The Impact of Crop Insurance Participation on Water Use Under Extreme Heat: Evidence from U.S. Agriculture

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Abstract

Risk has always been central to agriculture, and climate change has amplified production challenges like droughts and heatwaves. While tools such as irrigation and federally subsidized crop insurance help manage uncertainty, the impact of crop insurance on water resource use under extreme heat remains underexplored. This study investigates how crop insurance participation affects irrigation water use, particularly under varying heat conditions. Using a county-level panel dataset from 2008–2020 that combines crop-specific irrigation, insurance, and weather data across the United States, we apply fixed-effects and instrumental variable approaches. Results show that higher crop insurance participation is associated with increased total irrigation water use, driven primarily by surface water. Groundwater use shows weaker and less consistent responses. Additionally, the effect of crop insurance on water use diminishes as heat intensity increases. Our findings reveal a trade-off between risk management and water sustainability, suggesting that integrating conservation incentives into crop insurance programs could help align climate risk mitigation with long-term resource goals.

Keywords: climate adaptation, irrigation behavior, risk management, surface and groundwater, water conservation
JEL classification: Q15, Q18, Q54

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1 Introduction

Risk remains a crucial aspect when making any farm business decisions, particularly as climate change exacerbates challenges such as droughts, flooding, and heat waves. These climatic pressures intensify uncertainties related to yields, prices, government policies, and foreign markets, making risk management a priority for farmers. In the United States (U.S.), federally-subsidized crop insurance has now become a preeminent farm safety net program and risk management instrument to attenuate wide swings in farm income (Lee et al., 2024). As reported by the Risk Management Agency (2025), insured acreage rose from 206 million acres in 2000 to 296 million acres by 2013. From 2016, insured acres grew rapidly—reaching 494 million acres for the 2022 crop year which covered 134 unique agricultural commodities. Furthermore, the share of cropland acres covered by any crop insurance program expanded, particularly among small- to medium-sized farms with the share of insured acres increasing by more than 20% from 2017 to 2022 (USDA ERS, 2024b).

In consonance with this policy-driven risk management efforts, farmers implement a range of on-farm strategies, including the adoption of new crop varieties, fertilizers, pesticides, innovative irrigation systems, and other advanced inputs to also mitigate the risks (Federico, 2010). Among these, irrigation management practices play a pivotal role in stabilizing yields, particularly in water-scarce regions where precipitation is insufficient to meet crop water demands. Irrigated agriculture accounts for 80% of the U.S. total water use. While irrigated land only represents less than 20% of harvested cropland, these operations generate more than $152 billion in annual farm sales every year, making a significant contribution to the national economy (USDA ERS, 2024a; Reyes et al., 2020). However, climate change is accelerating the timeline of water resource depletion through higher temperatures, increased evaporative losses, and increased frequency and duration of prolonged droughts that could exert stringent pressure on major water sources supporting crop production (Cotterman et al., 2018; Foster, Brozović, and Butler, 2015; McGuire, 2017; Edwards, 2016). This serious challenge underscores the urgent need to gain an in-depth understanding of the interplay

between crop insurance and irrigation water use in the face of extreme weather events that threaten both water resource sustainability and food security.

The objective of this study is to investigate the effect of crop insurance participation on water withdrawals for irrigation in U.S. agriculture under extreme heat stress. Specifically, we assess whether counties with greater insurance participation exhibit increased or decreased irrigation water use and estimate the heterogeneous effects of insurance on farmers' reliance on irrigation water use with respect to extreme climatic temperatures. We utilize crop-specific water use data for seven major crops (i.e., barley, corn, cotton, rice, sorghum, soybean, and wheat) across the continental U.S. from 2008 to 2020. A traditional linear fixed-effects (FE) panel regression approach is employed as the baseline model which controls for potential unobserved confounders caused by time- and county-specific unobservable (e.g., geographic conditions, technological growth, and macroeconomic shocks). An instrumental variable (IV) approach is also adopted by using the premium subsidy rate as an IV to address any potential endogeneity issue. Consistent with prior literature (Miao, 2020; Lee et al., 2024), the IVs are constructed based on exogenous government policy variations. In addition, we carry out several robustness checks using alternative empirical specifications and estimation methods (e.g., use of alternative IV, and inclusion of additional control variables).

A growing body of literature has examined the relationship between crop insurance and input use, highlighting a discourse on whether a farm input is risk-increasing or decreasing (Regmi, Briggeman, and Featherstone, 2022). According to Horowitz and Lichtenberg (1993), inputs are risk-reducing if they lower the likelihood of crop failure, whereas risk-increasing inputs may raise potential returns while amplifying exposure to loss. Previous studies find mixed responses to increasing crop insurance participation. Some of them suggest that insured farmers often apply less inputs such as fertilizers, pesticides, and high-yield seed varieties compared to uninsured farmers due to moral hazard (Lu et al., 2023; Weber, Key, and O'Donoghue, 2016; Annan and Schlenker, 2015; Wang, Rejesus, and Aglasan, 2021; Smith and Goodwin, 1996; Regmi, Briggeman, and Featherstone, 2022). While much

empirical works have been carried out to examine the impact of crop insurance on input use, extending this analysis to water use remains limited (Ghosh, Miao, and Malikov, 2023; Deryugina and Konar, 2017; Suchato et al., 2022). We contribute to the literature by analyzing the heterogeneous effects of crop insurance on water use under varying levels of extreme heat stress. Our findings contribute to current policy debates that argue that increasing participation in crop insurance poses barriers to water conservation and climate adaptation, thereby affecting the resilience of agricultural systems to climate change. By uncovering the link between crop insurance and irrigation water use, this research could inform the design of more balanced crop insurance policies that promote both agricultural resilience and water resource sustainability goals.

The second major contribution of this study is the use of a novel county-level panel dataset that combines high-resolution spatial and temporal estimates of irrigation water use, disaggregated by crop and water source with detailed crop insurance metrics. This dataset provides broader coverage than those used in prior studies, enabling a more systematic analysis of the relationship between crop insurance participation and irrigation water use. Previous research in this regard often relies on a single measure of insurance participation, covers limited or outdated time periods, or uses field-scale experimental data that lack crop-specific irrigation detail. For example, prior studies on crop insurance and water use do not capture both the extensive and intensive margins of insurance participation, limiting the robustness of their estimates (e.g., Deryugina and Konar (2017), Suchato et al. (2022), Ghosh, Miao, and Malikov (2023)). Moreover, Deryugina and Konar (2017) draws on data from before 1995, omitting the effects of major institutional changes in crop insurance. Both Deryugina and Konar (2017) and Ghosh, Miao, and Malikov (2023) also rely on data collected at five-year intervals, which inhibits the ability to estimate short-run responses in irrigation behavior.

The study finds that crop insurance participation metrics namely insured acreage ratio, weighted coverage level, and premium per acre, are generally positively associated with

agricultural water use per acre, with this relationship most robust under the FE-IV estimation strategy. The effect is particularly pronounced for total and surface water use, where premium per acre and weighted coverage level exhibit positive and statistically significant impacts. Crucially, these effects are moderated by extreme heat, as interaction terms with maximum temperature suggest that higher temperatures weaken the positive influence of insurance on water use, likely reflecting biophysical constraints such as reduced crop responsiveness and diminished irrigation efficiency. These climate-sensitive patterns hold across all water sources, including groundwater. Taken together, the findings suggest that crop insurance design has important implications for agricultural water demand, particularly under changing climatic conditions. From a policy perspective, this underscores the need to better align agricultural risk management tools with water sustainability goals, especially in regions facing increased water scarcity and heat stress.

The next sections of the paper are structured in the following sequence. Section 2 presents the background for the study, outlining key policy settings on crop insurance and a backdrop of the country's irrigation water use. Section 3 describes the data sources and variable construction, including a discussion of sample characteristics. Section 4 lays down the empirical strategy, detailing the identification approach and model specification. Section 5 reports the main results, including robustness checks. Finally, Section 6 concludes with a summary of findings, policy implications, and suggestions for future research.

2 Background

2.1 U.S. Federal Crop Insurance

Since its inception in 1938 in response to the Great Depression's impact on American agriculture, the U.S. Federal Crop Insurance Program (FCIP) has been a central component of the agricultural safety net, offering financial protection to farmers against the inherent risks associated with farming (e.g., adverse weather, pests, diseases, and fluctuating market

conditions). In 2019, it insured over 100 types of crops across 380 million of acres (Lu et al., 2023), representing a substantial commitment by the federal government to protect U.S. agriculture.

The FCIP is administered by the Risk Management Agency (RMA) within the United States Department of Agriculture (USDA) but relies on private insurance companies to deliver policies directly to farmers (Shields, 2015). Farmers pay premiums based on the coverage level they choose, with rates structured to be as actuarially fair as possible. However, to make the program financially accessible, the government provides significant subsidies to offset premium costs, covering about 60% of premiums in recent years (Shields, 2015). Additionally, the government compensates private insurers for program administration and claims management, making it feasible for them to offer this specialized insurance at scale. The most widely availed plans are yield protection (YP) and revenue protection (RP) which cornered 5.4% and 70.6% of the total liability in 2022 (Risk Management Agency, 2025).

Major legislative changes over the years have expanded the reach and accessibility of the FCIP. The Federal Crop Insurance Reform Act of 1994, for example, introduced fully subsidized catastrophic (CAT) coverage, which significantly boosted participation. This coverage guaranteed farmers a basic level of protection at no cost, encouraging smaller and more risk-averse farms to participate in the program. Following this, the Agricultural Risk Protection Act (ARPA) of 2000 and the Farm Bills (e.g., 1996, 2002, 2008, 2014, 2018) further increased subsidies and introduced new insurance options that provided more tailored and higher levels of coverage (Lu et al., 2023; Reyes et al., 2020). These enhancements reflect policymakers' recognition of the program's value and aim to support an increasingly diverse and vulnerable agricultural sector.

2.2 Agricultural water use in the U.S.

Water serves as an essential resource for crop irrigation, livestock watering, and aquaculture. Water for irrigation represented 42% of all freshwater withdrawals and more than 60% of

the total freshwater consumption in 2015 (Maupin, 2018; Dieter, 2018). There are two types of water source namely surface water and groundwater which are both important for agricultural production. Historically, groundwater use for irrigation expanded considerably in the U.S. since the start of the Green Revolution in the 1940s driven by infrastructure development and advancements in pumping technology (Ruess et al., 2023; USDA ERS, 2025). On the other hand, surface water for irrigation grew from 1950 to 1980 but eventually declined between 1980 and 2015 (Dieter, 2018; Kenny et al., 2009). In 2015, total irrigation withdrawals were 118,000 million gallons per day (Mgal/d), which accounted for 42% of total freshwater withdrawals. Withdrawals from surface-water sources were 60,900 Mgal/d, which accounted for 52% of the total irrigation withdrawals. Groundwater withdrawals for 2015 were 57,200 Mgal/d (Dieter et al., 2018). As of the 2017 Census of Agriculture, about 58 million acres of cropland were irrigated, with high concentrations in the western states like Nebraska (14.8%) and California (13.6%) followed by other states including Arkansas (8.4%), Texas (7.5%), and Idaho (5.9%). Nebraska with 8.6 million acres of irrigated cropland, led all states largely due to its access to groundwater from the High Plains (Ogallala) aquifer (USDA ERS, 2025).

Over the years, the geographic distribution of irrigation has shifted as well—irrigated land declined in states like Texas (1.5 million acres decrease) and California (1 million acres decrease) while increasing in Nebraska (1.6 million acres increase) and Arkansas (1 million acres increase). Crop types under irrigation have also changed, with corn and soybean acreage expanding to meet rising market demand, overtaking traditional irrigated crops like cotton and hay. Irrigation from surface and groundwater sources is managed by a network of local organizations. Pressurized irrigation systems, such as sprinklers and drip irrigation, have increasingly replaced gravity systems due to their water-use efficiency, especially in the western U.S., where their adoption rose from 37% in 1984 to 72% in 2018 (USDA ERS, 2025).

3 Data description

3.1 Water use for crop production

The main dependent variable of interest is the irrigation water use obtained from the calculations performed in a study by Ruess et al. (2023) which was made publicly available at the Illinois Data Bank of the University of Illinois at Urbana-Champaign. Ruess et al. (2023) employed a well-established grid-based global hydrology and water resources model (i.e., PCR-GLOBWB 2) with high resolution input data on agricultural production and climate within the Continental United States. The 5 arc-min grid-cell water use estimates generated from the model were then aggregated up to counties using zonal statistics methods. This was carried out by Ruess et al. (2023) to obtain the crop-specific irrigation water use (IWU) estimates measured in km^3 from 2 water sources namely, surface water withdrawals (SWW) and total groundwater withdrawals (GWW) for 20 crops and crop groups, 13 years (2008-2020), and 3,142 counties. Notably, these data were statistically scaled to matched total water volumes provided in the U.S. Geological Survey (USGS) Water Use statistical database as a benchmark and thus ensure consistency with widely accepted and credible irrigation information source. The original dataset captures IWU estimates for 20 crops namely barley, corn, cotton, millet, oats, peanuts, potatoes, pulses, rapeseed, rice, rye, sorghum, soybeans, sugar beets, sunflower, sweet potatoes, wheat, other grains, other produce, and other animal feed. However, for purposes of this study, we only focused on 7 major crop types including corn, cotton, rice, sorghum, soybeans, wheat, and barley.

3.2 Crop insurance participation measures

The measures of crop insurance participation are our main independent variables of interest. These were sourced primarily from the historical Summary of Business (SOB) data files[1],

[1]The county-level crop insurance data from SOB can be obtained from the following website: https://www.rma.usda.gov/tools-reports/summary-of-business/state-county-crop-summary-business.

which are maintained by the USDA-RMA. These data files are based on actual administrative information from all insurance policies covered by the federal crop insurance program over the years, instead of obtaining data from farm surveys. Thus, less measurement error is expected. The SOB dataset provides yearly county-level crop insurance participation information, which includes insured acreage, coverage level, premium amount, and premium subsidy for each crop. The insurance policies in the study include widely available policies in the U.S. such as yield protection (YP), revenue protection (RP), and revenue protection with harvest price exclusion (RPHPE). In addition to this, county-level data on planted acreage for each crop were collected from the USDA National Statistics Service (NASS) and combined with crop insurance data to produce seamless values for crop insurance participation measures.

Based on crop insurance data from SOB, we construct three annual county-level variables to measure insurance participation. The first indicator for insurance participation is the "insured acreage ratio". This has already been adopted in multiple studies in the past (i.e., Lee et al. (2024); Lu et al. (2023); Connor, Rejesus, and Yasar (2022); and Che, Feng, and Hennessy (2020)). However, it should be noted that this measure does not reflect the variation in coverage levels chosen (i.e., the changes in the participation measure only depend on insured acreage but do not capture any changes in the coverage level choices). Thus, it is recognized as an "extensive margin" measure. The study likewise utilized the "weighted coverage level" which is calculated by taking the acre-weighted average of the coverage levels for any given county-year. This approach embodies the variation in the amount of coverage level chosen for the enrolled acres and reflects both types of margins. Finally, the third crop insurance participation indicator that was adopted in the study is the "premium per acre" which corresponds to the dollar amount of insurance premium spent before subsidy per planted acre. Similar to the latter indicator, premium amount captures both extensive and intensive margins as it varies depending on both the insured acreage and selected coverage level. Lu et al. (2023) and Weber, Key, and O'Donoghue (2016) used this measure for crop

insurance participation.

3.3 Weather variables

Aside from data on irrigation water use and crop insurance participation, the study also requires weather data as control variables since weather outcomes are fundamental factors affecting production decisions such as the application of water for irrigation in any given crop year. Specifically, two weather variables such as maximum temperature and precipitation were considered in the study. The data source for these variables is the National Oceanic and Atmospheric Administration of the U.S. Department of Commerce to construct the county-crop-year panel data used in this empirical analysis. The advantage of incorporating warming temperature in this way is that it allows for capturing the association of temperatures with irrigation water use under extreme heat condition. The period from May to August is the assumed growing season in this calculation. Since the data that could be obtained from the Global Historical Climatology Network (GHCN-D) dataset of NOAA is station-level daily maximum and minimum temperatures, averaging these daily maximum temperatures from all stations in each county is performed to transform the data into county-level daily data. From the same source, the precipitation was also collected which represents the cumulative sum of precipitation received (in mm) over the same growing period (May-August) in each county-year.

By combining these datasets for the weather variables with irrigation water use and crop insurance participation measures, county-crop-year panel data was formed for this analysis. Descriptive statistics of the main variables used in the empirical analysis are summarized in Table 1. Figures 1, 2 and 3 present the spatial distribution of total water use, groundwater use, and surface water use levels for 7 major crops (i.e., barley, corn, cotton, rice, sorghum, soybean, and wheat) across the continental U.S. over the period 2008-2020.

4 Empirical methods

The main empirical specification applied in the study to sufficiently analyze the effect of the crop insurance participation on irrigation water use is given by the following:

$$ln(water_{ijt}) = \beta_0 + \beta_1 Ins_{ijt} + \beta_2 Tmax_{it} + \beta_3 Ins_{ijt} \times Tmax_{it} + \mathbf{X_{it}}\omega + \alpha_i + \lambda_j + \theta_t + \varepsilon_{ijt} \quad (1)$$

where $water_{ijt}$ is the amount of water withdrawn for irrigation in county i, crop j, and year t, Ins_{ijt} is the insurance participation measure (i.e., insured acreage ratio, weighted coverage level, and premium per acre), $Tmax_{it}$ is the average daily maximum temperature level, and $\mathbf{X_{it}}$ is the set of control variables such as precipitation, θ_t represents time fixed effects (i.e., to control for unobservable trends that affect all counties the same way), α_i represents county fixed effects (i.e., to capture unobservable time-invariant confounders), λ_j represents crop fixed effects and ε_{ijt} is the idiosyncratic error term. In this study, β_1 and β_3 are the key parameters of interest that indicate whether the participation of crop insurance has a statistically significant relationship with irrigation water use.

As shown in equation (1), the traditional linear panel FE model was first utilized to better account for heterogeneity (i.e., control for endogeneity due to time-invariant unobserved confounders). For example, location-specific geographic conditions (Lu et al., 2023; Lee et al., 2024) such as soil types (e.g., clay, sandy, loam, etc.), topography, and relative electrical conductivity of the field for a county is largely considered as a time-invariant factor that would likely influence insurance participation decisions, production yields, and the application of water for irrigation. It was also cited by Lee et al. (2024) the aggregate management ability of all farmers in a county as a potential unobserved time-invariant confounder that can cause endogeneity issues as it can affect the decisions to avail of crop insurance and water use for crop production. These potential time-invariant unobserved factors are absorbed by the county fixed effects specified in the baseline model and facilitate better identification of the effect of insurance participation on irrigation water use. Including the time fixed effects in the model likewise allows for proper identification of such effect and helps address endo-

geneity issues as it accounts for time-varying unobserved factors or time-specific shocks that could affect all counties in the same manner such as overall technological growth Lee et al. (2024), and macroeconomic shocks (Connor and Katchova, 2020; Lu et al., 2023). To ensure valid statistical inference, robust standard errors clustered at the county level were used to account for potential correlations in errors across years within each county.

Despite the advantages of the traditional linear panel fixed-effects (FE) model, one potential shortcoming of this approach for estimating equation (1) is the possibility of residual endogeneity, even after accounting for unobserved heterogeneity and including relevant controls in the model. This residual endogeneity may arise from unobserved confounding factors that vary over time and across counties, affecting both the outcome and the main independent variable of interest. To control for the potential presence of residual endogeneity, the common solution employed in previous studies is to use instrumental variable (IV)-based panel FE models (FE-IV) in which IVs must satisfy the exclusion restrictions to become valid instruments. In other words, IVs must be correlated with the potentially endogenous main independent variable of interest but uncorrelated with the outcome variable. Cognizant of this, recent empirical literature proposed various ways to construct plausible IVs which are built on government-set exogenous variation in premium subsidy rates (Lu et al., 2023; Connor, Rejesus, and Yasar, 2022; Connor and Katchova, 2020; Miao, 2020; DeLay, 2019; Yu, Smith, and Sumner, 2018; Schoengold, Ding, and Headlee, 2015). For proper instrumentation, the study followed the approach by Miao (2020) and Lee et al. (2024) wherein the overall premium subsidy rate for insurance policies serves as the main IV for insurance participation. The overall premium subsidy rate is computed by taking the ratio of the total premium subsidies for all insurance policies to the total premium of these policies for the crop. It is believed in this analysis that this IV plausibly satisfies the exclusion restrictions for the following premise: (a) the premium subsidy rate is correlated with crop insurance participation; and (b) it is exogenously determined through the 1994 Crop Insurance Reform Act and the 2000 Agricultural Risk Protection Act. As such, it is unlikely that the premium

subsidy rate is directly linked to irrigation water use being the outcome of interest through channels other than crop insurance (Miao, 2020; Lee et al., 2024). Moreover, clustering standard errors by county provides robustness to both heteroscedasticity and potential spatial correlation of errors between counties (Cameron, Gelbach, and Miller, 2011).

We perform three primary robustness checks to assess the strength and stability of our main regression results using the baseline empirical specification and estimation methods mentioned earlier. First, we introduce an additional control variable which is irrigation share followed by the interaction between crop insurance participation measures and precipitation. Second, we conduct robustness checks by applying the IV, particularly the interaction of subsidy rate and 1-year lagged insurance participation suggested by Yu, Smith, and Sumner (2018), and DeLay (2019) as alternatives to the Miao (2020) approach. Third, alongside the traditional IV method, we will implement instrumental variables estimation using heteroskedasticity-based instruments recently developed "external-IV-free" method (Lewbel, 2012) as part of our next steps.

5 Results and discussions

5.1 Baseline results

The estimation results in analyzing the effect of crop insurance on agricultural water use per acre for each of the total water, groundwater, and surface water sources are presented in Tables 2, 3, and 4, respectively. The estimated coefficients of the crop insurance participation metrics in columns (5) to (7) are considerably higher under FE-IV approach compared to their counterparts under FE approach. This discrepancy suggests that the FE estimates may be biased downward, potentially due to reverse causality where improved access to irrigation reduces the demand for crop insurance, thereby attenuating the observed effect in the absence of an instrumental variable strategy that addresses any endogeneity issue. This is consistent with the findings of Ghosh, Miao, and Malikov (2023) in terms of the downward

bias between subsidy rate and water use.

Among the key findings under the more robust FE-IV estimation strategy, crop insurance participation metrics viz. insured acreage ratio, weighted coverage level, and premium per acre across all water sources, reveal a generally positive and statistically significant relationship with water use which means that greater involvement in crop insurance programs is associated with increased water application per acre. This pattern is particularly evident for total and surface water use, where both the weighted coverage level and premium per acre consistently exhibit positive and significant effects under FE-IV. This implies that more comprehensive insurance coverage and higher premium contributions may encourage more intensive water use. Although the insured acreage ratio does not always reach statistical significance, its positive sign under FE-IV points to a potential association in the same direction. In terms of elasticity, the study finds that total freshwater withdrawals for irrigation are less responsive to changes in the weighted coverage level—at 2.95% compared to the premium per acre, which has a higher elasticity of 6.76% when evaluated at their respective sample means and average maximum temperature. [2] Similarly, surface water use responds more strongly to changes in the premium per acre (4.69%) than to the weighted coverage level (2.29%), reflecting the pattern observed for total water use. However, irrigation-related groundwater withdrawals do not appear to respond significantly to crop insurance participation.

The economic mechanisms that could explain the positive short-term effect of crop insurance on irrigation water use at the intensive margin in this study are grounded in several potential factors. First, the structure of insurance contracts may encourage farmers to withdraw additional water, assuming crop type and acreage remain constant (Deryugina and Konar, 2017). The USDA's Federal Crop Insurance Corporation (FCIC) typically requires farmers to maintain "normal" irrigation levels to qualify for indemnity payouts in the event of crop loss. Farmers, being risk-averse, may be inclined to irrigate their crops even when

[2]The formula to calculate the elasticity at the sample means is the product of the marginal effect of crop insurance participation on water use per acre and the mean of crop insurance participation. Given the study's annual-data-based estimates, it is believed that the estimated elasticity is a short-run elasticity.

it is clear that the crop has failed, in order to ensure they meet the conditions necessary to receive their insurance compensation. Second, given subsidized insurance coverage, farmers might also change their crop mix planting decisions (Deryugina and Konar (2017); Cole, Giné, and Vickery (2017); Wu (1999)) by shifting to water-intensive crops.

Another particularly important aspect of these results is the heterogeneous effect of these insurance participation metrics with respect to temperature, which is directly related to one of the central objectives of the analysis, understanding how extreme heat stress modifies the insurance–water use relationship. The interaction terms in the FE-IV model suggest that the positive impacts of weighted coverage level and premium per acre on water use are moderated under hotter conditions. For instance, the interaction of weighted coverage level and Tmax is -0.340 in the FE-IV model for total water, indicating that the water-increasing effect of higher insurance coverage tends to weaken as extreme temperatures continue to surge. In the same vein, the premium per acre and the Tmax interaction become -0.012, suggesting that the influence of premiums on water use also tends to drop under more elevated extreme heat intensity. These patterns imply that while insurance participation promotes greater water use overall, but its impact is not uniform and may be significantly dampened during periods of extreme heat, possibly due to biological limits on crop response, increased evapotranspiration that reduces irrigation efficiency, or constraints on water availability. It is noteworthy that this temperature-moderating effect is also evident in the FE-IV estimates for both groundwater and surface water use. Thus, this evidence represents the effect of insurance on water use varies with respect to extreme climatic stress, adding more nuance to the broader finding that insurance participation encourages higher agricultural water requirements.

In the case of the weather variables, climatic controls such as temperature and precipitation remain significant and directionally stable across all models, reinforcing the credibility of the estimated effects. This supports current agronomic literature which found strong negative correlations between precipitation and irrigation withdrawals (Nie et al., 2021; Ghosh,

Miao, and Malikov, 2023). On the other hand, it is found as expected following recent studies (Wada et al., 2013; Nie et al., 2021; Ghosh, Miao, and Malikov, 2023) that increased incidence of extreme heat given higher Tmax tends to encourage more water application, especially during the growing season as an adaptive mechanism to avoid crop failure. Overall, the FE-IV results not only strengthen the general findings from the FE models but also provide an explicit view of how both insurance design and climatic conditions jointly alter on-farm water use decisions in agriculture.

5.2 Robustness check results

As previously discussed, the robustness and stability of the main linear panel FE and FE-IV results are assessed through a series of additional empirical specifications and sensitivity analyses, designed to confirm the consistency of the observed relationships between crop insurance participation and agricultural water use. First, we introduce the stress degree days (SDD) as a replacement for Tmax that captures the sum over growing season days of degree in Celsius above a threshold, a level which is already potentially harmful to the crop (See Tables A.1 to A.3). Consistent with the baseline results, a significant and positive influence of crop insurance participation on irrigation water use occurs largely at the intensive margin for both total water use and surface water use.

Second, an additional control variable specifically for irrigation share is incorporated in the analysis. This is based on the premise from previous studies like Puy et al. (2021) hypothesizing that larger irrigated areas drive irrigation water withdrawals. In reference to Tables A.4 to A.6, we still find evidence of crop insurance disincentive effect on water application consistent with the baseline results. However, "extensive margin" participation (i.e., insured acreage ratio) remains statistically not significant under the FE-IV approach.

Third, we conduct a robustness check to investigate whether our inferences will change if we use interaction for crop insurance participation and precipitation. The parameter estimates still generally display that counties with higher crop insurance participation tend

to have higher water demand as shown in Tables A.7, A.8, and A.9. However, it is important to note that there is no statistically significant evidence indicating that the effect of insurance participation on freshwater withdrawals for irrigation varies with changes in precipitation levels.

Finally, we use a different instrumental variable which is the interaction of subsidy rate and 1-year lag of insurance participation (See Tables A.10 to A.12). Our main inferences still hold in terms of the direction of the relationship between the outcome and the variables of interest but with bigger magnitude of effect relative to the baseline, specifically for weighted coverage level and premium ratio under three water sources.

6 Conclusions

This study investigates the effects of crop insurance participation on irrigation water withdrawals across the continental U.S., with a particular focus on its heterogeneous impacts under varying levels of extreme heat intensity. To achieve this objective, a county-level panel dataset spanning the years 2008 to 2020 is constructed. An instrumental variable strategy is employed to address potential endogeneity in the crop insurance participation variable. Furthermore, the analysis incorporates key weather controls to mitigate the risk of omitted variable bias, a limitation observed in some previous studies. From the results discussed above, the study provides empirical evidence that per-acre total and surface water use are positively associated with crop insurance participation at the intensive margin with elasticities greater than unity. However, such dynamics are moderated when the maximum temperature starts to pick up which would lead to a significant drop in water use under a more extreme heat stress. The results indicate that, under constant maximum temperature conditions, insured farmers are more likely to raise water use per acre, suggesting limited evidence of moral hazard in such contexts. However, in counties experiencing higher levels of extreme heat stress, the relationship shifts wherein per-acre water use tends to decline de-

spite insurance participation, implying that moral hazard may emerge as a more influential factor under climatic stress. This pattern suggests that under extreme heat, insured farmers may adjust their behavior not by overusing water, but by withdrawing less potentially due to diminishing returns to irrigation or constraints on water availability which highlights a climate-sensitive moral hazard dynamic in irrigation practices.

Furthermore, we do not always find a statistically significant effect of the federal crop insurance program on groundwater withdrawals for irrigation, suggesting that insurance participation may have a more limited influence on farmers' decisions regarding this particular water source. This result may reflect several underlying factors. First, groundwater use is often constrained by well capacity, pumping costs, and regulatory or institutional limits, which may reduce farmers' ability to adjust groundwater withdrawals in response to insurance incentives. Second, groundwater tends to be used more intensively in regions with already limited surface water availability, where irrigation decisions may be more tightly linked to hydrological necessity than to risk mitigation behavior. Third, it is possible that groundwater users are less sensitive to insurance coverage because they already rely on groundwater as a buffer against production risk.

The results from this study forward several policy implications for crop insurance design and agricultural water resource management. First, the finding that crop insurance participation is associated with increased surface and total water use at the intensive margin suggests that federal crop insurance may unintentionally incentivize higher irrigation intensity, potentially exacerbating water demand in already stressed basins. As such, policymakers should consider incorporating water sustainability objectives into crop insurance program design. This could include linking insurance subsidies to conservation practices, such as the adoption of water-efficient irrigation technologies or participation in water-saving programs. By doing so would help align agricultural risk management with resource conservation goals, especially in regions vulnerable to over-extraction and drought. In addition, insurance risk rating could be adjusted to reflect water scarcity or local water use practices, thereby inter-

nalizing environmental costs and promoting more sustainable on-farm decision-making.

Second, the study's evidence that insurance-related water use behavior changes under extreme heat where per-acre water use declines despite insurance participation underscores the need for climate-sensitive adaptations in crop insurance policy. As rising temperatures may impose physical and economic constraints on irrigation efficiency, program rules and payouts could be revisited and tailored to account for reduced water productivity or increased vulnerability in heat-prone areas. Moreover, since the relationship between insurance and groundwater use is weak or absent, differentiated policies may be warranted across water sources to ensure effective and equitable resource management. This nuanced approach would enhance the resilience of agricultural systems by recognizing both the spatial heterogeneity in water use responses and the evolving risks posed by climate change.

While our research represents a step forward in understanding the relationship between water use and crop insurance especially in the face of extreme temperature shocks, it is essential to acknowledge that this study is currently underway and there are limitations and areas that warrant future investigation. For further robustness checks, the next stage of this draft will incorporate a recently developed moment-based IV approach (Lewbel, 2012) which exploits heteroskedasticity in the error terms from the first-stage regression (e.g., regression of the potentially endogenous crop insurance participation variable on the observable exogenous covariates) to identify the coefficients of the endogenous variables even without the traditional exclusion restrictions or traditionally defined IVs. Furthermore, the data used in this study was at the county-level and only focuses on seven major crops. Access to individual farm-level panel data with broader geographic coverage would likely enhance the generalizability of the findings by improving external validity and offering greater insight into the heterogeneous effects of crop insurance across different regions and crop types. Utilizing a nationally representative, farm-level dataset would allow for more precise identification of spatial and crop-specific variations in insurance impacts, thereby strengthening the policy relevance and applicability of the results. We leave all these suggested research directions in

the next iteration of this paper.

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Figure 1: Agricultural water use ($ft^3/acre$) for seven major crops across counties in the continental United States. Values presented are the average for the period 2008-2020 for total water use and for specific crops such as barley, corn, cotton, rice, sorghum, soybean, and wheat.

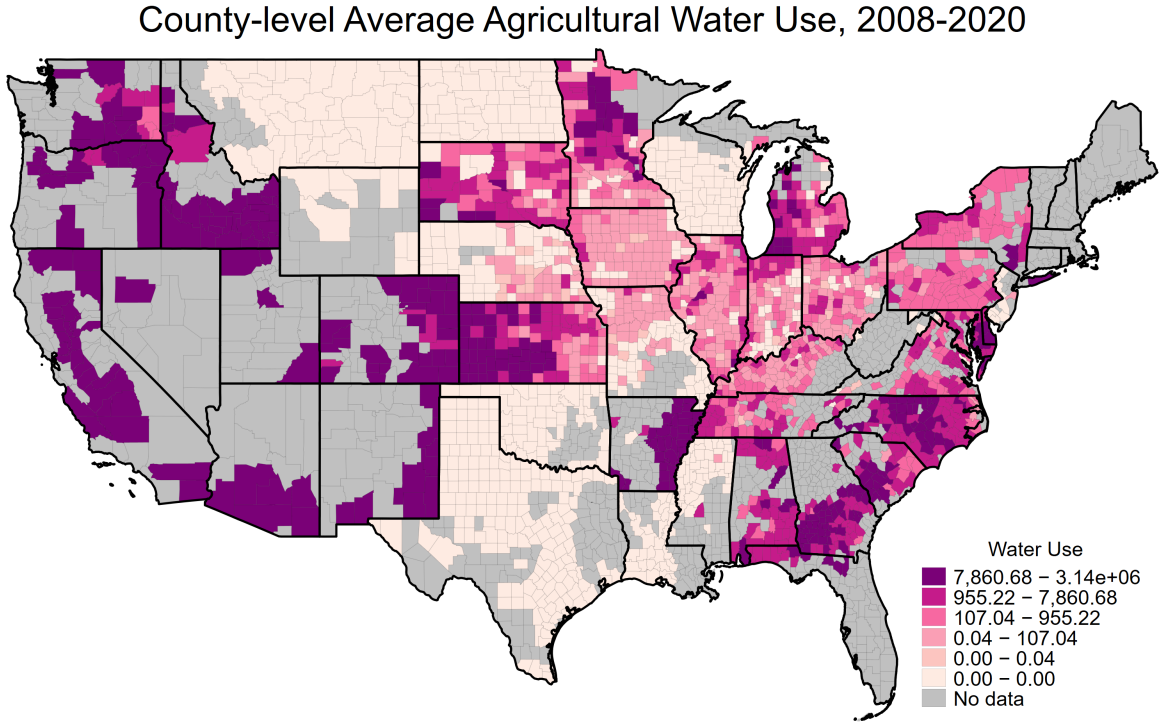


Figure 2: Agricultural groundwater use ($ft^3/acre$) for seven major crops across counties in the continental United States. Values presented are the average for the period 2008-2020 for total water use and for specific crops such as barley, corn, cotton, rice, sorghum, soybean, and wheat.

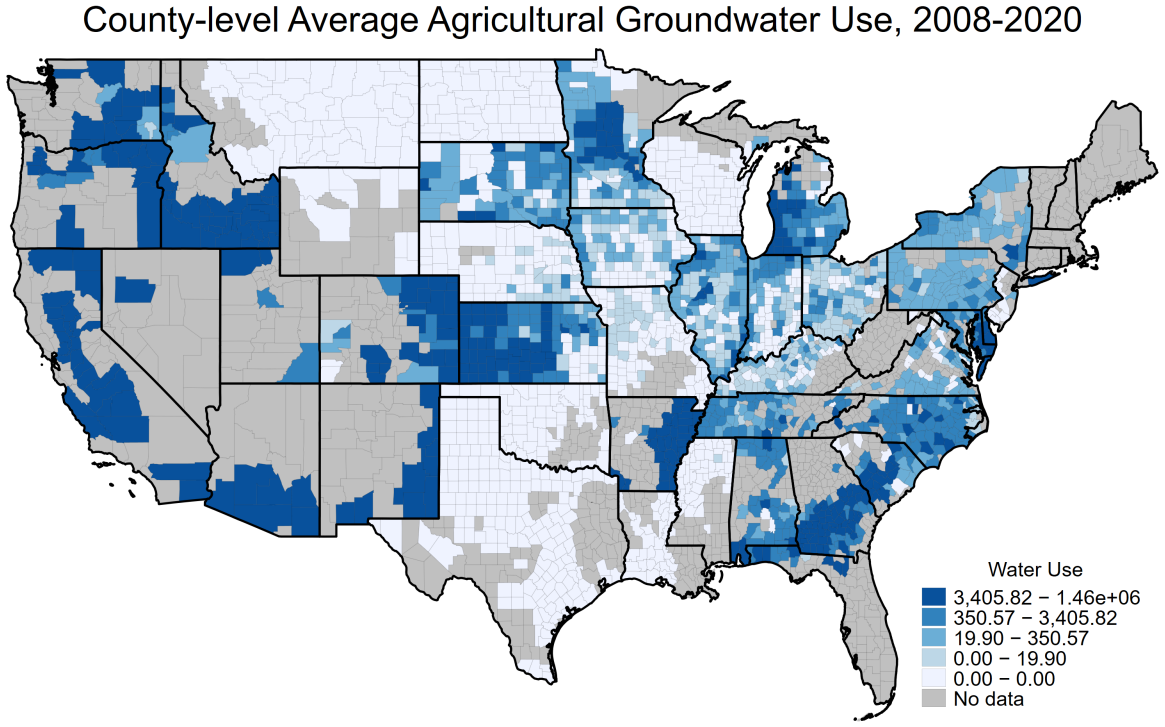


Figure 3: Agricultural surface water use ($ft^3/acre$) for seven major crops across counties in the continental United States. Values presented are the average for the period 2008-2020 for total water use and for specific crops such as barley, corn, cotton, rice, sorghum, soybean, and wheat.

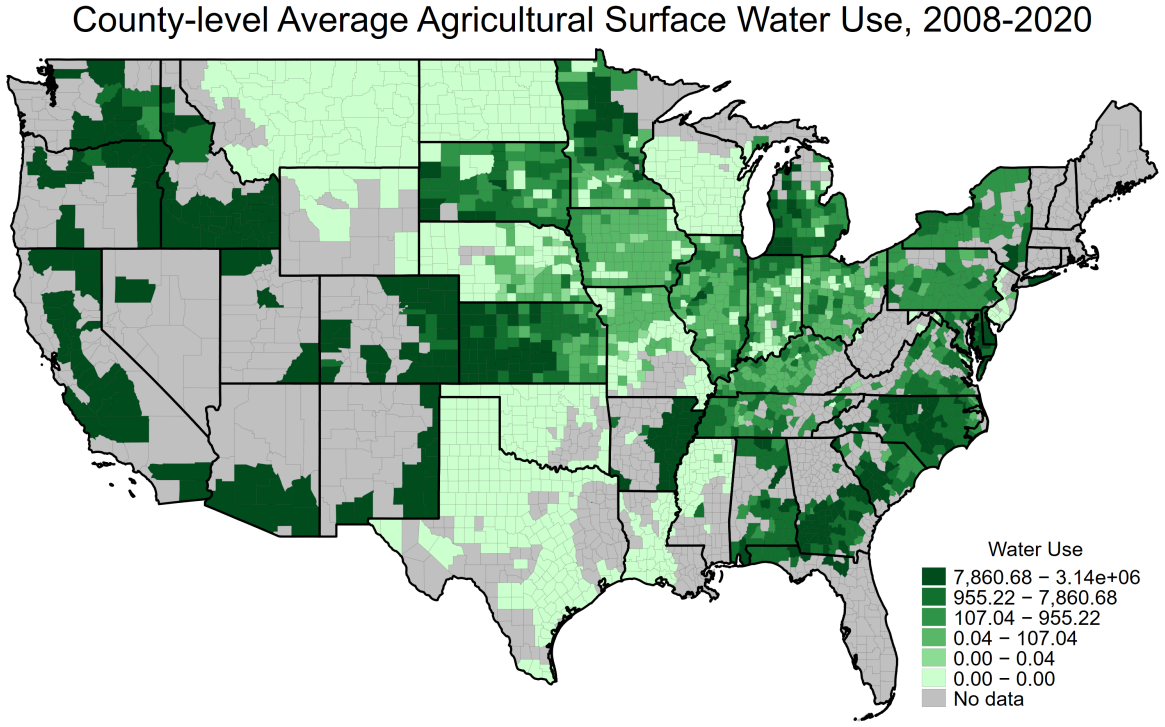


Table 1: Descriptive Statistics on Main Variables

Variable	Description	Obs	Mean	St. Dev.
Total water use	The sum of groundwater and surface water use ($ft^3/acre$)	23,786	25,372.3	168,092.7
Groundwater use	The total groundwater use ($ft^3/acre$)	20,373	10,153.78	74,905.11
Surface water use	The total groundwater use ($ft^3/acre$)	18,049	14,488.41	84,905.94
Insured acreage ratio	The ratio of insured acres over total planted acres	23,786	0.65	0.31
Weighted coverage level	Average coverage level weighted by insured acres	23,786	0.68	0.08
Premium per acre	The ratio of premium amount over total planted acres ($100 per acre)	23,786	24.55	23.40
Tmax	Average maximum temperature during May to August (in hundred °C)	23,786	28.48	2.90
Precipitation	Precipitation (in thousand mm)	23,786	2,521.02	3,140.87

Table 2: Baseline Model Results for Total Water Use

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	1.596***			-3.211		
	(0.522)			(6.432)		
Weighted Coverage Level		6.071**			14.017***	
		(2.827)			(4.369)	
Premium Per Acre			0.011*			0.617**
			(0.006)			(0.311)
Tmax	0.165***	0.227***	0.141***	0.445***	0.364***	0.340***
	(0.024)	(0.070)	(0.020)	(0.127)	(0.099)	(0.131)
Insured Acreage Ratio × Tmax	-0.047**			-0.339*		
	(0.019)			(0.183)		
Weighted Coverage Level × Tmax		-0.133			-0.340**	
		(0.098)			(0.146)	
Premium Per Acre × Tmax			-0.000			-0.012*
			(0.000)			(0.006)
Precipitation	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23786	23708	23786	23708	23708	23708
Adjusted R^2	0.719	0.719	0.719	-1.123	0.009	-6.650

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table 3: Baseline Model Results for Groundwater Use

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	1.097*			-9.253		
	(0.579)			(6.757)		
Weighted Coverage Level		2.439			7.133	
		(3.493)			(5.455)	
Premium Per Acre			0.002			0.502*
			(0.008)			(0.275)
Tmax	0.106***	0.081	0.083***	0.274**	0.137	0.204*
	(0.026)	(0.086)	(0.024)	(0.131)	(0.126)	(0.110)
Insured Acreage Ratio × Tmax	-0.032			-0.127		
	(0.021)			(0.186)		
Weighted Coverage Level × Tmax		0.014			-0.070	
		(0.122)			(0.186)	
Premium Per Acre × Tmax			0.000			-0.009
			(0.000)			(0.006)
Precipitation	-0.000***	-0.000***	-0.000***	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20373	20315	20373	20315	20315	20315
Adjusted R^2	0.664	0.666	0.665	-1.007	0.005	-4.666

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table 4: Baseline Model Results for Surface Water Use

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	-0.289			-0.175		
	(0.480)			(6.498)		
Weighted Coverage Level		-0.874			15.640***	
		(2.681)			(4.224)	
Premium Per Acre			0.001			0.419**
			(0.006)			(0.165)
Tmax	0.076***	0.023	0.086***	0.352***	0.357***	0.231***
	(0.022)	(0.066)	(0.020)	(0.107)	(0.097)	(0.078)
Insured Acreage Ratio × Tmax	0.023			-0.359**		
	(0.017)			(0.176)		
Weighted Coverage Level × Tmax		0.108			-0.405***	
		(0.094)			(0.147)	
Premium Per Acre × Tmax			0.000			-0.008**
			(0.000)			(0.003)
Precipitation	-0.000*	-0.000*	-0.000**	-0.000	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18049	17986	18049	17986	17986	17986
Adjusted R^2	0.746	0.745	0.747	-1.044	-0.000	-4.712

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Appendix

Table A.1: Baseline Model Results for Total Water Use with Stress Degree Days (SDD)

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	0.390***			-11.180***		
	(0.118)			(4.241)		
Weighted Coverage Level		2.652***			5.550***	
		(0.618)			(1.118)	
Premium Per Acre			0.007***			0.262**
			(0.001)			(0.120)
SDD	0.008***	0.013***	0.008***	0.021***	0.026***	0.017***
	(0.001)	(0.004)	(0.001)	(0.008)	(0.004)	(0.006)
Insured Acreage Ratio × SDD	-0.003***			-0.015		
	(0.001)			(0.010)		
Weighted Coverage Level × SDD		-0.011**			-0.030***	
		(0.005)			(0.007)	
Premium Per Acre × SDD			-0.000***			-0.001**
			(0.000)			(0.000)
Precipitation	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23786	23708	23786	23708	23708	23708
Adjusted R^2	0.719	0.719	0.720	-0.946	0.009	-4.527

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.2: Baseline Model Results for Groundwater Use with Stress Degree Days (SDD)

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	0.239*			-11.850***		
	(0.136)			(4.321)		
Weighted Coverage Level		2.923***			6.025***	
		(0.706)			(1.250)	
Premium Per Acre			0.006***			0.266**
			(0.001)			(0.120)
SDD	0.006***	0.008	0.006***	0.013	0.017**	0.014**
	(0.001)	(0.005)	(0.001)	(0.009)	(0.007)	(0.006)
Insured Acreage Ratio × SDD	-0.001			-0.004		
	(0.001)			(0.012)		
Weighted Coverage Level × SDD		-0.004			-0.018*	
		(0.008)			(0.010)	
Premium Per Acre × SDD			-0.000			-0.000**
			(0.000)			(0.000)
Precipitation	-0.000***	-0.000***	-0.000***	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23786	23708	23786	23708	23708	23708
Adjusted R^2	0.719	0.719	0.720	-0.946	0.009	-4.527

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.3: Baseline Model Results for Surface Water Use with Stress Degree Days (SDD)

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	0.376***			-10.124**		
	(0.122)			(4.141)		
Weighted Coverage Level		2.383***			5.960***	
		(0.618)			(1.108)	
Premium Per Acre			0.008***			0.226**
			(0.002)			(0.095)
SDD	0.005***	0.010***	0.007***	0.024***	0.030***	0.016***
	(0.001)	(0.004)	(0.001)	(0.009)	(0.005)	(0.005)
Insured Acreage Ratio × SDD	-0.000			-0.023*		
	(0.001)			(0.012)		
Weighted Coverage Level × SDD		-0.008			-0.039***	
		(0.006)			(0.007)	
Premium Per Acre × SDD			-0.000***			-0.000***
			(0.000)			(0.000)
Precipitation	-0.000*	-0.000*	-0.000*	-0.000	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18049	17986	18049	17986	17986	17986
Adjusted R^2	0.746	0.746	0.747	-1.163	0.001	-4.990

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.4: Baseline Model Results for Total Water Use with Irrigation Share as an Added Control

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	1.567***			-2.411		
	(0.511)			(6.554)		
Weighted Coverage Level		6.150**			13.313***	
		(2.841)			(4.411)	
Premium Per Acre			0.009			0.609*
			(0.006)			(0.347)
Tmax	0.166***	0.239***	0.141***	0.480***	0.363***	0.300**
	(0.025)	(0.070)	(0.022)	(0.137)	(0.099)	(0.122)
Irrigation Share	0.014**	0.014**	0.014**	-0.003	0.014**	0.061
	(0.006)	(0.006)	(0.006)	(0.020)	(0.006)	(0.040)
Insured Acreage Ratio × Tmax	-0.048***			-0.356*		
	(0.018)			(0.186)		
Weighted Coverage Level × Tmax		-0.148			-0.337**	
		(0.099)			(0.148)	
Premium Per Acre × Tmax			-0.000			-0.011*
			(0.000)			(0.007)
Precipitation	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20671	20599	20671	20599	20599	20599
Adjusted R^2	0.720	0.720	0.720	-1.090	0.010	-7.252

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.5: Baseline Model Results for Groundwater Use with Irrigation Share as an Added Control

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	1.044*			-8.930		
	(0.583)			(7.209)		
Weighted Coverage Level		2.709			6.320	
		(3.510)			(5.513)	
Premium Per Acre			0.000			0.504
			(0.007)			(0.310)
Tmax	0.116***	0.108	0.094***	0.331**	0.144	0.195*
	(0.027)	(0.086)	(0.025)	(0.143)	(0.126)	(0.109)
Irrigation Share	0.013**	0.013*	0.013**	-0.005	0.013**	0.052
	(0.006)	(0.006)	(0.006)	(0.021)	(0.007)	(0.034)
Insured Acreage Ratio × Tmax	-0.030			-0.149		
	(0.021)			(0.195)		
Weighted Coverage Level × Tmax		-0.007			-0.061	
		(0.124)			(0.188)	
Premium Per Acre × Tmax			0.000			-0.009
			(0.000)			(0.006)
Precipitation	-0.000***	-0.000***	-0.000***	-0.000*	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17736	17684	17736	17684	17684	17684
Adjusted R^2	0.668	0.669	0.668	-1.112	0.007	-5.216

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.6: Baseline Model Results for Surface Water Use with Irrigation Share as an Added Control

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	-0.222			0.141		
	(0.442)			(6.576)		
Weighted Coverage Level		-0.839			13.889***	
		(2.526)			(4.137)	
Premium Per Acre			-0.002			0.412**
			(0.006)			(0.188)
Tmax	0.081***	0.033	0.085***	0.371***	0.329***	0.206***
	(0.023)	(0.064)	(0.021)	(0.109)	(0.094)	(0.078)
Irrigation Share	0.007	0.006	0.007*	0.000	0.007	0.036
	(0.005)	(0.005)	(0.004)	(0.014)	(0.005)	(0.024)
Insured Acreage Ratio × Tmax	0.019			-0.362**		
	(0.016)			(0.179)		
Weighted Coverage Level × Tmax		0.099			-0.361**	
		(0.090)			(0.144)	
Premium Per Acre × Tmax			0.000*			-0.007**
			(0.000)			(0.004)
Precipitation	-0.000*	-0.000	-0.000*	-0.000	-0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15724	15664	15724	15664	15664	15664
Adjusted R^2	0.752	0.752	0.753	-1.062	0.001	-5.564

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.7: Baseline Model Results for Total Water Use with Interaction for Insurance Participation and Precipitation

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	1.635***			-6.552		
	(0.526)			(8.251)		
Weighted Coverage Level		6.493**			14.514***	
		(2.887)			(4.531)	
Premium Per Acre			0.015**			0.611**
			(0.007)			(0.301)
Tmax	0.163***	0.230***	0.142***	0.433***	0.371***	0.338***
	(0.023)	(0.070)	(0.020)	(0.136)	(0.101)	(0.127)
Insured Acreage Ratio × Tmax	-0.046**			-0.285		
	(0.019)			(0.202)		
Weighted Coverage Level × Tmax		-0.138			-0.351**	
		(0.098)			(0.149)	
Premium Per Acre × Tmax			-0.000			-0.012*
			(0.000)			(0.006)
Precipitation	-0.000**	-0.000	-0.000***	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Insured Acreage Ratio × Precipitation	-0.000			0.000		
	(0.000)			(0.000)		
Weighted Coverage Level × Precipitation		-0.000			-0.000	
		(0.000)			(0.000)	
Premium Per Acre × Precipitation			-0.000*			-0.000
			(0.000)			(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23786	23708	23786	23708	23708	23708
Adjusted R^2	0.719	0.719	0.719	-1.322	0.009	-6.195

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.8: Baseline Model Results for Groundwater Use with Interaction for Insurance Participation and Precipitation

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	1.209**			-12.119		
	(0.582)			(8.162)		
Weighted Coverage Level		3.275			8.450	
		(3.497)			(5.670)	
Premium Per Acre			0.006			0.491*
			(0.008)			(0.261)
Tmax	0.103***	0.087	0.084***	0.265*	0.155	0.200*
	(0.026)	(0.085)	(0.024)	(0.136)	(0.127)	(0.105)
Insured Acreage Ratio × Tmax	-0.031			-0.079		
	(0.021)			(0.198)		
Weighted Coverage Level × Tmax		0.003			-0.099	
		(0.121)			(0.190)	
Premium Per Acre × Tmax			0.000			-0.009
			(0.000)			(0.005)
Precipitation	-0.000**	0.000	-0.000***	-0.000*	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Insured Acreage Ratio × Precipitation	-0.000			0.000		
	(0.000)			(0.000)		
Weighted Coverage Level × Precipitation		-0.000*			-0.000	
		(0.000)			(0.000)	
Premium Per Acre × Precipitation			-0.000			-0.000
			(0.000)			(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20373	20315	20373	20315	20315	20315
Adjusted R^2	0.665	0.666	0.665	-1.159	0.006	-4.133

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.9: Baseline Model Results for Surface Water Use with Interaction for Insurance Participation and Precipitation

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	-0.233			-1.820		
	(0.480)			(7.665)		
Weighted Coverage Level		-0.356			16.411***	
		(2.714)			(4.224)	
Premium Per Acre			0.003			0.417***
			(0.006)			(0.158)
Tmax	0.075***	0.028	0.086***	0.344***	0.368***	0.230***
	(0.022)	(0.066)	(0.020)	(0.112)	(0.096)	(0.075)
Insured Acreage Ratio × Tmax	0.024			-0.332*		
	(0.017)			(0.188)		
Weighted Coverage Level × Tmax		0.101			-0.423***	
		(0.095)			(0.146)	
Premium Per Acre × Tmax			0.000			-0.008**
			(0.000)			(0.003)
Precipitation	-0.000	0.000	-0.000*	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Insured Acreage Ratio × Precipitation	-0.000			0.000		
	(0.000)			(0.000)		
Weighted Coverage Level × Precipitation		-0.000			-0.000	
		(0.000)			(0.000)	
Premium Per Acre × Precipitation			-0.000			-0.000
			(0.000)			(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18049	17986	18049	17986	17986	17986
Adjusted R^2	0.746	0.745	0.747	-1.144	-0.000	-4.111

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.10: Baseline Model Results for Total Water Use with Alternative IV

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	1.596***			1.521		
	(0.522)			(1.129)		
Weighted Coverage Level		6.071**			67.159**	
		(2.827)			(28.215)	
Premium Per Acre			0.011*			0.037
			(0.006)			(0.023)
Tmax	0.165***	0.227***	0.141***	0.193***	-2.212*	0.166***
	(0.024)	(0.070)	(0.020)	(0.036)	(1.179)	(0.029)
Insured Acreage Ratio × Tmax	-0.047**			-0.077*		
	(0.019)			(0.043)		
Weighted Coverage Level × Tmax		-0.133			-3.518**	
		(0.098)			(1.776)	
Premium Per Acre × Tmax			-0.000			-0.001
			(0.000)			(0.001)
Precipitation	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23786	23708	23786	23708	23708	23708
Adjusted R^2	0.719	0.719	0.719	-1.123	0.009	-6.650

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.11: Baseline Model Results for Groundwater Use with Alternative IV

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	1.097*			4.115***		
	(0.579)			(1.180)		
Weighted Coverage Level		2.439			46.740	
		(3.493)			(28.489)	
Premium Per Acre			0.002			0.035*
			(0.008)			(0.020)
Tmax	0.106***	0.081	0.083***	0.229***	-1.622*	0.137***
	(0.026)	(0.086)	(0.024)	(0.040)	(0.940)	(0.032)
Insured Acreage Ratio × Tmax	-0.032			-0.181***		
	(0.021)			(0.045)		
Weighted Coverage Level × Tmax		0.014			-2.625*	
		(0.122)			(1.425)	
Premium Per Acre × Tmax			0.000			-0.001*
			(0.000)			(0.001)
Precipitation	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20373	20315	20373	16055	16029	16055
Adjusted R^2	0.664	0.666	0.665	-0.004	-0.191	0.006

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table A.12: Baseline Model Results for Surface Water Use with Alternative IV

Dependent Variable: ln(Crop-Specific Water Use per Acre)						
	FE	FE	FE	FE-IV	FE-IV	FE-IV
Insured Acreage Ratio	-0.289			2.802**		
	(0.480)			(1.100)		
Weighted Coverage Level		-0.874			81.649***	
		(2.681)			(29.046)	
Premium Per Acre			0.001			0.034
			(0.006)			(0.036)
Tmax	0.076***	0.023	0.086***	0.045	-1.572*	0.113***
	(0.022)	(0.066)	(0.020)	(0.032)	(0.889)	(0.032)
Insured Acreage Ratio × Tmax	0.023			-0.087**		
	(0.017)			(0.041)		
Weighted Coverage Level × Tmax		0.108			-2.519*	
		(0.094)			(1.355)	
Premium Per Acre × Tmax			0.000			-0.001
			(0.000)			(0.001)
Precipitation	-0.000*	-0.000*	-0.000**	-0.000*	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18049	17986	18049	14018	13992	14018
Adjusted R^2	0.746	0.745	0.747	0.001	-0.116	-0.003

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.