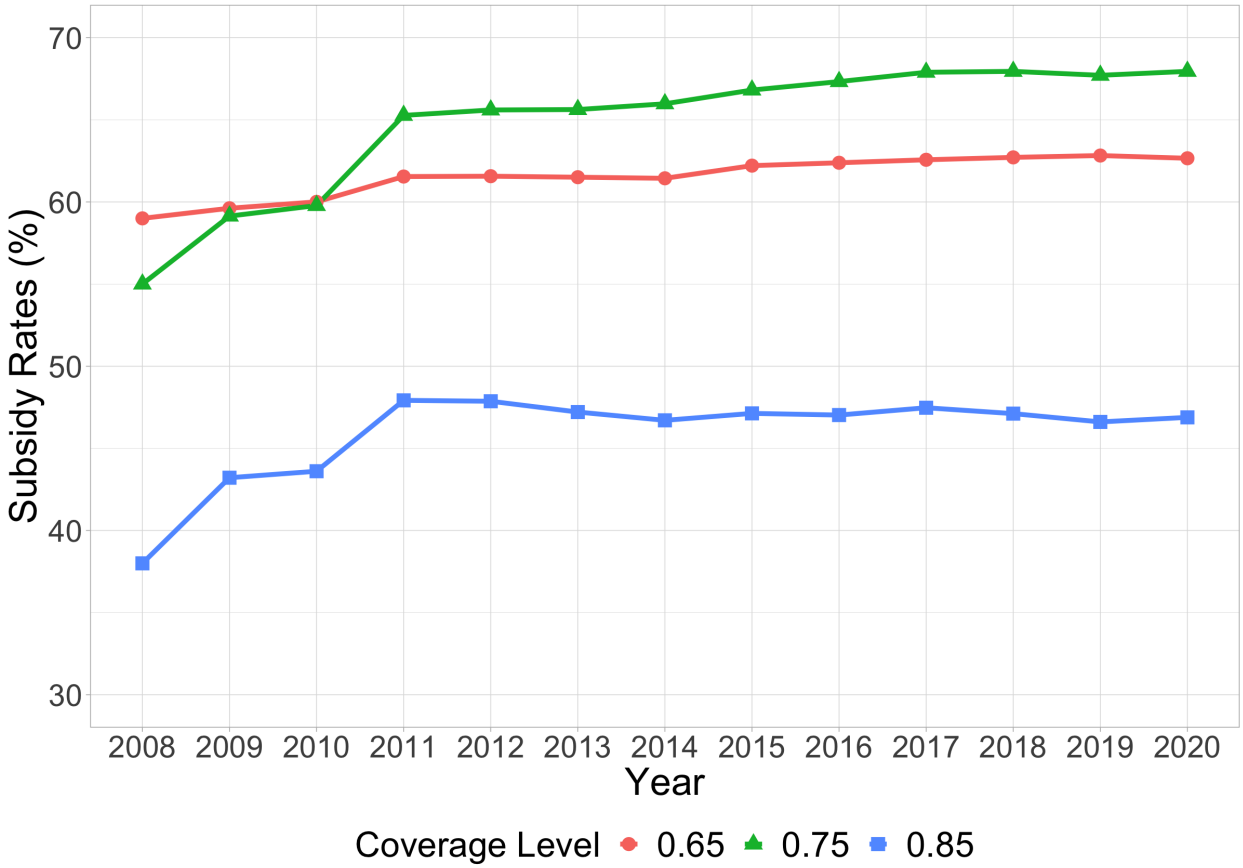

Figure 3.1 **Changes in premium subsidy rates between 2008 and 2020**: This figure represents aggregated subsidy rates for corn, soybeans, wheat, sorghum, and cotton. The subsidy rates are defined as the ratio of premium subsidies to total premiums.

With groundwater extraction rates surpassing natural recharge rates, many parts of the HPA have witnessed rapid declines in water levels (McGuire, 2017). The substantial declines in water level in the HPA can be in part attributed to introduction of center pivot irrigation system during the 1960s (Perez-Quesada et al., 2023). Geographically, declines in the water table are more prominent in the Central and Southern High Plains than the declines in the Northern High Plains. The largest average water-table declines from pre-development to 2015 were observed in Texas and Kansas, with declines of 41.1 feet and 26.2 feet, respectively (McGuire, 2017). South Dakota and Nebraska, which overlie the Northern High Plains, experienced only slight changes in water levels, an increase of 0.5 feet and a decrease of 0.9 feet, respectively, during the same period (McGuire, 2017). These large differences in changes of water levels across regions on the HPA might have been affected by differences in natural recharge rates. While the recharge rates in the Northern High Plains are large

enough to offset a substantial portion of the outflows, the Central and Southern High Plains suffer depletion due to relatively low recharge rates (Dennehy et al., 2002; Scanlon et al., 2012; Karki et al., 2021).

Figure 3.2 illustrates the changes in the depth to groundwater tables between 2008 and 2020 across counties within our study area. During this period, groundwater levels generally increased in the Northern High Plains, while they declined in many counties in the Central and Southern High Plains.

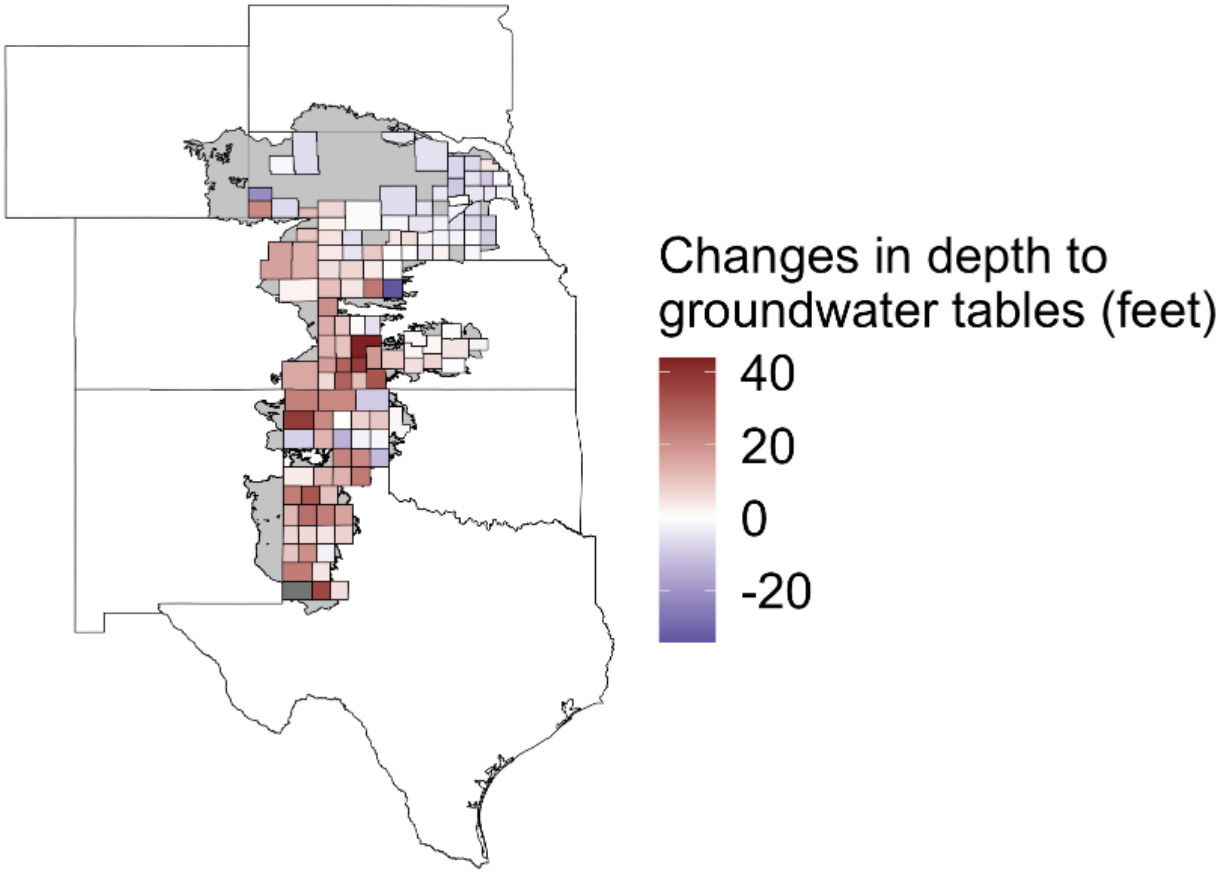

Figure 3.2 **Changes in depth to groundwater tables between 2008 and 2020**: Positive numbers indicate a fall in groundwater tables, while negative numbers indicate a rise. Gray areas represent regions overlying the HPA that are not included in the analysis.

3.3 Conceptual Framework

We present a simple conceptual framework of moral hazard behavior in input use, drawing from the works of Babcock and Hennessy (1996) and Horowitz and Lichtenberg (1993). We aim to

demonstrate conditions under which per-acre water use may increase or decrease when insurance uptake increases. We explain that even with the moral hazard behavior, we may not observe a decrease in per-unit water use under certain conditions. Furthermore, we attempt to demonstrate that changes in irrigation costs can affect water use response to participation in crop insurance.

Consider a representative farmer who chooses the amount of water applied, X, at the price of W_X, and insured yield level, Y^I, for their YP insurance plan.[4] Farmers are paid for a yield of Y^I whenever their actual yields fall below this value. Therefore, a larger value of Y^I implies a greater level of insurance. Assuming $X^*(Y^I)$ is the farmer's optimal water choice in response to Y^I (derived below), then we say that we observe moral hazard when $\frac{dX^*(Y^I)}{dY^I} < 0$.

We assume that crop yield Y is stochastic and that its distribution is conditional on X. Specifically, let $g(Y|X)$ be the probability density function (pdf) of Y.[5] Under the YP, the farmer's yield from an insured acre is determined as the maximum of the realized yield, Y, and insured yield level, Y^I. Then, the farmer's profit function can be written as follows:

$$\pi = max(PY, P^I Y^I) - W_X X \tag{3.1}$$

where P and P^I denotes the output price and the indemnity price. These profits are uncertain and we assume the farmer is risk-averse with an increasing, concave utility function $U(\pi)$. Assuming Y is distributed between a and b with $Y^I \in (a, b)$, then the farmer's maximization problem is as follows:

$$\max_{\{X\}} EU = \int_a^{Y^I} U(\pi_1) g(Y|X) dY + \int_{Y^I}^b U(\pi_2) g(Y|X) dY \tag{3.2}$$

where $\pi_1 = P^I Y^I - WX$ and $\pi_2 = PY - WX$.

The first order condition (FOC) of this maximization problem is

$$\int_a^{Y^I} U(\pi_1) \frac{\partial g(Y|X)}{\partial X} dY + \int_{Y^I}^b U(\pi_2) \frac{\partial g(Y|X)}{\partial X} dY - WEU'(\pi) = 0 \tag{3.3}$$

[4]We can draw the identical implications for RP insurance plan by considering the distribution of revenue, rather than yield. The underlying assumption of this approach is that insured farmers choose insured revenue level when purchasing insurance.

[5]The pdf $g(Y|X)$ describes the stochastic relationship between yield and water use. An alternative approach is to define a stochastic production function $Y(X, \phi)$, where ϕ is a random weather variable with pdf $h(\phi)$. Focusing on Y rather than ϕ as the random variable facilitates our analysis by letting us introduce the indemnity level Y^I into the expected utility function (see Equation 3.2).

where $EU'(\pi) = \int_a^{Y^I} U'(\pi_1)g(Y|X)dY + \int_{Y^I}^b U'(\pi_2)g(Y|X)dY$.

$$\int_{Y^I}^b U(\pi_2)\frac{\partial g(Y|X)}{\partial X}dY = WEU'(\pi) - \int_a^{Y^I} U(\pi_1)\frac{\partial g(Y|X)}{\partial X}dY \tag{3.4}$$

The optimal amount of water, $X^*(Y^I)$, solves the FOC, conditional on the insurance parameter Y^I. We obtain Equation 3.4 by rearranging the FOC given in Equation 3.3. If we assume that additional water improves yields, then, the left-hand side of the equation represents the marginal benefit of additional water use, or an increase in the expected utility resulting from changes in the probabilities of achieving high yields ($Y > Y^I$). The elements on the right-hand side represent the marginal cost of additional water use. The first element, $WEU'(\pi)$, is the marginal change in expected utility from an increase in water use, conditional on initial yield distribution, $g(Y|X)$. This term implies a loss in expected utility when additional water does not affect yield levels. The second element, $\int_a^{Y^I} U(\pi_1)\frac{\partial g(Y|X)}{\partial X}dY$, refers to a decrease in expected utility resulting from changes in the probabilities of achieving low yields ($Y < Y^I$). $X^*(Y^I)$ is chosen to ensure that the marginal benefit equals the marginal cost.

The effect of an insured level of yield on optimal water use can be derived through a comparative analysis of the FOC. The total derivative of the FOC gives:

$$\frac{\partial^2 EU}{\partial X^2}dX + \frac{\partial^2 EU}{\partial X \partial Y^I}dY^I = 0 \tag{3.5}$$

Rearranging Equation 3.5, we obtain:

$$\frac{dX^*}{dY^I} = -\frac{\frac{\partial^2 EU}{\partial X \partial Y^I}}{\frac{\partial^2 EU}{\partial X^2}} \tag{3.6}$$

Using Leibniz's Rule, Equation 3.7 is obtained through comparative statics:

$$\frac{dX^*}{dY^I} = -\left(\frac{\partial^2 EU}{\partial X^2}\right)^{-1}\left[-WP^I U''(\pi_1)\int_a^{Y^I} g(Y|X)dY + P^I U'(\pi_1)\int_a^{Y^I}\frac{\partial g(Y|X)}{\partial X}dY\right] \tag{3.7}$$

$\frac{\partial^2 EU}{\partial X^2}$ is assumed to be negative due to diminishing marginal returns. Equation 3.7 can be rearranged as:

$$\frac{dX^*}{dY^I} = -\left(\frac{\partial^2 EU}{\partial X^2}\right)^{-1} P^I U'(\pi_1)\int_a^{Y^I} g(Y|X)dY\left[W\frac{-U''(\pi_1)}{U'(\pi_1)} + \frac{dlog\int_a^{Y^I} g(Y|X)dY}{dX}\right] \tag{3.8}$$

Equation 3.8 is identical to Equation (5) in Babcock and Hennessy (1996), which analyzes the effect of insurance on fertilizer application. The term outside of the bracket in Equation 3.8 is positive as $U'(\pi_1)$ is assumed to be positive. The first term inside the bracket, $W\frac{-U''(\pi_1)}{U'(\pi_1)}$, captures the risk aversion of the farmer, where the term $-\frac{U''(\pi_1)}{U'(\pi_1)}$ is the Arrow-Pratt absolute risk aversion measure. If we assume that the farmer is risk-averse, then the first term in the bracket is positive. This suggests that farmers with higher risk aversion would experience higher utility from a marginal increase in water use.

The second term inside the bracket is the change in the cumulative density at Y^I when additional water is applied. This term represents moral hazard behavior, which captures the marginal effect of water use on the probability of being indemnified. We assume that water is risk-reducing, meaning that additional water decreases the probability of low yields ($Y < Y^I$).[6] Consequently, the second term in the bracket becomes negative. Hence, in cases where an input is risk-reducing, as in our case, the farmer reduces the input use to increase the chances of being indemnified.

The optimal water use response to the change in an insured yield level depends on the relative magnitudes of the two terms in the bracket, and the direction of the response remains ambiguous based on our conceptual model. If the farmer is risk-averse to the point where the marginal increase in the utility from additional water outweighs the marginal decrease in the probability of receiving indemnity, an increase in Y^I would lead to a rise in optimal water use. This suggests that even when the moral hazard behavior exists, captured in the term $\frac{dlog\int_a^{Y^I} g(Y|X)dY}{dX}$, the effect may not be observed when it is outweighed by the risk aversion.

What happens to $\frac{dX^*}{dY^I}$ when the cost of water, W, increases? When W increases, the first term in the bracket of Equation 3.8, $W\frac{-U''(\pi_1)}{U'(\pi_1)}$, increases. In addition to this direct effect, an increase in W would indirectly lower the optimal use of water, X^*, which affects the second term in the bracket of Equation 3.8, $\frac{dlog\int_a^{Y^I} g(Y|X)dY}{dX}$. We assume that the marginal effect of increasing water use on reducing the probability of receiving indemnity is greater when X^* is smaller. This assumption would hold when additional water has a greater impact on crop growth at lower initial water use

[6]While additional water usage can potentially elevate yield risk, contingent upon subsequent weather conditions post-irrigation, our framework primarily concentrates on scenarios where irrigation is considered risk-reducing.

levels. Under this assumption, the term $\frac{dlog \int_a^{Y^I} g(Y|X)dY}{dX}$ would become more negative as irrigation cost increases. Therefore, the effect of W on $\frac{dX^*}{dy_1^I}$ would depend on the relative sizes of these direct and indirect effects.[7] In the following section, we turn to the empirical analysis to explore how water use responds to crop insurance participation and examine the effects of irrigation costs on this water use response.

3.4 Empirical Setting and Data

We focus on 128 counties in five states overlying the HPA that primarily use groundwater for irrigation: Colorado, Kansas, Nebraska, Oklahoma, and Texas.[8] Since we use pumping costs to extract groundwater as a source for irrigation costs, we need to ensure the availability and accessibility to groundwater. Following Perez-Quesada et al. (2023), we first limit our study area to counties with a proportion of their total area over the HPA larger than 60% and exclude counties in Nebraska whose proportion of their total area lie over the sand hills by more than 55%. The sand hills in Nebraska predominantly consist of sand dunes and are generally unsuitable for crop production, with over 90% of the area being covered by grassland or pasture land (USDA NRCS, 2022). We further restrict the study area to counties where groundwater is the source for more than 70% of the total water used, on average across the study period from 2008 to 2020.[9] Table 3.1 shows the summary statistics of the main variables used in our analysis. Observations with zero values constitute about 1.6% of the total observations.

Annual crop-specific water use information at the county level is derived from a dataset generated by applying the methodology of Ruess et al. (2023) to the United States Geological Survey (USGS)'s "Total Irrigation" category, created by the authors of Ruess et al. (2023).[10] This category includes both agricultural irrigation and irrigation for other purposes, such as irrigation for golf courses.

[7] Babcock and Hennessy (1996) examines the effect of risk aversion, $\frac{-U''(\pi_1)}{U'(\pi_1)}$, on the response of fertilizer use to an increase in insurance uptake, similar to our argument. They find that dX^*/dY^I decreases as the risk aversion increases, implying that the indirect effect is larger than the direct effect.

[8] New Mexico, South Dakota and Wyoming are excluded based on the criteria outlined above on the HPA and groundwater use, as well as other data limitation.

[9] We use other cutoffs including 60%, 80% and no cutoffs to check the robustness. The results using different the cutoffs remain consistent.

[10] Ruess et al. (2023) utilize a hydrology model and high-resolution landcover information to estimate crop-specific water use data based on the USGS's water use database.

Table 3.1 Summary Statistics on Main Variables

Variable	Mean	Std. Dev.	Min	Max
Total water use (acre-feet)	36,583	49,106	0	487,447
Total water use per acre (acre-feet/acre)	0.41	0.34	0.00	2.5
Area-based Insurance Participation (%)	72.77	28.18	0.00	100.00
Liability-based Insurance Participation (%)	59.68	27.40	0.00	100.00
Pumping costs ($/acre-inches)	3.21	2.39	0.16	14.33
Growing Season Precipitation (mm)	514.46	174.30	61.79	1,004.32
Growing Season Precipitation Squared (mm^2)	295,039	185,932	3,818	1,008,649
Instrumental Variable, Area-based (%×%)	5,109	1,209	191	7,066
Instrumental Variable, Liability-based (%×%)	3,826	1,212	89	6,759
Premium Subsidy Rates (%)	65.0	3.3	58.1	70.7
2007 Area-based Insurance Participation (%)	41.9	26.2	0.0	96.8
2007 Liability-based Insurance Participation (%)	35.0	22.2	0.0	88.5

Ruess et al. (2023) provides a county-level data set that is created based on the USGS's "Irrigation - Crops" category. While the "Irrigation - Crops" category captures water use specifically for agricultural irrigation, it lacks information for some highly irrigated states overlying the HPA, such as Nebraska and Texas, due to missing information in the USGS data. As over 95% of groundwater extracted from the HPA is used for agricultural use, to address the loss in spatial coverage, we use the data set based on "Total Irrigation" category (Dennehy, 2000; Miller and Appel, 1997). Our data shows that the overall difference between the two categories is 0.1% of the "Total Irrigation".

The water use data provides county-level and crop-specific water use information, measured in km^3, for the contiguous United States from 2008 to 2020. This dataset differentiates water use by sources (groundwater and surface water) and major crops (e.g., corn, soybeans, and wheat). We construct a county-level variable measuring crop-specific per-acre water use in acre-inches, which serves as our dependent variable. Data on planted acreage for each crop are obtained from the USDA National Agriculture Statistics Services (NASS).

Information on crop insurance is from the RMA's Summary of Business (SOB). The SOB provides detailed county-level information on insured acres, total liability, total premium, and premium subsidy by insurance plans, crops, and coverage levels (Yu et al., 2018). We consider

insurance plans related to RP and YP.[11] We construct the crop insurance participation variable, our main independent variable, in two ways: (1) area-based insurance uptake, and (2) liability-based insurance uptake. Area-based participation is the ratio of insured area to planted area, while liability-based participation is the ratio of actual liability to total possible liability. Total possible liability is computed by multiplying the futures price, the average crop yield over the past 10 years, planted area, and the highest available coverage level (Goodwin et al., 2004). Area-based insurance uptake reflects the extensive margin of participation, and liability-based uptake captures both the extensive and intensive margins (Goodwin et al., 2004; Connor and Katchova, 2020; Biram et al., 2024).

Information on premium subsidy rates, used to construct an IV, also comes from the RMA's SOB. The premium subsidy rate is computed by dividing the premium subsidy amount by the total premium amount. The premium subsidy may include federal and state subsidies. The premium subsidy rate represents the percentage of each premium dollar that has been subsidized. Specifically, the premium subsidy rates are calculated for 70% and 75% coverage levels.[12] The IV is constructed by multiplying these premium subsidy rates with insurance uptake in 2007, a year preceding the sample period.

Irrigation costs for farmers are assumed to be the cost of pumping groundwater to the surface. Following Rogers and Alam (2006) and Hendricks and Peterson (2012) , the cost to pump an acre-inch of groundwater is computed by Equation 3.9:

$$PC = \phi_{energy} \times P_{energy} \times Depth \tag{3.9}$$

where PC is pumping cost. ϕ_{energy} is a parameter that represents pumping conditions. For ϕ_{energy}, we assume that pumps are operating at the full capacity of the Nebraska Pumping Plant Criteria.[13] $Depth$ denotes groundwater depth from the surface to the groundwater table. P_{energy} is the price of energy used to pump groundwater.

[11] Plans considered include RP, YP, RP-Harvest Price Exclusion, Actual Production History, and Revenue Assurance.

[12] We also use IVs based on premium subsidy rates for other coverage levels, such as 60% and 65%. The results remain robust to our main analysis.

[13] The Nebraska Pumping Plant Criteria are recognized as the standard across the United States (Rogers and Alam, 2006).

Information on depth to groundwater is obtained from the National Ground-Water Monitoring Network which provides groundwater depth information by monitoring stations. We compute the annual county-level groundwater depth by averaging data from monitoring stations located within a county. We use a 30-km radius from each county's centroid to construct county-level groundwater depth as a robustness check and provide results in the appendix. The results are consistent to our main results.

In determining energy prices, we construct annual state-level prices, weighted by the proportions of pumps utilizing electricity, and diesel/natural gas. The Irrigation and Water Management Survey, conducted by the USDA every five years, provides state-level data on the number of pumps by their energy sources. For survey years in 2003, 2008, 2013, and 2018, we calculate the proportions of pumps using electricity and the combined proportions of pumps using diesel and natural gas, which are used as weights. We interpolate values for years between the survey years and extrapolate for 2019 and 2020. Our data shows that Kansas and Nebraska rely more on diesel and natural gas-powered pumps, whereas Colorado and Texas primarily depend on electricity-powered pumps. State-level electricity and natural gas prices are obtained from the U.S. Energy Information Administration and are deflated by the Producer Price Index. We use natural gas prices for pumps using natural gas or diesel, as natural gas and diesel prices are highly correlated (Hendricks and Peterson, 2012). The electricity and natural gas prices in our analysis are the average of monthly industrial prices from April to September. When converted into a common unit, we see that electricity prices are consistently higher than natural gas prices.

Figure 3.3 illustrates the fluctuations in pumping costs across states over the sample period. Notably, Kansas and Nebraska consistently exhibit relatively lower pumping costs and have experienced minor fluctuations. On the other hand, Texas initially had the highest pumping costs in 2008, but they have declined since and remained stable since 2012. Colorado's pumping costs show small variations, maintaining levels above those in other states.

The data on planted areas comes from the USDA NASS. Precipitation and temperature data are from the PRISM Climate Data. We use monthly precipitation along with maximum and minimum

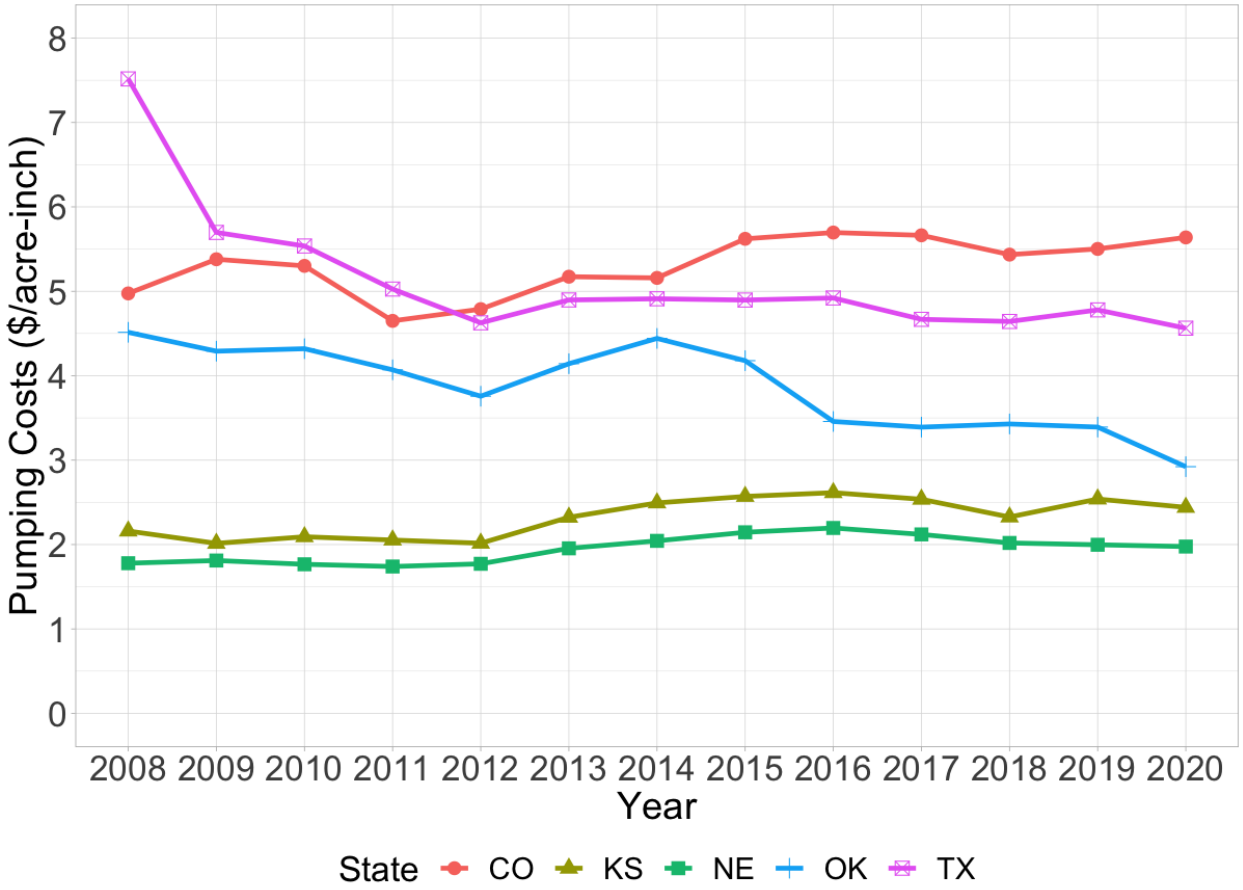

Figure 3.3 **Changes in Pumping Costs between 2008 and 2020**: This figure presents the changes in pumping costs between 2008 and 2020 for the states included in the study area. Although pumping costs in Colorado surpassed those in Texas starting in 2012, the relative ranking of states has remained largely stable over time.

temperatures from April to November. In the following subsection, we present estimation and identification strategies.

3.5 Estimation Strategy

Our empirical model aims to estimate the effect of insurance participation on water use for irrigation. We control for several observed characteristics, such as precipitation and temperature. To control for unobserved time-invariant heterogeneity, such as soil texture and crop-specific water needs, we include county fixed effects and crop-by-year fixed effects. Even after including relevant control variables and fixed effects, our estimates may still be subject to potential bias from reverse causality between water use and insurance participation, a concern widely discussed in previous studies (Deryugina and Konar, 2017; Ghosh et al., 2021). Based on the accessibility to water

for irrigation or expectation about how much water to apply, farmers may adjust the coverage levels of their insurance plans. This possibility of reverse causality can bias our estimates. The direction of the bias is not immediately clear. Since premium rates for farmers with access to water for irrigation ($15 per acre in 2020) are much lower than those for non-irrigated production ($34 per acre in 2020), reverse causality can either underestimate or overestimate the true effect. Unfortunately, we do not observe accessibility to water or expectation of water use. Instead, we observe aggregated water use and insurance participation at the crop-by-county level. To address this potential endogeneity, we adopt an IV approach and use the interaction term between premium subsidy rates and insurance participation in a year prior to the sample period as our instruments.

The regression equation is as follows:

$$ln(WU_{ijt}) = \beta_0 + \beta_1 CI_{ijt} + \beta_2 PC_{it} + \beta_3 CI_{ijt} \times PC_{it} + \boldsymbol{X'}_{it}\boldsymbol{\gamma} + c_i + v_{jt} + u_{ijt} \tag{3.10}$$

where $ln(WU_{ijt})$ is the natural logarithm of the amount of water used per acre for crop j in county i in year t. We use a natural logarithmic transformation on the outcome variable, WU_{ijt} to account for different scales of water use across crops. For example, an additional gallon of water may have varying marginal effects on yields depending on the crops. The term CI_{ijt} denotes area-based or liability-based crop insurance participation, measured as a percentage. The pumping costs to extract groundwater (PC_{it}), measured in $/acre-inch, is included in the equation. Note that PC_{it} varies only across counties and years. An interaction term between insurance participation and the pumping costs ($CI_{ijt} \times PC_{it}$) captures the potential heterogeneous responses to insurance participation based on the pumping costs. $\boldsymbol{X}_{it}$ is a vector of control variables, including growing season precipitation, precipitation squared, and monthly maximum and minimum temperatures. County fixed effects (c_i) absorb time-invariant factors specific to each county, such as soil characteristics and proximity to major surface water sources. Crop-by-year fixed effects (v_{jt}) control for unobserved heterogeneity that may vary across years and crops. For instance, these fixed effects control for the expected price of each crop that varies across years, as well as crop-specific factors that are common across years such as each crop's base water demand for growth. The term u_{ijt} is an idiosyncratic error term.

In Equation 3.10, β_1 and β_3 are the parameters of interest. β_1 represents the moral hazard behavior in water use when the pumping costs are zero. β_3, the coefficient for the interaction term, represents variation in response based on pumping costs. Unlike the typical expectation regarding the effect of insurance on input use, our discussion from the conceptual framework suggests that β_3 can be either positive or negative, which depends on the relative levels of risk aversion and risk reduction.

In the main analysis, we exclude observations with zero values for water use. We report estimation results of both linear models and models with the logarithmic transformation where zero values are replaced with 0.001, in the appendix. The results are consistent with those presented in our main analysis.

Following Hendricks and Peterson (2012), pumping costs are assumed to be exogenous, despite the possibility that the water use in a given year may affect the depth to groundwater table and pumping costs in the subsequent years. One possible explanation for this assumption is that as energy prices are generally considered exogenous, the pumping costs variable can be similarly treated as exogenous, as suggested in Annan and Schlenker (2015). In addition, the assumption on exogenous pumping costs implies that farmers are myopic when determining the amount of groundwater use, focusing solely on the current year's conditions. Myopic behavior would hold when the future private benefits from reducing current pumping is negligible (Hendricks and Peterson, 2012). For example, in aquifers with instantaneous lateral flows, farmers may not benefit much from reducing withdrawal. To test whether water use in the previous year affects groundwater levels in the current year, we estimate an additional regression of Ln(groundwater depth) on a one-year lag of water use, controlling for growing season precipitation and county and year fixed effects. The results are presented in the appendix. While there is a negative correlation, the estimated coefficient on lagged water use is not statistically significant. Moreover, the magnitude of the estimate is relatively marginal. An increase in lagged water use by the sample mean (87,816 acre-feet) lowers the groundwater level by 0.4%.

We estimate the same specification, presented in Equation 3.10, using crop-specific total water

use excluding crop fixed effects. These estimation results are expected to show the effect of insurance participation on total change in water use, allowing for changes in crop mix and cropping areas. If insurance participation results in shifts toward more water-intensive crops or increased crop acreage, we anticipate that the estimated coefficient on total water use will be greater than the coefficient on per-acre water use.

3.5.1 Identification Strategy

To address the endogeneity between water use and insurance participation, we take an IV approach exploiting exogenous changes in the premium subsidy rates. This approach has been adopted by recent studies to deal with the endogeneity of insurance uptake and farm management decisions (Connor et al., 2022; Yu et al., 2018; Weber et al., 2016; DeLay, 2019). In particular, we use interactions between premium subsidy rate and county-level insurance uptake in 2007, prior to our sample period, building on the literature (DeLay, 2019; Connor and Katchova, 2020; Connor et al., 2022; Yu et al., 2018; Biram et al., 2024). We utilize premium subsidy rates with 70% and 75% coverage levels for yield and revenue protections for our IV. Insurance uptake in the previous year is expected to be correlated with the current year's participation, possibly due to general risk preferences and production environment shared within a county. Table 2A.1 shows the first stage regression results on the insurance participation and the interaction term between insurance uptake and pumping costs. Columns (1) and (2) present the results on area-based insurance participation, and Columns (3) and (4) report those on liability-based insurance participation. The instruments are strongly correlated with the variables of our interest. The F-statistics for the null hypothesis that the coefficients on the instruments are zero are above the common rule of thumb criterion ($F < 10$) for weak instruments.

The other condition required for identification using an IV is the exclusion restriction. The exclusion restriction implied by our IVs are that, conditional on the control variables included in the regression, (1) premium subsidy rates set by the federal government do not affect the amount of irrigation water applied, and (2) prior year's insurance participation does not directly affect current year's water use other than their effects through insurance participation. It is improbable that

legislative changes in subsidy rates are affected by factors related to crop production or input use. Hence, we can treat changes in premium subsidies as exogenous. Insurance participation decisions are made and any relevant payouts are resolved annually. Since previous year's insurance does not carry over to current year's coverage and indemnity, it is plausible that the insurance participation in a year prior to the sample period meets the exclusion restriction. The same IV is used to construct an IV for the interaction term by multiplying it with pumping costs, under the assumptions that any function of a valid IV is uncorrelated with an error term and that the interacted IV is correlated with the endogenous interaction term (Wooldridge, 2010).

3.6 Results

3.6.1 Results on Moral Hazard Behavior in Water Use

We first estimate Equation 3.10 to show the effect of insurance participation on water use per acre, representing moral hazard behavior in water use. Table 3.2 shows the estimation results. Columns (1) and (2) report the results using area-based insurance participation measure, which captures the extensive margin. Columns (3) and (4) report the results based on liability-based insurance participation, reflecting both intensive and extensive margins. Columns (1) and (3) are estimated by the FE method and Columns (2) and (4) use FE-IV method. The results in Column (4) represent our preferred specification. We find that the FE models' estimated coefficients for insurance participation are larger than those of the FE-IV models. This suggests that more access to water is positively correlated with higher insurance uptake, possible due to lower premium rates, as discussed in the previous section.

From our estimated results in Column (4), we find that the effect of insurance participation on per-acre water use is positive when pumping costs are low. When pumping costs are zero, a one percentage point increase in insurance participation leads to a 0.4% increase in water use per acre. For the interaction term, we find that the estimated coefficient is negative, suggesting that pumping costs mitigate the effect of insurance uptake on water use. As the pumping costs increase, the effect of insurance participation on water use decreases and eventually becomes negative for pumping costs greater than \$1.7/acre-inch, which is about 0.65 standard deviations away from the sample

mean. At the sample mean value of the pumping costs, which is $3.21 per acre-inch (see Table 4.1), the per-acre water use response to insured area is estimated to be −0.4%. This result suggests that in areas where irrigation costs are low, insurance participation leads to an increase in water use. However, in areas with average or high irrigation costs, additional insured area may lead to a decrease in per-acre water use.

Figure 3.4 illustrates the marginal effects of insurance participation by counties, using the temporal average pumping costs for each county. We find that we observe moral hazard behavior in the majority of counties in our study area. In the Northern and Central HPA where pumping costs are relatively low, we find small increases in water use in response to insurance coverage. Notably, some counties in northern Texas exhibit greater moral hazard effects in water use.

The estimated coefficient on pumping costs in Column (4) shows that an increase in pumping costs leads to lower water use when insurance uptake is zero, though the estimate is not statistically significant. As insurance participation increases, the water use response to pumping costs becomes more negative. These findings suggest that in situations where farmers face higher production risks (lower coverage), they tend to decrease water use less when water prices increase. However, when farmers are insured and have reduced their risk exposure, they become more responsive to price signals, leading to a larger reduction in water use as water prices rise.

Different factors may contribute to the positive effects of insurance participation on water use when pumping costs are relatively low. First, the positive effects may occur, as suggested by the conceptual model in Equation 3.8, when the marginal change in the probability of low yields is relatively smaller than the level of risk aversion. The requirement to use sufficient irrigation to get indemnified when insured for irrigated practice may also play a role and discourage farmers from using less water.

Another possible explanation for this positive effect can be attributed to a dynamic component of insurance plans. Insurance plans calculate expected yields based on the APH, which is the average yield over the past four to ten years. Then, insured yields are determined by multiplying these expected yields by the coverage level that farmers choose (e.g., 75%). Therefore, insured

Table 3.2 Estimation Results for Per-Acre Water Use

	(1)	(2)	(3)	(4)
	Area-based		Liability-based	
	FE	FE-IV	FE	FE-IV
Insurance Participation (%)	0.014***	0.000	0.006***	0.004*
	(0.003)	(0.009)	(0.002)	(0.002)
Insurance Participation ×	−0.0015***	−0.0026**	−0.0011**	−0.0025**
Pumping Costs	(0.0007)	(0.0011)	(0.0006)	(0.0009)
Pumping Costs ($/acre-inch)	−0.027	−0.057	−0.039	−0.078
	(0.071)	(0.074)	(0.072)	(0.079)
Growing Season	0.005***	0.005***	0.005***	0.005***
Precipitation (mm)	(0.002)	(0.002)	(0.002)	(0.002)
Growing Season	−0.00001***	−0.00001***	−0.00001***	−0.00001***
Precipitation Squared	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Temperature Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Crop-by-year FE	✓	✓	✓	✓
First stage F-statistics:				
Insurance		81.4		605.4
Insurance × Pumping Costs		314.8		219.2
Number of Observations	3,954	3,954	3,942	3,924
Adjusted R-squared	0.324		0.321	

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

Temperature controls include monthly maximum and minimum temperatures

farmers have an incentive to achieve higher yields to raise the expected yield levels and indemnity levels (Mieno et al., 2018). This incentive may lead to more intensive water use when pumping costs are low.

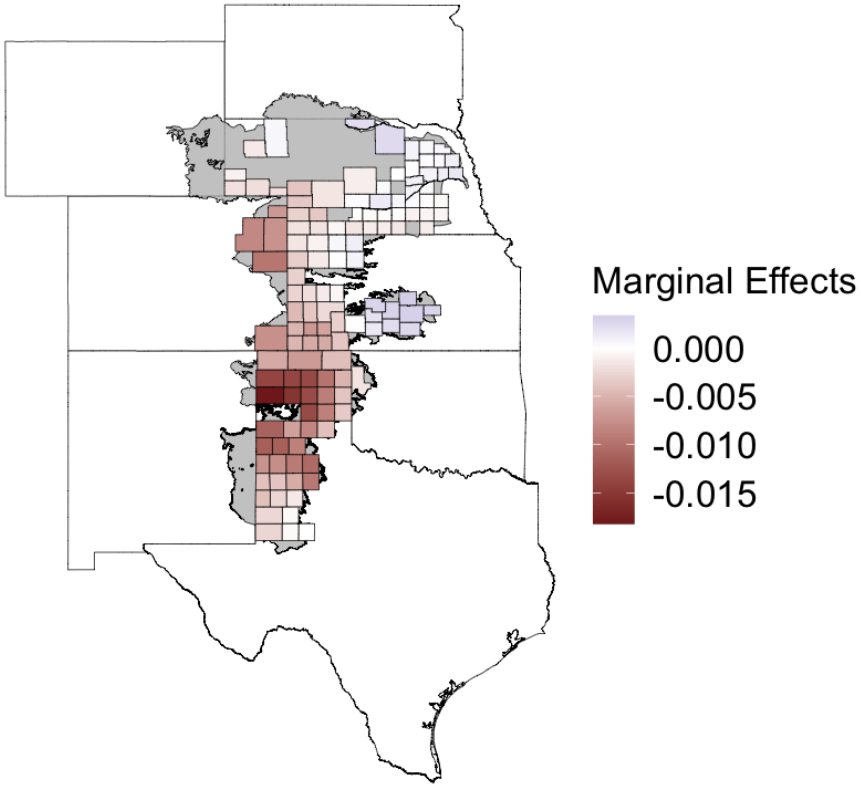

Figure 3.4 **Marginal effects of insurance coverage**: This figure illustrates the water use response to a one percentage point increase in insurance coverage by counties based on the county-level average pumping costs over the sample period.

3.6.2 Robustness Checks

In this subsection, we present additional estimation results for robustness checks of our results. We consider the following: (1) Non-linear effects and (2) heterogeneity by dry/non-dry years.

Non-linear Effects

Our main specification assumes that the marginal effect of pumping costs on the water use response to insurance participation remains constant across all levels of pumping costs. However, farmers might respond differently to the same increase in pumping costs depending on their initial cost level. We evaluate this possibility by estimating additional regressions with a nonparametric

specification. We use a set of dummy variables for pumping costs to flexibly characterize the effects of pumping costs on the water use response to insurance participation. We use the following dummy variables to indicate the pumping cost levels that farmers face: \$0-\$2/acre-inch, \$2-\$4/acre-inch, \$4-\$6/acre-inch, \$6-\$8/acre-inch, \$8-\$10/acre-inch, \$10-\$12/acre-inch, \$12-\$14/acre-inch, and above \$14/acre-inch. We report the results with alternative cutoffs for robustness checks in the appendix.

$$Ln(WU_{ijt}) = \beta_0 + \beta_1 CI_{ijt} + \sum_s \{\theta_s PC_{it}^s + \gamma_s CI_{ijt} \times PC_{it}^s\} + \boldsymbol{X'}_{it}\boldsymbol{\gamma} + c_i + v_{jt} + u_{ijt} \quad (3.11)$$

In addition to the terms defined in Equation 3.10, PC_{it}^s represents a set of dummy variables that equal one when pumping costs fall within the corresponding interval s.

Figure 3.5 shows the estimated coefficients of β_1 and γ_s in Equation 3.11. They represent the estimated marginal effects of insurance participation on per-acre water use at different levels of pumping costs. The solid line represents point estimates and the bands are 95% confidence intervals. We find some non-linear responses of water use to pumping costs depending on pumping cost levels. The results suggest that water use is statistically not responsive to insurance participation when pumping costs are lower than \$4/acre-inch. We find that as pumping costs increase, we tend to observe more moral hazard behavior in water use.

Heterogeneity by Dry Years

We also examine how the water use response to insurance coverage varies during dry years. We define dry years as those with annual growing season precipitation lower than the average precipitation across the sample years. In our sample, the dry years include 2011 to 2013 and 2020. The remaining years are considered non-dry years. On average, the dry years had 139 mm less precipitation than the full sample average.

The results, presented in Table 3.3, show that per-acre water use during dry years is more responsive to insurance participation than during non-dry years. The estimated coefficients for the results during non-dry years are smaller in magnitude and are not statistically significant. When pumping costs are zero, a one percentage point increase in insurance coverage is estimated to raise water use during dry years by 0.7%, compared to an increase by 0.1% during non-dry years. In

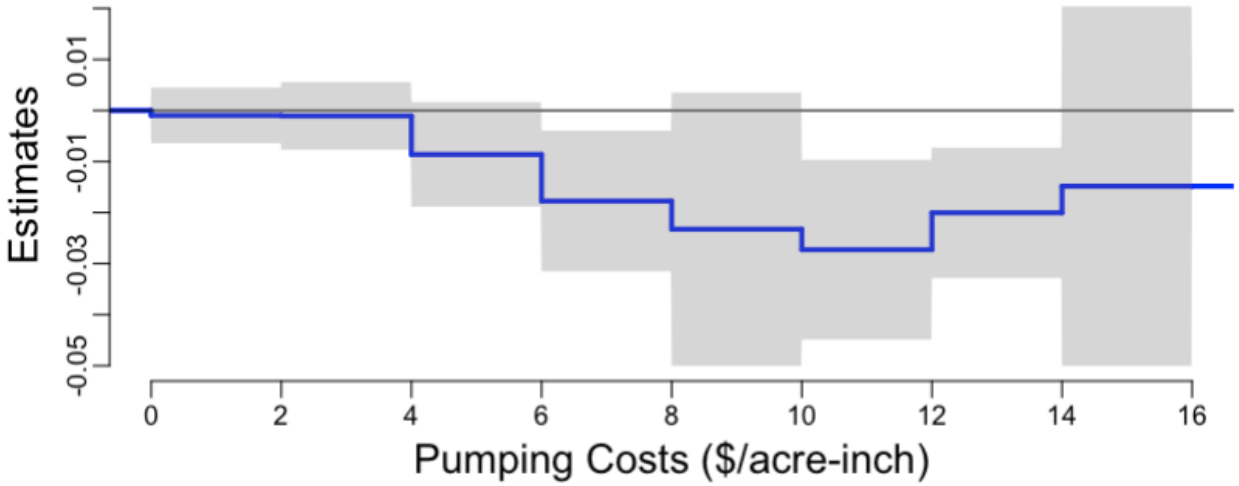

Figure 3.5 **Marginal effects of insurance coverage by pumping cost levels**: This figure depicts the estimated coefficients of the interaction terms between insurance participation and dummy variables for pumping costs from Equation 3.11.

light of our conceptual framework, this difference suggests that additional water use during dry years may have a larger impact on the probability of low yields, thereby encouraging farmers to use more water. The estimated coefficient on pumping costs during dry years is smaller (more positive) than that during non-dry years. This suggests that irrigation is more responsive to pumping costs in non-dry years, as farmers have relatively sufficient rainfall during those times.

3.6.3 Results on Total Water Use

In this subsection, we estimate the effects of crop insurance on total water use. When crop insurance participation increases, total water use in an area may be affected by changes in crop mix, changes in acreage, and moral hazard in water use (Deryugina and Konar, 2017). While this study primarily examines the moral hazard behavior in water use, it is important to assess the effects of insurance on total water use to understand relative magnitude of moral hazard behavior compared to the overall response.

We estimate the same equation to our main specification:

$$Ln(TWU_{ijt}) = \beta_0 + \beta_1 CI_{ijt} + \beta_2 PC_{it} + \beta_3 CI_{ijt} \times PC_{it} + \boldsymbol{X'}_{it}\boldsymbol{\gamma} + c_i + v_t + u_{ijt} \tag{3.12}$$

where TWU_{ijt} denotes total water use, not divided by planted acreage, for crop j in county i in year t. Year FE, v_t, is included instead of crop-by-year FE. All other notation remains consistent

Table 3.3 Subsample Results: Dry and Non-dry Years

	(1)	(2)	(3)	(4)
	Dry Years		Non-dry Years	
	FE	FE-IV	FE	FE-IV
Insurance Participation (%)	0.007***	0.007***	0.005	0.001
	(0.002)	(0.002)	(0.004)	(0.003)
Insurance Participation ×	−0.0006	−0.0030***	−0.0012	−0.0020**
Pumping Costs	(0.0004)	(0.0010)	(0.0009)	(0.0010)
Pumping Costs ($/acre-inch)	−0.058	0.057	−0.161*	−0.189*
	(0.083)	(0.100)	(0.088)	(0.096)
Growing Season	0.001	0.001*	0.001	0.001
Precipitation (mm)	(0.001)	(0.001)	(0.003)	(0.003)
Growing Season	−0.00000	−0.00000**	−0.00000	−0.00000
Precipitation Squared	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Temperature Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Crop-by-year FE	✓	✓	✓	✓
First stage F-statistics:				
Insurance Participation		271.6		323.5
Insurance Participation × PC		108.1		175.6
Number of Observations	1,362	1,330	2,669	2,594
Adjusted R-squared	0.748		0.301	

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

Temperature controls include monthly maximum and minimum temperatures

with Equation 3.10. Total water use, TWU_{ijt}, captures changes in crop mix and acreage, as well as changes in per-acre water use. For instance, an increase in total water use for corn may result from transitions from other crops or from the conversion of idle/fallow lands.

Table 3.4 presents the estimation results on the total water use. The estimated coefficients, reported in Columns (1) and (2), report the total water use response to area-based insurance participation, while the coefficients in Columns (3) and (4) report the total water use response to liability-based insurance uptake. We find that total water use is more responsive to insurance participation than per-acre water use, suggesting that changes in crop mix and acreage have larger effects on water use. When pumping costs are zero, a one percentage point increase in insurance uptake is estimated to raise water use by 4.5%. In addition, we find consistent results that pumping costs mitigate the water use response to insurance uptake. However, the relative magnitude of the estimate on the interaction term is smaller than the one for per-acre water use response. At the sample mean of the pumping costs, a one percentage point increase in insurance participation raises water use by 1.0%. This suggests that while total water use is still affected by pumping costs, other mechanisms such as changes in crop mix and areas are not as responsive to pumping costs as per-acre water use.

3.7 Counterfactual Analysis

Our analyses show that an increase in insurance uptake lowers per-acre water use when pumping costs are high, but increases water use when costs are low. Here, we conduct counterfactual analysis on how much additional water would have been used in 2020 if insurance participation had been lower than its 2020 level based on the results in Table 3.2. This calculation provides a conservative estimate, as it only accounts for the effect of moral hazard behavior and does not include potential changes in crop choice or acreage. We consider two scenarios where insurance uptake is reduced by 10% or 20% relative to their 2020 levels.

We first obtain the baseline water use level for each county in 2020 by computing the predicted value based on the result presented in Table 3.2. We then re-calculate predicted water use by adjusting only the insurance uptake variable, holding all other factors constant at the 2020 level.

Table 3.4 Estimation Results for Total Water Use

	(1)	(2)	(3)	(4)
	Area-based		Liability-based	
	FE	FE-IV	FE	FE-IV
Insurance Participation (%)	0.047***	0.098***	0.011**	0.045***
	(0.005)	(0.016)	(0.005)	(0.013)
Insurance Participation ×	−0.0045***	−0.0154***	−0.0005	−0.0108***
Pumping Costs	(0.0010)	(0.0032)	(0.0012)	(0.0038)
Pumping Costs ($/acre-inch)	−0.038	−0.005	−0.113	−0.221**
	(0.082)	(0.108)	(0.081)	(0.105)
Growing Season	0.006***	0.004**	0.005***	0.004**
Precipitation (mm)	(0.002)	(0.002)	(0.002)	(0.002)
Growing Season	−0.00001***	−0.00000***	−0.00001***	−0.00000***
Precipitation Squared	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Temperature Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
First stage F-statistics:				
Insurance Participation		349.9		1,255.9
Insurance Participation × PC		337.2		625.7
Number of Observations	3,954	3,954	3,942	3,924
Adjusted R-squared	0.318		0.303	

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

Temperature controls include monthly maximum and minimum temperatures

The difference between these two predicted values represents the estimated change in water use attributable to the hypothetical reduction in insurance uptake.

Table 3.5 presents the results. Column (1) reports per-acre reductions in water use, while Column (2) shows the corresponding percentage change relative to the baseline. Column (3) aggregates the total water savings across the study area, measured in million acre-feet (maf). A 10% decrease in insurance uptake results in a 0.010 af/acre reduction in water use, equivalent to a 2.3% decrease and a total savings of approximately 0.3 maf. To put this estimate in context, the total estimated savings correspond to about eight times the average annual water use per county in our sample (0.37 maf). A 20% reduction in insurance uptake yields a 0.021 af/acre decrease, representing a total savings of 0.6 maf. These findings illustrate the potential scale of water conservation benefits from modest changes in crop insurance participation, particularly in regions with high groundwater extraction costs.

Table 3.5 Counterfactual Analysis

Changes in Insurance Uptake	(1) Per-acre Changes (af/acre)	(2) Percentage Changes (%)	(3) Total Changes (maf)
10% decrease	0.010	2.3	0.3
20% decrease	0.021	4.8	0.6

3.8 Conclusions

The U.S. federal crop insurance program has experienced substantial growth, leading more farmers to join this program to manage production and market risks. While crop insurance provides a risk management tool for farmers, it also can affect other on-farm management decisions, such as water use for irrigation. Existing research suggests that crop insurance leads to an increase in water use (Deryugina and Konar, 2017; Ghosh et al., 2021). However, there remains a gap in our understanding of the mechanisms by which crop insurance affects water use, as well as how changes in pumping costs might affect water use responses to crop insurance.

This study provides empirical evidence that insured farmers tend to increase per-acre water use for irrigation when pumping costs are low. As pumping costs increase, the water use response to

crop insurance diminishes, eventually leading to a decrease in water use at higher pumping costs. These results suggest that at average water price levels, insured farmers are more likely to increase per-acre water use, and we do not observe moral hazard behavior in water use. However, in counties with higher pumping costs, we do observe moral hazard behavior, as indicated by a decrease in per-acre water use.

Furthermore, our results show that insured farmers increase total water use, consistent with the findings of existing research. We find that the response in total water use is larger in magnitude than that in per-acre water use, suggesting that changes in crop mix and acreage are likely contributing to increased water application.

This study contributes to the knowledge of moral hazard behavior in water use and the impacts of water pricing on groundwater depletion. At the current level of water prices, crop insurance can unintentionally support the sustainability of water resources and the adaptability of farmers for future weather shocks, as insurance participation leads to less per-acre water use.

The results of this study provide several policy implications for water resource management. First, our results suggest that policies aimed at raising water prices to manage water resources and foster sustainable water use may have unintended and indirect benefits from moral hazard behavior in water use, as discussed in Suchato et al. (2022). If water pricing fails to consider this unintended impact from moral hazard behavior, it could result in the overpricing of irrigation and inefficient utilization of groundwater resources to mitigate the effects of extreme weather events, such as droughts.

Second, our findings suggest that insurance participation may serve as a potential means to reduce water use in areas experiencing substantial declines in groundwater levels. The mitigated effect on per-acre water use, particularly in regions facing substantial declines in groundwater levels, underscores the broader significance of subsidies on crop insurance. By strategically incentivizing insurance enrollment among farmers in regions grappling with significant aquifer depletion, policymakers can leverage moral hazard behavior to encourage a collective reduction in water use. However, it is worth noting that providing incentives for a specific crop, particularly if

it is water-intensive, could inadvertently result in an increase in water use. This is because crop production may shift towards this water-intensive crop, leading to greater water use.

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APPENDIX 3A

LOGARITHMIC TRANSFORMATION WITH REPLACING ZERO VALUES

Table 3A.1 Estimation Results: With Replacement of Zero Values

	(1)	(2)	(3)	(4)
	Area-based		Liability-based	
	FE	FE-IV	FE	FE-IV
Insurance Participation (%)	0.016***	0.002	0.007***	0.005**
	(0.004)	(0.009)	(0.003)	(0.002)
Insurance Participation ×	−0.0020***	−0.0030***	−0.0026***	−0.0023**
Pumping Costs	(0.0007)	(0.0011)	(0.0006)	(0.0009)
Pumping Costs ($/acre-inch)	−0.057	−0.081	−0.071	−0.110
	(0.070)	(0.075)	(0.069)	(0.075)
Growing Season	0.005***	0.005***	0.006***	0.006***
Precipitation (mm)	(0.001)	(0.001)	(0.002)	(0.001)
Growing Season	−0.00001***	−0.00001***	−0.00001***	−0.00001***
Precipitation Squared	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Temperature Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Crop-by-year FE	✓	✓	✓	✓
First stage F-statistics:				
Insurance		85.6		609.6
Insurance × Pumping Costs		303.5		287.4
Number of Observations	4,017	3,954	4,005	3,987
Adjusted R-squared	0.342		0.339	

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

Temperature controls include monthly maximum and minimum temperatures

APPENDIX 3B

RESULTS USING A 30-KM RADIUS

Table 3B.1 Estimation Results using a 30-km radius

	(1)	(2)	(3)	(4)
	Area-based		Liability-based	
	FE	FE-IV	FE	FE-IV
Insurance Participation (%)	0.014***	−0.001	0.006***	0.004*
	(0.003)	(0.009)	(0.002)	(0.002)
Insurance Participation ×	−0.0015**	−0.0023**	−0.0011*	−0.0024**
Pumping Costs	(0.0006)	(0.0010)	(0.0006)	(0.0009)
Pumping Costs ($/acre-inch)	−0.043	−0.067	−0.053	−0.089
	(0.065)	(0.070)	(0.066)	(0.072)
Growing Season	0.005***	0.005***	0.005***	0.005***
Precipitation (mm)	(0.002)	(0.002)	(0.002)	(0.002)
Growing Season	−0.00001***	−0.00001***	−0.00001***	−0.00001***
Precipitation Squared	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Temperature Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Crop-by-year FE	✓	✓	✓	✓
First stage F-statistics:				
Insurance		82.1		602.9
Insurance × Pumping Costs		287.0		227.1
Number of Observations	3,954	3,954	3,942	3,942
Adjusted R-squared	0.324		0.321	

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

Temperature controls include monthly maximum and minimum temperatures

APPENDIX 3C

ESTIMATION RESULTS WITH INSURED AREA

Table 3C.1 Estimation Results with Insured Area

	Dependent Variable: Ln(Crop-specific Water Use per Acre)			
	(1) FE	(2) FE-IV	(3) FE	(4) FE-IV
Ln(Insured Acres)	0.272***	0.198	0.512***	0.407
	(0.082)	(0.201)	(0.167)	(0.250)
Ln(Insured Acres) ×			−0.0673**	−0.0585*
Pumping Costs			(0.0300)	(0.032)
Pumping Costs ($/acre-inch)			−0.375***	−0.330**
			(0.117)	(0.154)
Ln(Planted Acres)	−0.203**	−0.132	−0.497***	0.616**
	(0.085)	(0.212)	(0.180)	(0.284)
Ln(Planted Acres) ×			0.0839***	0.0718**
Pumping Costs			(0.0321)	(0.0361)
Growing Season	0.005***	0.005***	0.005***	0.005***
Precipitation (mm)	(0.002)	(0.002)	(0.002)	(0.002)
Growing Season	−0.00001***	−0.00001***	−0.00001***	−0.00001***
Precipitation Squared	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Temperature Controls	✓	✓	✓	✓
County FE	✓	✓	✓	✓
Crop-by-year FE	✓	✓	✓	✓
First stage F-statistics:				
Ln(Insured Acres)		273.8		141.1
Ln(Insured Acres) × PC				400.1
Number of Observations	3,948	3,930	3,948	3,930
Adjusted R-squared	0.328			0.328

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

Temperature controls include monthly maximum and minimum temperatures

APPENDIX 3D

ESTIMATION RESULTS OF LAGGED WATER USE ON GROUNDWATER DEPTH

Table 3D.1 Estimation Results: Lagged Water Use on Groundwater Depth

	(1) 50-km Boundary	(2) 30-km Boundary
Lagged Water Use	−0.00000	−0.00000
	(0.00000)	(0.00000)
January-March Precipitation (mm)	0.00003	0.00004
	(0.0001)	(0.0001)
April-September Precipitation (mm)	0.00004**	0.00001
	(0.00002)	(0.00003)
October-November Precipitation (mm)	0.00001	−0.00001
	(0.00004)	(0.0001)
County FE	✓	✓
Year FE	✓	✓
Number of Observations	1,467	1,467
Adjusted R-squared	0.992	0.992

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

CHAPTER 4

THE IMPACT OF CROP INSURANCE PREMIUM SUBSIDIES ON THE WETLAND EASEMENT PROGRAM PARTICIPATION

4.1 Introduction

Wetlands in the United States have historically been under constant pressure to be converted for other uses, such as agricultural and commercial development. The total area of wetlands declined by more than 50% between the 1780's to the 1980's (Dahl, 1990). This trend has continued in recent years, with wetland areas decreasing by 221 thousand acres between 2009 and 2019 (Lang and Griffin, 2024). Agriculture development played a primary role in wetland loss. Over the 20 years between the 1950's and the 1970's, the United States lost 9 million acres of wetlands, with 87% of this loss attributed to agricultural expansion (Tiner, 1984). With growing recognition of the environmental benefits of wetlands since the 1970's, various programs and regulations to reduce wetland degradation and restore wetlands have been implemented.

Wetland and floodplain easement programs are among these initiatives focused on restoring wetlands that have been farmed or converted to agricultural uses. These programs pay farmland owners the easement value and the restoration fees to retire land from production and restore it to wetlands or floodplains. The most common wetland easement program in the United States is the Wetland Reserve Program (WRP), with approximately 2.8 million acres of eased wetlands in 2024. Restored lands are expected to provide various environmental benefits, such as flood risk mitigation (Taylor and Druckenmiller, 2022; Gourevitch et al., 2020), improved water quality (Singh et al., 2019), and enhanced wildlife habitat (Kaminski et al., 2006; NRCS, 2023). In addition, wetlands may offer private benefits to nearby farmers, such as yield improvements (Karwowski, 2022).

While these easement programs aim to restore wetlands from converted farmlands, other concurrent farm programs may affect their enrollment and success. Notably, crop insurance has often been argued and shown to encourage planting on marginal lands, including those that may be eligible for conservation programs (Yu et al., 2022; DeLay, 2019; Yu et al., 2018; Goodwin et al., 2004). Since the 1994 Crop Insurance Reform Act, the overall premium subsidy rates (premium

subsidy over total premium) have exceeded 50%, leading to increased participation in the crop insurance program (Glauber, 2004, 2013). The number of net insured acres increased from 8.4 million acres in 1993 to 397.6 million acres in 2020 (Risk Management Agency, 2024a,b).

This study explores the relationship between crop insurance premium subsidies and enrollment in wetland/floodplain easement programs. Specifically, we estimate if premium subsidies discourage participation in these conservation programs. We conduct a panel analysis focusing on states in the Mississippi River Basin with a high volume of eligible acres, covering the period from 1997 to 2020. To address the frequent zero values in the outcome variable, we employ a Poisson quasi-maximum likelihood estimation (QMLE).

Subsidies on crop insurance can encourage farmers to expand crop production onto marginal lands (Young et al., 2001; Goodwin et al., 2004; Yu et al., 2018). Goodwin et al. (2004) finds a positive acreage effect of premium subsidies where a 30% increase in premium subsidies for corn and soybeans leads to a 0.28% increase in corn acreage. Yu et al. (2018) estimates a larger acreage effect than previous studies, finding that a 10% increase in premium subsidy results in a 0.43% increase in crop acreage. The authors further identify two mechanisms through which insurance subsidies affect crop acreage: by increasing expected profit and by encouraging higher coverage levels, which reduces variability of farm revenues.

Several studies, more closely related to this study, have examined whether premium subsidies or insurance participation discourage enrollment in conservation programs such as the Conservation Reserve Program (CRP) (Feng et al., 2013; Claassen et al., 2017; DeLay, 2019; Yu et al., 2022). These studies generally find some evidence that increased insurance uptake or higher subsidy levels lead to reduced conservation enrollment. For example, Feng et al. (2013) shows that a $1 per acre increase in premium subsidies reduces the amount of land offered for CRP enrollment by 6,000 acres in North and South Dakota. DeLay (2019) estimates that a 1,000-acre increase in insured area reduces CRP enrollment by 3 acres. Similarly, Yu et al. (2022) finds that the introduction of Pasture, Rangeland, and Forage Index Insurance reduces CRP enrollment by 0.8 to 1.0 percentage points, with the effects becoming larger with time. Building on this literature, our analysis focuses

on wetland easement programs and provides insights into how subsidies on insurance premium influence long-term conservation commitments, which often extend beyond 30 years.

A key empirical challenge in identifying the effect is the potential endogeneity of county-level premium subsidy levels. Subsidy levels may also be driven by choices of crops, coverage levels, and insurance plans, which may also be correlated with the propensity to enroll in easement programs. For example, counties growing crops that are more resilient to wetter climates may choose lower coverage levels, which increases their subsidy rates (i.e., subsidy divided by total premium). However, both crop choices and coverage levels may also affect the decision to participate in easement programs, as they change the expected profitability of production. To address this concern, we employ an instrumental variable (IV) approach. Specifically, we take a control function (CF) approach to estimate an exponential model. We base our instrument on two sources: federally determined annual subsidy rates and the county-level base premium rates, following the methodology outlined in Tsiboe and Turner (2023a). As an alternative approach, we also estimate a fixed effects Poisson regression focusing on periods surrounding major legislative changes that substantially raised subsidy rates.

We find that a 1% increase in the subsidy level leads to a 3.2% annual decrease in enrollment in easement programs. The average partial effect of premium subsidy is estimated to be a reduction of 2.7 enrolled acres per county per year. While this suggests that premium subsidies may reduce participation in conservation programs, the overall magnitude appears relatively modest. Our counterfactual analysis suggests that we would have observed additional 90.7 thousand enrolled acres in 2020 in our study area, if the subsidy level had remained at the 1997 level. This counterfactual enrollment amounts to approximately 136% of the typical annual enrollment area.

We contribute to the literature in two key ways. First, we examine the relationship between crop insurance and wetland easement programs. While previous research has explored the relationship between crop insurance and CRP (DeLay, 2019; Yu et al., 2022), to our knowledge, this is the first study to provide empirical evidence on the effect of premium subsidies on wetland/floodplain easement programs. Considering that wetland/floodplain easement programs typically are under

permanent or 30-year contracts, analyzing how premium subsidies affect the wetland easement program can provide valuable insights into how farmland owners adjust long-term conservation commitments in response to shifts in policy incentives. Second, our findings underscore the importance of accounting for the broader agricultural policy environment when examining conservation enrollment decisions. Prior work has largely focused on the effects of farmer and farmland characteristics, such as perceptions on conservation and the market value of farmland (Welsh et al., 2018; Bastian et al., 2017). However, changes in agricultural policies, including adjustments in crop insurance subsidies, can also influence participation by altering the expected returns on marginal lands eligible for easement programs. Our study fills this gap in the conservation adoption literature by directly analyzing the effect of premium subsidies.

The remainder of this study proceeds as follows. Section 4.2 provides background information on wetland/floodplain easement programs and the premium rating system. Then, we propose a conceptual model to demonstrate how premium subsidies may discourage participation in conservation programs. This motivates our empirical strategy detailed in Section 4.4 and Section 4.5. Our findings and interpretations are presented in Section 4.6 and Section 4.7, and the study concludes with Section 4.8.

4.2 Background

4.2.1 Wetland/Floodplain Easement Programs

In the United States, there are four wetland easement programs designed to protect wetlands and floodplains: Agricultural Conservation Easement Program - Wetland Reserve Easement (ACEP-WRE), Wetland Reserve Program (WRP), Emergency Wetland Reserve Program (EWRP), Regional Conservation Partnership Program-WRE (RCPP-WRE), and Emergency Watershed Protection Program-Floodplain Easement Option (EWPP-FPE). The WRP, which began as a pilot project under the 1990 Farm Bill (officially the Food, Agriculture, Conservation and Tract Act) has been available nationwide since 1995 (NRCS, 2023, 2011). The WRP, including the EWRP, was consolidated into the ACEP under the 2014 Farm Bill, along with the Grassland Reserve Program and the Farmland Protection Program. These programs are expected to have multiple environmental

benefits including carbon sequestration, reduced flooding, and improved wildlife habitat.

Eligible land types for the WRP include (1) farmed wetland or converted wetland and (2) former or degraded wetlands that have been used as rangeland, pastureland, hayland, and forest lands. Converted wetlands are only eligible if the conversion was commenced before 1985. The EWPP-FPE is the only program intended to restore and protect floodplains. Lands eligible for this program include those damaged by flooding during a specific natural disaster, or those damaged by flooding at least twice during the last 10 years or at least once during the last 12 months (NRCS, 2022).

The easement programs pay a share of easement values and restoration costs, depending on the duration of the contract, 100% for permanent easement and 75% for 30-year easement. Participants in these programs voluntarily waive the right to plant crops on their land, while retaining the ownership of the land. As of July 2024, approximately 2.9 million acres were enrolled in wetland easement programs, and 192 thousand acres were enrolled in EWPP-FPE. Figure 4.1 shows the acres enrolled in wetland easement programs by counties in our study area as of 2020. Notably, the Delta states (Mississippi, Louisiana, and Arkansas) have the largest areas enrolled in these programs. Counties along the Mississippi and Ohio Rivers generally show higher levels of enrollment.

The easement compensation is based on the lowest of the following options: (1) the fair market value of the land, (2) the geographic area rate cap (GARC), and (3) an amount voluntarily offered by the landowner. Each year, state conservationists determine the GARCs in each state, with the option to establish multiple GARCs based on counties or other geographic regions. The GARCs never exceed the fair market value, as landowners still retains some property rights. The easement compensation value for non-permanent contracts must not exceed 75% of the permanent easement value. If a landowner fails to convey the easement after signing the contract, the landowner may be required to pay the Natural Resources Conservation Service (NRCS) any costs incurred (NRCS, 2020).

Contracts are typically permanent in duration, requiring a longer-term commitment compared to other conservation programs, such as CRP and Environmental Quality Incentives Program

which generally have 10-year contracts. Of the easement contracts signed between 1992 and 2022, more than 80% of wetland easement contracts were permanent, while the remaining were 30-year agreements.

Landowners may reserve certain property rights as permitted or authorized by the contract. For example, undeveloped hunting and fishing may be conducted subject to the terms of the contract. However, it needs to be noted that any compatible use is not permanently granted; it is authorized for a maximum of 10 years and is subject to approval by the NRCS.

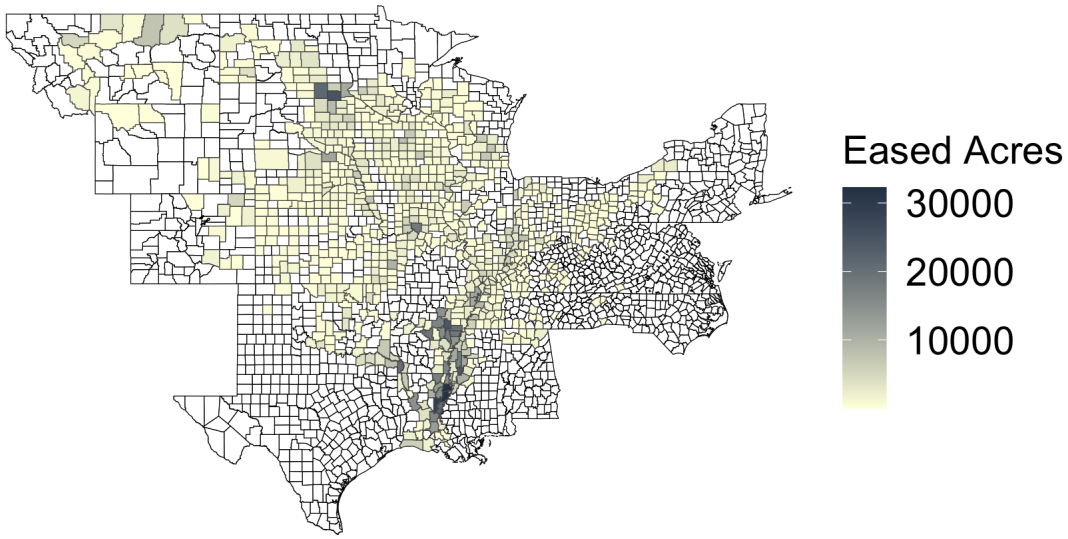

Figure 4.1 **Acres enrolled in wetland/floodplain easement programs**: The map shows the cumulative acres enrolled in wetland/floodplain easement programs in 2020. Counties highlighted in yellow or dark gray colors represent the study area.

4.2.2 Premium Rating System

Federal Crop Insurance Program is a highly subsidized program, with subsidy rates (subsidy over premium) ranging from 38% to 80% (Plastina and Drollette, 2021). Subsidy rates are determined at the federal level and vary by coverage levels and unit levels (e.g., basic unit, whole farm unit, and enterprise unit[1]) (Shields, 2015). Subsidy rates decline as coverage levels increase, and are higher for enterprise units and whole farm units than basic and optional units. For instance, while the

[1]There are four types of unit selection available: basic, optional, whole farm, and enterprise. A basic unit covers land in one county with the same farmer. An optional unit is a basic unit divided into smaller by township section. An enterprise unit covers all land of a single crop in a county for a farmer. A whole farm unit covers more than one crop.

subsidy rates for a basic unit at the 85% coverage level is 38%, it rises to 50% at the 65% coverage level. For an enterprise unit at the 85% coverage level, the subsidy rate is 53%.

The actual subsidy that producers receive depends on total premium (or premium rates), as well as subsidy rates. The RMA's premium rating has two primary components: (1) county base rates, and (2) adjustment to obtain the rate for an insured unit (Coble et al., 2010). Factors that are considered for adjustment include coverage level, crop type, and crop practice, which are chosen by individual producers. Premium rates are updated every year.

The default premium rating formula, for yield protection, is given as below (Coble et al., 2010; Tsiboe and Turner, 2023a).

$$\tau(\overline{y}, \theta, u; \alpha, \beta, \delta, \overline{y}_c) = [\alpha(\overline{y}/\overline{y}_c)^{\beta} + \delta]\vartheta(\theta)\rho(u) \tag{4.1}$$

where the premium rate, denoted by $\tau(\cdot)$, is determined by both exogenous factors (α, β, δ, and $\overline{y}_c$) and endogenous factors ($\overline{y}$, θ, u). α and β are a county base rate and a fixed loading factor, respectively. A fixed loading factor is added to account for infrequent but severe losses that may not be fully captured by the base rate. The base rate α is adjusted based on the insured's historic average yields $\overline{y}$, known as the Actual Production History (APH), and a county reference yields $\overline{y}_c$. This assumes that the risk profile of the farmer or farmland, which is not observed, is captured by her productivity relative to the average productivity of their peers (Tsiboe and Turner, 2023a). β is an exponent to the relative productivity, and takes a negative value. When $\overline{y} > \overline{y}_c$, meaning the farmer's productivity is relatively higher than others, the county base rate, α, is adjusted downward, and vice versa. Coverage levels and unit levels are multiplied as differential factors, where $\frac{\partial \vartheta(\theta)}{\partial \theta} > 0$ and $\frac{\partial \rho(u)}{\partial u} < 0$ meaning more disaggregated units would face a higher premium (Tsiboe and Turner, 2023a).

4.3 Conceptual Framework

We present a conceptual framework demonstrating how premium subsidies affect planting and easement decisions, building on the model by Yu et al. (2018). This framework highlights the trade-off faced by a farmer when allocating farmland between crop production and enrollment in wetland easement program. We assume that this farmer purchases insurance for the portion of

farmland used for crop production, given that land considered for easement typically consists of marginal farmland. For simplicity, we assume that the farmland is homogeneous in its productivity, though we later briefly discuss how a decline in productivity affects land allocation decisions.

Consider a representative farmer making a planting decision on a field of size S acres, which is eligible for wetland easement program. We assume that this farmer is also the farmland owner and can decide whether to participate in the easement program. The farmer decides how many acres of the field, denoted as A, to allocate to crop production, for which she purchases crop insurance. We assume the farmer selects revenue protection, which is the most widely adopted insurance plan (Risk Management Agency, 2024c). The remaining acres, $S - A$, are enrolled in the easement program.

The farmer maximizes her profits over two periods by choosing the cropping area of the field, A, in the first period. In the second period, the farmer continues to farm the same area selected in the first period. This represents that the part of the field enrolled in the easement program is removed from production for both periods. While modeling an infinite time horizon may be more appropriate considering that easements are often permanent, for simplicity, we assume that restored wetlands do not affect the yield of nearby farmlands. Additionally, we assume that only a single crop is produced on the field. The farmer's profit can be written as:

$$\pi = \sum_{t=1}^{2} \delta_t [max(R_t, \theta \overline{R}_t)A - (1 - s(\theta))p(\theta)\theta \overline{R}_t A - C_t(A)] + (S - A)E \tag{4.2}$$

The per-acre revenue in period t is the larger of the realized revenue R_t and the insured revenue $\theta \overline{R}_t$, where θ represents the coverage level. This assumes that the stochastic per-acre revenue in period t has a mean of $\overline{R}_t$. The per-acre costs for crop insurance is given as $(1 - s(\theta))p(\theta)\overline{R}_t$, where $s(\theta)$ represents the subsidy level and $p(\theta)$ represents the price for the coverage level θ. $C_t(A)$ represents the cost function to farm the area A. The farmer receives the one-time easement payment of $(S - A)E$ where the per-acre easement payment is denoted as E. The discount factor for each period is denoted by δ_t, where $\delta_1 = 1$.

Suppose the farmer maximizes the mean-variance utility function by choosing A, following the

previous studies (Goodwin, 1993; Yu et al., 2018; Tsiboe and Turner, 2023a).

$$\max_{\{A\}} U = \mu - \kappa\sigma \tag{4.3}$$

where μ and σ are the expected farm profit and the standard deviation of the profit, respectively. κ is the risk aversion parameter of the farmer, which takes a positive value for risk-averse farmers. A more risk-averse farmer would have lower utility for the same values of μ and σ, as her utility is more penalized by larger κ. The mean-variance model is typically applicable in two cases: (1) when the decision-maker exhibits constant absolute risk aversion and the underlying random variable is normally distributed, and (2) when preferences are represented by a quadratic utility function (Chavas, 2004).[2] While this model is fairly flexible in risk analysis and relatively easy to apply, it can be restrictive in accounting for rare but extreme events and in differentiating between downside and upside risks.

The expected farm profit, μ, can written as below using $max(R_t, \theta\overline{R}_t) = R_t + max(0, \theta\overline{R}_t - R_t)$.

$$\begin{aligned}\mu = \sum_{t=1}^{2} \delta_t [(\overline{R}_t + \int_0^{\theta\overline{R}_t} (\theta\overline{R}_t - R_t) f(R_t) dR_t A - (1 - s(\theta)) p(\theta) \theta\overline{R}_t A - C_t(A)] \\ + (S - A)E\end{aligned} \tag{4.4}$$

where $f(R_t)$ is the probability density function of R_t.

An actuarially fair premium rate is set when it equals the expected loss (i.e., expected indemnity):

$$p(\theta) = \frac{1}{\theta\overline{R}_t} \int_0^{\theta\overline{R}_t} (\theta\overline{R}_t - R_t) f(R_t) dR_t \tag{4.5}$$

This simplifies Equation 4.4 to:

$$\mu = \sum_{t=1}^{2} \delta_t [(1 + s(\theta) p(\theta) \theta)\overline{R}_t A - C_t(A)] + (S - A)E \tag{4.6}$$

The variance of farm profit σ^2, given in Equation 4.7, is driven by the variances of revenues in each period and the covariance of revenues between the periods. If the correlation between

[2]Nelson and Escalante (2004) developed a mean-variance model based on constant relative risk aversion, where it is derived as $V(\sigma, \mu) = -(\mu^2 - \gamma\sigma^2)^{-1}$. γ denotes the coefficient of relative risk aversion.

revenues across periods is zero, the second term in Equation 4.7 would equal zero.

$$\begin{aligned}\sigma^2 &= var(\sum_{t=1}^{2} \delta_t [max(R_t, \theta\overline{R}_t)A]) \\ &= A^2 \sum_{t=1}^{2} var(\delta_t max(R_t, \theta\overline{R}_t)) + 2Acov(\delta_1 max(R_1, \theta\overline{R}_1), \delta_2 max(R_2, \theta\overline{R}_2))\end{aligned} \tag{4.7}$$

Taking the derivative of Equation 4.7 with respect to the cropping area A can be expressed as in Equation 4.8. The first two terms represent the direct acreage effect on the variance of farm profit. The third term captures the acreage effect (equivalently, a decrease in wetland area) on farm profit variability. If wetlands reduce the flood risks of nearby cropping areas, an increase in A might raise the variance of farm profit in the second period. Note that wetland does not affect the first period's variance of farm profit as we assume that wetland is only restored after the first period. The last term represents the acreage effect on the covariance of between-period profits. Again, if the between-period revenues are uncorrelated, only the first and the third terms would remain.

$$\begin{aligned}\frac{\partial \sigma^2}{\partial A} =& 2A \sum_{t=1}^{2} var(\delta_t max(R_t, \theta\overline{R}_t)) + 2cov(\delta_1 max(R_1, \theta\overline{R}_1), \delta_2 max(R_2, \theta\overline{R}_2)) + \\ & A^2 \frac{\partial var(\delta_2 max(R_2, \theta\overline{R}_2))}{\partial A} + 2A \frac{\partial cov(\delta_1 max(R_1, \theta\overline{R}_1), \delta_2 max(R_2, \theta\overline{R}_2))}{\partial A}\end{aligned} \tag{4.8}$$

The first-order condition is:

$$\frac{\partial U}{\partial A} = \sum_{t=1}^{2} \delta_t [(1 + s(\theta)p(\theta)\theta)\overline{R}_t - \frac{\partial C_t}{\partial A}] - E - \kappa \frac{\partial \sigma}{\partial A} = 0 \tag{4.9}$$

The optimal A^* is determined by equating the marginal return from an additional acre of cropping to the sum of the marginal costs: the easement payment (E), marginal production costs ($\sum_{t=1}^{2} \delta_t \frac{\partial C_t}{\partial A}$), and the marginal changes in variance in profits ($\kappa \frac{\partial \sigma}{\partial A}$). Condition 4.9 shows that an increase in subsidy rate, $s(\theta)$, raises the expected return of production, resulting in an increase in cropping area A^*.

We now consider a case where productivity of the farmland declines, allowing to examine the outcomes for more marginal farmlands. We can take expected revenue, $\overline{R}_t$ as a proxy for the farmland's productivity or profitability. From Equation 4.9, a decrease in $\overline{R}_t$, meaning the farmland becomes less productive, leads to a decline in A^*. When $\overline{R}_t = 0$, all the farmland would be enrolled in the easement program.

4.4 Data

Our study area covers 16 states within the Mississippi River Basin (see Figure 4.1). Our sample period spans from 1997 to 2020. We consider five wetland/floodplain easement programs: the ACEP-WRE, the EWRP, the RCPP-WRE, the WRP, and the EWPP-FPE. The EWPP-FPE is for conserving floodplains, while the other programs are for conserving wetlands. We exclude counties that have zero enrollment in any easement programs over the sample period.

Table 4.1 Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Acres enrolled in easement programs	85.2	376.8	0.0	11,167.7
Easement programs for preserving wetlands	77.3	358.4	0.0	11,167.7
Easement program for preserving floodplains	7.9	107.6	0.0	5,666.0
Cumulative restored acres	1,327.2	3,216.0	0.0	43,081.5
Subsidy per liability	0.066	0.034	0.007	0.278
Premium per liability	0.109	0.048	0.028	0.407
Acres damaged from flooding in past 5 years	1,771.2	4,550.0	0.0	119,579.4
Farmland price ($/acre)	2,044.3	1,147.5	423.0	5,319.9
Historic growing season temperature (˚C)	19.5	2.7	12.8	26.0
Historic growing season precipitation (mm)	577.3	112.4	117.4	1,011.1
IV (Subsidy rate × Base premium rate)	35.3	10.6	7.6	66.6
Subsidy rate	56.3	12.7	27.2	66.7
Base premium rate	0.63	0.13	0.27	1.13

We obtain our data on wetland easement program enrollment from the United States Department of Agriculture (USDA) NRCS. The NRCS provides the numbers of acres that are acquired and restored, respectively, at the county level. The acquisition refers to entering into contracts between the NRCS and farmland owners. It takes about 21 months on average from application to contract, during which the NRCS evaluates the potential benefits and costs of restoration. Restoration must be completed within three years of the contract. The enrollment data includes details on the specific program under which the enrollment falls (e.g., the WRP or ACEP) and the duration of the contract (e.g., permanent or 30 years).

Figure 4.2 illustrates the changes in eased acres from 1997 to 2020. First, we observe that wetland easement programs are larger than a floodplain easement program. Enrollment trend

of wetland/floodplain easement program enrollment are closely correlated with that of wetland easement program enrollment. The enrolled acres for a floodplain easement program show zero enrollment for many years, particularly between 2012 and 2019. Low enrollment in the EWPP-FPE is likely attributable to limited funding. Unlike the WRP which receives annual appropriations, the EWPP-FPE is funded only through supplemental disaster appropriations (Dorothy, 2022).

Second, the graph reveals a decreasing trend, with a surge in enrollment in the early years of the programs, followed by a decrease and subsequent plateau at lower levels in recent years. The sudden declines in 2006 to 2008 were likely due to the WRP acreage cap of 2.275 million acres, established by the 2002 Farm Bill.[3] The 2008 Farm Bill raised the acreage cap to 3.041 million acres through 2012, which led to a sharp increase in enrollment in 2009 (Blackwoods Group, LLC, 2023). Enrolled acres in 2014 declined to 2008 levels and remained relatively stable through 2020. The 2014 Farm Bill replaced the acreage cap to authorized funding levels. As the 2014 Farm Bill consolidated multiple easement programs into the ACEP, such as the WRP, the Grassland Reserve Program, and the Farmland Protection Program, it authorized significantly less annual funding compared to the 2008 Farm Bill, in part resulting in a decline in enrollment.[4] The 2018 Farm Bill increased mandatory funding for the ACEP to $450 million per year from 2019 to 2023, up from $250 million in 2018 (Stubbs, 2019).

We construct county-level variables for wetland easement program enrollment, using the number of enrolled acres. We use the application year, rather than contract year, as the enrollment year, since they are more directly related farmer's decision-making. The application years are determined subtracting the average state-level duration of the acquisition process from the county-level acquisition years.

The data on crop insurance premium subsidies is obtained from the Summary of Business (SOB) by the USDA Risk Management Agency (RMA). The SOB provides county-level information on insured acres, total premium, total subsidy, and liability that are categorized by crops, plans, and coverage levels. We define a subsidy level as the share of premium subsidy to the total liability,

[3]The 2002 Farm Bill increased the acreage cap from 1.075 million acres to 2.275 million acres.

[4]https://www.ers.usda.gov/topics/farm-bill/2014-farm-bill/conservation

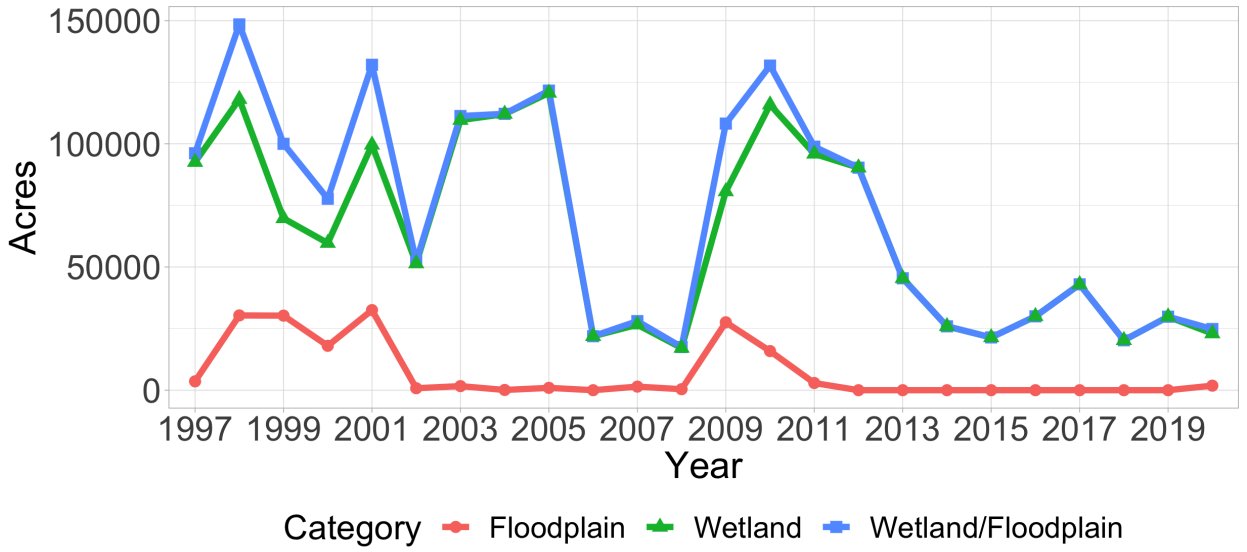

Figure 4.2 **Trends of acres enrolled in wetland/floodplain easement programs**: This figure displays annual changes in enrolled acres by easement programs in the study area. The green line represents acres enrolled in wetland easement programs, while the red line shows those in floodplain easement program. The blue line is the total enrolled acres.

which is the effect subsidy that farmers receive per their insurance uptake. Figure 4.3 illustrates the changes in these subsidy levels, showing a sharp increase between 2000 and 2009 followed by a decline thereafter. One possible explanation for this recent decline is that the rising proportion of insured acres with higher coverage levels. For instance, the share of insured acres at the 65% coverage level decreased from 16% in 2009 to 7% in 2020, while the share at the 85% coverage level increased from 8% to 26% over the same period.

Information on past damages from flooding is derived from the RMA's Cause of Loss (COL) data. The COL provides details on the specific causes of loss for claims, the total amount of loss, and the corresponding year and month in which the loss occurred. We calculate the total damages from flooding over the past five years. Since the COL data only covers damages of farmlands that have enrolled in crop insurance, it represents a subset of the total damages.

The value of the easement is determined based on the farmland value. While it would be more direct to include the per-acre payment of the easement programs, due to the lack of the data, we include county-level average farmland prices, obtained from the USDA National Agricultural Statistics Service (NASS), as a proxy. Farmland prices are deflated using the Producer Price Index

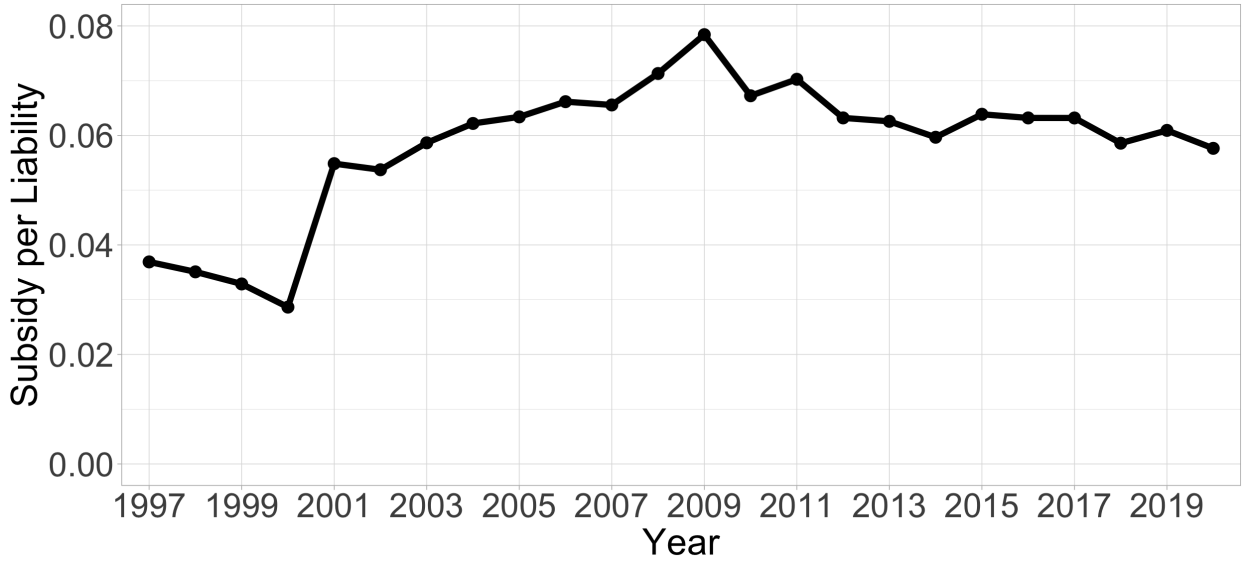

Figure 4.3 **Trends of subsidy per liability**: This figure presents annual changes in the average subsidy per liability across the contiguous United States. Both subsidy and liability values are aggregated across all crops, coverage levels, and insurance plans.

obtained from the Bureau of Labor Statistics.

Weather data come from PRISM, aggregated to the county level.[5] Historic 15-year average total precipitation and mean temperature variables during the growing season from April to September are constructed to represent long term climatic environment related to crop production.

4.5 Empirical Strategy

To investigate the effect of premium subsidy on easement enrollment, we employ a Poisson quasi Maximum Likelihood Estimation (QMLE) approach, a procedure to estimate an exponential model incorporating nonnegative outcomes with a high frequency of zero values. Our exponential model is written as follows:

$$E(y_{it}|\mathbf{X_{it}}) = exp(\mathbf{X_{it}^{'}}\boldsymbol{\beta}) \tag{4.10}$$

where y_{it} is the number acres enrolled in easement programs in county i in year t and $E(\cdot)$ is the expectation operator. $\mathbf{X_{it}}$ is a vector of explanatory variables and $\boldsymbol{\beta}$ is a vector of corresponding coefficients.

Poisson QMLE, or Poisson regression, is different from the basic Poisson MLE which assumes

[5]https://data.prism.oregonstate.edu/time_series/us/an/800m/ppt/monthly/. The resolution of the data is 800 meters.

that $y|\mathbf{X}$ follows a Poisson distribution. While the basic Poisson MLE is more efficient conditional on that the distributional assumption is correct, the Poisson distribution's assumption on its variance, namely $var(y|\mathbf{X}) = E(y|\mathbf{X})$, is often too restrictive as we commonly observe over-dispersion in applications where $var(y|\mathbf{X}) > E(y|\mathbf{X})$. Our data is also likely to show over-dispersion, given the high frequency of zero values and absence of an upper bound on the outcome variable. Poisson QMLE overcomes this restriction by focusing on $E(y|\mathbf{X})$.[6]

Poisson QMLE has some nice statistical properties suitable for our setup. One important property is that Poisson QMLE is consistent when the conditional mean, $E(y|\mathbf{X})$, is correctly specified. Other features of the Poisson distribution, such as $var(y|\mathbf{X}) = E(y|\mathbf{X})$ and y being a count variable, do not need to hold. Hence, we adopt Poisson QMLE, where our dependent variable is a continuous variable and its conditional variance exhibit over-dispersion.

The log likelihood function to estimate $\boldsymbol{\beta}$ is equivalent to that of the basic Poisson MLE when the conditional mean is correctly specified. Note that this does not require other distributional assumptions on the variance and the discreteness. For simplicity, the log likelihood function in a cross-sectional setting is presented below:

$$\ell_i(\boldsymbol{\beta}) = -exp(\mathbf{X_i}'\boldsymbol{\beta}) + y_i\mathbf{X_i}'\boldsymbol{\beta} \tag{4.11}$$

We assume that $E(y_{it}|\mathbf{X_{it}})$ takes the below form:

$$E(y_{it}|\mathbf{X_{it}}) = E(y_{it}|Subsidy_{it}, \mathbf{Z_{it}}) = exp[\beta Subsidy_{it} + \mathbf{Z'}_{it}\boldsymbol{\gamma} + c_i + v_t] \tag{4.12}$$

where premium subsidy per liability, our main explanatory variable, is denoted as $Subsidy_{it}$. Control variables are denoted as $\boldsymbol{Z}_{it}$. $\boldsymbol{\gamma}$ represents a vector of coefficients. We control for premium rates (premium divided by liability) as it is correlated with subsidy level and also likely to affect enrollment decisions. Lagged damages from flooding over the past five years are included to control for frequency and intensity of flooding in a county, which is expected to increase the probability of enrolling in easement programs. We include the cumulative number of acres enrolled in the

[6]Poisson QMLE also accommodates cases of under-dispersion case. However, over-dispersion is more commonly observed in empirical applications.

easement programs as a proxy for the availability of eligible farmlands. Our assumption is that as the cumulative area enrolled in the programs increases, the remaining farmlands eligible would decrease and the probability of enrolling in those programs is subsequently reduced. Having lagged dependent variable can lead to downward bias (Nickell, 1981). However, we argue that this is less problematic in our study for two reasons. First, our primary interest is in estimating the causal effect of subsidies on enrollment, rather than estimating the dynamic effect of past enrollment. Second, our panel spans a relatively long period ($T = 24$), and the bias diminishes at a rate of $\frac{1}{T}$ (Nickell, 1981). We estimate additional regression without cumulative restored area in the control as a robustness check.

We include county-level farmland prices to control for program payments. We also control for average temperature and average precipitation over the past fifteen years. County fixed effects, denoted c_i, are included to control for time-invariant unobserved heterogeneity by counties including soil characteristics and the average number of eligible converted farmlands. Year fixed effects, v_t, control for yearly shocks that are common across all counties, such as federal policy changes, acreage caps, and authorized funding levels.

4.5.1 Identification strategy

One identification concern is that the premium subsidy variable (i.e., premium subsidy per liability) is partly endogenous to other farm decisions (Yu et al., 2018; Tsiboe and Turner, 2023b). Subsidy per liability is calculated as the product of the subsidy rate (i.e., subsidy divided by premium) and the premium rate (i.e., premium per liability). Although premium subsidy rates are determined exogenously at the federal level and are identical across crops and locations, they vary by coverage levels and insurance unit levels, which are chosen by farmers. Premium rates are also affected by these factors as in Equation 4.1.

Since farmers with higher risk profile farmlands or greater risk aversion tend to select higher coverage levels, this results in lower subsidy rates and higher premium rates. However, as we use aggregated data, these individual-level risk factors are not directly observable. In addition, this unobserved risk factors are likely to be directly correlated with easement enrollment decisions as

riskier lands are arguably more prone to be enrolled. These omitted variables will bias the usual ordinary least squares (OLS) or Poisson regression whose identification assumption relies on the observables. The direction of the bias is not straightforward, as we are unsure about the relationship between unobserved risk profile and subsidy level. While riskier crops or counties generally have higher premium rates for a given crop and coverage level (Yu et al., 2018), riskier production is more likely to be associated with higher coverage levels. This complicates the relationship, as subsidy rates decrease as coverage levels rise.

Previous studies have attempted to address endogeneity problem of premium subsidy or insurance participation by largely two approaches: (1) different timings in roll-out of an insurance program, and (2) instrumental variable approach (Yu et al., 2018, 2022; Tsiboe and Turner, 2023b; Woodard and Yi, 2020; DeLay, 2019). In this study, we adopt an instrumental variable approach, particularly using the policy rating parameters following Tsiboe and Turner (2023b).

Our IV consists of two components: (1) subsidy rates and (2) premium rates. First, we calculate annual subsidy rates for the 65% and 75% coverage levels and use the average of these two rates as a source for the IV, following the literature (Yu et al., 2018; DeLay, 2019; Ghosh et al., 2021).[7] Since subsidy rates are set at the federal level, they are assumed to be exogenous to individual farm-level management decisions. Naturally, subsidy rates are closely correlated with the actual subsidy received by producers. While this variation in subsidy rates has been widely adopted as a source of an IV in previous studies, it only provides temporal variation, which may limit its capability to capture cross-sectional differences in subsidy exposure.

We complement this using county-level base premium rates, which are determined based on county-level historic loss cost ratios, building on (Tsiboe and Turner, 2023a). As outlined in Chapter 3.2.2 (Premium Rating System), premium rates are determined by base premium rates and individual-level adjustments. Since the base rating parameters are available only from 2011 from the RMA's Actuarial Data Master data and our sample period starts from 1992, we approximate

[7]For robustness checks, we use alternative sets of subsidy rates: (1) subsidy rates for the 65% coverage level, (2) subsidy rates for the 75% coverage level, (3) including subsidy rates for both the 65% and 75% coverage levels separately, and (4) a liability-based weighted average of subsidy rates across coverage levels. The estimation results, reported in Table 4C.1, are consistent with our main findings.

these parameters using the method proposed by Tsiboe and Turner (2023a). Tsiboe and Turner (2023a) shows that this method closely approximates the rates produced by the RMA for the period from 2011 to 2020.

Our county-level base premium rates are the weighted average of (1) historic loss cost ratio of the targeted county and (2) adjoining counties' loss cost ratio, where loss cost ratio is calculated by $min[1, max(0, \frac{indemnity}{liability})]$. First, we compute the historic average of loss costs ratio for each county using data up to two years prior to the given crop year, in accordance with the RMA's recommended rating practices. This rate is referred to as a burn rate, The burn rate is loaded by dividing by 0.88 to account for infrequent but extreme losses, resulting in the raw base rate. Then, we use the raw base rates from adjacent counties to spatially smooth out potential sampling errors in a single county's data, a similar approach to one of the RMA's spatial smoothing procedure. A surrounding county group rate is calculated as a weighted average of the raw rates of all adjoining counties by the historic sum of the liability up to two periods prior. The final target rate, which is used as the source of our IV, is a weighted average of the target county's raw rate and the county group rate, with weights of 0.6 and 0.4, respectively. The weights are based on the RMA's past practice before 2006 (Coble et al., 2010).

The resulting target premium rates approximate $\alpha+\delta$, which is the RMA's base rate $\alpha(\overline{y}/\overline{y}_c)^{\beta}+\delta$, prior to adjustments for coverage level and unit level. This RMA's base rate is further simplified to $\alpha + \delta$, when the APH, $\overline{y}$, equals the reference yield, $\overline{y}_c$. Since these rates closely approximate the actual base rates used to determine premium rates, they are expected to be highly correlated with subsidy levels. They are assumed to be exogenous as they are determined two years in advance and farm-level decisions are unlikely to have significant impacts on future base rates.

We adopt the CF approach as we estimate a non-linear model. The CF Poisson estimation is implemented in two stages. First, we estimate the reduced form first-stage regression of the potentially endogenous variable on the instruments and control variables. Then we obtain the residuals from this reduced form regression. Second, we estimate a fixed effect Poisson regression including the residuals from the first stage as a control. A statistical test on the estimated coefficient

of the residuals provide a valid test whether the potentially endogenous variable can be considered exogenous. To obtain the valid standard errors in the second stage, we bootstrap in both estimation steps.

Table 4A.1 reports the first stage regression results. We find that our instrumental variables are strong enough with the F-statistic (207.4) exceeding the common rule of thumb threshold of 10 and a more strict threshold of 50 suggested by the recent studies (Keane and Neal, 2024).

4.6 Results

Table 4.2 reports the estimation results of premium subsidy levels on the area enrolled in wetland/floodplain easement programs. Columns (1) and (2) show the results with cumulative restored acres included as a control, while Columns (3) and (4) present the results excluding this variable. Columns (1) and (3) are estimated by Poisson QMLE, and Columns (2) and (4) are obtained by using CF Poisson. Column (2) represents our preferred model. The estimated coefficients on the residuals from the first stage are statistically significant, suggesting for potential bias in the Poisson regression and supporting our IV estimation. The estimated coefficient on Ln(Subsidy per Liability) from the CF Poisson regression is smaller (more negative) than those from the Poisson regression. The differences in the estimates suggest that omitted riskiness is likely to be positively correlated with subsidy per liability, resulting in an upward bias.

Across various specifications, we consistently find that premium subsidy reduces enrollment in easement programs. Based on the results by CF Poisson regression in Column (2), we estimate that a 1.0% increase in subsidy per liability lowers the number of acres enrolled in easement programs by 3.2%. The average partial effect is estimated to correspond to a reduction of 2.7 enrolled acres.[8] This suggests that while we find some evidence that premium subsidies may discourage conservation program enrollment, the economic magnitude of the effect is relatively marginal. The estimated coefficients remain consistent when Cumulative Restored Acres is excluded as a control variable, as shown in Columns (3) and (4), though their magnitudes are smaller than those in Columns (1) and (2). The estimate on Ln(Subsidy per Liability) is statistically significant at the

[8]The average partial effect is calculated by $\frac{1}{100} \times \widehat{\beta} \times \overline{\widehat{y}}$, where $\overline{\widehat{y}}$ denotes the average of the predicted values.

1% level in the Poisson regression, reported in Column (3), but it is only marginally significant in the CF Poisson regression in Column (4), with a p-value of 0.15.

One possible explanation for this small effect is that farmlands enrolled in the easement programs are typically marginal lands, which are often unsuitable for profitable production or attract tenants on a sustainable basis. While subsidized insurance ensures a certain level of protection against production and market risks, if crop failures occur over an extended period of time, it is unlikely to generate profits through making claims due to deductibles and reduced guarantees resulting from previous crop failures. Hence, these farmlands may not be considered suitable for farming, suggesting a minimal crowding-out effect as they are not farmable regardless of changes in subsidy levels. We examine this possibility using additional data in the next subsection.

Higher premium rates are estimated to increase enrollment, with the effect statistically significant at the 1% level. Specifically, a 1% increase in premium rates raises the enrollment area by 3.0%. This finding aligns with the result for subsidy, as higher premiums conditional on subsidy level raise the marginal cost of farming, encouraging participation in easement programs.

The estimated coefficients on the past areas damaged by flooding, a proxy for flood risk of an area, are positive, but they are not statistically significant. This result suggests that though wetlands may prevent some flood damages of nearby farmlands, the enrollment decisions are not largely driven by this prevention effect. One possible explanation is that flood risk mitigation from nearby wetlands may be relatively limited and more costly compared to other adaptation options, such as purchasing insurance.

In addition, the estimation results suggest that the cumulative number of acres restored reduces the likelihood of enrollment in wetland easement programs. This negative association may be explained by two factors. One is that as more land is enrolled, there would remain fewer eligible farmlands. Second, since the remaining lands are likely more productive than those already eased, landowners may be less inclined to participate in wetland easement programs.

Interestingly, farmland price is estimated to have a negative effect on wetland easement program enrollment. As farmland price is positively correlated with easement value, the negative effect may

Table 4.2 Estimation Results

	(1) Poisson	(2) CF Poisson	(3) Poisson	(4) CF Poisson
Ln(Subsidy per Liability)	−1.058***	−3.214***	−0.755***	−1.159
	(0.247)	(0.945)	(0.253)	(0.802)
Ln(Premium per Liability)	0.644**	2.960***	0.667**	1.108
	(0.302)	(1.032)	(0.313)	(0.906)
Lagged 5-year Sum of Acres	0.007	0.005	0.006	0.005
Damaged by Flooding (1000 acres)	(0.007)	(0.005)	(0.007)	(0.006)
Cumulative Restored Acres	−0.085***	−0.104***		
(1000 acres)	(0.017)	(0.016)		
Ln(Farmland Price)	−0.811**	−0.580**	−0.529*	−0.484*
	(0.325)	(0.260)	(0.312)	(0.268)
Lagged 15-year Avg Precipitation	0.002	0.000	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Lagged 15-year Avg Temperature	−0.638	−0.930**	−0.998*	−1.060**
	(0.513)	(0.417)	(0.555)	(0.426)
Residuals from the First Stage		2.341**		0.444
		(1.043)		(0.886)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Number of Observations	18,897	18,897	18,897	18,897
First-stage F Statistics		207.4		225.5

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

seem counterintuitive. However, considering that farmland price reflects the productivity of the land, the direction of the effect would depend on the relative magnitude of these two effects. Our result on wetland easement program suggests that the productivity effect outweighs the easement price effect.

4.6.1 Characteristics of enrolled farmlands

In this subsection, we examine whether lands enrolled in the easement programs were actively being farmed for crop production prior to their restoration to wetlands. Our hypothesis is that if the share of wetlands that had previously been used for crop production is relatively small, farmland owners may be less responsive to changes in crop insurance subsidy levels and therefore less likely to be discouraged from enrolling in easement programs.

We focus on restored wetlands in 2020 and examine if crops were produced on these lands in previous years, concentrating on four states where restoration has been most active in our study area: Iowa, South Dakota, Missouri, and Louisiana. For each restored wetland as of 2020, we assess whether it was classified as cropland or non-cropland in 2005, 2010 and 2015. If a wetland was already classified as wetland in 2015, implying that restoration likely occurred between 2010 and 2015, we include this wetland only when calculating cropland shares for 2005 and 2010.

We first generate buffers for each restored wetland using available information on acreage and coordinates. Since each wetland is represented by a single point and a reported acreage, we assume that this point represents the centroid and draw a circular boundary whose area equals the reported acreage.

We then use the USDA's Cropland Data Layer (CDL)[9] to determine whether any crops were grown on these lands in earlier years. For each restored wetland in 2020, we assign land use categories based on the most frequent (modal) land cover class within the circular boundary. For example, if corn pixels are the most common within a boundary, we classify the area as previously used for corn production. Wetlands are considered to have been used for crop production if any row crops were identified. The non-cropland category includes fallow/idle cropland, grass/pasture, and forest.

Due to potential mismatches between the actual shapes of wetlands and the circular boundaries we create, not all restored wetlands were classified as wetlands with the CDL. We limit our analysis

[9]The CDL, provided by the USDA NASS, is a land cover dataset with 30-meter resolution created using satellite imagery, except for the 2006 data for South Dakota whose resolution is 56-meter. Each cell represents a specific land cover category, indicating whether a crop was grown or the land is classified as wetland or another use.

to those restored wetland that are identified as wetlands based on the CDL and examine their land cover in years 2005/2006, 2010, and 2015.[10]

Figure 4.4 presents the share of restored wetlands that were previously farmed in each of these years. Although the shares fluctuate across years and states, they generally remain below 30%. This finding suggests that many restored wetlands may not have been actively farmed prior to restoration, potentially due to poor suitability for production. Hence, the influence of crop insurance subsidy levels on landowners' enrollment decisions may be limited in these cases.

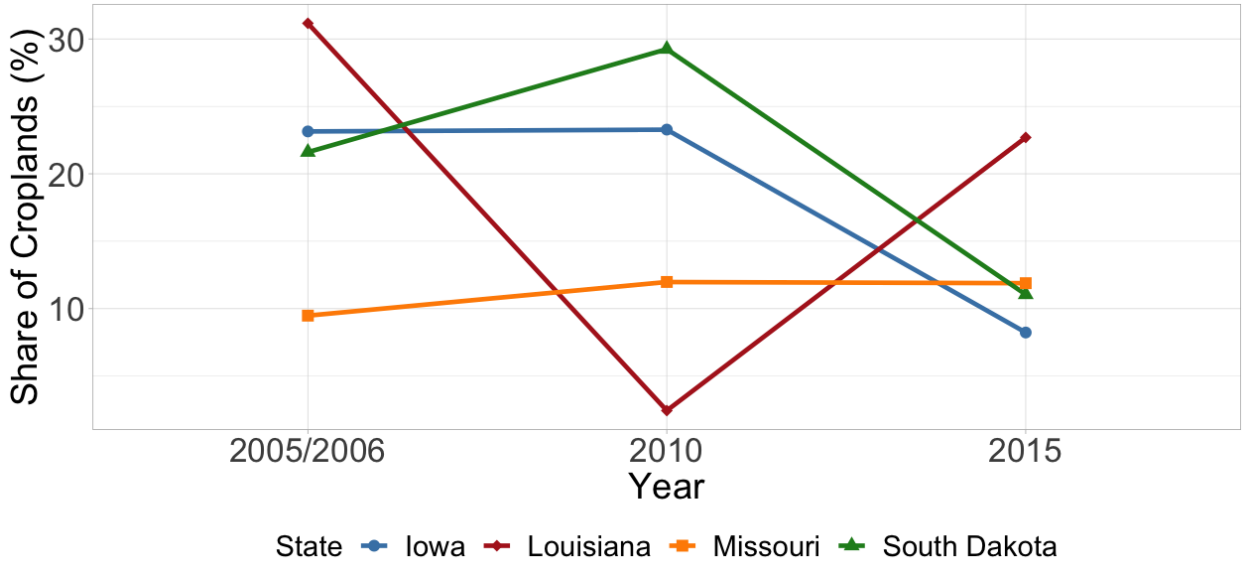

Figure 4.4 **Changes in the share of restored wetlands previously used as croplands**: This figure presents changes in the share of restored wetlands in 2020 that were classified as cropland in the years of 2005/2006, 2010, and 2015 for Iowa, Louisiana, Missouri, and South Dakota. We first identify the locations of restored wetlands in 2020, then trace whether these areas were cropland or non-cropland in each of the earlier years.

4.6.2 Robustness checks

In this section, we conduct two sensitivity analyses: (1) estimations using a subset of data before and after the 2000 Agricultural Risk Protection Act (ARPA) and the 2002 Farm Bill, and (2) linear regression.

Subsample Analysis Around Major Agricultural Acts

[10]We use the 2006 CDL data for South Dakota as the data for South Dakota only begins in 2006. For the other states, we use the 2005 data.

As previously discussed, one identification concern is that the subsidy per liability variable may be affected by other endogenous factors, such as risk profile and risk preference. Here, in addition to our instrumental variable approach, we employ an alternative approach to identify the effect by focusing on large shifts in subsidy rates triggered by the enactment of new agricultural legislation, rather than relying on the full sample. The underlying assumption is that the changes in subsidy per liability is primarily driven by exogenous changes in subsidy rates, rather than by changes in other factors, such as crop choices and coverage levels.

First, we estimate a Poisson QMLE using data from the years surrounding the ARPA of 2000, which introduced a large increase in subsidy rates (O'Donoghue, 2014). As shown in Figure 4.3, there is a notable jump in subsidy per liability between 2000 and 2001. We focus on two subsamples: (1) 2000 to 2001 and (2) 1999 to 2002. The estimation results based on these subsamples are presented in Table 4.3. Consistent with our main findings, we find that higher subsidies discourage enrollment in easement programs. Specifically, a 1% increase in subsidy per liability is estimated to reduce enrollment by 1.1 to 1.4%.

Second, we estimate an additional Poisson QMLE using a subsample around the 2002 Farm Bill. While using the exogenous variations in subsidy rates introduced by the 2000 ARPA helps with identification, a concern remains that enrollment decisions may have been constrained by acreage caps on easement programs during this period, as suggested in Figure 4E.1. Such constraints could lead to an upward bias in the estimated effects, as they may suppress observed enrollment regardless of underlying incentives. The acreage caps were raised in 2001 by 100 thousand acres under the 2001 Consolidated Appropriation Act, and expanded further by 1.2 million acres under the 2002 Farm Bill.

We estimate a Poisson QMLE using data from the years before and after the 2002 Farm Bill using the data in the years 1997 to 1999 and 2003 to 2005. These two periods had different subsidy levels, while the acreage caps on easement programs were not binding. Although the 1996 Farm Bill (the Federal Agriculture Improvement and Reform Act of 1996) maintained the previously set acreage cap of 975,000 acres for the WRP, this cap was not a binding constraint, as the total enrolled

acres remained below 250,000 acres by 1996. However, by 2002, total enrolled acres under the WRP increased to approximately 968,000 acres, prompting the 2002 Farm Bill to raise the acreage cap to 2.275 million acres. The results, presented in Column (3) in Table 4.3, remain consistent with the main findings and the results based on the 2000 ARPA.

Table 4.3 Subsample Estimation Results

	(1) 2000-2001	(2) 1999-2002	(3) 2002 Farm Bill
Ln(Subsidy per Liability)	-1.105^{***}	-1.361^{***}	-1.641^{***}
	(0.435)	(0.352)	(0.435)
Ln(Premium per Liability)	3.222^{**}	1.992^{***}	1.202^{**}
	(1.343)	(0.747)	(0.592)
Lagged 5-year Sum of Acres	−0.016	-0.053^{*}	0.039^{*}
Damaged by Flooding (1000 acres)	(0.035)	(0.032)	(0.020)
Cumulative Restored Acres	0.077	-0.164^{**}	-0.091^{***}
(1000 acres)	(0.127)	(0.070)	(0.020)
Ln(Farmland Price)	−1.976	2.368	-1.685^{**}
	(0.4.012)	(2.020)	(0.857)
Lagged 15-year Avg Precipitation	0.029^{*}	−0.000	-0.005^{*}
	(0.016)	(0.010)	(0.003)
Lagged 15-year Avg Temperature	0.143	−1.725	0.434
	(5.555)	(2.867)	1.033
County FE	✓	✓	✓
Year FE	✓	✓	✓
Number of Observations	689	1,708	3,198

*p<0.1; **p<0.05; ***p<0.01
Standard errors clustered at the county level are presented in parentheses

Linear Regression

We estimate linear models as a robustness check to our main analysis presented in Table 4.2. First, we use the number of enrolled acres as a dependent variable, with results presented in Columns (1) and (2) in Table 4B.1. We then estimate another model using the logarithm of the

outcome variable. To account for zero values, we add one to zero outcome values before taking the logarithm. The results remain consistent when using alternative adjustments such as adding 0.1 or 0.01 to the zero values. The first-stage F statistics indicate strong correlation between the IV and Ln(Subsidy per Liability), satisfying the relevance condition.

The results report that higher subsidy per liability reduces enrolled acres, aligning with our main findings. Using the IV fixed effects estimation with enrolled acres as the outcome variable, we find that a 1% increase in subsidy per liability results in a decrease of approximately 450 enrolled acres. This is a greater effect than the average marginal effect of our main specification (2.7 acres). The results using log-log model, reported in Column (4) of Table 4B.1, show similar results to the main results. Though the estimated coefficient (-1.48) is smaller than that from the main specification (-3.21 in Table 4.2), the direction and relative magnitude of the effect remain consistent.

The estimates on other explanatory variables remain similar to the main findings. The estimates on Ln(Premium per Liability) are positive and statistically significant, with the magnitude close to the estimates on subsidy level.

4.7 Counterfactual Analysis

In this section, we calculate a counterfactual estimate on the number of enrolled acres in easement programs in 2020, assuming that the premium subsidy level remained at the 1997 level. Based on our preferred model, we compute a predicted value for enrolled acres using the 1997 subsidy level, holding all covariates and fixed effects constant at 2020 levels.

$$\widehat{y}_t = \sum_{i=1}^{I} \widehat{y}_{it} = \sum_{i=1}^{I} exp[\widehat{\beta} \times subsidy_{it} + \boldsymbol{Z'}_{i,2020}\widehat{\boldsymbol{\gamma}} + \widehat{c}_i + \widehat{v}_{2020}] \tag{4.13}$$

where $\widehat{y}_{it}$ is the counterfactual value of enrolled acres for county i in 2020 if the subsidy level had remained at the value in year t. $\widehat{y}_t$ is the sum of the counterfactual enrolled acres across counties.

We calculate the counterfactual enrolled acres in 2020 as follows:

$$\widehat{\Delta y_{2020}} = \widehat{y}_{1997} - \widehat{y}_{2020} \tag{4.14}$$

The counterfactual calculation suggests that if the subsidy level had remained at its 1997 level, approximately 90.7 thousand additional acres would have been enrolled in easement programs

in our study area. The subsidy per liability increased by about 34% between 1997 and 2020. The associated 95% confidence interval is [12,134, 511,843], estimated by the bootstrapping procedure.[11] Given that the annual average enrollment in our study area is 66.2 thousand acres, this counterfactual represents about 136% of the typical yearly enrollment.

We estimate the effect of this counterfactual loss in enrolled acres in the easement programs on the flood damage claims in the National Flood Insurance Program (NFIP) using the estimates from Taylor and Druckenmiller (2022). This calculation assumes that the lost easement acres are spatially distributed similarly to the wetlands studied in Taylor and Druckenmiller (2022). It is important to note that this only represents partial damages from wetland losses as it only captures the flood mitigation benefits and flood-related damages claimed through the NFIP. Taylor and Druckenmiller (2022) estimates the effect of wetlands on damage claims in the NFIP using the zip-code level data between 2001 and 2016. They find that a one hectare (about 2.47 acres) loss of wetlands increases NFIP claims by $1,840/year. Applying this estimate, we calculate that the counterfactual loss in enrolled acres would result in approximately $67.5 million in additional annual flood-related damages.

4.8 Conclusion

The crop insurance program plays a central role in agricultural policy in the United States, serving as an important risk management tool for farmers. While crop insurance offers protection against production and market risks, there have been concerns about its potential to conflict with other agricultural policies, such as conservation programs, and to encourage riskier production decisions (Goodwin and Smith, 2013). Insured farmers may expand crop acreage, select riskier crops, and alter their decisions regarding enrollment in conservation programs (Goodwin et al., 2004; Yu et al., 2018; DeLay, 2019; Yu et al., 2022).

This study examines the effect of premium subsidy on enrollment in wetland/floodplain easement programs which restore wetlands permanently or for 30 years. We adopt an instrumental variable approach to address potential endogeneity between subsidy level and enrollment decision.

[11] We estimate the 95% confidence interval using a bootstrap procedure, recognizing that the distribution of predicted values is skewed due to the non-negativity constraint inherent in the exponential model.

Using county-level data spanning from 1997 to 2020, we find that an increase in premium subsidy reduces enrollment in easement programs. Specifically, we estimate that a 1% increase in the subsidy level reduces easement enrollment by approximately 2.7 acres per county per year. Our results are robust across various specifications and identification strategies, although the estimated magnitude of the effect is relatively modest in economic terms.

Our counterfactual analysis suggests that if the subsidy level had remained at the 1997 level, the enrolled area would have been 90.7 thousand acres more in 2020, equivalent to about 136% of the typical annual enrollment in our study area. Using the estimated effect of wetlands on the damage claims in the NFIP from Taylor and Druckenmiller (2022), we calculate that the counterfactual loss in restored wetlands would have resulted in about $67.5 million in additional flood-related damages.

This research opens several avenues for future research. While our findings suggest that a majority of restored wetlands were not actively farmed likely due to limited productivity, further investigation into the characteristics of lands enrolled in easement programs would deepen our understanding of the environmental outcomes of these conservation programs. In addition, participation in wetland easement programs appears to be more strongly affected by acreage caps or authorized funding for these programs. In recent years, enrolled acreage has declined to its lowest levels since 1997, coinciding with reductions in authorized program funding rather than increases in insurance subsidies. Investigating how these institutional factors interact with farm-level economic incentives could yield valuable insights into improving the cost-effectiveness and environmental impact of conservation programs.

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APPENDIX 4A

FIRST-STAGE REGRESSION RESULTS

Table 4A.1 First-Stage Regression Results

	(1)	(2)
	Dependent Variable: Ln(Subsidy per Liability)	
Instrumental Variable	−0.018***	−0.019***
	(0.001)	(0.001)
Ln(Premium per Liability)	1.086***	1.096***
	(0.015)	(0.015)
Lagged 5-year Sum of Acres Damaged by Flooding (1000 acres)	−0.001	−0.001**
	(0.001)	(0.001)
Cumulative Restored Acres (1000 acres)	−0.006***	
	(0.001)	
Ln(Farmland Price)	0.096***	0.097***
	(0.013)	(0.013)
Lagged 10-year Avg Precipitation	−0.001***	−0.001***
	(0.000)	(0.000)
Lagged 10-year Avg Temperature	−0.076***	−0.075***
	(0.020)	(0.020)
County FE	✓	✓
Year FE	✓	✓
F-statistic	207.4	225.5
Number of Observations	18,897	18,897

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

APPENDIX 4B

LINEAR REGRESSION

Table 4B.1 reports the results from linear regressions. Columns (1) and (2) use enrolled area as the outcome variable, while Columns (3) and (4) use the natual logarithm of enrolled area. To account for zero in the outcome variable, we add one to zero outcomes before taking the logarithmic transformation.

Table 4B.1 Linear Regression Results

	(1)	(2)	(3)	(4)
	Level-Log		Log-Log	
	FE	IV-FE	FE	IV-FE
Ln(Subsidy per Liability)	−148.15***	−449.78***	−0.20	−1.48***
	(34.29)	(112.95)	(0.17)	(0.55)
Ln(Premium per Liability)	107.86**	421.42***	0.32	1.66***
	(35.35)	(112.83)	(0.204)	(0.59)
Lagged 5-year Sum of Acres Damaged by Flooding (1000 acres)	1.76**	1.51*	0.01	0.01
	(0.87)	(0.82)	(0.01)	(0.01)
Cumulative Restored Acres (1000 acres)	−76.60***	−79.48***	−0.20***	−0.22***
	(7.82)	(8.11)	(0.02)	(0.02)
Ln(Farmland Price)	−21.00	15.03	−0.53***	−0.37**
	(18.76)	(23.84)	(0.13)	(0.15)
Lagged 15-year Avg Precipitation	−0.10	−0.06	0.00	0.00
	(0.13)	(0.15)	(0.00)	(0.00)
Lagged 15-year Avg Temperature	−17.55	−49.76	0.21	0.07
	(32.28)	(33.17)	(0.19)	(0.20)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Number of Observations	18,897	18,897	18,897	18,897
First-stage F Statistics		1,729.3		1,729.3
Adjusted R-squared	0.258		0.253	

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

Table 4B.2 reports the log-level estimation results using alternative logarithmic transformations, where different constants are added to zero outcomes before the transformation. Columns (1) and (2) add 0.1 to the zero outcomes, and Columns (3) and (4) add 0.01. The results are consistent with those reported in Column (4) of Table 4B.1.

Table 4B.2 Linear Regression Results: Alternative Logarithmic Transformations

	(1)	(2)	(3)	(4)
	Adding 0.1		Adding 0.01	
	FE	IV-FE	FE	IV-FE
Ln(Subsidy per Liability)	−0.19	−1.95**	−0.19	−2.41**
	(0.24)	(0.78)	(0.30)	(1.01)
Ln(Premium per Liability)	0.37	2.19***	0.42	2.73**
	(0.29)	(0.85)	(0.38)	(1.10)
Lagged 5-year Sum of Acres	0.02	0.02	0.02	0.02
Damaged by Flooding (1000 acres)	(0.01)	(0.01)	(0.01)	(0.01)
Cumulative Restored Acres	−0.26***	−0.28***	−0.33***	−0.22***
(1000 acres)	(0.03)	(0.03)	(0.03)	(0.04)
Ln(Farmland Price)	−0.77	−0.56***	−1.00***	−0.74***
	(0.19)	(0.21)	(0.25)	(0.27)
Lagged 15-year Avg Precipitation	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Lagged 15-year Avg Temperature	0.37	0.18	0.53	0.29
	(0.27)	(0.29)	(0.35)	(0.37)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Number of Observations	18,897	18,897	18,897	18,897
First-stage F Statistics		1,729.3		1,729.3
Adjusted R-squared	0.241		0.233	

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

APPENDIX 4C

RESULTS WITH ALTERNATIVE IV

This section presents estimation results using alternative IVs, constructed from different sets of subsidy rates. Columns (1), (2), and (4) each include a single IV, whereas Column (3) includes two IVs. Columns (1) and (2) utilize subsidy rates for 65% and 75% coverage level, respectively. Column (3) reports results with these two IVs to instrument Ln(subsidy per Liability). Column (4) uses liability-weighted average subsidy rates across coverage levels.

The different sets of IVs show strong first-stage correlations with the instrumented variable, the F statistics being larger than 100. The results using a single IV, whether based on premium rate for a single coverage level or weighted across coverage levels, suggest that Ln(Subsidy per Liability) is likely endogenous, whereas we do not find statistically significant evidence of endogeneity when using multiple IVs. The Sargan test for over-identification reports that the null hypothesis is rejected, raising some concerns of including the two IVs separately.[1]

We find that the estimated coefficients remain consistent with the main findings presented in Table 4.2. The results show that a 1% increase in subsidy level decreases enrolled area by 1.4% to 4.9%. The estimates for other control variables are also similar in both direction and magnitude to those reported in Table 4.2.

[1] Sargan test is conducted for the two-stage least squares estimation, where the outcome variable is in logarithmic form.

Table 4C.1 Estimation Results: Alternative Instrumental Variables

	(1) $IV_{65\%}$	(2) $IV_{75\%}$	(3) $IV_{65\%}$+$IV_{75\%}$	(4) Weighted Avg. IV
Ln(Subsidy per Liability)	−4.875***	−2.495***	−1.368*	−3.987***
	(1.239)	(0.826)	(0.765)	(1.088)
Ln(Premium per Liability)	4.715***	2.190**	0.974	3.774***
	(1.332)	(0.908)	(0.837)	(1.176)
Lagged 5-year Sum of Acres	0.004	0.005	0.006	0.004
Damaged by Flooding (1000 acres)	(0.006)	(0.006)	(0.006)	(0.006)
Cumulative Restored Acres	−0.121***	−0.097***	−0.088***	−0.111***
(1000 acres)	(0.018)	(0.014)	(0.013)	(0.016)
Ln(Farmland Price)	−0.407	−0.651**	−0.772***	−0.496*
	(0.277)	(0.263)	(0.267)	(0.272)
Lagged 15-year Avg Precipitation	−0.001	0.001	0.001	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Lagged 15-year Avg Temperature	−1.127***	−0.863**	−0.679*	−1.010**
	(0.423)	(0.402)	(0.399)	(0.412)
Residuals from the First Stage	3.994***	1.596*	0.351	3.101***
	(1.311)	(0.927)	(0.865)	(1.165)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Number of Observations	18,897	18,897	18,897	18,897
First-stage F Statistics	109.4	255.1	132.1	147.0
Sargan test			7.1	

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

APPENDIX 4D

RESULTS FOR WETLAND EASEMENT PROGRAMS

Table 4D.1 Estimation Results: Wetland Easement Programs

	(1) Poisson	(2) CF Poisson
Ln(Subsidy per Liability)	−0.908***	−3.557***
	(0.274)	(1.009)
Ln(Premium per Liability)	0.576*	3.419***
	(0.323)	(1.106)
Lagged 5-year Sum of Acres	0.003	0.001
Damaged by Flooding (1000 acres)	(0.007)	(0.001)
Cumulative Restored Acres	−0.076***	−0.098***
(1000 acres)	(0.016)	
Ln(Farmland Price)	−0.453	−0.149
	(0.407)	(0.278)
Lagged 10-year Avg Precipitation	0.001	−0.000
	(0.002)	(0.001)
Lagged 10-year Avg Temperature	−0.835	−1.211***
	(0.554)	(0.432)
Residuals from the First Stage		2.863**
		(1.116)
County FE	✓	✓
Year FE	✓	✓
F-statistic		207.4
Number of Observations	18,564	18,564

*p<0.1; **p<0.05; ***p<0.01

Standard errors clustered at the county level are presented in parentheses

APPENDIX 4E

CUMULATIVE EASED AREA

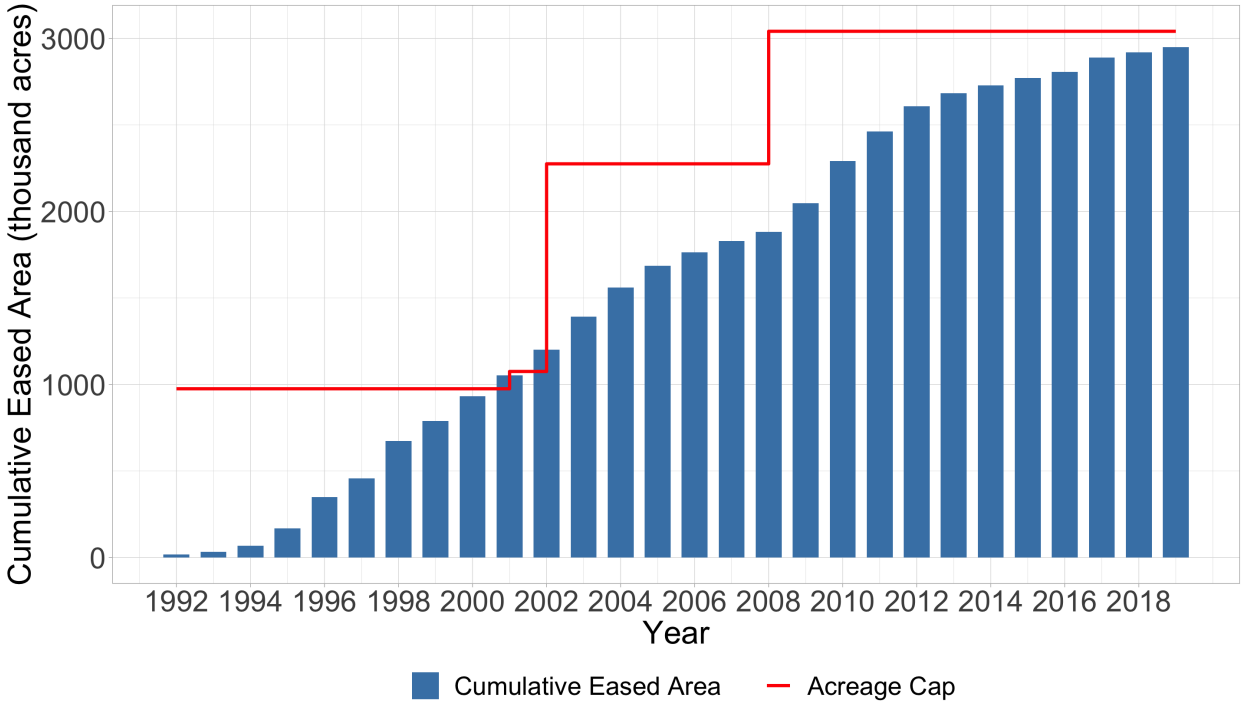

Figure 4E.1 **Cumulative Eased Area**: This figure shows the cumulative WRP eased acreage and the corresponding acreage caps, measured in thousands of acres, in the United States from 1992 and 2019. The acreage caps were established by major agricultural legislation, such as the 2000 ARPA and the 2002 Farm Bill.