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# Insurance and extraction incentives in a common pool resource: Evidence from groundwater use in the high plains

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ABSTRACT

Although insurance is an important risk management tool in many resource-dependent sectors, its connections to natural resource use are not well understood. We estimate the impact of US federal crop insurance pricing policy on the private use of common pool groundwater in the High Plains region of the United States. Field level panel data on insurance purchases and groundwater extraction allow us to exploit spatial discontinuities in insurance prices at county borders while instrumenting for endogenous prices. A theoretical model describes the mechanisms connecting insurance and resource extraction through groundwater intensity and irrigated acreage. Empirical results demonstrate that a 1% increase in irrigated insurance prices decreases total groundwater use by 0.501%, irrigated acreage by 0.266%, and irrigation per acre by 0.283%. Simulation results suggest that reducing subsidies for irrigated insurance by a recently considered 6.2 percentage points decreases groundwater use by 7.47%. These results suggest that insurance price subsidies may have unintended consequences for natural resource use but could be designed to complement conservation objectives.

## 1. Introduction

Economists recognize that society's common pool resources are subject to overuse, and that policies can improve welfare by decreasing the extraction of natural resources with imperfect property rights (Gordon, 2019; Ostrom et al., 1994; Hughes and Kaffine, 2017). At the same time, market failures in insurance markets (Pauly, 1968; Miranda and Glauber, 1997) lead governments and policymakers to intervene through mechanisms that include mandatory purchase (e.g., car insurance), coverage requirements (e.g., pre-existing health conditions), and subsidization (e.g., agricultural revenue insurance). These two areas frequently intersect when risk and insurance policies are used in natural resource-dependent sectors, including fishing (Mumford et al., 2009), forestry (Zhang and Stenger, 2014), and agriculture (Coble and Barnett, 2012). While risk management policies often affect behavior with external costs (e.g., auto insurance (Loughran, 2001; Weisburd, 2015), health insurance (Einav et al., 2013; Richards and Tello-Trillo, 2019), and public insurance programs such as Medicare (Dague et al., 2017) or agricultural insurance (Cai, 2016)), little is known about the alignment of

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public risk management policies with the goal of conserving common pool resources.

In this paper, we examine the mechanisms through which US federal insurance pricing policy affects the private use of common pool resources. First, we develop a theoretical model that captures the producer's decision-making process related to resource use (land and water) and insurance coverage level. The model is used to demonstrate how subsidizing insurance prices for a resource-dependent activity (e.g., irrigated crop production) can increase resource use through extraction intensity and irrigated acreage decisions, while subsidizing insurance prices for alternative production practices (e.g., non-irrigated crop production) could also impact the use of the shared resource.[1] Next, we empirically identify the causal impact of crop insurance prices, which are set by the US Department of Agriculture's (USDA's) Risk Management Agency (RMA), on common pool groundwater use in Kansas and Nebraska where interest in conserving groundwater has surged (Deines et al., 2019; Ifft et al., 2018). We address endogeneity in insurance prices using an instrumental variables approach that exploits the change in insurance price at county borders. Finally, we illustrate the policy relevance of our results by using econometric estimates to simulate the impact of previously proposed changes to crop insurance subsidies on groundwater use in the region.

Recent research (Ifft and Jodlowski, 2024) demonstrates a connection between crop insurance and environmental outcomes through conservation practice adoption and soil nutrient balances. We describe an additional insurance-conservation linkage by separately estimating the effect that irrigated and non-irrigated insurance products have on groundwater use.

For example, our simulation shows that a 6.2 percentage point reduction in federal subsidies to insurance policies covering irrigated production (resulting in a 14.9% increase in insurance prices for irrigated crops) could decrease groundwater use by 7.47%. The effect is economically significant and comparable to an increase in pumping costs ranging from 9.45% to 29.7% depending on the own-price elasticity of groundwater demand (Schoengold et al., 2006; Pfeiffer and Lin, 2014). A similar proportional reduction in non-irrigated insurance subsidies is not statistically significant.

This study has substantial implications for risk mitigation policies in agriculture and natural resource management. Subsidies in crop insurance are applied proportionally to all insurance products (7 U.S.C. § 1508) and only vary with the coverage level. Our results show that practice-based insurance subsidies may work against resource conservation goals. For example, we find that higher insurance prices decrease groundwater use by reducing the amount of irrigated land and the amount of groundwater applied per unit of land. This suggests that subsidies that lower the price of insurance may increase groundwater extraction and lead to lower groundwater stocks over time. Our findings also provide important information regarding the design of federal policies where multiple, potentially competing, objectives exist across national and regional levels. The question of whether national agricultural risk management policies such as crop insurance can be better designed to reflect their impact on groundwater use and aquifer health is relevant to our study region.

The connection between federal crop insurance and resource extraction is particularly relevant in regions of the US where common pool groundwater depletion threatens the economic viability of irrigated agriculture (Haacker et al., 2016). The common pool nature of groundwater means that pumping externalities lead to excess resource extraction and significant welfare losses (Pfeiffer and Lin, 2012). Our simulation results suggest that subsidized irrigated crop insurance in areas with substantial irrigated acreage may work against local (Peterson et al., 2003) and federal (Monger et al., 2018) policies implemented to conserve groundwater by creating an incentive to increase pumping, and thus exacerbating the common pool problem.

This study also contributes to work on risk management policy in general. As in past studies focused on auto insurance (e.g., Loughran, 2001; Weisburd, 2015), unemployment insurance (e.g., Lalive et al., 2015), public health insurance (e.g., Dague et al., 2017), and disability insurance (e.g., Gelber et al., 2017), we show that crop insurance may have unintended consequences on behavior.

The remainder of the paper is laid out as follows. The next section provides background on the existing literature that studies the Federal Crop Insurance Program in the US, and how it connects to resource use. Then, we develop a theoretical model that highlights the mechanisms connecting insurance prices to natural resource use for a risk averse producer. This is followed by a description of the data and context used to test the theoretical hypotheses. We then describe our empirical methods, present results, and conduct a policy simulation to place our econometric estimates in context. Finally, we conclude with a discussion of policy implications and lessons for future research.

## 2. Background on crop insurance and resource use

In this section we provide background on the Federal Crop Insurance Program. We then summarize the two branches of literature our study most directly contributes to: (1) the impact of insurance on behavior and (2) the determinants of groundwater use.

### 2.1. Federal crop insurance program

The Federal Crop Insurance Program is the largest agricultural aid program in the US (Glauber, 2013), with a cost of $7.2 billion per year (Congressional Research Service, 2018). The USDA's RMA determines insurance pricing for many (but not all) counties and crops in the US. For each crop, prices for insurance also depend on the agricultural practices used. For example, insurance for irrigated and non-irrigated corn have distinct prices. While the RMA aims to set actuarially fair insurance rates, there is evidence that they do not

[1] We use 'subsidizing insurance' and 'subsidizing insurance prices' interchangeably. Since insurance prices are set by federal policy, by examining impacts of insurance prices, we describe the impact of policy.

always succeed (Goodwin and Smith, 2013; Ramirez et al., 2011). RMA rates may also fail to account for the full range of heterogeneity within counties (Woodard, 2016B).

Crop insurance purchases and indemnity payments follow an annual cycle. At the beginning of every year, the RMA releases information on updates to insurance pricing and product availability. Then, producers can either purchase new crop insurance policies or update existing policies, all through a private insurance agent. If a loss occurs during the season, the producer makes a claim through the insurance agent, and an indemnity is paid from the insurance agency.

The most common insurance products include yield protection (Babcock and Hennessy, 1996), revenue protection, and income protection.[2] For a given product, a producer selects a coverage level, which is a percent of insured yield or revenue. A farm's insurable yield depends on the producer's production history,[3] while prices used for revenue insurance are the greater of futures prices when the insurance is bought and spot prices at the time of harvest (Mahul and Wright, 2003).

Crop insurance subsidies vary by coverage level and by the way in which multiple fields are grouped. The farmer pays a subsidized insurance price to the private insurance agent and the difference between this subsidized price and the actuarially fair premium is paid to the private insurance agent by the USDA. The result is that the price paid by the producer for crop insurance is lower than it would be without subsidization. To examine the impact of subsidies on groundwater use, we estimate how producers respond to changes in the subsidized price they face.

### 2.2. *Insurance policies, behavior, and groundwater*

Insurance programs attempt to minimize or eliminate undesirable behavior changes that increase risk (Einav et al., 2013). From a welfare perspective, this is especially important when changes in behavior produce external costs or benefits (e.g., Loughran, 2001). In some cases, unintended behavioral responses can undermine specific policy goals. For instance, tobacco surcharges in the Affordable Care Act that were supposed to reduce tobacco use led to lower coverage rates without reducing tobacco use (Friedman et al., 2016). Understanding how individuals change their behavior can also reveal strategies for improving insurance programs (e.g., Cabral and Mahoney, 2019). Agricultural insurance has also been shown to influence farm household management decisions, including lowering agricultural production diversification and savings (Cai, 2016).

Numerous studies have examined whether the federal crop insurance program influences behavior. For example, Claassen et al. (2016), Walters et al. (2012), Miao et al. (2012), and Yu et al. (2017) show that crop choice and total area are affected by insurance price. Further, Wu (1999) demonstrates that changes in insurance cause a change in chemical input use and Schoengold et al. (2014) observe that crop insurance and disaster relief programs affect tillage practices in Iowa, Nebraska, and South Dakota. While considerable evidence exists documenting the impact of insurance prices on producer behavior, the impacts on environmental quality are thought to be small (Walters et al., 2012; Weber et al., 2016; Claassen et al., 2016). Often, the relationship between resource use and insurance is tied to moral hazard. Forward-looking producers may also introduce moral hazard concerns when future insurance coverage depends on current input use (Mieno et al., 2018). While most literature considers potential negative environmental externalities from crop insurance, it could also produce environmental benefits. For example, Ifft and Jodlowski (2024) find that federal crop insurance facilitates adoption of profit-maximizing conservation practices, leading to better nutrient management.

The only paper to explicitly examine crop insurance and water use is Deryugina and Konar (2017). Using a county level panel, they find that cheaper insurance increases irrigation at the county level, driven in part by farmers switching to more water intensive crops. Our study builds upon Deryugina and Konar (2017) in two significant ways. First, we disentangle the effects of insurance prices for irrigated and non-irrigated practices. Second, our study benefits from a fine-scale dataset of field level insurance purchases and water use, which allows us to observe field level crop insurance prices and to pursue a novel identification strategy.

Many studies have considered other factors that influence groundwater use, often using data from the Ogallala and High Plains Region of the US. Not surprisingly, pumping costs, climate, and management policies all impact the volume of groundwater pumped. For example, Hendricks and Peterson (2012), Pfeiffer and Lin (2014), and Burlig et al. (2021) show that producers decrease water use when energy prices increase. Since the price of electricity reflects the price of pumping (unpriced) groundwater, this result confirms that the derived demand for groundwater slopes downward. Pfeiffer and Lin (2014) find that the adjustment is largely due to less water applied per unit of irrigated land, though Burlig et al. (2021) find groundwater reductions in California occur mostly from crop switching and land fallowing. Consistent with this, Smith et al. (2017) find that taxes on groundwater extraction result in decreased use. Kreins et al. (2015) demonstrate that water use increases in dry conditions. Cotterman et al. (2018) predict that climate change and declining groundwater levels will lead producers to decrease irrigated corn acreage by 60% under current management scenarios.

Across the High Plains Region, there are examples of conservation policies that limit groundwater use (Ifft et al., 2018). Drysdale and Hendricks (2018) show that self-imposed groundwater pumping caps led to a 26% reduction in groundwater use in a small region in western Kansas. The authors find that this reduction is almost entirely through a decline in irrigation intensity (measured as irrigation per unit of land) instead of changes in the amount of irrigated land. Hydro-economic models have also been used to explore how hypothetical, realistic groundwater management strategies (i.e., constant over space and time) influence water use and profitability over time (Guilfoos et al. 2013, 2016; Hrozencik et al., 2017). These hydro-economic models generally omit the role of crop insurance

[2] Other options include area yield insurance (Miranda, 1991) and index-based insurance (Barnett and Mahul, 2007).

[3] A producer's Actual Production History (APH) is calculated by averaging the historic production levels over the recent history of an insurance unit. At a minimum, four years is required to calculate an APH. The maximum number of years included is ten. If a producer lacks sufficient history, a county-level 'transitional yield' is used.

in affecting land and water use decisions because of a lack of understanding regarding how they relate. Here, we contribute to this literature by examining the mechanisms through which insurance prices influence groundwater extraction.

## 3. Theoretical model of insurance and resource use

To describe the margins along which producers can adjust common pool natural resource use in response to insurance prices, we consider a producer who, over the course of a season, makes a series of resource-based production decisions (i.e., land and water use) along with an insurance decision.[4] At the start of the agricultural season the producer chooses how many acres to irrigate, $A$, to maximize the expected utility of net revenue, conditional on a vector of subsidized insurance prices,[5] $\boldsymbol{r}$, including irrigated ($i$) and non-irrigated ($ni$) coverage, and other prices, $p$. At this time the producer also chooses a level of insurance coverage, $\alpha$, to protect against the negative effects associated with catastrophic environmental events such as a disease outbreak, extreme weather, or the presence of pests. This uncertainty is reflected by $\theta$, a stochastic environmental variable, that influences profitability per unit of land.[6] They receive $\alpha$ per unit of land covered when there is a bad realization of $(\theta)$, otherwise their per unit of land payment, net of insurance costs, is solely a function of their acreage choice, groundwater choice, and other prices. The within season problem of the producer corresponds to the choice of how much groundwater to apply, $g$, per unit of irrigated land. This decision is made conditional on the planting and insurance decisions made at the start of the season, but before the environmental uncertainty has been fully realized.

Mathematically, the producer's problem at the start of the season can be expressed as follows:

$$\max_{A,\alpha} E[U(A^*\pi(g^*(A,\alpha;p,\theta),A,\alpha;\boldsymbol{r},p,\theta))] \tag{1}$$

Where $\pi(.)$ is the stochastic net revenue earned per unit of land planted,[7] $U(.)$ is the producer's utility function, $E[.]$ is the expectations operator, and $g^*(A,\alpha;p,\theta)$ denotes the optimal groundwater application decision. The inclusion of $A$ and $\alpha$ in optimal groundwater use highlights that the solution to this first-stage problem, $A^*$ and $\alpha^*$, are both functions of the optimal anticipated changes in $g$. This reflects the fact that groundwater use decisions are made after the acreage and insurance decisions, when more information than what is available at the time of planting is available but before knowing the full weather realization with certainty.

Optimal groundwater use, $g^*$, is the solution to the within season problem which is expressed mathematically as follows:

$$\max_{g} E\left[U\left(A^*(\boldsymbol{r},p)^*\pi(\theta,g,A^*(\boldsymbol{r},p),\alpha^*(\boldsymbol{r},p);\boldsymbol{r},p)\right]\right. \tag{2}$$

Importantly, given this setup, $g^*$ is not directly a function of $\boldsymbol{r}$. Because the groundwater decision is made after the producer has already made insurance and acreage decisions, $\boldsymbol{r}$ only influences water use through its impact on acreage and insurance purchases.

Taken together, total groundwater use, $W^*(\boldsymbol{r},p)$, is the product of the optimal amount of irrigated land and the amount of water applied per unit of land:

$$W^*(\boldsymbol{r},p) = A^*(\boldsymbol{r},p)^*g^*(A^*(\boldsymbol{r},p),\alpha^*(\boldsymbol{r},p),p) \tag{3}$$

$W^*(\boldsymbol{r},p)$ does not contain the weather realization $\theta$, because decisions regarding irrigation are made prior to the realization of weather outcomes. To examine the margins of adjustment in response to a change in insurance price that affects total water use, we differentiate equation (2) with respect to $r^v$, where $v \in \{i, ni\}$:

$$\frac{dW^*}{dr^v} = \frac{dA^*}{dr^v}g^*(\bullet) + \frac{dg^*}{d\alpha^*}\frac{d\alpha^*}{dr^v}A^* + \frac{dg^*}{dA^*}\frac{dA^*}{dr^v}A^* \tag{4}$$

The impact of a change in insurance price on the private use of groundwater can be decomposed into three effects. The first relates the price of insurance to irrigated land ($A^*$), conditional on groundwater use per unit of land (effect 1). Then, groundwater use per unit of land responds to the insurance price because of indirect impacts through insurance coverage (effect 2) and land use decisions (effect 3). We discuss each of these below, first considering an increase in the price of irrigated crop insurance, $r^i$.

For a change in irrigated insurance price, the first effect $\left(\frac{dA^*}{dr^i}g^*(A^*)\right)$ is through a change in irrigated land, conditional on

[4] For simplicity, we do not explicitly model the producer's decision on which crop to produce. In Appendix 5, we investigate how crop switching may affect water use per irrigated unit of land.

[5] In practice, the price paid for insurance is a function of the coverage level chosen. This simplification is consistent with our empirical approach and with others who have used a single price to model behavior in settings with non-constant marginal prices (e.g., Hrozencik et al., 2022). In the empirical section we address potential endogeneity concerns associated with this explicitly, but here we note that this simplification is made without significant loss of generality, to elicit the relationship more clearly between irrigated and non-irrigated insurance price and water use.

[6] The parameters of the distribution of $\theta$ have been suppressed for conciseness.

[7] We model per acre profitability $\pi(.)$ as a function of total acres (A) and assume that the relationship is negative for two reasons. First, given heterogeneity in land quality, profit maximization would imply that producers first irrigate acres where, all else equal, the marginal value product of water is highest. Increasing acreage would require enrolling land for which the marginal value product of water was lower than the average value product of water to that point. Second, for producers facing pumping constraints, limited water can make it difficult to time applications in response to varying climate conditions. Depending on the plant stage, overstressing the plant can have a significant, negative impact on yields (Perry et al., 2009). Increasing acreage, while holding pumping capacity constant, can exacerbate this problem.

groundwater applied per unit of land. We refer to this as the direct acreage effect. Since increasing the insurance price for irrigated land decreases the marginal returns to irrigated land, we expect this effect to be negative in practice, though its theoretical sign ultimately depends on the shape of the producer's utility function and the degree of risk aversion.

The second effect, $\left(\frac{dg^*}{d\alpha^*}\frac{d\alpha_i^*}{dr^i}A^*\right)$, represents the indirect effect of a change in insurance prices on groundwater use per unit of land through its impact on insurance purchases - conditional on acres planted. We refer to this as the coverage indirect effect. Conditional on $\frac{d\alpha_i^*}{dr^i} < 0$ (i.e., demand for insurance coverage is downward sloping with respect to own price), the sign of the coverage indirect effect provides important insight into whether groundwater and insurance are used as substitutes or complements. A positive (negative) coverage indirect effect implies $\frac{dg^*}{d\alpha_i^*} < 0$ ($\frac{dg^*}{d\alpha_i^*} > 0$) and the two goods are used as substitutes (complements).

While the sign of $\frac{dg^*}{d\alpha_i^*}$ is uncertain, we hypothesize it is positive for two reasons. First, groundwater represents a risky input with certain costs, but uncertain benefits. For risk averse producers, higher coverage levels reduce the downside risk and, all else equal, increase the expected marginal utility of groundwater use by increasing the lower bound of net revenue a producer can receive from each unit of groundwater applied. This is especially true in those instances when indemnity payments are made because of events whose probability of occurrence is not impacted by groundwater use (e.g., pests, hail, etc.). In these instances, insurance protects the producer's "investment" in increasing crop yields by applying groundwater. The second reason is mechanistic, relating to the nature of crop insurance. Although not explicitly modeled here, in practice, producers face an additional source of uncertainty related to their insurance: whether they receive the indemnity payout. Federal Crop Insurance requires producers to continue irrigation even when it may no longer be economically rational to do so.[8] Deryugina and Konar (2017) note that this aspect of crop insurance may cause risk averse producers to water more than they otherwise would to guarantee they receive payment. Given that larger coverage levels result in larger payments (all else equal) we would expect this behavior to increase in the coverage level. For these reasons we expect the coverage indirect intensity effect to be negative $\left(\frac{dg^*}{d\alpha_i^*}\frac{d\alpha_i^*}{dr^i}A^*\right) < 0$.

The third effect $\left(\frac{dg^*}{dA^*}\frac{dA^*}{dr^i}A^*\right)$ occurs because less irrigated land changes the optimal amount of groundwater applied per unit of land. We refer to this as the acreage indirect effect. We expect this effect to be positive because $\frac{dA^*}{dr^i} < 0$ and with fewer units of irrigated land planted, a given amount of water per unit of land can be better timed to increase its impact on crop growth. In addition, we hypothesize that $\frac{dg^*}{dA^*} \le 0$ due to constraints on pumping. As acreage increases, limits on the total amount of groundwater available necessitate a decrease in the amount of water that can be applied per acre.

Taken together, the net impact of an increase in irrigated insurance price has a theoretically ambiguous impact on groundwater use. The impact depends on the relative magnitude of a direct acreage effect (likely negative), a coverage indirect intensity effect (likely negative), and an acreage indirect intensity effect (likely positive). Consistent with Manning et al. (2017) these effects can be characterized as being on the extensive margin (irrigated acres) or the intensive margin (irrigation intensity). Both the coverage indirect (effect 2) and the acreage indirect effect (effect 3) fall into the intensive margin category. Effect 2 captures how producers substitute water and insurance holding constant the extensive margin (acres), while effect 3 captures how farmers change irrigation per acre planted as the number of acres changes. The direct acreage effect (effect 1) is an extensive margin change because it describes changes in irrigated acreage. In the empirical application of this paper, we estimate the sign and magnitude of the net impact as well as these individual channels.

Theoretical predictions corresponding to a change in the price of insurance for non-irrigated crops, $r^{ni}$, can be described as above. However, we would expect two main differences. First, we would expect $\frac{dA^*}{dr^{ni}} > 0$ because increasing the non-irrigated insurance price decreases the opportunity cost of planting irrigated land (though note that the sign of this effect depends on the shape of the producer's utility function and the degree of risk aversion). This implies that the direct acreage effect is positive while the acreage indirect intensity effect is negative for non-irrigated insurance prices. Second, the sign of the coverage indirect effect would depend on the relationship between the price of non-irrigated insurance and the coverage level for irrigated acres ($\frac{\partial\alpha_i^*}{\partial r^{ni}}$). We do not have a strong prior on this other than that it depends on the producer's preferences toward risk across their portfolio of irrigated and non-irrigated crops, as well as income. Taken together, this means that the effect of non-irrigated insurance prices is theoretically ambiguous.

The theoretical model reveals an ambiguous relationship between insurance and the use of groundwater. In total, the impact of increasing crop insurance prices depends on how irrigated and non-irrigated prices change as well as how responsive water use is to each of the prices. This informs our choice to include both irrigated and non-irrigated crop insurance prices in our empirical analysis. Often, natural resources are described as substitutes for insurance, possibly providing 'natural insurance' in the absence of market insurance (Pattanayak and Sills, 2001). Resource access and the ability to respond to a negative event by applying groundwater may allow the resource to substitute for insurance. Our model demonstrates that, conditional on having access to groundwater, insurance can increase the intensity of resource use before uncertainty is resolved if the resource is costly (e.g., because of energy costs from extraction). For example, a producer commits financial resources to irrigating a crop before knowing if a pest outbreak or hailstorm could destroy the crop. In this case, insurance can increase the intensity of natural resource use, conditional on access.

[8] https://www.rma.usda.gov/en/Policy-and-Procedure/Final-Agency-Determinations/Basic-Provisions-9b-FAD-289.

## 4. Data and context

To explore the ambiguities described in our theoretical model, we turn to an empirical application. Our study region includes the state of Kansas and the Republican River Basin in Nebraska (see Fig. 1). A large part of our study region overlies the Ogallala aquifer, which is the largest aquifer in the US. The region relies heavily on groundwater use for irrigation (Konikow and Kendy, 2005). We also include wells in Kansas that access groundwater from other aquifers. Main crops in the region include corn, wheat, soy, and sorghum. Accor ding to our dataset and calculations (see Section 4.1), an average of nearly 6.5 million acres of agricultural production in the study region (78% of total) were insured through the Federal Crop Insurance Program between the years 2007 and 2013. From this region, we have rich data on insurance purchases, groundwater use, and soil type at the field level. We also observe the location of each field, which allows spatial merging with weather, climate, and soil data. The details of the data are described below.

We obtain spatially explicit field-level crop insurance purchase information from USDA RMA. The data report numerous insurance variables at the Common Land Unit Level (CLU).[9] For every CLU enrolled in insurance in our study region (n = 41,935) we observe the premium paid for insurance and the amount of liability purchased annually between 2007-2013.[10] The dataset also provides information on the number of insured acres planted in each crop, as well as if the crop is insured as irrigated or non-irrigated. To create a panel over time, and to facilitate merging with well information, we aggregate CLUs to the tract level (n = 34,231), where a tract is defined as a contiguous unit of land that is under single ownership and is either operated as a farm or as part of a farm.[11] Each tract included in the analysis contains one or more CLUs.

Next, we merge the insurance data with groundwater pumping data. Groundwater pumping data for each well in Kansas are obtained from the Water Information Management and Analysis System (WIMAS) (Kansas Department of Agriculture Department of Water Resources, 2018). This dataset contains information on well location and characteristics, as well as the annual volume of water pumped. The same variables for wells in the Republican River basin of Nebraska come from the Republican River Compact Administration.[12] From both datasets, we use annual data from 2007 to 2013.

Well-level data for 75,160 wells,[13] including volume of water pumped, were mapped to the tract in which water was applied and spatially merged (by tract) with the crop insurance data. This was done in conjunction with collaborators at the USDA's Economic Research Service (ERS) by first identifying the four wells nearest to the centroid of each irrigated CLU. These wells may be within, on the border, or just outside a given CLU. Each CLU is matched to the nearest well (among the four closest) that reports the same crop type and irrigated acreage in both the insurance and groundwater databases. If a single well's crop type and irrigated acreage do not match that of the CLU, we eliminate it from the data set. Matched wells are assigned to the tract that contains the matched CLU. Several wells were assigned to CLUs in multiple tracts or assigned to CLUs in different tracts in different years, but we limit our sample to the set of tracts that had a consistent mapping to wells across the entire time frame (2007–2013). Since we only observe tracts with CLUs that merge consistently with wells, we do not have access to the universe of unirrigated fields (though we observe unirrigated acreage decisions in tracts that merge with wells).

Our decision to aggregate at the tract level is driven largely by challenges associated with mapping wells to a spatial unit. At both the CLU and tract level we are confident that all management decisions are taken by the same producer. Using the CLU as the unit of analysis would increase the number of observations, but this would come with a significant cost. Namely, there would be a higher chance of a particular observation being associated with the wrong well. By aggregating to the tract level, we lose observations but reduce the probability of incorrectly matching wells with the insurance data.

Soil also influences optimal groundwater use (Hrozencik et al., 2017) while affecting crop production risk (Woodard and Verteramo-Chiu, 2017). Therefore, we obtain data on the soil within each tract from the USDA NRCS SSURGO dataset (USDA Natural Resource Conservation Service). Relevant soil variables include the percent of soil that is clay, silt, and sand, water storage at 100 cm, the NCCPI,[14] and the land capability class. We also include the latitude and longitude of wells for additional spatial controls.

For our analysis, we focus on tracts that use yield, income, and/or revenue insurance, representing 80% of insurance plans in the region. Further, we only observe tracts that have at least some irrigated insurance coverage (identified using the insurance data) that we link to a well. This means that our analysis represents insured tracts in the study region that have at least some irrigation but does not capture behavior on tracts with no irrigation.

For each insurance product available to the producer, the Federal Crop Insurance Corporation (FCIC) identifies a "base price" or "unsubsidized price" which is designed to make the product actuarially fair. The base price varies across counties (based on differences in county yield distributions) and individuals within a county based on an individual's actual production history (APH) relative to their county average. The insurance price paid by the producer also reflects a subsidy. The portion of the total premium paid for by the

[9] A CLU is the smallest administrative unit on a farm and stays relatively stable over time. Additional data on CLUs can be found here:https://www.fsa.usda.gov/programs-and-services/aerial-photography/imagery-products/common-land-unit-clu/index.

[10] The field level insurance data are not made available for later years.

[11] A farm may have one tract or be comprised of many tracts. Therefore, the size of the tract is not necessarily equal to the size of a farm. This is not to be confused with a census tract.

[12] Data from the Republican River Compact Administration are publicly available at: http://www.republicanrivercompact.org/.

[13] Agriculture is the primary end use for all wells in our dataset. While we observe the crop mix and acreage associated with each well, we do not observe if the well is used for other agricultural purposes (e.g., livestock).

[14] More details regarding the National Crop Commodity Productivity Index (NCCPI) can be found here: https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/16/nrcs143_020559.pdf.

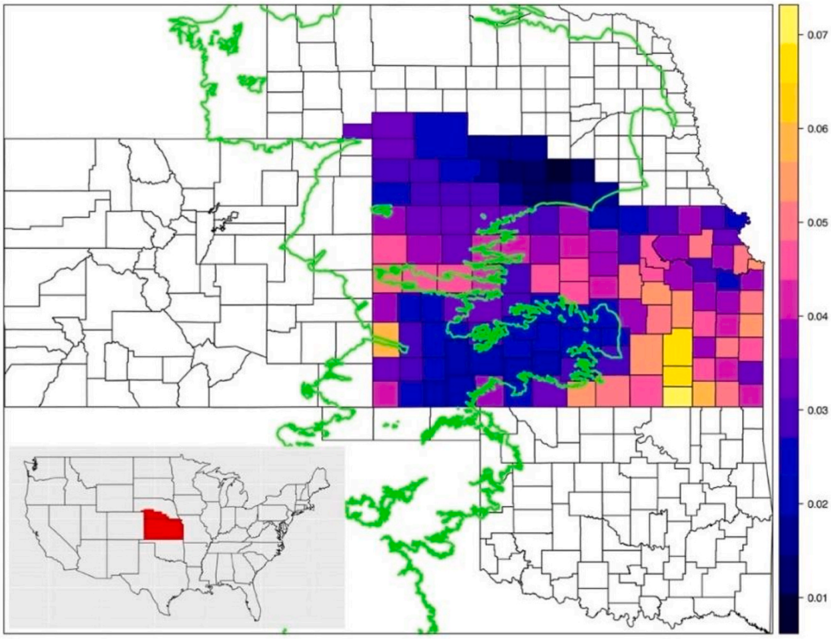


**Fig. 1.** The study region (shaded counties) and associated county-level base prices for irrigated insurance. Units are dollars paid per dollar of liability purchased (pre-subsidy). The green border represents the boundary of the Ogallala Aquifer. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

government (i.e., the subsidy rate) ranges from approximately 80 to 40 percent and, importantly, differs depending on the coverage level chosen (Shields, 2015). In effect, the subsidy creates a rate schedule, where the amount paid by the producer per unit of coverage ("subsidized price") increases in the level of coverage purchased by the producer.

We do not observe the menu of irrigated and non-irrigated insurance prices faced by each producer. To overcome this, for each tract we calculate the average annual subsidized insurance price paid for irrigated acres across all policies within a tract by dividing the total premium paid across all irrigated acres within the tract by the total dollar amount insured ('liability') across all irrigated acres within the tract. We repeat this for non-irrigated acres to obtain a non-irrigated insurance price. For tracts that have only irrigated production ($n = 37$) we predict average non-irrigated insurance prices based on a tract's irrigated insurance price, acreage, climate and soil controls, state-year fixed effects, and county-pair fixed effects. Additional details of price prediction can be found in Appendix 1. As seen in Table 1, the average tract level insurance prices are 0.04 and 0.07 for irrigated and non-irrigated crops respectively. The tract average prices faced by producers are lower than would occur in the absence of subsidies. Table 1 also presents the average amount of irrigation volume in our sample. We see that on average a tract has about 211 acres of irrigated acreage, and pumps approximately 195 acre-feet of water, resulting in an average of about 0.92 acre-feet per acre.

Next, we calculate county average insurance base prices that reflect risk over an entire county, but do not reflect the subsidy. Our empirical identification strategy (described below) relies on exogenous differences in county insurance price parameters near county borders. For county $c$, crop $i$, and year $t$, we use the Risk Management Agency's rate-making dataset (Risk Management Agency, 2023) to obtain county-level base prices ($CP_{cit}$) for each county for four different crops (corn, wheat, soy, sorghum) for both irrigated and non-irrigated practices, resulting in 8 county-level $CP_{cit}$ variables that vary over time and county.[15] $CP_{cit}$ does not include subsidies to avoid additional endogeneity issues beyond those discussed below (Yu et al., 2017). Fig. 1 shows the spatial variation in average $CP_{cit}$ for irrigated crops over our study region during the period 2007–2013 for each county in the study region (average county insurance prices are presented in Table 1).

We also include data on weather, climate, and soil for each tract. Weather and climate data come from the Parameter-elevation Regression on Independent Slopes Model PRISM dataset (Oregon State Climate Group, 2018). We use growing season averages for precipitation and temperature (mean, minimum, and maximum).[16] Since weather is unknown as of planting, we also use 30-year growing season averages of each variable to measure expectations. The climate and weather data are gridded and reported at 800m resolution. Each weather and climate variable (e.g., the average minimum temperature in 2013) is aggregated to the tract level by averaging the variable across the tract. The climate data are 30-year averages of weather variables.

Variable averages for the sample used in our analysis are presented in Table 1. Additional details about how the final sample was created are explained in section 5.2 on identification.

[15] These county base prices represent the county loss-cost ratio.

[16] Our results are not sensitive to using annual weather and climate variables instead.

**Table 1**
Summary statistics.

| Variable | Mean | St. dev. | Mean difference[a] | t-value |
|---|---|---|---|---|
| **Tract-level insurance price and irrigation (units)** | | | | |
| Irrigated price (USD per unit liability) | 0.039 | 0.021 | 0.004*** | 3.741 |
| Non-irrigated price (USD per unit liability) | 0.069 | 0.035 | 0.007*** | 3.805 |
| Irrigated acres (Acres) | 211.819 | 161.838 | 32.934*** | 5.056 |
| Total irrigation (Acre feet) | 195.434 | 191.984 | 36.714*** | 3.574 |
| Irrigation per acre (Acre feet per acre) | 0.919 | 0.448 | 0.088*** | 2.847 |
| **County insurance base price (USD per unit liability)** | | | | |
| County base price, irrigated corn | 0.065 | 0.19 | 0.108*** | 3.822 |
| County base price, non-irrigated corn | 0.123 | 0.185 | 0.105*** | 3.573 |
| County base price, irrigated wheat | 0.531 | 0.47 | 0.099*** | 7.292 |
| County base price, non-irrigated wheat | 0.907 | 0.28 | 0.018 | 0.821 |
| County base price, irrigated soy | 0.089 | 0.186 | 0.106*** | 3.651 |
| County base price, non-irrigated soy | 0.28 | 0.374 | 0.088** | 1.994 |
| County base price, irrigated sorghum | 0.087 | 0.186 | 0.106*** | 3.823 |
| County base price, non-irrigated sorghum | 0.126 | 0.182 | 0.104*** | 3.712 |
| **Tract characteristics (units)** | | | | |
| NCCPI (unitless ratio) | 0.405 | 0.138 | 0.025 | 1.608 |
| Sand (percent) | 30.076 | 27.615 | 6.239** | 2.361 |
| Erodibility index (ratio) | 9.159 | 6.791 | 1.442*** | 2.811 |
| Mean Precipitation (mm per month) | 75.876 | 12.287 | 1.032 | 0.694 |
| Mean temperature (degrees Celsius) | 20.57 3 | 1.255 | 0.134 | 0.765 |
| Tracts | 3453 | | | |
| Observations | 15,483 | | | |

[a] .The mean difference is the mean absolute value difference for a variable across county boundaries within a group (see section 5 on identification strategy for the definition of a group). We calculate this by subtracting the average variable value on each side of county boundaries and taking the absolute value. The null hypothesis is that this difference is 0. Standard errors are clustered at the county-pair level for this test.

## 5. Empirical model and identification

We estimate reduced form empirical models which allow us to identify the net effect of insurance prices on water use, as well as the direct acreage, coverage indirect, and acreage indirect effects outlined in Section 3. We describe each model along with the identification strategy used to address endogeneity concerns related to insurance prices. In all cases, we cluster standard errors at the county level. Our instrumental variables are county level menus of insurance prices. Clustering at the county level, as opposed to a smaller unit like a township, is consistent with literature that recommends clustering at the level of treatment (Abadie et al., 2017). Another benefit of this approach is that, due to the larger clusters, the inference is more robust than if standard errors are clustered at a higher resolution land unit.[17]

For all specifications, we perform logarithmic transformations on the dependent variables as well as the irrigated and non-irrigated insurance prices. Therefore, the coefficients on irrigated and non-irrigated insurance prices can be interpreted as elasticities. One drawback of this approach is that the logarithmic transformation cannot be performed on zero-valued variables; thus, these are dropped (100 observations dropped, or approximately 0.6%)

### 5.1. Empirical specifications

To examine the net effect of insurance price on water use at tract $j$ in year $t$, $W_{jt}$, we estimate equation (5).

$$log(W_{jt}) = \mu_g + \gamma_{st} + \beta_1 \; log(r_{jt}) + \beta_2 X_{jt} + \varepsilon_{jt} \tag{5}$$

Where $\mu_g$ is a spatially determined, group fixed effect that controls for unobserved differences across space (e.g., topography, electricity price, market access) that could influence groundwater use but would not be controlled for by latitude and longitude. A group is defined as a subset of neighboring tracts on either side of a county boundary. They are precisely defined in Section 5.2 below.

The variable $\gamma_{st}$ is a state-year fixed effect that controls for unobserved time-varying shocks (e.g., output prices) common to all tracts within a state. This also controls for changes in state regulations and taxation that could influence groundwater pumping decisions. $r_{jt}$ is a vector containing both irrigated and non-irrigated insurance prices for tract $j$ in year $t$. Furthermore, $X_{jt}$ is a vector of controls that vary across space and/or time within a group and includes soil variables, annual growing season weather, 30-year

[17] It can be shown that the theoretical predictions large clusters might benefit from implementing wild bootstrapping (e.g., Cameron et al., 2008; Canay et al., 2021). Though the number of clusters in our study is large, it is important to note that because we restrict our sample to only those wells within a 3-mile buffer of a county line, there are not as many observations per cluster as there would be if we included the entire county. As a robustness check, we performed three alternative clustering strategies. We performed wild bootstrapping, Conley standard errors, and clustering at the township level. In all three cases, the alternative clustering strategies resulted in similar significance levels as in our main results.

growing season climate averages, latitude, and longitude. The error term is $\varepsilon_{jt}$.

We use equations (6) and (7) to identify the irrigated acreage and intensity indirect effects, where $A_{jt}$ and $g_{jt}$ correspond to the number of acres planted and groundwater intensity in year $t$ for tract $j$. For both equations (6) and (7), the right-hand side variables are defined as before.

$$log(A_{jt}) = \mu_g + \gamma_{st} + \beta_1 \, log(r_{jt}) + \beta_2 X_{jt} + \varepsilon_{jt} \tag{6}$$

$$log\left(g_{jt}\right) = \mu_g + \gamma_{st} + \beta_1 \, log(r_{jt}) + \beta_2 X_{jt} + \varepsilon_{jt} \tag{7}$$

We estimate equation (7) with irrigated acres included in $X_{jt}$ and then again excluding irrigated acres. We include both weather and climate controls as in equation (5). In the results presented here, we include controls for growing season weather, even though the weather is not fully known at the time of planting. Early season weather, however, may provide a signal that producers use to adjust planting decisions (Ahmed et al., 2023). When excluding weather from the acreage models, results do not change in economically or statistically significant ways. Conditioning on acres, which are predetermined as of the time of irrigation events, identifies the coverage indirect effect, while not conditioning provides the net impact of the two indirect effects (coverage and acreage). The difference reveals the sign and magnitude of the acreage indirect effect. Appendix 2 describes the mechanism through which insurance prices affect groundwater intensity, noting that the estimated impact of insurance prices on groundwater per acre when not controlling for acreage captures both the coverage indirect effect and the acreage indirect effect. Across all three models, the vector $\beta_1$ contains the coefficients of interest.

### 5.2. Identification

Two sources of endogeneity complicate the identification of crop insurance price impacts on water use. First, the insurance price paid in each tract is a function of the coverage level chosen by the producer, as well as producer characteristics related to past performance. To address this, we instrument for price using county base prices (described above in Section 4.1) and their square.[18] Importantly, county base prices vary between counties and across time, and are assumed to be exogenous to the individual tract at a county boundary given the large number of tracts in each county.

Second, producer decisions may be driven by a wide variety of observed (e.g., climate) and unobserved (e.g., distance to markets) factors that vary across space. These unobserved factors may drive differences in county level insurance prices that we use as instruments. To address this, we use the sharp discontinuity of county level base prices at the county boundary along with fixed effects to identify the model. First, we restrict our analysis to tracts within 3 miles of a county border ('inclusion buffer,' Fig. 2). This reduces the number of tracts in our sample to 3453 tracts. If a well borders a county that is not included in the study region, it is dropped. We test robustness to the choice of 3-mile buffers by presenting results with 7-mile, 5-mile, 2-mile, 1-mile, and ½-mile buffers in Appendix 3. We also discuss alternative group definitions in Appendix 3, including using county pairs and townships as groups. Next, we place wells into local "groups." To do this, for a given county boundary, we begin by randomly selecting one tract (e.g., tract A in Fig. 2). We then identify the closest tract in the opposite county (e.g., tract B). These two tracts are placed into a group (e.g., Group 1). We then choose another tract at random (e.g., tract C) and identify the closest tract in the opposite county. If the tract in the opposing county is already in a group (e.g., tract A was closest to tract C) then it is placed in the already existing group (Group 1). If the tract in the opposing county is not already in a group, then it, along with the randomly selected tract (tract D), is placed in a new group (Group 2). This process is repeated until all tracts within 3-miles of a county border are part of a group.

The effect of insurance prices is identified by using a two-stage least squares approach that makes use of the discontinuity in insurance base prices at the county boundary, rather than a more conventional spatial discontinuity approach. We do this because the two-stage least squares model can simultaneously use the exogenous change at the border along with the variation in the difference between prices at county borders. It allows us to isolate the elasticities associated with irrigated and non-irrigated insurance. Our approach builds upon those highlighted in Tsiboe and Turner (2023). One approach that Tsiboe and Turner (2023) highlight involves using FCIP county base prices as instruments. Our approach combines the FCIP base price identification strategy with the spatial identification strategy described above to improve the statistical power of the FCIP base prices in the first stage.

Our algorithm for constructing spatial groups uses a process to group tracts while ensuring each group contains tracts on both sides of a county border. By not employing any strict distance cutoff conditions (beyond being within 3 miles of a border), it also ensures that no wells are dropped. To examine the effect of group definitions on our results, we conduct a robustness check by using townships and county-pairs instead of groups as fixed effects and find that results have the same sign, though the estimates from the county-pairs model have less precision (Appendix 3).[19]

The grouping process results in an average of approximately 5.26 groups along each county border. Within these groups, the average distance between wells and the county border is 1.63 miles, with a standard deviation of 0.59 miles. The average group contains 5.4 tracts. The average maximum distance between two wells in each group is 2.18 miles, with a standard deviation of 0.69

[18] Inclusion of squared base prices greatly improves the fit of the first-stage model. We perform both a weak instrument test and a test for endogeneity in Appendix A3.

[19] As an additional robustness check, we construct the groups using different starting points, which can result in slightly different group compositions. We find that our results are robust to the starting point of the algorithm.

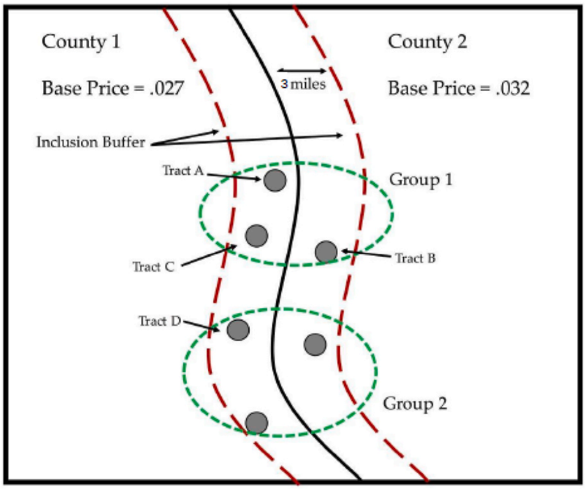


**Fig. 2.** Spatial discontinuity in insurance pricing using county border.

miles. The identifying assumption is that tracts near a county border and within the same group are similar in terms of the risks and other conditions they face over time, conditional on controls and other fixed effects. Yet, differences in insurance prices faced by two tracts within the same group, but across county boundaries, reflect exogenous variation in insurance prices. From the perspective of tracts at the county border in each group, county-level price changes over space and time are exogenous. Soil, climate, and distance variables further control for factors that could vary within a group and affect groundwater use. In some areas, the county boundaries are also the dividing lines between power providers. To test whether this impacts our results, we perform a robustness check by removing wells that are in county pairs with different power providers (approximately 28% of our sample) and find that it does not meaningfully impact the magnitudes of our estimated coefficients.

Since our identification strategy uses estimates from a subsample of wells in the region, we test if our subsample differs from the region on average in terms of irrigation volume, irrigated acres, and insurance liability purchased. To do this, we include controls used to estimate equations (5)–(7) (excluding group fixed effects), in addition to a dummy variable indicating whether a tract is included in our 3-mile subsample. The coefficient on this additional dummy is statistically insignificant, which suggests that wells within counties are qualitatively similar to the wells at county borders, conditional on observed controls. The results of this exercise are shown in Appendix 3.

To examine similarity in conditions faced by producers within a group, we test if the absolute value of differences in tract characteristics on either side of a county line differs from zero. The comparison of differences across counties indicates that tracts within a group face similar soil and weather conditions on average (see Tract Characteristics Section of Table 1). We observe that insurance prices that individuals select, as well as decisions regarding irrigation, vary substantially along county lines. We see that in the majority of cases, the base prices also have statistically significant variation across county lines. We find that the percent sand and erodibility index differ significantly across county lines; however, the variation in NCCPI across county lines is not statistically significant. The difference in erodibility might be due to differences in farming practices between county lines which can impact soil (Boulal et al., 2011). The statistical significance of the differences in sand content and erodibility justifies their inclusion as controls in our model. We find that neither precipitation nor temperature differ across county lines. This similarity is key to our identification strategy and indicates that tracts within a group likely face similar levels of weather risk. On average, county-level insurance prices differ significantly at the county border. This difference is important for our identification strategy, and Fig. 3 shows that there are differences in insurance prices across county borders (i.e., the difference between counties each year). Fig. 3 plots the absolute difference in insurance price (averaged across irrigated and non-irrigated) for county-pairs with non-zero differences in at least 1 year (>75% of within-year differences).[20]

Furthermore, Table 1 shows that irrigation levels also differ across county boundaries. On average, we observe a difference of approximately 36 acre-feet of irrigation across wells on the county boundary. This pattern holds for both irrigated acreage (a difference of approximately 32 acres) and irrigation per acre (a difference of approximately 0.1 feet per acre). This is evidence that the crop insurance price changes occurring between counties may also be driving changes in irrigation patterns.

## 6. Empirical results

In this section, we present the results of our empirical analysis that explores the net impact of insurance price on groundwater use

[20] Some of the within-year differences for a particular crop/practice are equal to zero, or close to zero in a given year but over time this difference varies.

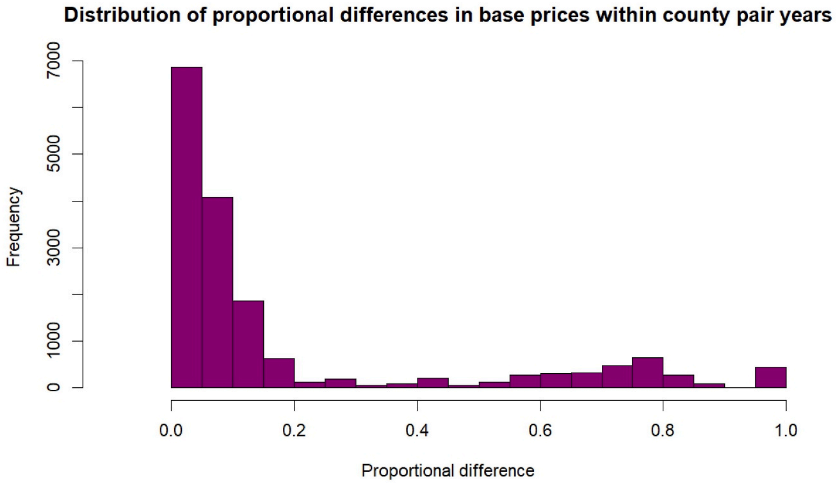


**Fig. 3.** Histogram of proportional differences in county base prices between county borders, averaged across practice (irrigated and non-irrigated).

and then separately examines the different effects described in our theoretical model. First-stage results, including all controls in addition to instrumental variables, and associated test statistics can be found in Appendix 4.

## 6.1. Overall impact

We begin by examining the effect of crop insurance prices on total groundwater use. Table 2 presents the impact of irrigated and non-irrigated insurance prices on annual water use using the sample of tracts in groups within 3 miles of county borders. Column 1 is our preferred specification because it instruments for endogenous insurance prices while also controlling for other factors that could influence groundwater use and correlate with insurance prices. The coefficient on irrigated insurance price is negative and significant, and the elasticity indicates that a 1% increase in the price of coverage, *ceteris paribus*, decreases groundwater use by 0.501%. Column 1 also shows that we do not detect an impact of non-irrigated insurance prices on total irrigation. All models include both group fixed effects and state-year fixed effects.

Column 2 of Table 2 demonstrates that failing to control for soil and weather leads to very small differences in the estimated impact of irrigated insurance prices. The small difference suggests that group fixed effects control for much of the spatial heterogeneity in our model. Column 3 shows that failure to instrument for the irrigated insurance price leads to smaller estimated impacts of insurance price on water use. In other words, the coefficient on irrigated insurance price is biased upwards (towards 0). This suggests that higher individual insurance prices correlate with higher-than-expected groundwater use. This is intuitive if, for example, producers choose more expensive insurance products and use more water on tracts with greater (unobserved) production risks. Column 3 also demonstrates that failure to instrument for non-irrigated insurance price biases the coefficient and leads to a statistically significant estimate.

## 6.2. Impact on irrigated land

Next, we examine the mechanisms through which insurance prices affect groundwater use. Table 3 presents the impact of irrigated and non-irrigated insurance prices on the number of irrigated acres in a tract. Again, column 1 is our preferred specification because it instruments for endogenous insurance prices and controls for climate and soil. As predicted in the theoretical model, a higher irrigated insurance price decreases the number of irrigated acres. Specifically, the elasticity suggests that a 1% increase in the price of irrigated insurance decreases the number of irrigated acres by approximately 0.266%. The non-irrigated price also decreases the number of irrigated acres planted, but the effect is statistically insignificant. Column 2 demonstrates that the magnitude of the effect of irrigated insurance price is not greatly affected by the inclusion of controls. The effect of non-irrigated prices remains statistically insignificant without controls. The irrigated and non-irrigated insurance price coefficients and elasticities get closer to zero without instrumenting, though again, only the irrigated price remains statistically significant.

## 6.3. Impact on groundwater intensity

Finally, we present results describing the impact of insurance prices on groundwater use per acre. Table 4 presents the impact of insurance price on groundwater use per acre for models that condition on total acreage and for models that do not. Columns 3 and 4 condition on the log of irrigated acres. As shown in the theoretical model, conditioning on acres isolates the coverage indirect effect of irrigated insurance price on the intensity of groundwater use. The negative sign on irrigated insurance is consistent with our theoretical predictions. Higher insurance prices mean producers choose lower coverage levels (Goodwin, 1993; Serra et al., 2003) and choose to

**Table 2**
The effects of crop insurance prices on total irrigation.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Log(acre feet)[a] | Log(acre feet) | Log(acre feet) |
| Log(irrigated price) | −0.501** | −0.486* | −0.161*** |
| | (-0.188) | (-0.191) | (-0.026) |
| Log(non-irrigated price) | 0.023 | 0.042 | 0.077*** |
| | (-0.172) | (-0.175) | (-0.02) |
| Instrumental variables | Y | Y | N |
| Climate controls | Y | N | Y |
| Weather controls | Y | N | Y |
| Soil controls | Y | N | Y |
| Spatial controls | Y | N | Y |
| Num.Obs. | 15483 | 15483 | 15483 |
| Num. Tracts | 3453 | 3453 | 3453 |
| R2 | 0.439 | 0.435 | 0.467 |
| R2 Adj. | 0.413 | 0.41 | 0.444 |

• +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.
[a] . All models include group and state-year fixed effects. Standard errors are clustered at the county level and reported in parentheses.

**Table 3**
The effects of crop insurance prices on irrigated acres.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Log(irrigated acres)[a] | Log(irrigated acres) | Log(irrigated acres) |
| Log(irrigated price) | −0.266* | −0.225+ | −0.081*** |
| | (0.115) | (0.129) | (0.024) |
| Log(non-irrigated price) | −0.082 | −0.196 | 0.018 |
| | (0.121) | (0.124) | (0.017) |
| Instrumental variables | Y | Y | N |
| Climate controls | Y | N | Y |
| Weather controls | Y | N | Y |
| Soil controls | Y | N | Y |
| Spatial controls | Y | N | Y |
| Num.Obs. | 15483 | 15483 | 15483 |
| Num. Tracts | 3453 | 3453 | 3453 |
| R2 | 0.287 | 0.260 | 0.307 |
| R2 Adj. | 0.254 | 0.228 | 0.276 |

• +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.
[a] . All models include group and state-year fixed effects. Standard errors are clustered at the county level and reported in parentheses.

**Table 4**
The effects of crop insurance prices on irrigation per acre.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Log(acre feet per acre)[a] | Log(acre feet per acre) | Log(acre feet per acre) | Log(acre feet per acre) |
| Log(irrigated price) | −0.283* | −0.080*** | −0.305* | −0.097*** |
| | (0.134) | (0.015) | (0.140) | (0.014) |
| Log(non-irrigated price) | 0.118 | 0.059*** | 0.111 | 0.052*** |
| | (0.132) | (0.009) | (0.131) | (0.014) |
| Instrumental variables | Y | N | Y | N |
| Climate controls | N | N | Y | Y |
| Weather controls | Y | Y | Y | Y |
| Soil controls | Y | Y | Y | Y |
| Spatial controls | Y | Y | Y | Y |
| Num.Obs. | 15483 | 15483 | 15483 | 15483 |
| Num. Tracts | 3453 | 3453 | 3453 | 3453 |
| R2 | 0.510 | 0.524 | 0.510 | 0.452 |
| R2 Adj. | 0.487 | 0.503 | 0.488 | 0.428 |

• +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.
[a] . All models include group and state-year fixed effects. Standard errors are clustered at the county level and reported in parentheses.

apply less water per acre as a result. While this may appear counterintuitive, as we discuss above, it suggests that applying costly groundwater is complemented by insurance that covers losses due to events for which water cannot substitute (e.g., hail, price changes, or pests).

Columns 1 and 2 of Table 4 present the unconditional impact of irrigated insurance price on groundwater use intensity, representing both coverage and acreage indirect effects. The coefficients are the same sign as those in columns 3 and 4, but they are smaller in magnitude. The coefficients moving closer to zero when acreage is removed could be a result of higher irrigated insurance prices leading to a reduction in irrigated acreage. As discussed in the theoretical section, a reduction in irrigated acreage would increase irrigation per acre due to a potentially less binding irrigation constraint. This offsets the negative coverage indirect effect and pushes the total effect closer to zero. To recover the acreage indirect effect, we subtract the coverage effects (columns 3 or 4) from the corresponding total effect (columns 1 or 2). For our preferred model, a bootstrapping exercise with 2000 replications produces a difference in coefficients of 0.0165 which is statistically significant at the 99% confidence level. Subtracting the coverage effect from the total effect gives the effect that insurance prices have on irrigation per acre produced solely by their effects on irrigated acreage.

Turning to the impact of the non-irrigated insurance price on water use intensity, we find a small but positive indirect impact of the non-irrigated insurance price on water use, conditional on acreage. However, we find it to be statistically insignificant after instrumenting. Without controlling for irrigated land, we find that the coefficient on non-irrigated insurance price is larger. This suggests a positive acreage indirect effect of non-irrigated insurance price, as the magnitude of the effect declines with the inclusion of acreage. Bootstrapping the effect using 2000 replications, we estimate an acreage indirect effect of 0.006 which is significant at the 99% confidence level.

In addition to the results reported in this section, we perform a set of robustness checks in which we vary the fixed effects included in the model. In Appendix 3, we report several alternative groupings and find that our results are qualitatively robust to the definition of a group. For example, we group all wells that share a common county boundary into the same group. This is similar to other spatial discontinuity approaches in the literature (e.g. Ludwig and Miller, 2007; Ito, 2014). Our results in Appendix 3 compare our grouping strategy to the more common use of county-pair fixed effects.

Our empirical results resolve the theoretical ambiguity around the net impact of insurance prices on total groundwater use. Overall, groundwater use decreases in the irrigated insurance price while not responding significantly to changes in non-irrigated insurance prices. The decrease in groundwater use derives from both decreases in irrigated acres and irrigation per acre. In Table 5 we summarize our empirical results and how they map to our theoretical hypotheses. It can be shown that the theoretical predictions for non-irrigated prices are the opposite direction of the predicted impacts of irrigated insurance prices, when there is a determinant direction predicted by the model. For example, whereas the number of irrigated acres is predicted to decrease as the price of irrigated insurance increases, it is expected to increase as the price of non-irrigated insurance increases.

Even though insurance expenditures make up a small fraction of per-acre expenditures, changes in insurance prices can have significant effects on irrigation because of how it affects expected revenue. By making it cheaper to insure against large economic losses, cheaper irrigated insurance makes the expected returns to irrigated agriculture higher and incentivizes increased irrigation. Other studies have shown that insurance prices can affect crop choice (e.g., Claassen et al., 2016), and that crop choice may affect irrigation (e.g., Hendricks and Peterson, 2012). To explore this mechanism, in Appendix 5, we present results from crop choice models that demonstrate that within our study region, insurance prices have an impact on irrigated crop choice. This suggests that crop switching likely plays a role in the irrigation intensity effects that we estimate.

To test whether the results are robust to different identification strategies, clustering, and data cleaning procedures, we present an alternative analysis in Appendix 6 using an identification strategy described in Weber et al. (2016). The alternative analysis yields a result smaller in magnitude but with similar sign and statistical significance to our main specification (negative, inelastic, and statistically significant).

**Table 5**

Clustering at the county level, as opposed Comparison of predictions and empirical results.

| Effect of irrigated insurance prices on: | Theoretical expectation* | Empirical result |
|---|---|---|
| Groundwater volume used | Indeterminant | Decrease |
| Irrigated acreage | Decrease | Decrease |
| Indirect Coverage Intensity | Decrease | Decreases |
| Acreage Indirect Intensity | Increase | Increase |
| **Effect of non-irrigated insurance prices on:** | | |
| Volume | Indeterminant | Insignificant |
| Acreage | Increase | Insignificant |
| Indirect Coverage Intensity | Increase | Insignificant |
| Acreage Indirect Intensity | Decrease | Insignificant |

*While we have theoretical expectations, the theoretical sign of effects is ambiguous and depends on the curvature of utility functions.

## 7. Policy implications

### 7.1. Policy simulation

The above results provide evidence of an important relationship between risk management policies such as crop insurance and natural resource use. To explore the policy relevance of our econometrically estimated parameters, we simulate the effect of a change to federal crop insurance subsidies. A previous congressional proposal to the CBO included a 6.2 percentage point reduction in crop insurance subsidies (Congressional Budget Office, 2018). While this proposal is no longer being considered, it provides a useful benchmark to further explore the implications of our results within the context of recent policy debates. We estimate the change in groundwater use that would result from this change if it were applied only to irrigated insurance products, only to non-irrigated products, and to all products. We calculate the average percent change in groundwater pumping using the estimated coefficients from equation (8):

$$\textit{Percent Change in } W = \left(\epsilon^{i}\%\Delta r^{i} + \epsilon^{ni}\%\Delta r^{ni}\right) \tag{8}$$

where $\epsilon^{v}$ are the elasticity estimates from our empirical model and $\Delta r^{v}$ is the percentage change in insurance price for either irrigated or non-irrigated practice (where practice is represented by the following superscripts: ($i$ = irrigated; $ni$ = non-irrigated). To calculate the percentage change in $r^{i}$ and $r^{ni}$, we first calculate the average subsidy rate in the sample used for our regressions, which is 58.4%. This is close to the national subsidy rate of 60% cited in CBO (2018). The decline in subsidy decreases the subsidy rate from 58.4% to 52.2% which results in a 14.9% increase in insurance prices.[21]

The results of this exercise are presented in Table 6. In row 1, $\%\Delta r^{i} = 14.9\%, \%\Delta r^{ni} = 0$ , in row 2, $\%\Delta r^{i} = 0, \%\Delta r^{ni} = 14.9\%$, and in row 3, both changes equal 14.9%. We also calculate the impact on irrigated acres and disentangle the irrigation intensity effect into its two indirect effects. The coverage indirect intensity effect is calculated using estimated parameters from column 1 of Table 4 while the coverage indirect effect plus the acreage indirect effect (referred to as the total intensive margin effect in Table 6) is based on parameters from column 3 of Table 4. The difference between the total intensive margin effect and indirect intensity effect leaves the acreage indirect intensity effect. We recover standard errors through bootstrapping using 2000 replications.

These results suggest that decreasing the subsidy for only irrigated insurance prices would decrease groundwater use by 7.47%. Alternatively, if the subsidy removal applies only to non-irrigated products, we do not detect a statistically significant impact. Finally, if the subsidy change leads to higher prices of all types of insurance products, this would decrease irrigation by 7.12% across our study region.

To put the impact of irrigated subsidy changes in context, mean groundwater extraction at the tract level in the region is 195 acre-feet. If only subsidies for irrigated insurance are cut, a 7.47% decrease would imply 14.57 fewer acre-feet of water per tract per year. Using Pfeiffer and Lin's (2014) estimated elasticity of 0.26 and Schoengold et al.'s (2006) elasticity of 0.79 for the responsiveness of water use to the price of energy, the impact of the 14.9% change in insurance price is equivalent to an increase in water price of between 9.45% and 28.7%.[22] Though there are many estimates of this elasticity found in the literature (e.g. Espey et al., 1997), the range we report is representative of a majority of existing estimates. For further context, Drysdale and Hendricks (2018) find that caps on the quantity of groundwater that can be extracted per year reduced groundwater use by 26%. Therefore, the impact of the change in subsidy on water use is roughly 29% of the impact of the groundwater management policy that was implemented.

Our model suggests that groundwater use is responsive to insurance prices. Though we do not find evidence of cross-price effects, we do find that irrigated prices have a statistically significant impact on total volume through changes in the number of irrigated acres and the amount of water applied per acre. This could be partly driven by crop switching. We find evidence that changes in insurance prices have resulted in crop switching in the study region over the timeframe we consider (see Appendix 5). Higher irrigated insurance prices reduce the likelihood of planting corn and increase the likelihood of planting a crop other than corn, wheat, sorghum, or soybeans. This indicates that changes in crop mix, irrigated acreage and irrigation intensity are all impacted by irrigated insurance prices. Insurance makes it less risky to expand irrigated acreage and increases the expected return of groundwater applied.

We now examine the implications of our results for groundwater depletion in the region. Based on total observed pumping in 2013, our simulation suggests that targeting subsidy changes to irrigated insurance products result in an estimated 420,824 fewer acre-feet being pumped across our study region per year. To calculate the change in aquifer levels across our study region that result from the policy experiment, we assume an average aquifer specific storage of 0.2, which is within the range of many counties in Kansas (Gutentag and Stullken, 1976).[23] Aquifer specific storage is an aquifer quality related to the aquifer's ability to take in or produce water (Kuang et al., 2020) Additionally, we assume no change in aquifer recharge. The change in aquifer height, $\Delta d$, is given by equation (9):

[21] To see this, first note that the price the producer receives is Pp = Pb(1-s) where Pp is the producer price, Pb is the unsubsidized base price, and s is the subsidy level. The percent change in price given a change in subsidy from s1 to S2 is therefore P2-P1P1=Pb1-S2-Pb(1-S1)Pb(1-S1)=S1-S2(1-S1) = 0.0621-.584 = 0.149.

[22] This is calculated by taking the extraction price elasticity (−0.26) reported in Pfeiffer and Lin (2014) as well as the one reported in Schoengold et al. (2006) (−0.76) and using it to solve for the equivalent increase in extraction price needed to create a 7.47% decrease in irrigation. 7.47/0.26 = 28.7%. 7.47/0.79 = 9.45%. Extraction price is the estimated cost of pumping the water from the aquifer to the field for irrigation, and can consist of electricity costs, mechanical costs, and other costs associated with extracting groundwater.

[23] The definition of specific storage is the amount of water obtained per aquifer volume per change in aquifer level.

**Table 6**
Policy simulation results.

| Insurance price changed: | Total irrigation[a] | Irrigated acres (Acreage Direct Effect) | Coverage indirect effect | Acreage indirect effect | Total intensive margin[b] |
|---|---|---|---|---|---|
| Irrigated | −7.472** | −3.510* | −3.962* | 0.244*** | −4.208* |
| | (2.533) | (1.648) | (1.684) | (0.002) | (1.724) |
| Non-irrigated | 0.347 | −1.323 | 1.671 | 0.088 | 1.578 |
| | (2.502) | (1.901) | (1.853) | (0.002) | (1.839) |
| Both | −7.124* | −4.833* | −2.292 | 0.332*** | −2.629 |
| | (3.139) | (2.175) | (2.130) | (0.003) | (2.150) |

• +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.
[a] . All results are reported as percent changes in the variable of interest (e.g. Total irrigation) given a 14.9% change in the insurance price changed (irrigated, non-irrigated, or both).
[b] . The total intensive margin effect is the sum of the coverage indirect effect and the acreage indirect effect.

$$\Delta d = \frac{\Delta V}{S_s}\frac{1}{A} \tag{9}$$

Where $\Delta V$ is the change in volume pumped, $S_s$ is the specific storage, and $A$ is the area. Using equation (9) and the number of irrigated acres in our study region as the area (12,464,215), we calculate $\Delta d$ from the policy change as 0.169 feet per year on average across our study region. This is comparable to the additional saturated thickness provided by the Upper Arkansas River Basin Conservation Reserve Enhancement Program (UARBCREP), an existing water right retirement program in the region. Saturated thickness is the distance between the top and bottom of an aquifer and relates to the depth of the aquifer. Manning et al. (2020) find that the UARBCREP, which has cost more than $45 million, increases saturated thickness in the basin on average by 0.21, 0.19, and 0.15 feet per year after 15, 30, and 50 years of water right retirement, respectively.

Table 6 also presents the mechanisms driving the impacts of the subsidy change. Consistent with theory, decreasing the subsidy (i.e., increasing the price) on irrigated insurance reduces the number of irrigated acres (row 1 of Table 6). The acreage indirect intensive margin effect is positive while the coverage indirect effect is negative. The overall irrigation intensity effect (the indirect coverage effect together with the indirect acreage effect) is negative and reinforces the direct acreage effect. Taken together, these results suggest that groundwater use responds to changes in irrigated insurance pricing policies in economically significantly ways. Our results highlight the importance of insurance for resource-dependent activities (e.g., irrigated agriculture) in determining the use of natural resources.

### 7.2. *Interpreting the magnitude of impacts*

Our findings suggest that the effects of crop insurance prices on irrigation are inelastic. Specifically, we find that a 1% increase in the price for irrigated insurance reduces groundwater use by 0.50%. Our results indicate that increases in subsidies for irrigated insurance products lead to more irrigation, which is consistent with findings in Deryugina and Konar (2017) who find that a 1% increase in insured acreage leads to a 0.22% increase in water used. Though the magnitudes found in our study are not directly comparable to those in Deryugina and Konar (2017), both this study and their study find an effect that is inelastic and in the same direction. Our study differs from Deryugina and Konar (2017) by focusing on insured irrigated acreage and by distinguishing between irrigated and non-irrigated insurance.

Our results are also comparable to several studies examining the effects of pumping prices and regulations on groundwater extraction. For instance, Pfeiffer and Lin (2014) find that the extraction price elasticity is approximately −0.26; however, an earlier study by Schoengold et al. (2006) found an extraction price elasticity of −0.76. A later study by Mieno and Brozović (2017) found an elasticity of approximately −0.5. Interestingly, the elasticity we recover for crop insurance prices is within the same range of magnitudes as those found for extraction costs. However, it is important to note that own price elasticities for groundwater extraction may be underestimated due to attenuation bias (Mieno and Brozović, 2017).

Crop insurance has been investigated as a potential driver of other farming decisions as well. Notably, (Weber et al., 2016) examine how expanded insurance subsidies change fertilizer and chemical use, farmland harvested, productivity, and crop specialization, finding little effect.[24] Our results complement these by showing that insurance also alters the use of groundwater.

Our results suggest that targeted insurance subsidies may result in changes in irrigation levels. Several other studies address insurance, irrigation, and policy. Salazar et al. (2019) finds that adoption of some alternative irrigation technologies may lower the likelihood of being insured. Another area that may have impacts on irrigation decisions is disaster insurance, specifically drought insurance (e.g., Mohor and Mendiondo, 2017). In addition, Echchelh et al. (2018) examine the use of recycled water from gas and oil production. In general, we find evidence that blanket subsidies for irrigated and non-irrigated insurance products may change irrigation levels. Targeted decreases in insurance subsidies could therefore complement the objectives of groundwater conservation.

[24] We also use the specification in Weber, Key, and O'Donoghue (2016) to test the robustness of our results. The results are presented in Appendix 6. The specification allows us to include all wells in the sample, and we obtain qualitatively similar results, though with smaller magnitudes.

## 8. Conclusion

To better understand how insurance interacts with the private use of common pool natural resources, we examine the impact of irrigated and non-irrigated crop-insurance policies on groundwater use in the High Plains Region of the US. Our results suggest that higher irrigated crop insurance prices lead to a decrease in private groundwater use. Higher non-irrigated crop insurance prices also decrease groundwater use, but the effect is statistically insignificant.

While current proposals center around broad cuts to subsidies, our results suggest that adopting differential pricing of insurance products by practice could enhance ongoing resource conservation efforts. This highlights how federal policy, designed considering a particular policy goal, might conflict with, or complement, regional resource conservation efforts.

To our knowledge, this is the first study to explicitly examine both the effect of irrigated and non-irrigated crop insurance prices on the quantity of irrigated land planted and water used. Access to novel, tract-level data on insurance purchases made this possible, allowing for an identification strategy that combines an instrumental variable approach with a spatial discontinuity in insurance prices that occurs because of county borders. The spatially explicit data facilitated the merging of variables from a range of datasets, including data on wells, climate, and soils allowing us to control for unobserved heterogeneity at a finer spatial scale than is common in this literature. The approach developed herein provides a novel, alternative approach to quantifying the impacts of policies on producer behavior and spatially explicit environmental and resource outcomes. While crop choice is not explicitly modeled, the effects of crop choice are reflected in our model of irrigation intensity. As others have found (Claassen et al., 2016; Deryugina and Konar, 2017), results in Appendix 5 demonstrate that crop choice is a potential driver of irrigation changes on the intensive margin.

Due to data limitations, we are unable to explore the potential impact of crop insurance on yields and revenues. Given the negative relationship between irrigated insurance price and groundwater use one might be tempted to conclude that this would lead to lower yields given the documented benefits of irrigation (Troy et al., 2015). However, this conclusion (less water applied results in lower yields) ignores possible changes in how and where the water is used which ultimately make the impact on yield and total production unclear. It also ignores the potential long-term impacts on producer behavior (e.g., technology adoption) that might influence yields (Wang et al., 2021). Despite the limitations of the current study, we note that the indirect impact of crop insurance pricing - through its impact on groundwater use - has important implications for regional food security and the health of rural, agriculturally dependent regional economies.

Our results can inform insurance policies in other natural resource sectors. They may also have implications for the broader literature on the use of shared natural resources as natural insurance (e.g. Pattanayak and Sills, 2001; McSweeney, 2004; McSweeney, 2005). The connection between private economic activities and common pool resource extraction suggests that insuring private activities (e.g., non-irrigated crop insurance) could have impacts on resource stocks and use (though the connection in our context was statistically insignificant). This is important for other risk-mitigating activities as well. Government assistance programs, especially disaster relief, may have similar risk-mitigating properties as insurance (Schoengold et al., 2014).

This research suggests several more potential avenues for future work. First, it remains unclear how insurance affects the costs and benefits of common pool groundwater management. While insurance may increase the use of a natural resource, it also increases its value to private decision-makers. A better understanding of how crop insurance impacts the benefit of conserving groundwater is necessary to design crop insurance and groundwater use policies jointly. Second, it is important to note that our results represent the average effect of insurance prices on groundwater use. Future research should explore the extent to which there is heterogeneity in the response of producers across space, as well as based on characteristics such as farm size. Another interesting extension of this work would be to explore the effects of groundwater pumping restrictions on insurance decisions. In addition, insurance prices might influence the decision to fallow land. Future work examining the relationship between fallowing and insurance prices may yield interesting results. Finally, hydro-economic models are increasingly being utilized to examine the impact of groundwater conservation policies on irrigated land and groundwater use (Kuwayama and Brozović, 2013; Guilfoos et al., 2013; Guilfoos et al., 2016). While these models focus on the impact of higher pumping costs on groundwater use and value, our results suggest that accounting for insurance impacts could lead to different predictions about groundwater use and value over space and time, especially when irrigated and non-irrigated insurance prices are not perfectly correlated.

### CRediT authorship contribution statement

**Matthew R. Sloggy:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **R. Aaron Hrozencik:** Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – review & editing. **Dale T. Manning:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Chris G. Goemans:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing. **Roger L. Claassen:** Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing – original draft, Writing – review & editing.

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## Declaration of competing interest

The authors report no conflicts of interest.

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## Appendix 1

*Predicting non-irrigated crop insurance prices*

A small group of tracts (n = 37) in our sample do not purchase insurance for non-irrigated production. Calculating the tract-specific non-irrigated insurance price directly from the data is therefore impossible for these tracts. Dropping these observations is also not desirable, as it may bias our sample. In order to keep these observations in our sample, we predict their non-irrigated prices based on a linear model, estimated on tracts that purchase insurance for non-irrigated crops. This model is given as:

$$r_{jt}^{ni} = \mu_g + \gamma_{st} + \beta_1 r_{jt}^{i} + \beta_2 X_{jt} + \beta_3 A_{jt}^{NI} + \beta_3 A_{jt}^{I} + \varepsilon_{jt} \tag{A.1}$$

Where $r_{jt}^{ni}$ is the price of non-irrigated insurance at tract *j* in year *t*, $r_{jt}^{i}$ is the price of irrigated insurance, $A_{jt}^{ni}$ is non-irrigated acreage, $A_{jt}^{i}$ is irrigated acreage, and $X_{jt}$ is a matrix of other tract-level control variables that include climate controls, soil controls latitude, longitude, and crop-specific dummies (the same as those in the main text). While $r_{jt}^{i}$ is endogenous, we do not use this model to identify causal impacts. Instead, we use it to predict non-irrigated insurance prices. The $R^2$ of the model is 0.45. Although noisy for a predictive model, the number of observations that require fitting are relatively small. The fitted model is then used to predict non-irrigated insurance prices for tracts that did not purchase insurance for non-irrigated crops.

## Appendix 2

*Insurance coverage and insurance prices*

Our empirical approach specifies groundwater use per acre as a function of insurance prices. The mechanism by which insurance prices effects groundwater use per acre can be split into two different effects. First, it may be the case that a farmer plants crops with some plan as to the level of irrigation to apply throughout the season. In this case, the insurance price would directly impact the groundwater intensity. In the theoretical model, we assume this direct effect to be zero but if that is not the case, we have the following model for groundwater use per acre:

$$g_{jt} = \mu_g + \gamma_{st} + \beta_1 a_{vjt}\left(r_{vjt}\right) + \beta_{1a} r_{vjt} + \beta_2 X_{jt}^{g} + \varepsilon_{jt} \tag{A.2}$$

Where $\beta_1$ is a vector of coefficients describing the indirect impact of the insurance price for practice $v$ on groundwater use per acre at tract *j* in year *t*. $\beta_{1a}$ describes the direct effect, assumed to be 0 in the theoretical model. As in the main text $\mu_g$ is group fixed effect and $\gamma_{st}$ is a state-year fixed effect. Though our empirical specification in the main text only includes price, we note that insurance coverage, $a_{vjt}\left(q_{vjt}\right)$, is a function of the insurance price level. Therefore, the coefficient that we estimate in our empirical specification includes the direct and indirect impacts of insurance prices on groundwater per acre (coverage indirect effect). This effect can may be conditioned on the number of acres planted. The total impact of insurance price on groundwater use per acre that we estimate is therefore equal to:

$$\frac{dg_{jt}}{dr_{vjt}} = \widehat{\beta_1^{i}} = \sum_{v'}\left(\beta_1^{v'}\frac{\partial a_{v'jt}}{\partial r_{vjt}}\right) + \beta_{1a}^{v'} \tag{A.3}$$

## Appendix 3

### 3.1Alternative group definitions

In the main body of the paper, we identify the effects of crop insurance prices on irrigation decisions. However, there was an important modeling choice made with respect to the definition of a spatial 'group.' To explore the robustness of our results to the definition of groups, we present the results for total irrigation with four additional group definitions. We include a specification in which groups only include wells within ½ mile, 1 mile, 2 miles, and 5 miles of a county border, and another specification in which they only include wells 7 miles from a county boundary. We include a specification which puts all wells that share a common county boundary (within 3 miles) into a single group, which we call a county pair. Finally, we include a specification that limits the analysis to wells within townships that span either side of a county border. The township itself becomes the group, in this case. The results of these robustness checks are presented in Table A1 and in Table A2.

**Table A1**
Robustness check: the effects of changing the group definition.

| | Base (group) | County pair | Township |
|---|---|---|---|
| | Log(acre-feet)[1] | Log(acre-feet) | Log(acre-feet) |
| Log(irrigated price) | −0.501** | −0.145 | −0.402** |
| | (0.188) | (0.190) | (0.152) |
| Log(non-irrigated price) | 0.023 | −0.159 | −0.092 |
| | (0.172) | (0.157) | (0.162) |
| Tracts | 3581 | 3581 | 3581 |
| Num.Obs. | 15483 | 15483 | 15483 |
| R2 | 0.439 | 0.391 | 0.328 |
| R2 Adj. | 0.413 | 0.383 | 0.325 |

- +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.

1. All models include group and state-year fixed effects. Standard errors are clustered at the county level and reported in parentheses.

From our results, we see that using a larger band lead to smaller effects of irrigated insurance prices. Statistical significance is weaker for the county-pair, five-mile sample and the seven-mile sample. We find that utilizing county pairs, and 7-mile bands results in estimates not being statistically significant. Results are still statistically significant with 5-mile bands. Using townships as groups also results in a similar magnitude as our preferred specification. This may be due to the low number of tracts, and consequently observations, in this model. Despite this, the magnitudes of the coefficients on irrigated insurance price have a similar effect than in our base model.

Next, we test the effect of using smaller bands on the effects. We run a robustness check with 2-mile, 1-mile, and ½ mile bands, which are found below in table A.2.

**Table A.2**
Robustness check: alternative distance bands for identification strategy.

| | Base (3-mile) | ½ mile | 1-mile | 2-mile | 5-mile | 7-mile |
|---|---|---|---|---|---|---|
| | Log(acre-feet)[1] | Log(acre-feet) | Log(acre-feet) | Log(acre-feet) | Log(acre-feet) | Log(acre-feet) |
| Log(irrigated price) | −0.501** | −0.961* | −0.821** | −0.705** | −0.339+ | −0.190 |
| | (0.188) | (0.409) | (0.313) | (0.233) | (0.174) | (0.158) |
| Log(non-irrigated price) | 0.023 | −0.128 | 0.016 | 0.113 | −0.138 | −0.275 |
| | (0.172) | (0.325) | (0.244) | (0.221) | (0.162) | (0.177) |
| Tracts | 3581 | 961 | 1393 | 2438 | 5377 | 7454 |
| Num.Obs. | 15483 | 4270 | 6246 | 10992 | 24060 | 32019 |
| R2 | 0.439 | 0.174 | 0.355 | 0.398 | 0.427 | 0.419 |
| R2 Adj. | 0.413 | 0.124 | 0.314 | 0.365 | 0.409 | 0.404 |

- +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.

1. All models include group and state-year fixed effects. Standard errors are clustered at the county level and reported in parentheses.

We see that as the band gets smaller, the effect of non-irrigated insurance gets larger. We also see that the statistical power declines as the number of tracts and observations decline as well.

Using variation between county boundaries is a common approach to spatial discontinuity design (e.g., Ludwig and Miller, 2007; Ito, 2014). This approach uses variation between counties, typically to examine county-level policies, as a means of identifying the impact of interest. The method we use in the main text is similar to this approach in that we utilize a policy discontinuity at county borders; however, our fixed effects are at a higher resolution than those found elsewhere. It is important to note that we also include distance to the county border, as explained in the main text. By using county-pair fixed effects instead of group fixed effects, we do not appropriately control for spatial variation within a county-pair. This is evident because the coefficients on irrigated insurance (Table A1, Column 2) is smaller in magnitude than those in the main body of the text. This has a larger effect on the point estimate than not including soil, weather, and climate controls in the results in the main text (Table 2, Column 2). County boundaries can be many miles in length, and across that distance there can be substantial variability in unobservables such as soil characteristics not controlled for with SSURGO or weather variables not included in the analysis. Therefore, using larger-scale group fixed effects likely leads to overestimates of the impact of irrigated insurance price on water use.

### *3.2Subsample representativeness*

In this section, we examine the representativeness of our subsample within the study region as a whole. In our main text, we examine the subset of wells that are within 33 miles of the county border. In this section, we consider the entire sample of wells in our dataset and construct a dummy variable that equals one if a well is included in the subsample, and 0 if it is not. We then test whether the inclusion dummy is statistically significant in models of total irrigation, irrigated acres, and liability. We apply the log transformation to all three models so that they resemble the main specification as closely as possible. A statistically significant coefficient on the inclusion dummy would indicate that there is a statistically significant difference between wells in our subsample and wells in the broader study region, which would cause concern when applying our coefficient estimates to the broader region. A statistically insignificant coefficient, on the other hand, would indicate that there is no statistical difference between the groups. This suggests that wells near county borders are similar to wells across the region as a whole. The results of this analysis are presented in Table A3.

**Table A3**
Testing the representativeness of the subsample.

| | Log (acre feet)[1] | Log (irrigated acres) | Log(liability) |
|---|---|---|---|
| In sample | 0.021 | −0.002 | −0.032 |
| | (0.028) | (0.022) | (0.043) |
| Climate controls | Y | Y | Y |
| Weather controls | Y | Y | Y |
| Soil controls | Y | Y | Y |
| Spatial controls | Y | Y | Y |
| Num.Obs. | 58862 | 58862 | 58862 |
| R2 | 0.086 | 0.148 | 0.174 |
| R2 Adj. | 0.084 | 0.147 | 0.172 |

• +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.
1. All models include group and state-year fixed effects, as well as all controls in the main specification. Standard errors are clustered at the county level and reported in parentheses.

In each of the models, we observe that the coefficient on the inclusion dummy is statistically insignificant. We therefore cannot reject the null hypothesis that the value of the dummy is 0. Although our results are clustered at the county level, even without clustering, the coefficient on the dummy variable is insignificance at the 10% level in all models. This provides support for using our estimated coefficients to describe behavior across the whole study region.

## Appendix 4

### *First stage results for insurance premiums and coverage*

Below, we present the first stage regression results for insurance prices where we use the county insurance prices for irrigated and non-irrigated versions of four major crops as an instrument. As discussed in the main text, we also include the squares of county prices as instruments. This greatly increases the predictive power of the instruments. Our regressions include the same fixed effects as our main specification, including group fixed effects and state-year fixed effects.

**Table A4**
First stage results.

| | Dependent Variable: | |
|---|---|---|
| | Irrigated Insurance Price[1,2] | Non-irrigated insurance price |
| County base price, irrigated corn | −0.240 | −0.797 |
| | (2.474) | (2.816) |
| County base price, irrigated corn squared | 23.726 | −37.900+ |
| | (19.544) | (19.857) |

(*continued on next page*)

**Table A4** (*continued*)

| | Dependent Variable: | |
|---|---|---|
| | Irrigated Insurance Price[1,2] | Non-irrigated insurance price |
| County base price, non-irrigated corn | 0.310 | 2.657** |
| | (0.693) | (0.855) |
| County base price, non-irrigated corn squared | −0.117 | −2.247 |
| | (2.207) | (2.475) |
| County base price, irrigated wheat | 0.695 | 0.294 |
| | (1.382) | (1.228) |
| County base price, irrigated wheat squared | −0.680 | −0.257 |
| | (1.325) | (1.174) |
| County base price, non-irrigated wheat | −5.317 | −6.364 |
| | (4.900) | (3.943) |
| County base price, non-irrigated wheat squared | 5.008 | 5.986 |
| | (4.605) | (3.722) |
| County base price, irrigated soybeans | 11.246*** | −0.960 |
| | (1.997) | (1.866) |
| County base price, irrigated soybeans squared | −54.122*** | −2.990 |
| | (10.626) | (9.878) |
| County base price, non-irrigated soybeans | 0.151 | 0.919+ |
| | (0.418) | (0.497) |
| County base price, non-irrigated soybeans squared | −0.167 | −0.806+ |
| | (0.382) | (0.465) |
| County base price, irrigated sorghum | −0.407 | −8.387* |
| | (3.465) | (3.506) |
| County base price, irrigated sorghum squared | 19.552 | 55.390** |
| | (20.472) | (21.067) |
| County base price, non-irrigated sorghum | −0.929 | 3.183* |
| | (1.339) | (1.426) |
| County base price, non-irrigated sorghum squared | 1.443 | −8.022+ |
| | (4.117) | (4.165) |
| Num.Obs. | 15483 | 15483 |
| R2 | 0.365 | 0.320 |
| R2 Adj. | 0.335 | 0.289 |
| AIC | 19505.6 | 20116.2 |
| BIC | 24774.7 | 25385.3 |
| RMSE | 0.43 | 0.44 |
| Std.Errors | by: FIPS | by: FIPS |

• + $p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.
• F-stats reported below.
[1] . The first stage of the regression also includes all the controls used in the second stage.
[2] . All models include group and state-year fixed effects, as well as all controls in the main specification. Standard errors are clustered at the county level and reported in parentheses.

We want to test whether our instrument is weak; however, because we are clustering standard errors at the county level, we cannot use the F-statistics reported in the table above for any rule of thumb test (e.g. Stock and Yogo, 2002). Instead, we calculate an F-stat that is robust to clustering at the county level as well as one that is robust to multiple endogenous variables, which we report in Table A5 along with Wu-Hausman test statistics for each model. To make our F-statistic robust, we utilize the methodology presented in Sanderson and Windmeijer (2016).

**Table A5**
diagnostic tests for first stage

| Model | Test | Statistic |
|---|---|---|
| Irrigated price | Cluster robust weak instrument[1] | 12.35 |
| Non-irrigated price | Cluster robust weak instrument | 10.14 |
| Total irrigation | Wu-Hausman | 38.08*** |
| Irrigated acres | Wu-Hausman | 34.06*** |
| Irrigation per acre | Wu-Hausman | 7.52*** |

Notes: 1. The Cluster Robust Weak Instrument test does not have associated p-values, and so does not include stars. Instead, a cutoff value of 10 is used once the F value is corrected for clustering. A value greater than 10 indicates that the instruments are not weak.

We find that in each of our regressions, the cluster robust F statistic is greater than the cutoff of 10 suggested by Stock and Yogo (2002). This indicates that the instrumental variables used in the first stage of our identification strategy are not weak. Additionally, Wu-Hausman tests inform us that endogeneity is a concern for any OLS specification of our models.

## Appendix 5

*Crop Choice and Irrigation per Acre*

In this section, we present a crop choice model to investigate a potential mechanism for how insurance prices change irrigation intensity. In the main text of the paper, we report that the overall intensive margin effect of a change in the price of irrigated insurance is approximately −2.04 (Table 6, row 1, column 6 of the main text). In what follows, we investigate what proportion of this is explained by crop switching.

Previous studies (e.g. Claassen et al., 2016; Deryugina and Konar, 2017) demonstrate that changes in insurance subsidies may lead to different mixes of crops. Specifically, subsidized insurance for irrigated crops leads farmers to switch to more water intensive crops (Deryugina and Konar, 2017). Crop switching represents one of several potential effects that drive changes on the intensive margin and may be construed as a form of moral hazard if farmers switch to riskier crops with higher water requirements.

Alternatively, cheaper insurance prices may result in more insurance being purchased for a given crop (Goodwin, 1993). Increases in coverage increase the expected return from an acre-foot of irrigation on a given crop since the risk of the farmer experiencing a financial loss declines. This can also increase water use.

In order to test what proportion of the total effect is due to the first mechanism (crop switching), we estimate a set of linear probability models explaining the probability of planting each of 5 crops as irrigated or non-irrigated. Crops include corn, wheat, soybeans, and sorghum, which are the top 4 crops in the dataset. We also include a fifth category, referred to as "other", which includes all other crops in our dataset. Table A6 (below) presents the percentage of insured acres by crop type for each of the four major crops in our sample (the remainder corresponds to "other").

**Table A.6**
percentage of insured acres by crop type for each of the four major crops in our sample (the remainder corresponds to "other").

| state | practice | corn | wheat | soy | sorghum | Tracts |
|---|---|---|---|---|---|---|
| Kansas | irrigated | 0.045 | 0.059 | 0.009 | 0.002 | |
| | non-irrigated | 0.015 | 0.030 | 0.011 | 0.034 | |
| | total | 0.060 | 0.089 | 0.020 | 0.035 | 23153 |
| Nebraska | irrigated | 0.083 | 0.011 | 0.030 | 0.000 | |
| | non-irrigated | 0.008 | 0.000 | 0.002 | 0.002 | |
| | total | 0.091 | 0.011 | 0.032 | 0.002 | 11078 |

We maintain the same functional form as Equation (5) in section 5.1 of the main text with the exception that we do not perform a log transformation on any of the data. This includes with the first stage of the regression, where we perform a first stage regression similar to the main text, with the exception that the price variables are not transformed using the log transformation. We keep the price variable in level form. This is because the coefficients on such a model would be difficult to interpret compared to a linear probability model. For each of the 5 crop categories, we estimate the following model:

$$crop^c_{jt} = \mu^c_g + \gamma^c_{st} + \beta^c_1 \ r_{vjt} + \beta^c_2 X_{jt} + \varepsilon^c_{jt} \tag{A.4}$$

Where $crop^c_{it}$ is a binary variable that indicates whether tract $j$ planted a given crop $c$ in year $t$.

We then examine the effect that irrigated and non-irrigated insurance prices have on the probability of planting an irrigated crop (Table A.7). Errors are clustered at the county level, as in the main text. We find very little evidence that insurance prices affect the probability of planting specific irrigated crops.

**Table A.7**
The effects of crop insurance prices on irrigated crop choice

| | Irrigated corn | Irrigated wheat | Irrigated sorghum | Irrigated soy | Irrigated other |
|---|---|---|---|---|---|
| Log(irrigated price) | −5.643* | 1.808 | −0.514+ | −0.971 | 5.320+ |
| | (2.482) | (1.267) | (0.311) | (0.672) | (3.098) |
| Log(non-irrigated price) | 0.614 | −0.392 | 0.012 | 0.069 | −0.275 |
| | (0.649) | (0.366) | (0.069) | (0.243) | (0.739) |
| Num.Obs. | 15483 | 15483 | 15483 | 15483 | 15483 |
| R2 | 0.192 | 0.301 | 0.060 | 0.066 | 0.159 |
| R2 Adj. | 0.155 | 0.269 | 0.018 | 0.024 | 0.121 |
| Std.Errors | County | County | County | County | County |

• +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.

We find evidence that, as the price of irrigated insurance rises, farmers may switch away from irrigated corn, and to a lesser extent, sorghum. Other irrigated crops increase in percent terms. Because crops in the “other”[25] category tend to require less water (Kansas Department of Agriculture Division of Water Resources, 2013), we may expect that higher non-irrigated insurance prices would push farmers to plant more irrigated acres. In our main specifications (Tables 2–4) we do not find statistically significant effects of non-irrigated insurance prices. This is consistent with results from Table A.7 in that the non-irrigated insurance prices mostly do not impact crop choice decisions.

Our models detect changes in crop mix as a result of changes in insurance prices. For example, a 1% change in irrigated insurance price (a .039 point change from the average insurance price of 3.9 dollars per 100 dollars of liability) leads to a decrease in the probability of planting corn of 5.6%. Therefore, changes in crop mix play a role in driving changes in intensive margin irrigation.

## Appendix 6

### *Alternative Identification Strategy*

In this section, we explore an alternative method to identify the effects of insurance prices on groundwater. In Weber et al. (2016), the authors employ an identification method based on the fact that farmers often do not lower their coverage levels after price decreases. We adopt Weber et al.’s (2016) approach using the summary of business reports data from the USDA to calculate the range of average prices at different coverage levels. We then construct an instrument using the price per dollar of liability. Unlike our construction in the main text, in this version we employ the unsubsidized premium, following the example of Weber et al. (2016). It is important to note that while Weber et al. (2016) calculate premiums per acre as a measure of coverage, we calculate premium per dollar of liability. Following Weber et al. (2016), our equation for the first stage is given by equation (A.5).

$$ln\left(r_{jt}\right) - ln\left(r_{jt-1}\right) = \beta\, ln\left(\frac{r_{jt}}{MAX\, r_{jt}}\right) + \gamma X_{jt} + \delta_t + \mu_g + \epsilon_{jt} \tag{A.5}$$

Where $r_{jt}$ is the unsubsidized price of insurance, and $ln\left(r_{jt}\right) - ln\left(r_{jt-1}\right)$ is the difference in the logged prices of period t and lagged period $t-1$. The instrument $ln\left(\frac{r_{jt}}{MAX\, r_t}\right)$ is the ratio of the current tract level price, and $MAX\, r_{jt}$. The variable $MAX\, r_{jt}$ is the maximum observed insurance price possible from the county level summary of business reports data. From Weber et al. (2016), the identifying variation derives from the fact that farmers rarely lower their coverage level. The closer the farmer is to the maximum payable insurance price, the less room they mustmust change their price; whereas the lower their current price is, the more room the farmers have to change their price. Once the first stage is estimated, we estimate the second stage, given by equation (A.6).

$$ln\left(V_{jt}\right) - ln\left(V_{jt-1}\right) = \beta\, ln\left(\widehat{ln\left(r_{jt}\right) - ln}\left(r_{jt-1}\right)\right) + \gamma X_{jt} + \delta_t + \mu_g + \epsilon_{jt} \tag{A.6}$$

Where $V_{jvt}$ is the volume of water applied to tract $j$ in time $t$. The dependent variable is the difference in the log volumes in years $t$ and $t-1$. Furthermore, $\left(ln\left(r_{jt}\right) - ln\left(r_{jt-1}\right)\right)$ is the estimated difference in premium rates from estimating equation (A.5). We include a set of control variables, $X_{jt}$ that vary over time and space. We also use two-way fixed effects, where $\delta_t$ and $\mu_g$ are fixed effects for year and township, respectively. It is important to note that in this model, as opposed to the one in the main text, we use all the wells in our dataset, rather than just those within 5 miles of the county boundary. We make several changes to the method in Weber et al. (2016). First, we construct instruments for both irrigated and non-irrigated prices. It is important to note that we have two endogenous variables and two instruments, meaning that our system is perfectly identified in this specification. In addition, whereas Weber et al. (2016) employ county fixed effects, we instead use township fixed effects. Results of this approach are presented in Table A8.

**Table A8**
The impacts of crop insurance on irrigation using the Weber et al. (2016) specification

| | Diff in Log(volume) | Diff in Log(irrigated acres) | Diff in Log(irrigation per acre) |
|---|---|---|---|
| Difference in logged irrigated prices | −0.068** | 0.009 | −0.077** |
| | (0.024) | (0.011) | (0.023) |
| Difference in logged non-irrigated prices | −0.040 | −0.010 | −0.031 |
| | (0.027) | (0.014) | (0.026) |
| Num.Obs. | 41054 | 41054 | 41054 |
| R2 | 0.264 | 0.180 | 0.259 |
| R2 Adj. | −0.006 | −0.120 | −0.013 |

• +p < 0.1, *p < 0.05, **p < 0.01, ***p < 0.001.

[25] Crops in the “other” category include sugar beets, oats, barley, rye, dry beans, sunflowers, pasture, turf grass, cotton, grapes, and other unspecified crops.

The Weber et al. (2016) identification strategy yields smaller estimates than those found in the main text, though qualitatively they arrive at similar conclusions. An explanation for the discrepancy is that the Weber et al. (2016) approach improves with variation in insurance prices over time, either through subsidy changes or some other mechanism. Though these prices are changing in our sample, the shorter time window of our data limits these changes. Our approach, on the other hand, relies on spatial variation of insurance prices, specifically at the county border. In our sample, the spatial variation of prices represents a greater source of variation, implying that our instrumental variables approach leverages additional sources of exogenous insurance price variation.

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