Data not available? Survey applications to carbon sequestration and irrigation water quality

by

Grant Gardner

B.S., Purdue University, 2017
M.S., University of Nebraska-Lincoln, 2019

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2022

Abstract

Essay 1: Cover crop and no-till adoption: What affects willingness to accept of cover crop and no-till contracts?

Carbon markets offer supplemental income to producers for implementing no-till and cover crop practices that sequester carbon in the soil. Using choice experiments, we find that 37% and 43% of our sample would not accept a hypothetical contract to enroll cover crop and no-till respectively, indicating that producers are unwilling to enroll in carbon contract offerings current payment rates. We estimate the marginal willingness to accept (MWTA) of producers for current contract attributes including contract length and portion of cropland enrolled for both cover crop and no-till. Using random parameters logit models, we find that MWTA of a cover crop contract for enrolling 33% of cropland acreage for a 5- and 10-year contract is $54.44/acre and $75.85/acre, or two to three times current program payments. We find comparable results with lower prices for no-till contracts.

In addition to indications that current payments are too low to incentivize widespread adoption, we find that MWTA of contracts increases with contract length because contractual agreements constrain producer decision making. We also find indications that arid regions may not receive enough precipitation for cover crop implementation which causes higher MWTA of cover crop contracts. Results indicate that conservation practices and payments under existing carbon contracts will limit enrollment in Kansas and other semi-arid regions of the High Plains.

Essay 2: Producer response to groundwater quality concerns: Are concerned producers watering less?

Increases in irrigation intensity across the High Plains Aquifer have led to declining water levels and deterioration of water quality due to runoff and salts accumulation. In this paper, we combine a survey of producer groundwater perceptions with data on groundwater use to determine how ground water quantity and quality concerns affect irrigation water use. We find that as well yield (i.e., water quantity) concern increases, producers typically irrigate a smaller number of acres at each well which results in less total water use. However, we find that major concern over water quality corresponds with an increase of water use which is driven by producers watering more acres on the extensive margin.

Our results indicate that water quality concerns mitigate the declines in irrigation water use caused by well yield concerns. When major water quality concern is present, producers apply 11.45 more acre-feet of water per well. We do not find significant changes in water use on the intensive margin due to well yield or water quality concerns. In looking at the effects of water quality concern on crop choice, we find that the planting decisions of producers with water quality concerns are not statistically different from producers without concern, which indicates producers are not changing their crop choice on average due to concern over water quality.

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Acknowledgements

This dissertation would not have been possible without the aid of my family, friends, and mentors. Huge thank you to my mom, dad, Ethan, and both sets of grandparents for their constant support and love. Thank you for raising me in a Christian family and always pushing me to look for guidance from "the man upstairs." In addition, thank you for always believing in me. Nine and a half years of college is not normal, but your support has been crucial.

To my countless friends, whether I met you at Purdue, Nebraska, Kansas State, or somewhere in between: I want to thank you for your support in each level of my education. I want to give special thanks to my cohort, Gerald, Hunter, Micah, Jody, and Lonnie, for dragging me through the rigorous Ph.D. course work. I also want to thank the students that finished ahead of me, specifically Hannah, Chelsea, and Kaitlyn, for giving me the confidence to complete the KSU Agricultural Economics Ph.D. program. To the new groups: If I did it, I know that you can do it too.

Finally, to my mentors: The Kansas State Agricultural Economics Faculty are unmatched, and I want to give thanks to my major advisor and committee members, Gabe Sampson, Glynn Tonsor, Andrew Barkley, Jennifer Ifft, and DeAnn Presley. In addition, I would like to thank Jesse Tack, Dustin Pendell, Mykel Taylor, Brian Briggeman, and Vincent Amanor-Boadu. You have all played a large part in my development as a future extension economist and human being.

Dedication

I dedicate this work to my Lord and Savior, Jesus Christ, and all the people that have aided me on my educational journey. Three different schools, three different degrees, and too many mentors and friends to count. I could not have done it without you.

Preface

In the following essays we use survey methods to analyze the willingness to accept of cover crop and no-till practices and the impact of water quality concerns on irrigation water use. In both essays, survey methods are used because data procured by other sources was unobtainable or too expensive. We deemed the best method to answer our questions to be surveys.

In respect to cover crop and no-till adoption, we could have paid for data on adoption rates in Kansas; however, without a producer survey, we would not have been able to find the minimum monetary payment producers in Kansas would accept to adopt either practice. The use of surveys also allowed us to tackle a secondary question asking, "Why are producers not adopting?" Previous research focuses largely on the benefits of cover crop adoption but does mention negative impacts. The use of producer surveys allowed us to gain input for this dissertation as well as future research on how factors including precipitation or crop rotation affect cover crop adoption.

In respect to water quality, the quality of water in each well is highly heterogeneous. One source of data that has been previously used are interpolations of water quality. We spent hours upon hours working on time-series interpolations, only to find that changes in water quality were highly localized to each well and that interpolations were not a viable option to assess the impact of water quality on irrigation water use. We thus turned to our Gardner, Sampson, and Presley (2021) survey and matched these estimates with each respondent's water use to determine how water quality is affecting changes in irrigation.

With the advancement of remote sensing and other technologies, surveys are becoming less prevalent but are still used regularly in agricultural economics and other disciplines. Survey methods provide the researcher with data to make insights on unique questions when, as the title says, data are not available. For example, widely used data from the USDA (e.g., the Agricultural Census and ARMS) are regularly obtained through surveys.

A large amount of literature focuses on the pitfalls which could occur when utilizing survey methods. Common examples are leading questions, using words with ambiguous meaning, or using jargon terms which may not be understood. These are only a few of the simpler items we thought about before sending our surveys. To mitigate biases in our research, we additionally had multiple researchers and producer focus groups assess each survey to make sure that our questions were asked in an acceptable order and format.

The results of our surveys answer two important questions: (i) What is the minimum monetary payment a producer in western Kansas would accept to implement cover crop and no-till practices on their operations and (ii) How does producer concern over irrigation water quality affect irrigation practices? The results of our analyses which use data collected from our surveys are in the following pages of this dissertation. The results speak for themselves and indicate that the use of survey methods in agricultural economics are needed to further the agricultural economic literature and will be crucial to the profession for years to come.

Chapter 1 - Essay 1: Cover Crop and No-Till Adoption: What Affects Willingness to Accept of Cover Crop and No-Till Contracts?

1.1 Introduction

Revitalized by the push for net-zero emissions under the Paris Agreement, carbon sequestration has become another source of potential income for producers at the farm level. In accordance with the agreement, payments can be obtained by producers through carbon credit programs (CCPs) and government subsidies for complying with carbon sequestrating regimes.

The carbon credit market, primarily led by voluntary agreements to offset private sector carbon emissions, focuses in part on sequestration of carbon in soils at the farm level (Lokuge and Anders, 2022). Intermediaries function as the quantifier and/or broker of farm level carbon off-sets to companies which have entered a voluntary agreement. Essentially, producers adopt management practices which sequester carbon and are either paid for the practice or paid for the quantity of carbon sequestered. The quantity of carbon sequestered is converted into carbon credits by intermediaries which sell the credits to companies seeking to offset carbon emissions (Shockley and Snell, 2021).

Each CCP varies in payment structure as well as acceptable practices, but two overarching practices include the adoption of cover crop and reduced or no-tillage (no-till) systems (Plastina and Wongpiyabovorn, 2021). To ensure that CCPs are mitigating climate risk, programs typically call for “additionality” and “permanence.” Additionality refers to activities that sequester carbon to a greater extent than what would have occurred in the absence of the approved conservation practice. Permanence refers to long-term sequestration of carbon and ensures that measures are in place to protect against the release of sequestered carbon back into the atmosphere (Dowell, 2022).

In addition to CCPs, the adoption of no-till and cover crop is also being subsidized via government conservation programs. For example, in 2018 the USDA's Environmental Quality Incentive Program (EQIP) provided $155 million in planned payments towards cover crops on about 2 million acres, with a smaller portion of funding going to no-till or conservation tillage (Wallander et al., 2021). Government subsidies are important to cover crop and no-till adoption because some CCPs allow stacking of payments, making the transition to new cropping practices easier by allowing two payment mechanisms (Plastina and Wongpiyabovorn, 2021).

Use of no-till on farm operations calls for the farm producers to eliminate tillage before planting in the spring. The definition falls under the broader USDA definition of conservation tillage which is defined by at least 30 percent of the soil surface being covered by plant residue after planting (Huggins and Reganold, 2008). As most CCP allow no-till or minimum tillage, the contracts themselves likely allow a small amount of tillage when needed (i.e., small areas with compaction) (Plastina and Wongpiyabovorn, 2021).

Cover crop is defined by RMA (2022) as a crop which is recognized as agronomically sound in the area it is planted and is used for erosion control, conservation related reasons, or soil improvement. However, some confusion lies in whether a cover crop is harvestable or grazable. For example, the NRCS (2014) allows grazing or forage harvest if the amount of biomass at termination is sufficient; however, some CCPs may not allow grazing as grazed land has been shown to have negligible carbon sequestration potential (Lajtha and Silva, 2022). The same holds for winter wheat planting. If winter wheat is harvested and is then followed by another harvested crop, the planting practice is termed a double crop by the NRCS (2013). However, if the wheat is terminated before harvesting, wheat could qualify as a cover crop.

Economic returns to cover crop and no-till adoption are typically capitalized indirectly through yield increases via changes in agronomic characteristics including reduced soil erosion, nutrient attrition, soil compaction, disease, and pests, as well as increased water infiltration, soil nutrients, and organic matter (Wallander et al, 2021; Aziz, Mahmood, and Islam, 2013; Hou et al., 2012; Mathew et al. 2012). Bergtold et al. (2019) highlight that cover crops can be profitable, but that profitability is dependent on establishment, management, and productivity among other factors. Returns to cover crops in the form of increased yield take time, with corn yield increases ranging from 0.5% after 1 year to 3% after 5 years (Myers, Weber, and Tellatin., 2019). Similarly, no-till has been found to increase yields, especially on larger farms of corn, soybeans, and wheat (Marcillo and Miguez, 2017; Decker et al., 2009).

Even with multiple payment mechanisms, agronomic, and probable economic benefits, the adoption rates of cover crop and no-till use widely differ. Approximately 26% of farmland in the contiguous United States used no-till in 2017 (Sawadgo and Plastina, 2022). Claassen et al. (2018) points out that no-till is used on 45% of wheat ground, 40% of soybean ground, and 27% of corn ground; however, it is often used in rotation with other tillage practices. To capitalize on carbon credit payments, producers typically need to continuously no-till for the entire contract duration which normally spans 5-10 years (Plastina and Wongpiyabovorn, 2021). Conversely, cover crops were planted on a much smaller 3.88% of contiguous United States land in 2017 (Sawadgo and Plastina, 2022).

In 2017, only 2-3% of land in the Prairie Gateway region which covers all of Kansas and parts of Nebraska, Colorado, Oklahoma, Texas, and New Mexico implemented cover crops (Sawadgo and Plastina, 2022). However, across the same region, mulch till or no-till practices were implemented on 60% of wheat ground, 90% of soybean ground, and 65% of corn ground

(Claassen et al., 2018). Looking at the maps of Sawadgo and Plastina (2022), we can tell that cover crop and no-till adoption cluster in distinct parts of Kansas. A larger percentage of cover crop utilization clusters in the eastern and central parts of the state where most counties use cover crop on 1-10% of their cropland. In the western regions, most counties use cover crop on less than l% of cropland. On the contrary, no-till acreage clusters in the northern half of the state where the bulk of the counties use no-till on more than 35% of crop acreage (Sawadgo and Plastina, 2022).

To comply with the Paris Agreement and meet the United States goal of net-zero emissions by 2050, management practices which sequester carbon need to increase drastically. Using choice experiments on cover crop and no-till adoption with supplemental survey data, we find misalignments between producers in Kansas and current program offerings. First, current payments are too low to incentivize enrollment in a cover crop contract for the producers in our sample, as producers do not want to be locked into to lengthy contracts. Second, increases in contract duration drastically increase MWTA as producers do not want crop practices and rotation to be constrained by multi-year contracts. Finally, production decisions and environmental factors such as wheat planting and precipitation place limitations on producer ability to engage in carbon contracts. Precipitation limitations in western Kansas are of particular importance to this study as precipitation is frequently insufficient to meet cover crop water demands. Additionally, cover crops could use valuable soil moisture which is crucial for cash crop water demand if timely rains do not occur.

1.2 Survey Methods, Response Rates, and Sample Representation

The nine Kansas Agricultural Districts as defined by the USDA are depicted in Figure 1.1. We chose to focus on the western (Northwest, West Central, and Southwest) and central districts (North Central, Central, and South Central) because they capture spatial variation in climate, irrigation, and cropping patterns. In contrast, the eastern portion of Kansas closely mimics the climatic conditions of the eastern midwest, with greater precipitation and higher quantities of corn and soybean planting. In this study we focus on areas with large fluctuations in climate and cropping patterns as climatic shifts likely make cover crop adoption more difficult and would thus require larger payments for adoption.

The addresses of Kansas landowners were obtained from the Kansas Property and Valuation Division. Surveys were sent by mail to Kansas landowners in the central and western regions in March and early April of 2022. The average Kansas producer is 58 years old, and thus mail surveys were used to mitigate technological challenges (Geiger et al., 2021). Sample stratification was used to target farm producers instead of landowners as past literature points out that 50-60% of United States farmland is owner-operated (Arnold, 2021; Bigelow, Borchers, and Hubbs, 2016). We therefore limit the survey to Kansas residents owning more than 300 agricultural acres to better target farm producers in comparison to recreational landowners. In Reno and Sedgwick County, we limit to Kansas residents owning more than 140 acres of land ownership as both counties have smaller average farm sizes and the 300-acre constraint did not provide enough addresses for sample demand. 500 surveys were sent to each of the six agricultural districts, with survey quantities divided evenly between the counties within each district.

The survey included questions on farm operations, perceptions of practices, and two choice experiments: one exploring cover crop contract agreements and the other exploring no-till contract agreements. Choice experiment design as well as survey results are presented in later sections. Postcards were sent pre- and post-survey to remind respondents they will/had received a survey. Of the 3,000 surveys sent, 563 surveys were returned resulting in a 18.76% response rate. 134 surveys were removed from analysis due the landowner not being the primary decision maker. These respondents indicated they rented their farmland for reasons including land in trusts, retirement, and the passing of a spouse. There were around 60 surveys returned where the participant did not answer the choice experiment questions. These respondents are included in the descriptive information sections but are not included in the choice experiment analysis. Final response rates for the descriptive section and choice experiments were 14.3% and 12.2%, respectively.

Figure 1.1 contains response rate by district. Table 1.1 follows with demographic comparisons of average land ownership, average cropland per district, and average wheat planting compared to estimates from the 2017 Census of Agriculture. We can see from Table 1.1 that a majority of our sample results are similar to the census with the exception of average cropland in the Central and South Central districts. These areas have numerous small farms, and our sampling strategy may have biased respondents in these areas to larger farming operations (USDA NASS, 2017 Census of Agriculture).

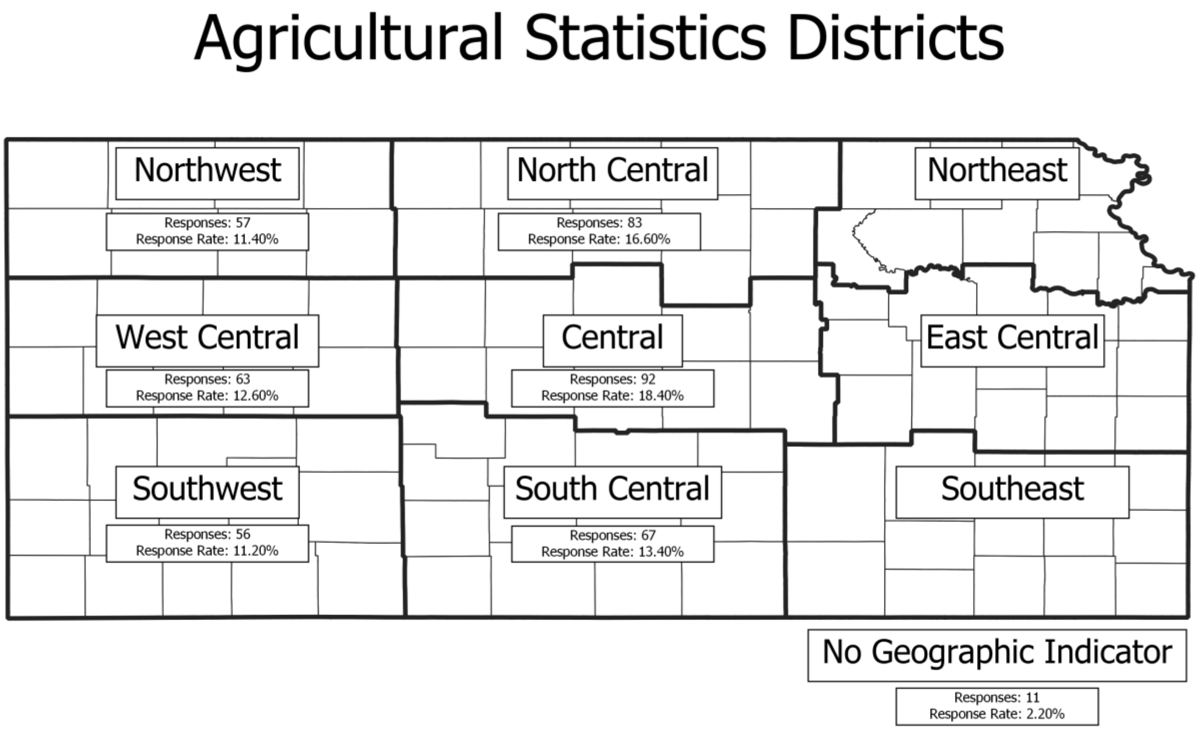

Figure 1.1 Kansas Crop Reporting Districts

Table 1.1 Comparison of Landownership (acres/farm) to 2017 Census of Agriculture

	District	Survey	2017 Ag Census	n
Average Land Per Farm	NW-10	1176	1538	57
	WC-20	1453	1684	63
	SW-30	1303	1470	56
	NC-40	1059	983	83
	C-50	995	763	92
	SC-60	1089	812	67
Average Cropland Per Farm	NW-10	872	685	57
	WC-20	1155	678	63
	SW-30	1049	664	56
	NC-40	764	527	83
	C-50	741	383	92
	SC-60	855	450	67
Average Wheat Acreage Per Farm	NW-10	250	233	57
	WC-20	366	298	63
	SW-30	373	247	56
	NC-40	209	159	83
	C-50	314	170	92
	SC-60	355	227	67

1.3 Kansas Background and Survey Descriptive Statistics

1.3.1 Adoption Rates

Utilizing results from our sample, we find that close to 30% of Kansas producers implement cover crop on some portion of their acreage and close to 80% implement no-till. Regional variations in adoption rates are depicted in Figure 1.2. Like the maps created by Sawadgo and Plastina (2021), we find that cover crop implementation clusters in central Kansas (eastern part of our sample) and that no-till adoption increases further north. Boxplots of cover crop utilization and no-till use by percentage of cropland and Agricultural District and can be found in Appendix A.

Looking at CCPs, 76% of respondents claimed they had little or no knowledge of how CCPs work. Only 18 survey respondents have enrolled in a CCP with a majority of this group using Indigo or Bayer carbon credit contracts. Expected payment levels for enrolling in programs widely varied regardless of whether producers had enrolled in a carbon credit program. The largest proportion of producers that have not enrolled in a program (30%) believed entering a carbon credit agreement would result in payments of $4.99/acre or lower (Appendix A). Asking a question on producer restraints to entering a CCP, like that of Thompson et al. (2021), we obtain comparable results. The largest restraint is low payment offerings; however, skepticism of the programs themselves and legal liability are possible detriments to CCP adoption. Some producers further indicated reasons including lack of knowledge on the programs, length of commitment, and political reasons (Appendix A).

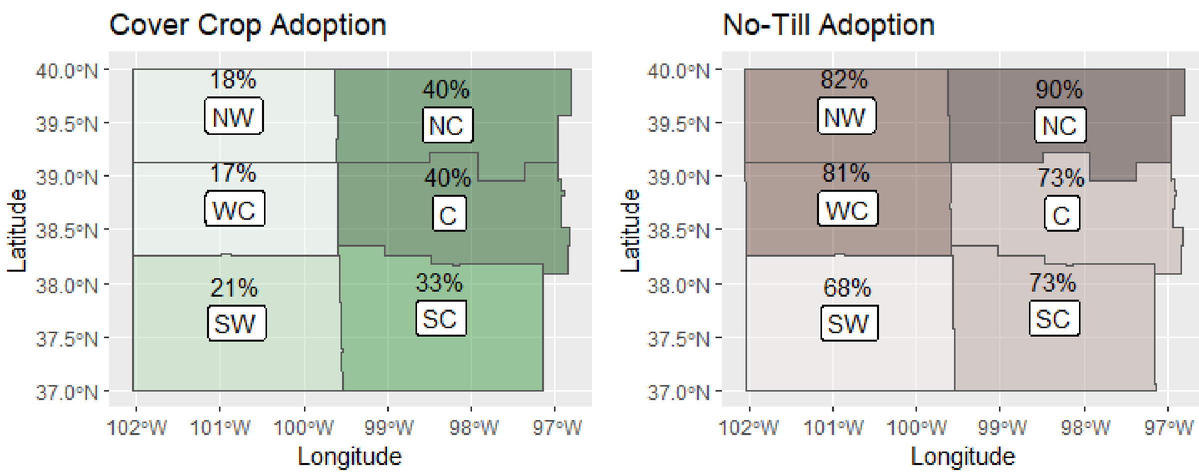

Figure 1.2 Average Cover Crop and No-Till Adoption by Region (% of Respondents)

1.3.2 Spatial Heterogeneity and Limitations

We chose the western six agricultural districts for our sample to maximize the effects of weather heterogeneity on cropping and management decisions and thus the effects of these decisions on cover crop and no-till practice implementation. In the central and western part of Kansas, conditions switch from a humid continental climate to a semi-arid midlatitude desert climate (HSOTR, 2014). These climate differences give rise to changes in production practices, especially as they pertain to the limitations of both cover crop and no-till implementation. Major limitations to cover crop practices include existing long-season cash crops, precipitation, expenditures on seeding, complications to management practices, and time spent on seeding and termination (SARE, 2015). Limitations to no-till include the formation of gullies, increased need for chemical use, herbicide resistant weeds, and increased risk of certain diseases (Al-Kaisi, Hanna, and Tidman, 2000; Recasens et al., 2020).

As cover crop is the limiting practice to carbon credit contract usage by producers, we ask an extensive set of questions on what factors limit producer adoption (Appendix A). The top three factors impacting cover crop adoption are precipitation, cover crop costs, and rotational difficulties. Although cover crop costs are an obvious concern, we focus on

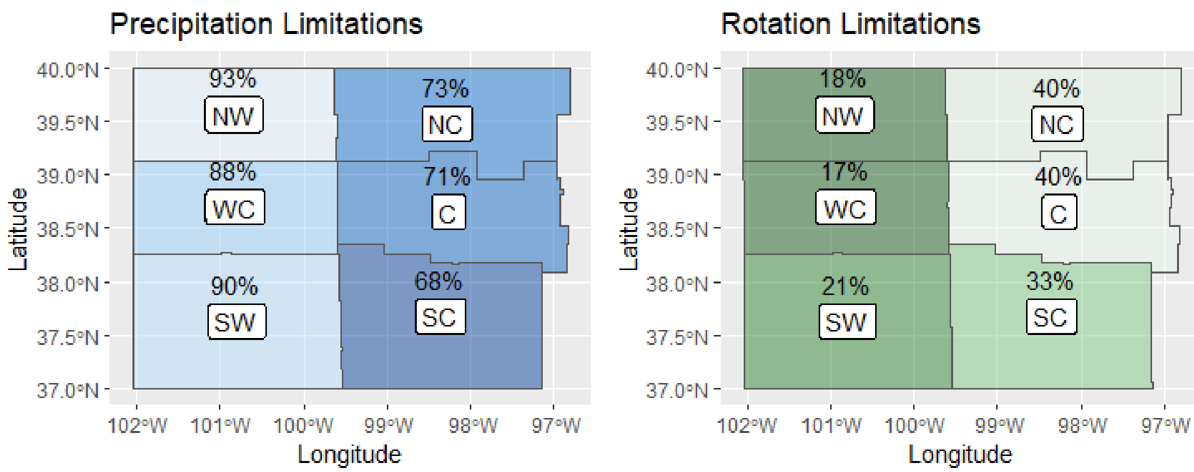

Figure 1.3 Precipitation and Rotation Limitations by Region

precipitation and rotational difficulties in Figure 1.3 which maps the percentage of respondents that denoted major or moderate concern by region.

Over 68% of respondents are concerned with the amount of precipitation they receive when cover crop adoption is considered. Unsurprisingly, the amount of concern increases in the western, more arid regions of Kansas which follows the county five-year average and five-year minimum precipitation for the months of October and November (Appendix A). A larger percentage of concern over rotational difficulties clusters in the central regions where winter wheat planning is likely to make cover crop adoption difficult, especially if a continuous cover is required by CCPs.

In addition, carbon credit contracts depend on a yearly stand of cover crops. If cover crops are planted, but do not have enough precipitation to create a stand or impact crop yield, producers could incur large financial penalties from the cost of the cover crop, the loss of the carbon credit or government subsidy, as well as the cost of planting and seed price (Dowell, 2022). The western regions of Kansas do not receive enough precipitation year-over-year to comply with contract incentives. Even on irrigated lands, irrigation allocations are generally given to meet corn water demand and there is not enough slack in allocations to water cover crop after corn harvest. Data on cover crop water use is sparse, but Kelly (2018) recommends adding up to 0.5” of irrigation water for better emergence. A substantial portion of western Kansas received less than 0.5” of rain during October and November within the past 5 years (Appendix A), indicating precipitation limitations could hinder cover crop adoption. This fact is likely capitalized in the results of Figure 1.3.

Additionally, winter wheat planting causes two major limitations to cover crop planting. First, winter wheat does count as cover crop and is eligible for CCPs, but only if the crop is terminated following the strict burndown periods enforced by CCPs (Plastina and Wongpiyabovorn, 2021). Although winter wheat planting sequesters carbon and covers ground to ensure permanence, producers in wheat growing states harvest winter wheat, making the crop ineligible for cover crop payments. Additionally, enrollment for cover crop carbon credit payments adds constraints to crop rotation for producers who implement winter wheat in their rotation. CCPs enforce continuous cover crop use which effectively limits the ground producers can plant winter wheat on.

The second limitation concerns the idea that volunteer winter wheat typically needs to be terminated to limit disease spread. Wheat disease, specifically wheat streak mosaic virus (WSMV) which can completely wipe out wheat fields, overwinters in volunteer wheat from the previous season and producers typically use tillage or herbicide to terminate volunteers (Jones et al., 2005). WSMV can also overwinter in cover crops, increasing disease spread (Chalupniková et al., 2017). Including a question on termination of winter wheat as well as other risk management practices for weed control, we find that producers often use tillage in combination with chemical application to control weeds. However, 56% of producers use only chemical application to control volunteer wheat. This may indicate that volunteer wheat control could play a part in no-till adoption, but chemical alternatives are widely used and are a viable option. We additionally find remarks in the comment section of our survey that point to worries of WSMV overwintering in cover crop.

Figure 1.3 likely capitalizes the impact of winter wheat planting as a constraint to cover crop adoption. Rotational difficulties occur more regularly in the central districts than the western districts which follows the quantity of winter wheat planted in each county (Appendix A).

1.4 Choice Experiments and Empirical Methods

Choice experiments are a commonly used method to estimate the value of nonmarket goods and services and have been applied to areas including energy and biofuels, land preservation, and water use (Mariel et al, 2021; Bergtold, Fewell, and Williams, 2014; Luo, Swallow, and Adamowicz, 2022; Barton and Bergland, 2010). We apply choice experiments to carbon sequestration by exploring the marginal willingness to accept (MWTA) of both cover crop and no-till as well as the regional effects of geographic location on MWTA. Past experiments have looked at the adoption of conservation practices and the timing in which adoption of other practices follow, adoption of tillage practices for the purpose of carbon sequestration, and cover crop adoption (Canales et al., 2015; Gramig and Widmar, 2018; Villanueva, Glenk, and Rodríguez-Entrena et al., 2017). We build off these studies by exploring the MWTA of both practices in mutually exclusive choice experiments to estimate MWTA for the entire region. We then explore how regional variation affects MWTA of cover crop practices by using Bayesian calculations to estimate each individual's MWTA. These individual estimates of MWTA provide insight into the districts which could be better targeted for lower cost carbon sequestration.

1.4.1 Attributes and Design

As we included two different choice experiments in our survey, we placed a high amount of importance on simplicity. Most choice experiments focus on one experiment, and we did not want to over complicate either experiment (Boxall, Adamowicz, and Moon, 2009). The primary purpose of this research is to estimate the minimum monetary value that producers need to be offered to induce adoption and the impact of geographic differences on these values. A secondary purpose is to see how less binding contracts (i.e., shorter contract length and enrollment) effect MWTA. Producers were provided with a half page write up on both choice experiments and contract attributes were varied similarly. Varying attributes included contract length, the portion of cropland the producer would be willing to enroll, and the payment in $/acre of each contract.

For each experiment we use a main effects design. By implementing the PLAN and OPTEX procedures in SAS we identified a design maximizing D-Efficiency score of 90.69. The final choice design resulted in 17 choice sets that were randomized and blocked into three groups each (5 or 6 scenarios) to cut down the number of choice tasks given to each participant (Tonsor et al., 2005). Each choice task also included a no-choice option in which producers would not accept a contract to adopt or implement the practice (Vermeulen, Goos, and Vandebroek, 2008). Figure 1.4 shows a choice set example and full choice set designs can be found in Appendix A.

Both choice experiments vary the portion of cash crop land to enroll in the practice at intervals of 33%, 66%, and 100% and the number of years of each contract at intervals of 1, 5, and 10. The main differences between each of the choice experiments are payment levels. The cover crop per-acre payments vary between $6-$60 with intervals of $6, $18, $24, $36, and $60. No-till per-acre payments vary between $1-$12 with intervals of $1, $3, $6, $9, and $12.

We use the portion of cash crop land because it is not dependent on farm size. Asking for a specified number of acres, would have made smaller operations ineligible if the acreage numbers were too high. The number of years a contract lasts is based on actual carbon credit contracts (Plastina and Wongpiyabovorn, 2021). We chose to offer a 1-year enrollment to see if producers would be willing to enroll in programs with minimal contractual commitment. Similarly, the payment rates of each practice were chosen based on actual contracts. In the case of cover crops, the minimum payment of $6 lines up with the pay-for-practice approach currently offered by Bayer crop science (Plastina and Wongpiyabovorn, 2021). The $18, $24, and $36 payments fall in line with actual cover crop contract payments and the weighted carbon price at the time of our survey (Plastina and Wongpiyabovorn, 2021; IHS Markit, 2021). We raise the largest payment to $60, as pre-survey focus groups led us to believe that the current payment mechanism is likely viewed as too low by producers. We reason that $60/acre payments may capture producers who are interested in cover crop adoption and implementation but cannot currently adopt due to financial reasons. The inclusion of larger payments could also provide empirical evidence that larger payments will be needed to gain widespread enrollment. No-till payments follow a similar reasoning but are based on already wide-spread use in Kansas. For this reason, we anchor the prices close to the current market offerings for no-till adoption.

The choice experiment instructions included a cover letter, a half page of instructions, and a cheap talk script to mitigate hypothetical bias and inform individuals how their responses could impact the conclusions of our research (Lusk, 2003; Tonsor, 2018).

Choice 1

Attributes	Contract A	Contract B	Option C
Length of Contract	1 Year	10 Years	I would not accept
Portion of Cash Crop Land	33%	100%	Contract A or Contract
Payment $/Acre/Year	$9	$12	B
I would choose	☐	☐	☐

Figure 1.4 Choice Question Example

1.4.2 Random Utility Theory, Models, and Willingness to Accept

Random utility theory assumes that economic agents seek to maximize their expected utility subject to the choice sets they are presented. Succinctly, individual i receives utility (U) from selecting option j in choice situation t which can be specified as:

$$(1)\qquad U_{ijt} = V\left(x_{ijt}\right) + \varepsilon_{ijt},$$

where $V\left(x_{ijt}\right)$ represents the deterministic components and ε_{ijt} represents the stochastic component. In our application, x_{ijt} is a vector of contract attributes (carbon credit payment, the contract duration, and share of cash crop land enrolled) for the adoption of a practice. ε_{ijt} is the stochastic error component which is independent and identically distributed over all individuals, alternatives, and choice situations (Revelt and Train, 1998). The systemic portion of our utility function specified as:

$$(2)\qquad V_{ijt} = \beta_{PMT}Payment_{ijt} + \beta_{P33}Acres_{ijt}^{33} + \ \beta_{P66}Acres_{ijt}^{66} + \beta_{P100}Acres_{ijt}^{100} + \beta_{L5}Length_{ijt}^{5} + \beta_{L10}Length_{ijt}^{10}$$

Where P_{ijt} is a continuous variable indicating the payment received by producers for practice implementation. $Acres_{ijt}^{33}$, $Acres_{ijt}^{66}$, and $Acres_{ijt}^{100}$ are effects coded variables indicating the contract attributes for the enrolling 33%, 66%, and 100% of cash crop land relative to not signing a contract (Hensher, Rose, and Greene, 2015; Hu et al., 2022). $Length_{ijt}^{5}$ and $Length_{ijt}^{10}$ are dummy coded contract attributes for enrolling in 5- and 10-year contracts with respect to a 1-year contract. Each β_i represents a parameter to be estimated.

The model described in equations (1) to (3) is estimated using random parameters logit (RPL) models. The RPL is used because the multinomial logit model assumes homogeneous preferences for the evaluated consumers. Since we expect climatic variables and farm practices to affect the WTA of each contract, we are reluctant to assume homogeneous preference. By using the random parameters logit model, we allow for preference heterogeneity across our sample (Hoyos, Mariel, and Fernández-Macho, 2009; Tait et al., 2012). Random effects are incorporated by the panel-nature of the data in which the cross-sectional element is individual i and the time series component is the choice situation (t) (Lancsar, Fiebig, and Hole, 2017; Lusk and Schroeder, 2004).

Application of the general random utility model in Equation (1) can be presented as

$$(4) \qquad U_{ijt} = \beta_i{}' x_{ijt} + \varepsilon_{ijt}$$

where x_{ijt} is a vector of observed variables, β_i is unobserved for each individual and varies within the population with density $f(\beta_i|\ \theta^*)$ where $\theta^*$are the true parameters of the distribution. ε_{ijt} represents the stochastic error term component which is independent and identically distributed across all individuals, alternatives, and choice situations. Denoting the alternative that individual i chooses in period t as $j(i,t)$, the unconditional probability of subject i's sequence of selection is given as (Revelt and Train, 1998):

$$(5) \qquad P_i(\theta *) = \int \prod \frac{e^{\beta_i' x_{ij(i,t)t}}}{\sum_j e^{\beta_i' x_{ijt}}} f(\beta_i|\theta *) d\beta_i.$$

In our estimation, we allow the portion of land to enroll and the contract length to vary normally in the population which allows for both negative and positive utility for each attribute level. We specify the price coefficient to be fixed, allowing us to focus on heterogeneity in preference for each of the contract attributes. Other specifications were evaluated; however, keeping price constant resulted in the minimum AIC when compared to various other distributions (Ghosh, Maitra, and Das, 2013).

While coefficients from utility models have little interpretative value, we calculate marginal willingness to accept (MWTA) of each of the effects coded attribute's levels (portion of cash crop land to enroll) using the formula:

$$(7) \qquad MWTA_{\beta_i,effects} = -\frac{\beta_i + \beta_i + \sum_{j=L}\beta_j}{\beta_{PMT}}$$

where β_i represents the coefficient for the level of interest, β_j represents the levels of each attribute that are not of interest, L represents the number of levels not of interest, and β_{PMT} represents the coefficient on $Payment_{ijt}$ (Hu et al., 2022). We estimate the MWTA of each of the dummy coded attribute's levels (length of contract) using the formula:

$$(8) \qquad MWTA_{\beta_i,dummy} = -\frac{\beta_i}{\beta_{PMT}}$$

where each variable is previously defined (Hu et al., 2022). All confidence intervals (CIs) are estimated using the Krinsky and Robb (1986) bootstrapping procedure.

As we are interested in how spatial location, management practices, and demographics may affect cover crop and no-till adoption, the RPL is particularly useful as we can estimate "individual specific estimates," and thus estimate the MWTA for each attribute level for each survey respondent. Individual MWTA is then matched with survey responses to estimate the percentage of respondents in each region that have a lower MWTA for attribute levels which would result in more acreage enrolled or longer contract durations, giving us insight into how to target specific regions, maximizing contract enrollment subject to producer constraints.

As shown by Train (2003), individual WTA is derived using Bayesian calculations which do not produce each person's value parameters but means of the conditional distribution based on the respondent's choices. These value parameters are not the same as the respondent's actual coefficients. However, Train shows that when the number of choice decisions made by a respondent increase, the difference of the coefficients and these parameters shrinks, improving the ability to predict which decision each person makes. While we call these estimates "individual specific estimates" they are the parameter distribution conditioned on each individual's actual choices (Lusk and Briggeman, 2009).

1.5 Serial Non-Participation

Serial non-participation, in which respondents repeatedly select the status quo option or in our case "I would not accept Contract A or Contract B" is a common issue in choice experiments. Serial non-participation, which biases WTA estimates, has been noted in numerous studies and various methods are proposed to correct for it (Burton and Rigby, 2009, von Haefen, Massey, and Adamowicz, 2005; Thiene, Meyerhoff, and De Salvo, 2012). In our experiment serial non-participation could occur due to remarkably high takers or protest responses which would also bias estimates downwards.

Calculating serial non-participation, which reflects respondents that did not accept a contract for a practice, 41% and 46% of the sample serially rejected cover crop and no-till contracts, respectively. 30% of respondents serially rejected all contracts offered regardless of practice type. Interestingly, more respondents rejected no-till even though close to 80% of respondents are already implementing the practice, likely indicating that continuous no-till may not work with their operation. Regional serial rejection is shown in Figure 1.4.

To control serial non-participation bias on our estimates, we leave serial rejectors in the analysis and effectively counting them as remarkably high takers and focus on protest responses. Before estimating RPL models, we correct for protest responses following Villanueva, Glenk, and Rodríguez-Entrena (2017) which claims that protesters are considered outside the market and should not be included in the analysis. Although, we did not include questions in our survey to indicate protest responses, 23 respondents made their protests known through comments on survey questions or in the additional information section. We cut these 23 responses from the analysis. Protests which resulted in observations being cut from the study included refusal of outside payments and political reasons.

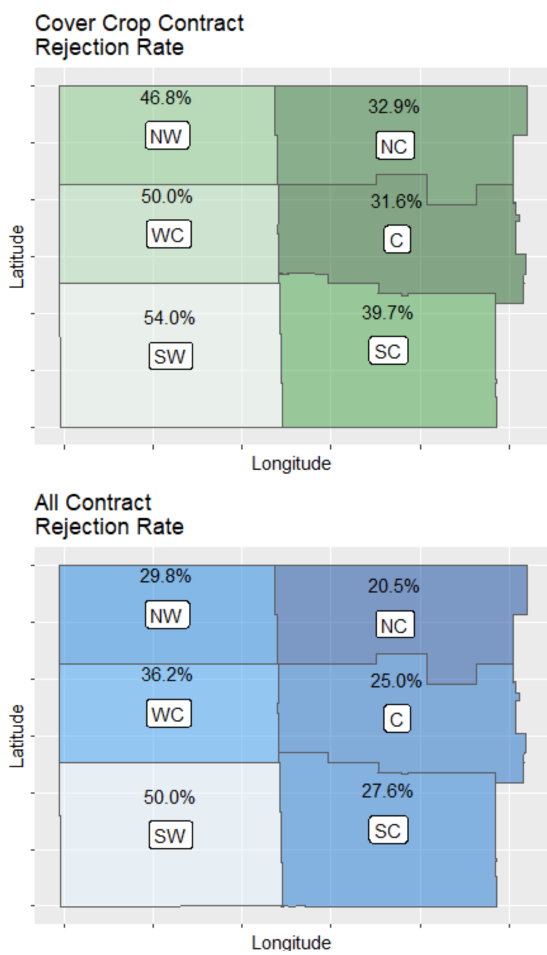

Figure 1.4 Rejection Rates by Contract and Region

1.6 Results

1.6.1 Random Parameters Logit Model Results

The coefficients of the parameters in the RPL models for cover crop and no-till are displayed in columns one and three of Table 1.2, respectively. The portion of cropland to enroll is effects coded with respect to the opt out option and thus indicates, the utility and MWTA values for enrolling each portion of cropland with respect to not signing a contract. The 5-year contract and 10-year contract are dummy coded with respect to a 1-year contract. 1-year contracts are the shortest contract available to producers and the shortest contract in our hypothetical contract options. Most pay-for-practice programs offer smaller payments for 1-year enrollment (Plastina and Wongpiyabovorn, 2021).

Starting with the no-contract coefficients for each attribute level, we find that the coefficient estimate for 33% of cropland in the cover crop contract is not statistically different from the utility gained by not-signing a contract and the 5-year contract level in the no-till contract are not statistically different from a 1-year contract. The remaining levels of each attribute for both models indicate that contractual commitments result in a loss of utility to the producer and utility is only gained through payments.

Results for the cover crop model indicate that utility coefficients follow economic intuition as smaller quantities of cropland devoted to a practice and shorter contract length result in the smallest utility reductions for the producer. Interestingly, the smaller loss of utility for the 66% of cropland level in the no-till estimation indicates that producers in our sample retain more utility by enrolling 66% of their acreage instead of 33%.

The coefficients for the 10-year length of contract levels are more negative than the 5-year contract in both models, indicating that producers prefer to enroll in the shorter contracts.

The large loss of utility for a 10-year contract likely stems from the fact that contracts do not allow cropping practices to change for the contract duration and thus constrain available cropping practices and rotations for the producer. The impact of the constraints likely resulted in the high rejection rates for both contracts in our sample but had a larger effect on no-till acceptance as we find that producers are already utilizing some no-till and prefer to enroll 66% of their cropland instead of 33%. Before moving to MWTA estimates, it is worth noting that the random parameters for both practices resulted in statistically significant diagonals in the Cholesky matrix which indicates preference heterogeneity. Thus, the MWTA estimates in the RPL are not representative of the entire sample (Gramig and Widmar, 2017).

The MWTA values with estimated CIs are shown in columns two and four of Table 1.2. We find that MWTA of a producer to enroll 33% of cropland, 66% of cropland, or 100% of cropland in a cover crop contract is \$45.73/acre/year, \$56.05/acre/year, or \$81.40/acre/year with respect to not signing a contract. As each of the estimates would require a minimum, 1-year contract length we assume that these estimates capture the premium for a 1-year contract. When the length of contract increases to 5-years from 1-year, each of these values increase by \$8.71/acre/year. When a jump from a 1-year contract to a 10-year contract occurs, MWTA estimates increase by \$30.12/acre/year which is again indicative that producer enrollment in 10-year contracts may be more difficult in arid regions.

Looking at the MWTA of no-till contracts, we find that MWTA of a producer to enroll 33% of cropland, 66% of cropland, or 100% cropland in a cover crop contract is \$12.54/acre/year, \$11.95/acre/year, or \$15.36/acre/year with respect to not signing a contract. MWTA for five-year contract is not statistically different from a 1-year contract as the CI contains zero, but MWTA for a 10-year contract is \$5.01/acre/year more than a 1-year contract.

To calculate the full cost of each contract we must assume our model is additive and compensatory. In our case, this means that the utility of each contract is the sum of the values at each attribute level and the positive and negative effect of each level of each attribute compensate one another (Johnson and Olberts, 2001; Louviere and Hout, 1988). One limitation to this assumption is that we chose to use a main effects design to simplify the survey and cannot estimate interaction terms for portion of cropland to enroll and length of contract. Thus, our additive point estimates do not account for the marginal effects between attributes.

Using the additive and compensatory assumptions, we tally the total MWTA/acre for 5- and 10-year contracts. Using the point estimates, our results indicate that MWTA for a 5-year contract for enrolling 33%, 66%, or 100% of cropland is $54.44/acre/year, $64.76/acre/year, or $90.11/acre/year, respectively. The MWTAs for 10-year contracts for the same portions are $75.85/acre/year, $86.17/acre/year, or $111.52/ acre/year. CIs are listed in Table 1.3.

As 66% of cropland for a no-till contract is not statistically different from enrolling 33% of cropland and carbon credit programs want to maximize acreage, we calculate the MWTA of a no-till contract for a 5-year contract which enrolls 66% or 100% of acreage to be $13.05/acre/year or $16.46/acre/year. Similar calculations for 10-year contracts result in MWTA of $16.96/acre/year for 66% enrollment or $20.37/acre/year for 100% enrollment. CIs are listed in Table 1.4.

Our RPL models indicate that producer MWTA for no-till contracts is relatively low, but MWTA for cover crop contracts far outweigh the payments currently offered by CCPs. Results of the cover crop model indicate that smaller portions of acreage committed, and shorter contract length may be one method to increase cover crop adoption; however, these types of contracts may conflict with carbon sequestration science and policy goals which call for large acreage enrollment as well as longer contract lengths to comply with ideas of additionality and permanence. In the next section of this paper, we focus on individual MWTA estimates to determine if some producers are better suited for cover crop contracts than others.

Table 1.2 Random Parameters Logit Model Results

	Cover Crop		**No-Till**	
Variable	**Coefficient Estimates (Std. Err.)**	**Marginal WTA per acre [95% Conf. Interval]**	**Coefficient Estimates (Std. Err.)**	**Marginal WTA per acre [95% Conf. Interval]**
33% of Cropland	0.01	$45.73	-1.32***	$12.54
	(0.18)	[$39.10, $52.05]	(0.25)	[$10.99, $14.23]
66% of Cropland	-1.04***	$56.05	-1.02***	$11.95
	(0.27)	[$48.44, $63.89]	(0.35)	[$10.25, $13.75]
100% of Cropland	-3.60***	$81.40	-2.76***	$15.36
	(0.43)	[$70.09, $92.91]	(0.43)	[$13.03, $17.83]
5-Year Contract	-0.88***	$8.71	-0.56	$1.10
	(0.26)	[$3.88, $13.53]	(0.35)	[-$0.36, $2.41]
10-Year Contract	-3.04***	$30.12	-2.56***	$5.01
	(0.49)	[$21.85, $38.90]	(0.42)	[$3.47, $6.43]
Payment	0.10		0.51***	
	(0.01)		(0.05)	

Table Footnotes: Full Regression Results for the RPL models including standard deviations on random parameters can be found in Appendix A.

Table 1.3 Total Marginal WTA for Cover Crop Contracts

		Portion of Cropland Enrolled 33% of Cropland	 66% of Cropland	 100% of Cropland
		Marginal WTA per Acre [95% Conf. Interval]	Marginal WTA per Acre [95% Conf. Interval]	Marginal WTA per Acre [95% Conf. Interval]
Contract Length	1-Year	$45.73 [$39.10, $52.05]	$56.05 [$48.44, $63.89]	$81.40 [$70.09, $92.91]
	5-Years	$54.44 [$46.52, $62.18]	$64.76 [$58.33, $72.11]	$90.11 [$76.87, $101.83]
	10-Years	$75.85 [$64.82, $87.19]	$86.17 [$75.58, $96.66]	$111.52 [$97.26, $125.31]

Table 1.4 Total Marginal WTA for No-Till Contracts

		Portion of Cropland Enrolled 33% of Cropland	 66% of Cropland	 100% of Cropland
		Marginal WTA per Acre [95% Conf. Interval]	Marginal WTA per Acre [95% Conf. Interval]	Marginal WTA per Acre [95% Conf. Interval]
Contract Length	1-Year	$12.54 [$10.99, $14.23]	$11.95 [$10.25, $13.75]	$15.30 [$13.03, $17.83]
	5-Years	$13.64 [$11.74, $15.71]	$13.05 [$11.72, $14.46]	$16.46 [$13.77, $19.53]
	10-Years	$17.55 [$15.54, $19.85]	$16.96 [$14.93, $19.04]	$20.37 [$17.87, $23.22]

1.6.2 Regional Willingness to Accept Results

One limitation of choice experiments estimated with entire samples of data and no regional covariates, is that they estimate the variable of interest, in our case MWTA, of the sample as a whole and do not account for regional heterogeneity. Various studies have looked at spatial differences in WTA. Past studies use different methods to explore regional WTA with the simplest relying on subsamples. Other more complicated methods include the use of distant gradients between the respondent and where the program of interest will take place and interpolation of individual WTA or WTP values (Martin-Ortega et al., 2012; Campbell, Hutchinson, and Scarpa, 2009; Czajkowski et al., 2017).

As multiple factors likely affect MWTA in our study (i.e., precipitation and wheat planting) we use a different approach in which we utilize individual MWTA estimates to look at heterogeneity between regions. Using these estimates, we find producers with lower MWTA for larger attribute levels in comparison to the smallest attribute levels (i.e., a 33% contract or a 1-year contract). We then aggregate these producers to their respective region to identify where contract attributes that could have a larger effect on carbon sequestration are more likely to be accepted. For this analysis, we focus solely on cover crop contracts as no-till is already widely adopted and resulted in trivial differences between regions. Result of the aggregate percentages by region can be found in Figure 1.5.

Figure 1.5 indicates that less than 7% of producers prefer to enroll 100% of their acreage in cover crops when they sign a cover crop contract, but by aggregating to region, we do find that a larger proportion of these respondents are located in the Central district where 12% of respondents prefer to enroll their entire acreage. These results are intuitive as we find that even though a large quantity of winter wheat production occurs in this region, the region is not as constrained by precipitation quantities. We also find that 7% of respondents in the North Central and 6% of respondents in the South Central district prefer to enroll 100% of their acreage, again pointing to lack of precipitation limitations. Interestingly we find that 7% of producers in the Southwest region are also willing to enroll 100% of their acreage. As this region is likely precipitation limited, we turn to the descriptive section of the survey and find that these producers use irrigation on their operation and likely irrigate most of their crop acreage.

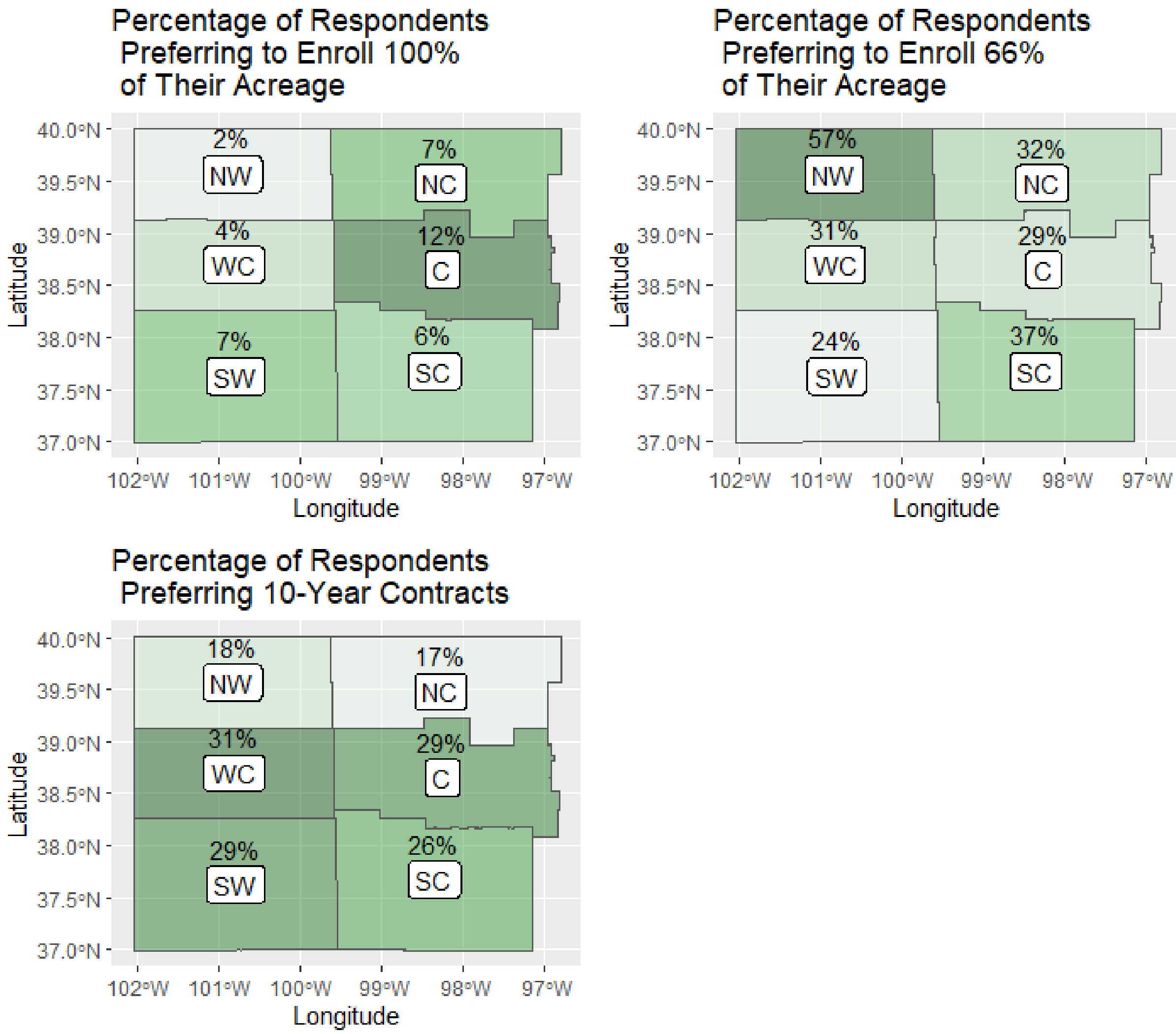

Figure 1.5 Percentage of Respondents Preferring to Enroll in Contracts which Call for Larger Enrollment or Longer Durations

The results for enrolling 66% of cropland over 33% of cropland follow much of the same intuition, in total we find that 34% of producers in our sample would prefer to enroll 66% of their cropland. Interestingly the split between the central and western regions indicates that a larger percentage of producers, 37% compared to 32%, are willing to enroll 66% of their cropland in the western districts; however, this result is mostly driven by the Northwest district. These results again follow intuition that the central regions have more precipitation and can thus enroll more dryland in cover crop planting, where producers willing to enroll 66% of their acreage in the west use irrigation and can thus enroll larger quantities of acreage in cover crop.

Another item of interest is that producers preferring a 10-year contract over a 5-year contract occur in the Central and West Central districts (30%) which is followed by the southern regions (24%) and the northern regions (17%). These results are not as intuitive as the proportion of acreage results. We do find that less producers plant winter wheat in the south which may indicate that producers in this region are willing to use cover crop contracts as a viable replacement for winter cash crops. The opposite may be occurring in the north. As to why the Central district would prefer longer contracts more often than the other regions, one speculation is that most of the producers in the Central district willing to enroll more acreage are also willing to enroll large quantities of acreage on a continuous basis.

1.7 Conclusions

To comply with the carbon sequestration goals of the Paris Climate Agreement, cover crop and no-till practices need to be expanded. Based on our sample of Kansas producers, cover crop is currently implemented by 30% of respondents on 33% of their crop ground, while no-till is used by a much larger 77% of respondents on 67% of their crop ground. Even with large adoption of no-till and 30% of the sample using some cover crop, only 4% of respondents have enrolled in a carbon credit contract.

To determine how to expand carbon farming and conservation programs, we use choice experiments to explore WTA of cover crop and no-till contracts. Our findings indicate that: (i) current carbon credit payments are priced below the minimum necessary payment needed to enroll producers in Kansas, (ii) MWTA is largely impacted by the length of the contract, and (iii) external factors such as precipitation also affect the MWTA of producers.

Of particular importance to current program administrators and government agencies is the fact that for most producers, carbon credit program payments are too low. Our random parameters logit models indicates that the MWTA of a contract that enrolls 33% of a producer's crop land and spans 10-years will cost the program close to $76/acre/year where a shorter, 5-year contract indicates costs of $54/acre/year. Results for no-till for 66% of cropland enrolled will cost the program close to $4/acre more for a 10-year contract in comparison to 5-year contract. As current CCP offerings are $20-$36/acre/year for the use of both cover crop and no-till when soils have high carbon sequestration capacity, we find that sequestration of carbon in arid regions will likely be too expensive unless payments increase drastically. One possible solution to already low payment rates would be to use stacking of payments to boost the payments received by enrollees. A downfall of this solution is that it calls for coordination between CCPs and the

United States government to make sure that enrollment in both programs is functional and simple.

The results reiterated in the previous paragraph additionally indicate that large increases in price occur when producers must sign a 10-year contract in comparison to a 5-year contract. One way to possibly increase contract adoption is to offer smaller 3–5-year contracts in which premiums are offered for continued enrollment. This strategy would ensure permanence if the producer re-enrolls. A limitation of this method is that it leaves space for the producer to leave the program after a smaller amount of time and thus any payment received before leaving could result in negligible carbon sequestration.

We do find that certain areas have more producers with smaller MWTAs for enrollment in contracts which call for a larger quantity of acres or longer contract durations. As MWTA for contracts is much higher than current payments, one way to possibly lower the costs of program implementation and increase the quantity of acres enrolled is to focus contract offerings to regions with less cover crop limitations (i.e., more precipitation).

Our last finding indicates that producers in more arid regions are more likely to have higher MWTAs for CCP enrollment than regions with more precipitation. One exception to this result is that a large quantity of acreage in western Kansas can supplement water deficits using irrigation. These results are of specific use to companies offering CCPs as they indicate that regions with ample precipitation or irrigation capability could be targeted to increase enrolled acreage.

One limitation of this paper is that we do not account for the potential sequestration quantities of the soils in our sample. As the amount of carbon that can be sequestered in arid regions is less than more precipitous regions, it may be possible that increased MWTA and negligible sequestration could result in loss of income for both the producer and the CCP. Thus, the program would fail.

As both companies and the U.S. government push for carbon neutrality, continued work needs to focus on how CCP structure and offerings need to evolve to bridge the gap between the producer constraints and current contract offerings. This paper uses choice experiments to point out some of the initial problems, specifically low payments, contract length, and contractual constraints, but for widespread carbon sequestration and eventual carbon neutrality, continued work will be required.

Chapter 2 - Essay 2: Producer Response to Groundwater Quality Concerns: Are Concerned Producers Irrigating Less?

2.1 Introduction

Irrigation is used for crop production in arid regions to supplement soil moisture when growing season precipitation is insufficient. Due the internal combustion engine, center pivot irrigation developments, access to shallow groundwater aquifers and incentives to minimize soil-moisture deficits, irrigation has rapidly expanded in the northern plains adding to the productivity and profitability of the agricultural sector (Green and White, 2009; Hrozencik, 2022; Hrozencik and Aillery, 2022). Reflecting irrigation expansion in the northern plains, Kansas and Nebraska which overlie the High Plains (Ogallala) Aquifer are some of the most intensive users of US groundwater resources (USGS, n.d.).

The effectiveness of groundwater in fulfilling soil moisture deficits hinges on two factors: quality and quantity. Previous water use research on the High Plains Aquifer has focused on water conservation or specifically conservation of water quantities through various management strategies (e.g., Palazzo and Brozović, 2014; Riley et al., 2019; Ashwell, Peterson, and Hendricks, 2018; Merrill and Guilfoos, 2017). However, a much smaller amount of research focuses on water quality (e.g., Gardner, Sampson, and Presley, 2021; Lee and Hendricks., 2022). Reasons for the disparity in research could be that concerns over well yield or the amount of water in the aquifer are more widespread. For instance, Gardner, Sampson, and Presley (2021) find that over 50% of irrigators have a concern over well yield, while a smaller 33% have concern over water quality. Additionally, it takes many years for irrigators to perceive a decrease in water quality (Lee and Hendricks, 2022). A few of the reasons that conceptualization of water quality concerns takes a large amount include lack of testing and complications of water movement within the aquifer which make the quantification of water quality difficult (Gardner, Sampson, and Presley, 2021; Suarez, 1989).

Water quality degradation is a biproduct of agricultural intensification which causes salts to accumulate in the aquifer (Scanlon et al., 2007; 2012). As agricultural intensification continues, the dependence on the High Plains Aquifer for irrigation water is particularly problematic. Excessive groundwater pumping triggers aquifer depletion which can change the intrusion rate or flow patterns of salinity in the aquifer (Rubin, Young, and Buddemeier, 2001). Additionally, saline water and other pollutants including agricultural pesticides and chemicals enter the aquifer via runoff. These factors cause lands which are continually irrigated, poorly drained, and have natural salts present to develop soil salinity levels which hinder crop production (Ghassemi, Jakeman, and Nix, 1995). It has been estimated that 25% to 30% of irrigated farmland in the United States suffers yield reductions due to salts intrusion and these intrusions have caused billions of dollars in lost crop production (Ghassemi, Jakeman, and Nix, 1995).

Previous economic studies which have focused on groundwater quality use optimal control methods to map the optimal use of saline water, mathematical programming of optimal cropland changes, and calibration of crop-water production functions (Kan, Schwabe, and Knapp, 2002; Khan et al., 2008; Schwabe, Kan, and Knapp, 2006). The study most closely related to this paper is the work of Lee and Hendricks (2022), which uses a geo-referenced image file to empirically estimate the changes in groundwater use based on background water salinity.

We take a similar approach to Lee and Hendricks (2022) by estimating the effects of groundwater salinity on irrigation behavior; however, we use survey data on water salinity concerns and match past irrigation and cropping decisions to each respondent. Survey data collection is detailed in Gardner, Sampson, and Presley (2021) which estimated willingness to pay for an incremental increase in water quality and found that 33% of irrigators have “moderate” or “major” concern over water quality and that 16% of these producers have noted impacts of groundwater quality on crop choice.

Using survey responses, we can delineate between producers’ levels of well yield concern (water quantity) and water quality concerns giving us a unique dataset which builds on previous findings. Of particular interest is the fact that water salinity is highly heterogenous and local to specific wells (Whittemore, 2004). Thus, any interpolation technique used to estimate water salinity may mask well-level heterogeneity. By matching survey responses to field-level water use and cropping decisions, we can better account for water quality concerns that may be highly spatially resolved.

2.2 Background

The High Plains Aquifer spans eight states, but the largest portions overlie Texas, Kansas, and Nebraska (Figure 2.1). Producers typically apply groundwater to row crops including corn, soybeans, sorghum, alfalfa, and wheat (Lamm et al., 2012). On average, the aquifer supplies 3.5 million acre-feet of water to three million acres annually (Lanning-Rush, 2016). Due to overuse, water levels within some portions of the aquifer have dropped so low that producers have had to abandon their wells (Little, 2009). Haacker, Kendall, and Hyndman (2016) estimate that water use will not be possible in 20 to 30 years if irrigation continues at high rates.

From the quality standpoint, nitrogen and agricultural chemicals have entered the aquifer via leaching and runoff, lowering the quality of water within the aquifer (Gurdak et al., 2009). Additionally, the salt content of the aquifer has increased via intrusion of brackish waters via oil well drilling and water intrusion from the highly saline Arkansas river (Whittemore, 1995; 2000). At the well level, excessive pumping of groundwater leads to “saltwater upconing” or upward movements of saline water which have increased well salinity (Ma et al., 1997).

When concerns arise over water quality, producers have a handful of options. Two of these options relate directly to water use on the intensive margin: reducing irrigation intensity to limit the saline content of the soil or over applying irrigation to move salt past the root zone, defined as the ‘intrusion’ and ‘washing’ effects respectively by Lee and Hendricks (2022). Lee and Hendricks (2021) find that water use declines when moderate levels of salinity (i.e., moderate water quality) are present. At higher levels of salinity, they find that changes in water use are not statistically significant and attribute this to the “intrusion” and “washing” effects canceling each other out.

On the extensive margins two options are to increase or decrease the number of acres irrigated at each at each well. If the producer retracts irrigation acreage at a well, they could irrigate different portions of their acreage each year to mitigate salts intrusion. Previous results indicate that producers reduce their irrigated acreage when elevated levels of salinity are present (Lee and Hendricks, 2022). On the contrary, the producer could increase the number of acres at each well to compensate the yield declines caused by inferior water quality. The final option is to plant more salt tolerant crops. Of the common Kansas crops, corn and alfalfa happen to be the most water intensive and the most sensitive to soil and water salinity (Brouwer and Heibloem, 1986; Tanji and Neeltje, 2002).

Using this information, we hypothesize that the effects of water quality concern on the intensive margin are indeterminable due to confounding between intrusion and washing behavior. We additionally hypothesize that producers reduce acreage on the extensive margin when water quality concerns are present. Finally, we hypothesize that producers who indicated a change in crop choice due to water quality concerns plant less acreage in corn and alfalfa which also results in less water use.

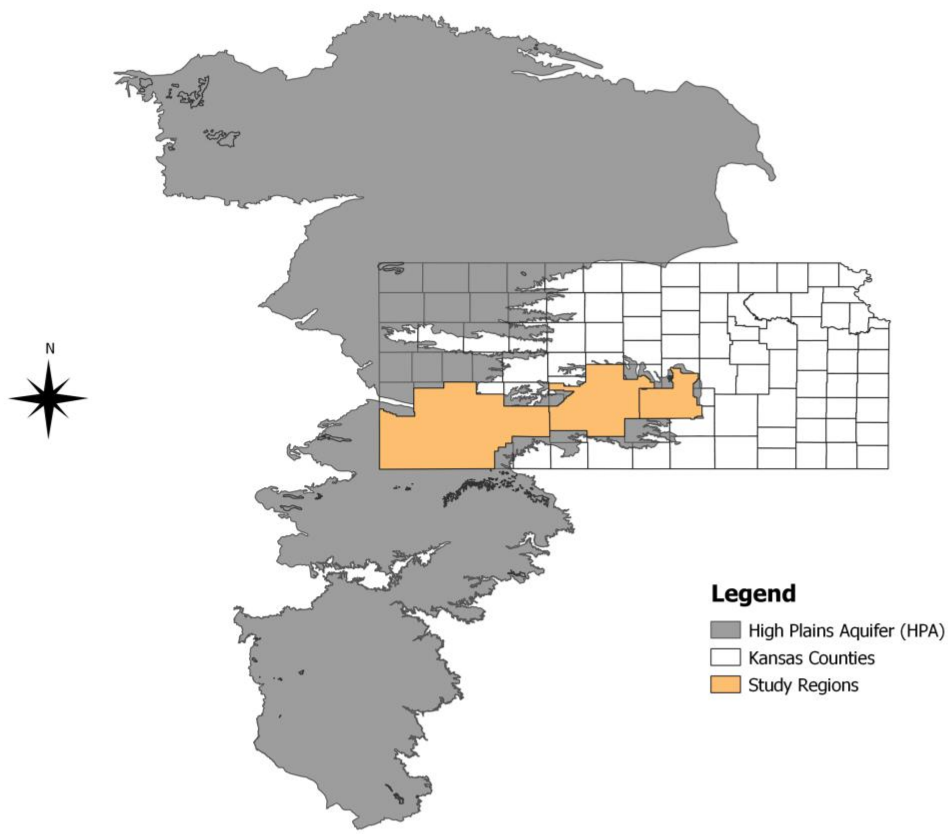

Figure 2.1 Study Locations in the High Plains Aquifer

2.3 Data

The data used in this analysis are obtained from multiple sources. Summary statistics can be found in Table 2.1. The details of each source are presented in sections 2.3.1-2.3.5.

2.3.1 Groundwater Salinity Concerns

The main variables of interest in this study are obtained from the survey used in Gardner, Sampson, and Presley (2021) to estimate WTP for improvements in groundwater quality. The main questions of interest asked, “To what extent are you concerned about irrigation water quality in your area?” and “To what extent are you concerned about well yield for irrigation wells in your area?” Response options were based on a 5-point Likert scale which included options for “not at all concerned,” “slightly concerned,” “somewhat concerned,” “moderately concerned,” and “very concerned.” To simplify regression results we aggregate the 5-point Likert scale responses for “slightly concerned” and “somewhat concerned” and form 4-point Likert scales which we deem no concern, minor concern, moderate concern, and major concern from this point forward. Figure 2.2 shows a histogram of respondent concerns and indicates that most respondents have no or minor concern over water quality while a much larger proportion have moderate or major concern over well yield.

The data from Gardner, Sampson, and Presley (2021) also includes information on whether water quality has affected yields or crop choice. However, we do not include responses in our main analysis because the impact of water quality on yields and crop choice is highly correlated with water quality concerns. We explore the effects of producer indications of changes in crop choice in Appendix B.

The survey data includes responses from 669 irrigators from three Kansas Groundwater Management Districts. Figure 2.2 indicates respondents which indicated concern over water

Table 2.1 Descriptive Statistics

Variable	Units	Obs.	Mean	Std. Dev.	Min	Max
Dependent Variables						
Total Water Application	Acre-Feet	17,752	141.18	122.11	0	819
Acres Irrigated	Acres	17,752	119.54	81.68	0	320
Irrigation Application	Inches/Acre	17,752	11.10	7.93	0	35.93
Independent Variables						
Well Yield Concern	1-4	17,752	2.64	1.03	1	4
Irrigation Quality Concern	1-4	17,752	2.25	0.94	1	4
Growing Season Water Deficit	inches	17,752	27.18	8.27	-1.92	46.79
Degree Days 10C-34	100 Degrees*days	17,752	23.66	1.34	19.24	27.52
Degree Days 34C and greater	Degrees*days	17,752	21.70	17.44	3.35	81.06
Soil Organic Carbon	Kg/meter^2	17,752	8.00	3.83	0.91	23.27
Saturated Hydraulic Conductivity (ksat)	μm/sec	17,752	18.86	24.60	0.32	111.79
pH Basic	0|1	17,752	0.60	0.49	0	1
Share of Acreage Planted in Corn	0-1	17,752	0.38	0.45	0	1
Share of Acreage Planted in Soybeans	0-1	17,752	0.10	0.28	0	1
Share of Acreage Planted in Wheat	0-1	17,752	0.08	0.21	0	1
Share of Acreage Planted in Alfalfa	0-1	17,752	0.03	0.17	0	1
Share of Acreage Planted in Sorghum	0-1	17,752	0.03	0.14	0	1
Share of Acreage Planted in Other	0-1	17,752	0.17	0.37	0	1
Lagged Corn Price	$/Bushel	17,752	4.81	1.43	3.41	7.84
Lagged Soybean Price	$/Bushel	17,752	11.45	2.35	8.08	15.93
Lagged Wheat Price	$/Bushel	17,752	6.17	1.62	3.41	8.33
Lagged Alfalfa Price	$/Bushel	17,752	4.49	1.24	2.75	6.76
Lagged Sorghum Price	$/Bushel	17,752	4.66	1.58	2.93	7.86
Dummy Variable Controls for Irrigation System						
LEPA	0-1	17,752	0.64	0.48	0	1
Center Pivot	0-1	17,752	0.06	0.24	0	1
Flood	0-1	17,752	0.03	0.16	0	1
Other	0-1	17,752	0.06	0.24	0	1

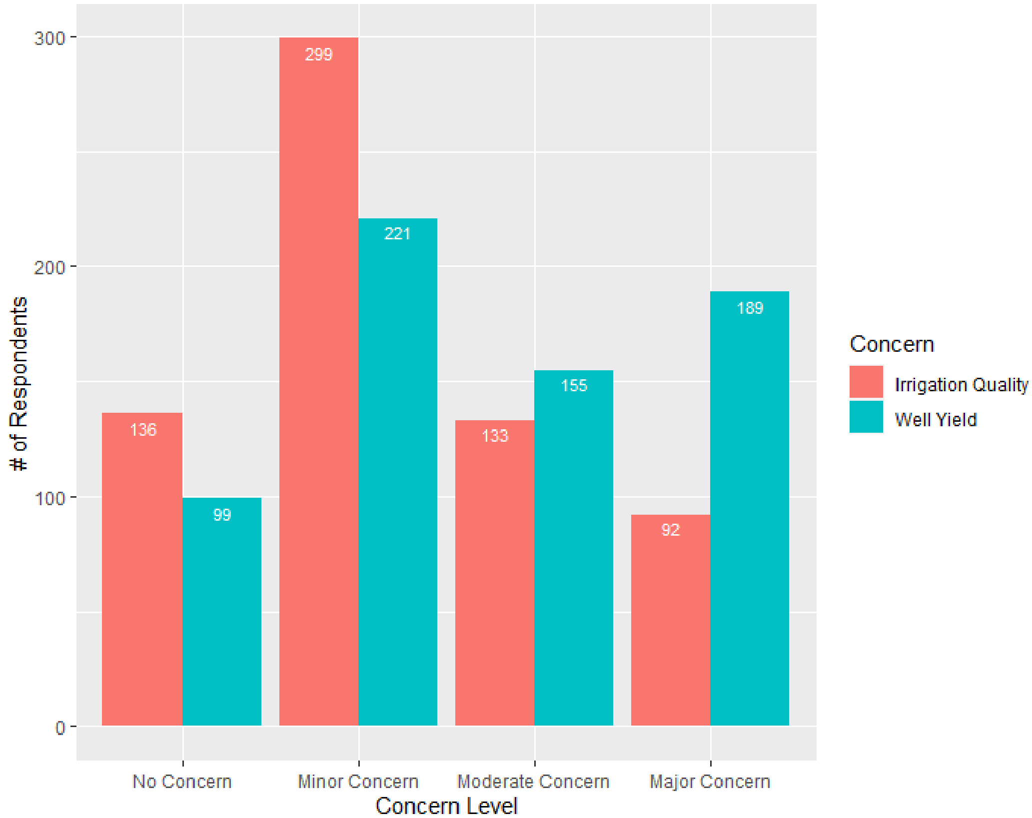

Figure 2.2 Histogram of Respondent Concerns

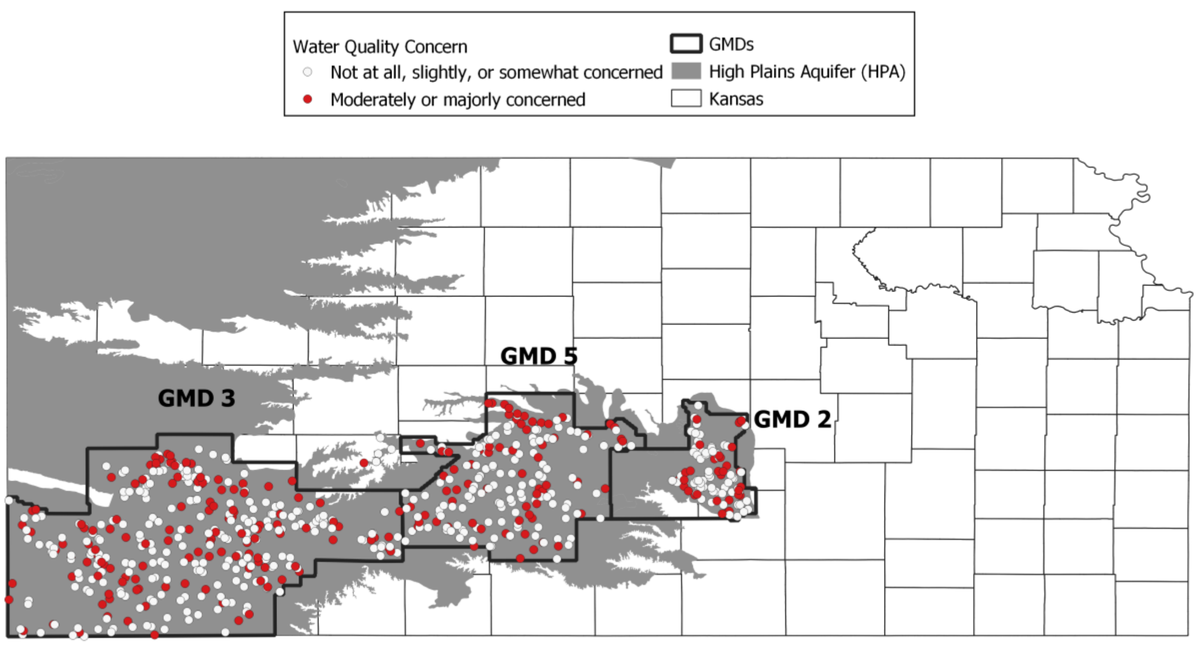

Figure 2.3 Location of Respondents Indicating Water Quality Concerns

quality. We can see that water quality concern by respondent is spatially heterogeneous which indicates the heterogeneity of salinity in the aquifer. The heterogeneity also indicates that interpolations of water quality indicators such as total dissolved solids or chlorine content to estimate salinity may not accurately capture concern over water quality at localized wells.

2.3.2 Irrigation, Water Use, and Crops

We obtain information on well location, irrigation water use, field size, cropping decisions, and irrigation technology for each survey respondent from the Water Information and Analysis System (WIMAS) of the Kansas Division of Water Resources. We use data on irrigated fields for the years 2009-2019 which includes 11 years of data prior to the Gardner, Sampson, and Presley (2021) survey. To prevent outliers from affecting our estimates, we drop observations where the number of acres irrigated by a well is greater than 0 and less than 40 (422 observations) and greater than 320 acres or two quarters sections (904 observations). We additionally drop estimates with over 3 acre-feet of water use per acre (27 observations). Typical field size for irrigated fields in Kansas is 160 acres (i.e., a quarter section) and 120-150 acres of each field is irrigated due to center pivot structures which do not irrigate field corners. Irrigation depth or the quantity of water applied to each acre and the number of acres irrigated at each well are taken directly from the WIMAS data set. After matching survey data by water right identification number, we have 17,752 observations on water use across the 11-year span.

The crops considered in our analysis are corn, soybeans, wheat, alfalfa, sorghum, and “other” which indicates crops which are outside of the five typical Kansas crops. If multiple crops are planted in a field, the WIMAS data set lists multiple crop types, but gives no indication of acreage for each crop. We thus assume that fields with multiple crop types split crops evenly and impute crop acreage by dividing the quantity of irrigated acres by n, the number of crops in the field. Using these assumptions, we further estimate the proportion of fields planted in each crop type.

We also use the information on irrigation systems in our analysis as water use efficiency varies widely by irrigation type. Each irrigation system is dummy coded to control the effects of each system on total water use, acres irrigated per well, and water applied per acre.

2.3.3 Climate

Daily gridded weather data for the growing season are linked to the irrigated fields in the WIMAS data. Climate data includes growing season water deficit which is calculated by subtracting growing season precipitation (April-September) from reference evapotranspiration, the number of growing degree days between 10°C and 34°C which indicates beneficial weather, and the number of growing degree days 34°C and greater which indicates detrimental weather. Degree days are calculated following Schlenker, Hanemann, and Fisher (2007) and growing season reference evapotranspiration is calculated following Hargreaves and Samani (1982).

2.3.4 Soils

We obtain soil characteristics which are likely to correlate with irrigation use and crop choice from the SSURGO soil survey of the USDA Natural Resources Conservation Service and matched to each irrigated field. In our analysis, we use data on saturated hydraulic conductivity (ksat) which indicates the speed at which water drains from the soil, soil organic carbon in the top 150 cm of the soil profile, and pH. Soil pH is dummy coded to acidic if pH is less than 5 and basic if greater than 7.5 (University of California, 2022). Results indicate no soils in our sample are acidic, so acidic soils are left out of each estimation and the basic soils indicator takes the value of 1 if the pH is basic.

2.3.5 Crop Price

Yearly crop price data are obtained from the National Agricultural Statistics Service for the five main crops planted in Kansas. Each price is measured in dollars per bushel and adjusted using CPI. We then lag crop price and use it in our crop acreage estimations.

2.4 Methodology

Following the work of Lee and Hendricks (2022) and Sampson, Al-Sudani, and Bergtold (2021), we conceptualize the total water use for well i in year t, as W_{it} which is determined by the number of irrigated acres and the water applied to each acre, N_{it} and A_{it} , as function of well yield concern (Y_i) and water quality concern (Q_i).

$$(2.1)\ W_{it} = N_{it}(Y_i, Q_i) \cdot A_{it}(Y_i, Q_i).$$

Totally differentiating Equation 2.1 with respect to each concern, we get equation 2.2.

$$(2.2)\ dW_{it} = \left[\frac{\partial N_{it}}{\partial Y_i}(Y_i, Q_i) \cdot A_{it}(Y_i, Q_i) + \frac{\partial A_{it}}{\partial Y_i}(Y_i, Q_i) \cdot N_{it}(Y_i, Q_i)\right] dY_i$$

$$+ \left[\frac{\partial N_{it}}{\partial Q_i}(Y_i, Q_i) \cdot A_{it}(Y_i, Q_i) + \frac{\partial A_{it}}{\partial Q_i}(Y_i, Q_i) \cdot N_{it}(Y_i, Q_i)\right] dQ_i$$

Holding one term constant and solving, we get equation 2.3 and 2.4 which can be broken into four parts: the effects of well yield concern and water quality concern on extensive margin which indicates changes in irrigated acreage due to each concern, and the effects of well yield concern and water quality concern on the intensive margin or changes in water application depth due to each concern.

$$(2.3) \quad \underbrace{\frac{dW_{it}}{dY_i}}_{\substack{\textit{Change in total water use} \\ \textit{due to well yield concern}}} = \underbrace{\frac{\partial N_{it}}{\partial Y_i}(Y_i, Q_i) \cdot A_{it}(Y_i, Q_i)}_{\substack{\textit{Change on the extensive} \\ \textit{margin due to} \\ \textit{well yield concern}}} + \underbrace{\frac{\partial A_{it}}{\partial Y_i}(Y_i, Q_i) \cdot N_{it}(Y_i, Q_i)}_{\substack{\textit{Change on the intensive} \\ \textit{margin due to} \\ \textit{well yield concern}}}$$

$$(2.4) \quad \underbrace{\frac{dW_{it}}{dQ_i}}_{\substack{\textit{Change in total water use} \\ \textit{due to water quality concern}}} = \underbrace{\frac{\partial N_{it}}{\partial Q_i}(Y_i, Q_i) \cdot A_{it}(Y_i, Q_i)}_{\substack{\textit{Change on the extensive} \\ \textit{margin due to} \\ \textit{water quality concern}}} + \underbrace{\frac{\partial A_{it}}{\partial Q_i}(Y_i, Q_i) \cdot N_{it}(Y_i, Q_i)}_{\substack{\textit{Change on the intensive} \\ \textit{margin due to} \\ \textit{water quality concern}}}$$

We estimate both margins separately with an estimation for the total margin, exploiting cross-sectional variation in water quality concerns across an 11-year period prior to survey responses. Our models compare total water use per well (acre-feet), acres irrigated per well, and irrigation intensity (inches/acre). Estimating equations for the total, extensive, and intensive margins respectively are:

$$(2.5)\ N_{it}A_{it} = \beta^{AN}Y_i + \mu^{AN}Q_i + \rho^{AN}x_{it} + \eta^{AN}S_i + \tau_t^{AN} + \lambda_C^{AN} + \varepsilon_{it}^{AN}$$

$$(2.6)\ N_{it} = \beta^{N}Y_i + \mu^{N}Q_i + \rho^{N}x_{it} + \eta^{N}S_i + \tau_t^{N} + \lambda_C^{N} + \varepsilon_{it}^{N}.$$

$$(2.7)\ A_{it} = \beta^{A}Y_i + \mu^{A}Q_i + \rho^{A}x_{it} + \eta^{A}S_i + \delta^{A}P_{it} + \tau_t^{A} + \lambda_C^{A} + \varepsilon_{it}^{A}$$

Where Y_i represents a vector of well capacity concern levels, Q_i represents a vector of water quality concern levels, and x_{it} represents a vector of field and irrigation characteristics which affect irrigated acreage or water application depth and vary through time. S_i represents soils characteristics which affect irrigated acreage or water application depth but are time invariant. P_{it} represents a vector of the proportions of each field planted to each crop type to control for the different crop water requirements. Year dummies, τ_t, are used to control for time-varying unobserved factors which may impact water uses such as input prices. County dummies (λ_C) are used to control for differences between counties that are not captured with our covariates and ε_{it} represents the error term. The remaining variables are parameters to be estimated.

We estimate each model as a cross-section and use Stata's "SUREG" command to estimate seemingly unrelated regression models which use a simultaneous variance-covariance matrix to correlate the error terms across equations. Identifying variation of water quality concerns is obtained from survey responses that differ within a county. One limitation of our empirical strategy is that we estimate water quality concern as fixed across the entire sample. Although water quality itself is changing over time and even fluctuates based on pumping decisions in a year, we assume that the concern level is constant across a ten-year span.

2.5 Results

2.5.1 Total, Extensive, and Intensive Margin Results

Table 2.2 reports the marginal effects of the simultaneous estimation of equations (2.5) – (2.7). Column 1 provides estimates for the total margin response (total water use). Columns 2 and 3 present estimates for the extensive and intensive margin. Each of the dummy coded concern variables are interpreted with respect to no concern.

Starting with the effect of well yield concern, we find that total water use decreases by 16.85 acre-feet per well when producers have major well yield concern. We find that most of the reduction in water use occurs due to less irrigated acreage on the extensive margin. When major well yield concern is present, producers irrigate 12.98 less acres on average. On the intensive margin, we obtain mixed results. We find that producers apply 0.38 less inches/acre of water when low well concern is present and 0.36 more inches/acre of water when moderate well concern is present. When major well concern occurs, water application depth is not statistically different from producers with no concern. These results indicate that irrigators adjust well yield concern by reducing the number of acres they irrigate at each well.

The effects of water quality concern on total water use indicate that producers with low concern over water quality irrigate 3.81 acre-feet less per well on the total margin and the effects of moderate water quality concern are not statistically different from no concern. Somewhat surprisingly, producers with major water quality concerns apply 11.40 acre-feet more water than producers with no concern. Again, looking to the extensive and intensive margin estimations we find that the increased water use is driven by increased acreage on the extensive margin. Producers with major water quality concerns irrigate 9.58 more acres per well on average, but intensive application is not significantly different from no concern.

In contrast, the effects of low concern on the extensive and intensive margin are not statistically different from no concern. At a level of moderate concern, we find producers water 6.32 more acres but reduce irrigation intensity by close to half an inch per acre, which results in the statistically insignificant effect on the total margin. The intensive margin results closely follow the results of Lee and Hendricks (2022) and indicate that producers lower irrigation intensity when moderate concern over water quality is present but low and major concern are not statistically different from no concern. Thus, producers irrigate the same quantity or slightly less which does not point to use of the “washing” or “waning” effects.

Table 2.3 lists the cumulative effects of water use for each unique combination of well yield and water quality concern. We find that water use on the total margin always decreases with the exception of producers who have no well yield concern and major water quality concern (which only occurs 3 times in the Gardner, Sampson, and Presley (2021) survey results). These results imply that well yield concerns cause a decrease in total water use but irrigation quality concern mitigates declines and could thus bias previous water demand estimations which do not control for water quality. We do find fluctuations in the signs of the coefficients on the extensive and intensive margin but increases in water use on either margin are canceled by a larger decrease in water use on the opposite margin.

The climate related covariates all have the expected sign and impact on water use on all margins. We find that growing season water deficit is positive and strongly significant on the total and intensive margin, but not significant on the extensive margin. We expect this to occur as larger water deficits should increase irrigation water use. Insignificance on the extensive margin is expected as contemporaneous weather should not affect the number of irrigated acres per well. The coefficients for beneficial growing degree days have the expected negative effect on irrigation water use and are statistically significant on all margins. As growing degree days are contemporaneous weather, we would not expect significance on the extensive margin. However, as the climate in Kansas is relatively consistent our estimation may be capturing effects that are indicative of yearly climate. On the total and extensive margin, detrimental degree days are not statistically different from zero and on the intensive margin the coefficient is positive and statistically significant as expected but is not economically significant.

The soil related covariates indicate that soil organic carbon which typically indicates water holding capacity indicate less water use on the extensive and intensive margin. Saturated hydraulic conductivity (ksat) has different effects on both margins. As ksat indicates soil permeability, soil with larger ksat needs more water. Looking at the direction of each coefficient, we do find the expected positive impact on the total and intensive margins. The negative sign on the extensive margin could indicate that producers irrigate less acreage when ksat is high because more intensive irrigation strategies are required. The indicator for basic pH indicates that basic pH values correlate with less water use on the intensive margin and a larger number of acres on the extensive margin which causes statistical insignificance on the total margin.

Table 2.2 Regression Results for Total, Extensive, and Intensive Margin

	Total Margin	Extensive Margin	Intensive Margin
Variables			
Well Yield Concern (WYC)			
Level 2	-15.16***	-7.79***	-0.38***
	(2.08)	(1.18)	(0.12)
Level 3	-11.92***	-13.49***	0.36***
	(2.26)	(1.29)	(0.13)
Level 4	-16.85***	-12.98***	-0.14
	(2.27)	(1.29)	(0.13)
Irrigation Quality Concern (IQC)			
Level 2	-3.81**	-0.79	-0.10
	(1.75)	(1.00)	(0.10)
Level 3	-0.65	6.32***	-0.49***
	(2.11)	(1.20)	(0.12)
Level 4	11.40***	9.58***	0.04
	(2.42)	(1.38)	(0.14)
Growing Season Water Deficit	1.51***	-0.12	0.14***
	(0.19)	(0.11)	(0.01)
Degree Days 10C-34C	-3.05***	-0.61***	-0.23***
	(0.19)	(0.18)	(0.02)
Degree Days 34C and above	-0.02	0.09	0.02*
	(0.19)	(0.11)	(0.01)
Soil Organic Carbon (0-150 cm)	-0.26	-0.62***	0.03**
	(0.22)	(0.12)	(0.01)
Saturated Hydraulic Conductivity	0.10***	-0.15***	0.02***
(ksat)	(0.03)	(0.02)	(0.002)
Basic pH	3.04	7.14***	-0.39***
	(2.11)	(1.20)	(0.12)
LEPA	171.37***	150.17***	12.22***
	(1.60)	(0.91)	(0.12)
Center Pivot	162.29***	149.27***	11.65***
	(2.77)	(1.58)	(0.18)
Flood	143.28***	122.58***	12.94***
	(4.03)	(2.29)	(0.24)
Other System	176.84***	158.37***	11.80***
	(2.84)	(1.62)	(0.18)

Table 2.2 Continued

Corn Share			1.90***
			(0.09)
Soybean Share			1.37***
			(0.11)
Alfalfa Share			2.39***
			(0.13)
Sorghum Share			0.06
			(0.15)
Other Crops Share			1.08***
			(0.09)
Controls			
Year Dummies	Yes	Yes	Yes
County Dummies	Yes	Yes	Yes
	17,752	17,752	17,752

Table 2.3 Changes in Water Use at Each Level of Well Yield and Water Quality Concern

Level WYC, IQC	Total Margin	Extensive Margin	Intensive Margin	Number of Observations
Base Case	0	0	0	59
Level 1, 2	-3.81**	-0.78	-0.10	31
	(1.75)	(1.00)	(0.10)	
Level 1, 3	-0.65	6.32***	-0.49***	5
	(2.11)	(1.20)	(0.12)	
Level 1, 4	11.40***	9.58***	0.04	3
	(2.42)	(1.38)	(0.14)	
Level 2, 1	-15.16***	-7.79***	-0.38***	37
	(2.08)	(1.18)	(0.12)	
Level 2,2	-18.97***	-8.57***	-0.48***	140
	(2.20)	(1.25)	(0.13)	
Level 2,3	-15.81***	-1.46	-0.87***	32
	(2.57)	(1.46)	(0.15)	
Level 2,4	-3.67	1.79	-0.33**	11
	(2.86)	(1.63)	(0.16)	
Level 3,1	-11.92***	-13.49***	0.36***	19
	(2.26)	(1.29)	(0.13)	
Level 3,2	-15.73***	-14.27***	0.26*	69
	(2.39)	(1.36)	(0.14)	
Level 3,3	-12.57***	-7.16***	-0.13	51
	(2.44)	(1.39)	(0.14)	
Level 3,4	-0.52	-3.90**	0.41**	15
	(2.83)	(1.61)	(0.16)	
Level 4,1	-16.85***	-12.98***	-0.14	21
	(2.27)	(1.29)	(0.13)	
Level 4,2	-20.67***	-13.77***	-0.24*	58
	(2.45)	(1.39)	(0.14)	
Level 4,3	-17.51***	-6.66***	-0.63***	45
	(2.49)	(1.42)	(0.14)	
Level 4,4	-5.46**	-3.40**	-0.09	62
	(2.53)	(1.44)	(0.15)	

The coefficients on the dummy variables for irrigation technology control for the average application rate and acres irrigated under each system with respect to fallowed acres (acres in which irrigation was possible but not used). Unsurprisingly a center pivot and LEPA system are less than 160 acres (a quarter section) and typically apply a similar amount of water. Flood irrigation is typically used on smaller acreages and more water is applied per acre. Other systems cover more acreage and apply quantities of water between a center pivot and a LEPA but are the most water intensive irrigation type.

The coefficients on crop shares which are only used in the intensive margin estimation control the quantity of water applied to each crop in comparison to wheat. Insignificance on sorghum indicates that producers apply the same amount of water to sorghum and wheat. The other coefficients indicate that the most water intensive crop is alfalfa which is followed by corn, soybeans, and other crops.

2.5.2 Crop Choice Estimation

To look more closely at crop choice, we estimate seemingly unrelated regressions of crop share percentage for the five main Kansas crops using the same water use concerns and covariates as the previous estimations in Table 2.2. We additionally add covariates for lagged crop price. The dependent variables are measured in percentage of land to normalize for field size. Results are found in Table 2.4.

The covariates follow much of the same pattern as our previous regressions. Surprisingly, we find that the coefficient on corn price is negative but insignificant. The remaining price variables are positive and significant at the 1% level with the exception of sorghum price which is negative and moderately significant. This indicates that corn is the main crop implemented on irrigated fields due to its high-water demand. As corn is implemented more often in crop rotation on irrigated cropland, our results likely indicate that that the proportion of corn planted is affected by the price of other crops rather than the price of corn itself. The main crop with the lowest quantity of acres in our sample is sorghum. Combining this information with the negative price coefficient, we speculate that producers only plant sorghum on irrigated acreage under certain, unknown conditions and thus price is not a factor in sorghum planting decisions.

Focusing on changes in crops, we do not find that changes in water quality indicate a smaller proportion of each field is planted in corn or alfalfa as both coefficients for major concern are not statistically different from no concern. We do find that producers with major water quality concern plant less sorghum on average in their rotation, but this finding is not intuitive to changes in crop choice as sorghum is resilient to salinity and uses less water than other crops. As our dependent variables measure the proportion of each field planted in each crop type and producers with major water quality concerns plant more acres on the extensive margin, results indicate that producers with quality concerns are planting the same proportion of each crop type and thus planting more acres of each crop type on average. The effects of major well yield concern indicate that producers plant a smaller proportion of their acreage in corn and more in sorghum which relates to crop water demand.

It is worth noting that the estimation of changes in crop type is strongly based on our assumption that irrigated acreage is evenly split by the number of *n* crops in each field. Thus, our estimates of the effects of each concern level on crop type are biased. Using corn as an example, if more corn is planted in each field than we calculate using our assumptions, we would overestimate the effects of each level of concern on the proportion of land planted in corn. Oppositely, a smaller proportion of land planted in corn would bias estimates downward. It is difficult to span this line of thinking across each crop type as over- or underestimation of proportions would result in the opposite effect on other crops. Although we find no average effect of water quality concern on crop choice, we do use the responses on whether water quality has affected crop choice to further explore changes in crop type in Appendix B.

Table 2.4 Regression Results for Crop Choice

Variable	Corn	Soybean	Wheat	Sorghum	Alfalfa
Well Yield Concern					
Level 2	0.84	-2.14***	-2.05***	1.19***	-2.51***
	(1.03)	(0.68)	(0.51)	(0.36)	(0.42)
Level 3	4.85***	-0.49	-1.40**	0.23	-0.80*
	(1.12)	(0.74)	(0.55)	(0.39)	(0.45)
Level 4	-2.95***	0.28	-0.51	1.53***	-0.42
	(1.12)	(0.75)	(0.56)	(0.39)	(0.46)
Irrigation Quality Concern					
Level 2	-4.98***	2.91***	-0.16	-0.34	2.46***
	(0.87)	(0.57)	(0.43)	(0.30)	(0.35)
Level 3	-4.47***	0.18	-0.30	0.26	0.71*
	(1.05)	(0.70)	(0.52)	(0.36)	(0.42)
Level 4	-1.36	1.17	0.05	-1.13***	0.14
	(1.20)	(0.79)	(0.59)	(0.42)	(0.48)
Growing Season Water Deficit	-0.11	0.001	0.05	-0.02	0.01
	(0.09)	(0.06)	(0.05)	(0.03)	(0.04)
Degree Days 10C-34C	0.78	-1.29**	-1.68***	0.81***	-1.13***
	(0.90)	(0.60)	(0.45)	(0.31)	(0.36)
Degree Days 34C and above	-0.04	0.10	0.07	0.001	0.11***
	(0.10)	(0.07)	(0.05)	(0.04)	(0.04)
Soil Organic Carbon (0-150 cm)	-0.19*	-0.17**	-0.09	-0.004	0.24***
	(0.11)	(0.07)	(0.05)	(0.04)	(0.04)
Saturated Hydraulic Conductivity (ksat)	-0.18***	-0.08***	-0.03***	0.003	0.18***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Basic pH	-0.71	-1.68**	1.40***	1.42***	0.19
	(1.04)	(0.69)	(0.52)	(0.36)	(0.42)
LEPA	47.55***	11.01***	11.06***	3.79***	4.86***
	(0.79)	(0.53)	(0.39)	(0.28)	(0.32)
Center Pivot	43.16***	12.92***	15.24***	5.78***	6.62***
	(1.37)	(0.91)	(0.68)	(0.48)	(0.56)
Flood	41.96***	16.62***	11.51***	5.78***	4.34***
	(2.00)	(1.33)	(0.99)	(0.70)	(0.81)
Other System	38.06***	10.30***	11.41***	3.42***	3.88***
	(1.41)	(0.94)	(0.70)	(0.49)	(0.57)

Table 2.4 Continued

Lagged Corn Price	-1.27				
	(3.83)				
Lagged Soybean Price		3.60***			
		(1.12)			
Lagged Wheat Price			4.27***		
			(1.13)		
Lagged Sorghum Price				-4.17**	
				(1.67)	
Lagged Alfalfa Price					3.70**
					(1.85)
Year Dummies	Yes	Yes	Yes	Yes	Yes
County Dummies	Yes	Yes	Yes	Yes	Yes
Observations	17,752	17,752	17,752	17,752	17,752

2.5.3 Potential Endogeneity of Acres Irrigated

There are potential endogeneity concerns in our analysis as we find that major water quality concerns coincide with close to ten more acres of irrigation at each well. This result could indicate reverse causality as producers with a larger number of acres per well could capitalize a larger decrease to their bottom line when water quality degradation occurs. In this situation, our estimates would be biased.

To determine if reverse causality is occurring, we look at how producers with the largest level of water quality concern have tested their well water quality or noted an impact of water quality on yield. We find that 53 of the 92 producers that noted major concern over water quality have tested their wells in the last 10 years and an additional 24 which have not tested noted a moderate or major impact of water quality on crop yields. In total we find that 84% of our producers with major concern over water quality noted a reason for the concern that does not pertain to irrigated acreage.

Taking a more robust approach and focusing on testing only, we compare the samples of producers with major concern over water quality who have tested their wells with those who have not. To do this, we compare the sample averages of each producer's maximum field size. We use maximum field size as it captures more heterogeneity in the quantity of acres irrigated than comparing the mean of means. Findings indicate that producers with a major concern over water quality that have tested their wells have an average maximum field size of 200 acres where producers who have not tested have an average maximum field size of 196 acres. Additionally, a two-sample t-test implies the samples are not statistically different. Thus, we conclude that reverse causality between acres irrigated and major water quality concern is minimal.

2.6 Conclusions

In this paper we find that retractions in water use occur due to well yield concern; however, producers with major water quality concern apply 11.40 more acre-feet of water per well. Water quality concerns indicate additional application of water is driven by irrigation application on a larger number of acres at each well. Interestingly, we find no evidence that water quality concerns affect crop choice as producers with major water quality concern plant the same proportion of acreage in corn and alfalfa as producers with no concern.

We additionally find no evidence that producers are using a "washing" or "waning" effect to control the effects of water quality on their irrigated acreage. As the intensive margin estimation for water quality concern results in changes of less than half an inch when statistically significant or is not statistically different from no concern, we conclude irrigation changes due to water quality on the intensive margin are indeterminable. If the washing or waning effects were occurring, we would see larger, consistent increases in water use per acre.

This study gives useful insight and increments the groundwater use literature when water quality concerns are present. Past studies have looked at the effects of changes in saturated thickness and thus well yield or water salinity separately; however, by using groundwater concerns we are able to distinguish between the effects of each concern. Additionally, we are more likely to find highly local, well level effects as concerns are noted by the producers rather than an interpolation.

One limitation of our strategy and the significance of results is that changes in water quality may be too local to capture at the producer level. As we have no way to identify wells which are causing water quality concern, we have to merge survey responses to every well operated by a producer. Producers typically operate multiple wells and if water quality concern arises at a single well, changes in irrigation use are likely to occur only at that well. Thus, null results for irrigation intensity and crop choice could be caused by our inability to identify wells with quality concerns. Although we find that producers with water quality concern are irrigating a larger number of acres on the extensive margin, this could be driven by larger acreages on wells without quality concern. One way a producer could compensate yield losses due to water quality is to expand irrigation on wells without quality issues. Additionally, producers could be adapting to declines in water quality by using strategies which we cannot control for with our data. One example could be over application of inputs to make up for yield declines.

Even with the limitations, we find evidence that not including variables for water quality in water use demand estimation may be biasing estimates on the extensive margin. Major well yield concerns correlate with a smaller irrigated acreage and major water quality concerns correlate with a larger irrigated acreage which could bias previous estimates if water quality issues were present and not controlled for.

As intensive agriculture and continued draining of the High Plains Aquifer continues, we will see continued degradation of water quality. To account for these effects, we need ways to measure water quality at the well level. Well level estimates would allow us to empirically estimate the effects of water quality degradation on irrigators water use decisions and increase the longevity of the High Plains Aquifer.

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Appendix A - Cover Crop and No-Till Adoption: What Affects Willingness to Accept of Cover Crop and No-Till Contracts?

Appendix A contains supplementary material for Essay 1, "Cover Crop and No-till Adoption: What Affects Willingness to Accept of Cover Crop and No-Till Contracts?", that is referenced in the main text as well as additional information captured in the survey. The appendix has four sections listed below:

Section 1: Additional Charts Referenced in the Text.

Section 2: Additional Charts and Survey Descriptive Information

Section 3: Full Choice Sets for Choice Experiments

Section 4: Random Parameters Logit Model Results

Appendix A, Section 1: Additional Charts Referenced in the Text

This section is used to further discuss additional information disclosed in the main text. The additional information in this section provides more context on Kansas background as well as survey descriptive statistics.

We start by using boxplots to visualize the proportion of each farm devoted to cover crop and no-till by district. To make these plots we used three survey questions. The first question asked for the size of operation. Response options were based on quarter sections. The second question asked for the percentage of cropland on the producer's operation which utilizes cover crop and no-till. We estimate cover crop and no-till acres by multiplying each farm size response by the respective proportion of land utilizing of cover crop and no-till. The estimates are likely biased downward as the max farm size allowed in our survey is 1,920 acres.

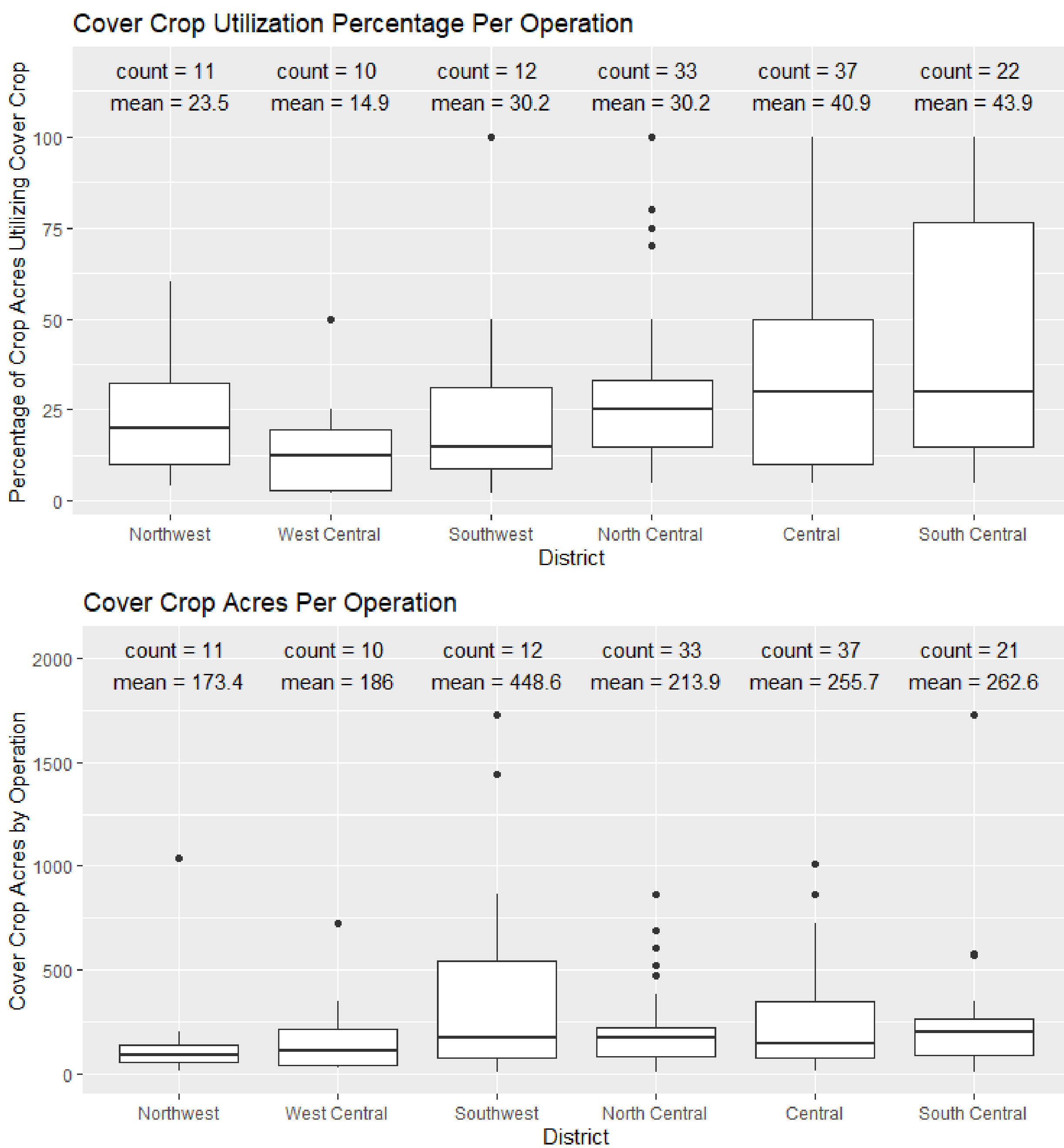

Figure A.1 Cover Crop Utilization by District

Figure A.1 indicates that a larger proportion of cover crop use occurs in the central regions. We do not find significant differences in the average number of acres using cover crop. This is result is likely due to the response options used in our farm size question. The Southwest is estimated to have the largest number of acres; however, this is likely driven by multiple farms which cover crop 100% of their acreage.

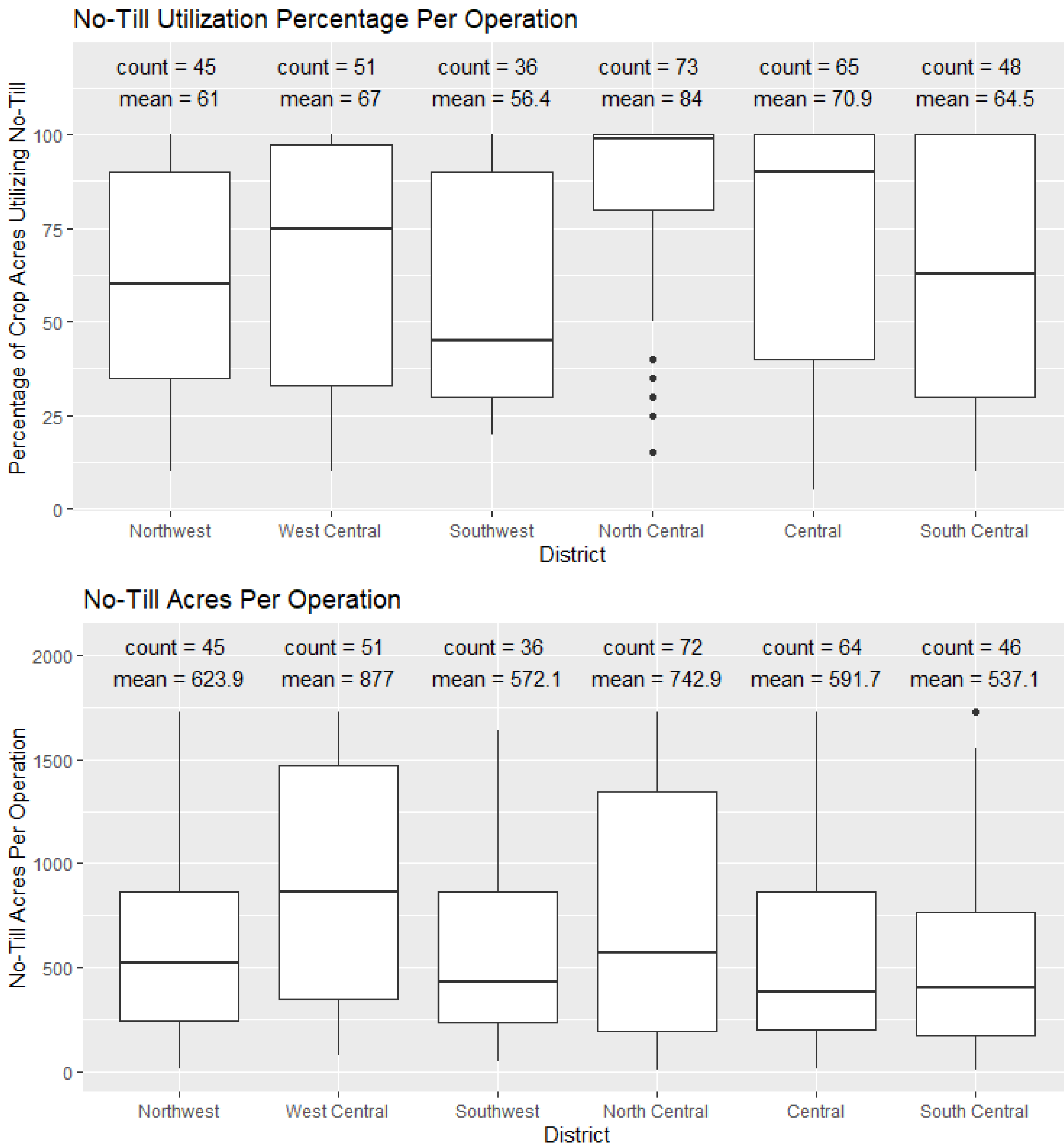

Figure A.2 No-Till Utilization by District

Figure A.2 indicates that no-till use occurs at much higher rates than cover crop, specifically in the more northern and central regions.

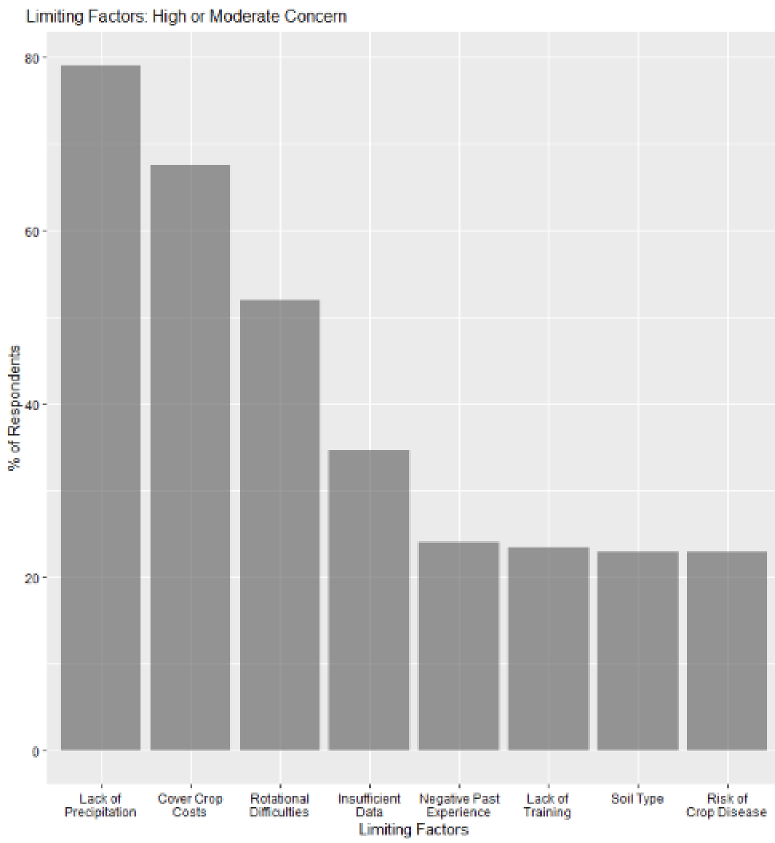

Figure A.3 Cover Crop Limitations

Figure A.3 indicates cover crop limitations which are discussed heavily in the main text.

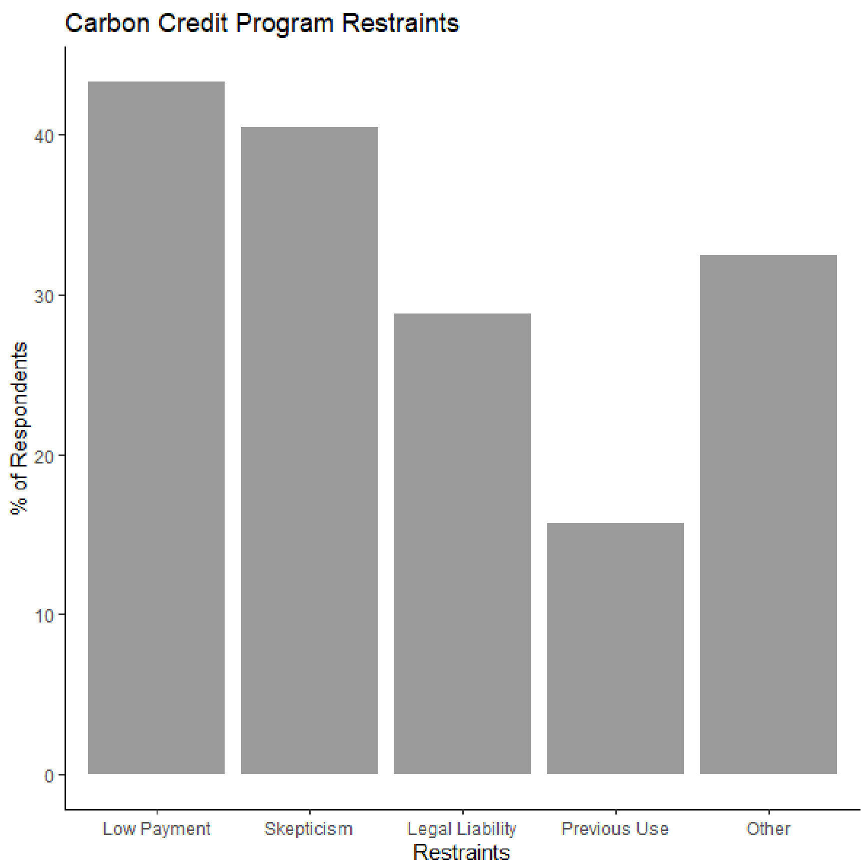

Figure A.4 Carbon Credit Program Restraints

Figure A.4 indicates that carbon credit restraints for our sample follow that of Thompson et al. (2021). The largest percentage of respondents indicated concern over low payments and skepticism of program viability.

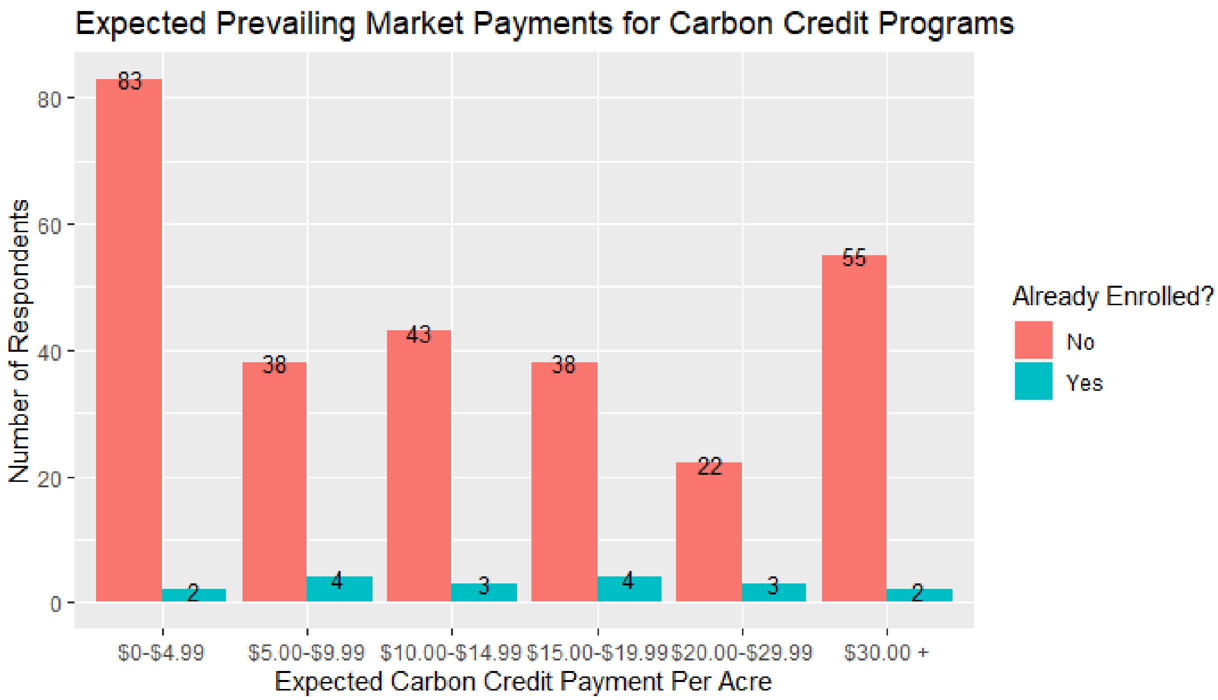

Figure A.5 Expected Carbon Credit Payment by Enrollment

Figure A.5 indicates that most producers expect payments under $15 per acre for participating in a CCP. Interestingly, we see a wide range of payments for the respondents which have already adopted. This result may indicate that payments by program largely differ.

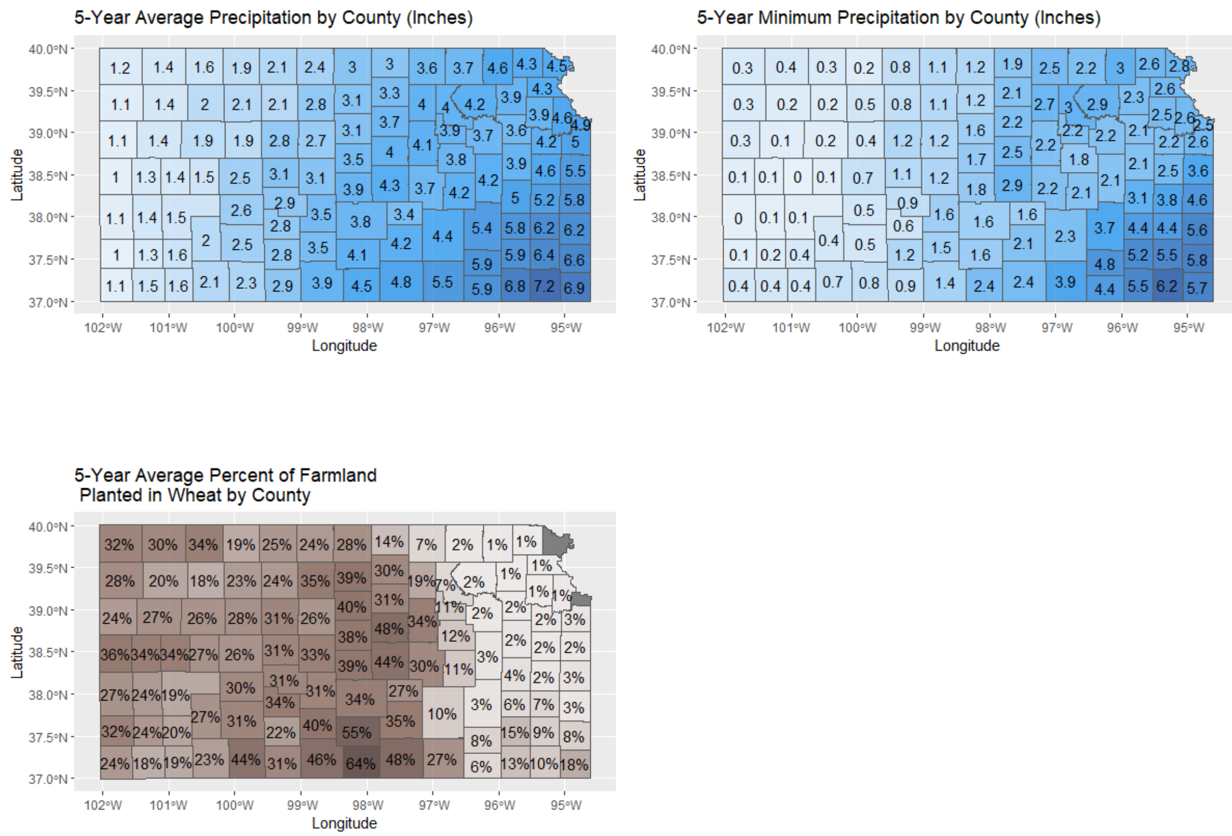

Figure A.6 Spatial Heterogeneity of Precipitation and Wheat Planting

Mapping 5-year average precipitation and 5-year minimum precipitation for the months of October and November, the crucial months for developing a cover crop stand (Gaudlip et al., 2019), we see drastic changes from east to west which coincide with the results of Figure 1.3. Many of the western counties have received less than 0.5”, the required amount of precipitation for cover crop emergence, at least once in the past 5 years. Drastic changes also occur in wheat planting which is more common in the western and central regions. Results indicate possible heterogeneous effects of crop rotation difficulties on cover crop and no-till adoption. Almost no wheat production occurs in the northeast which follows cropping patterns more closely related to the eastern corn belt.

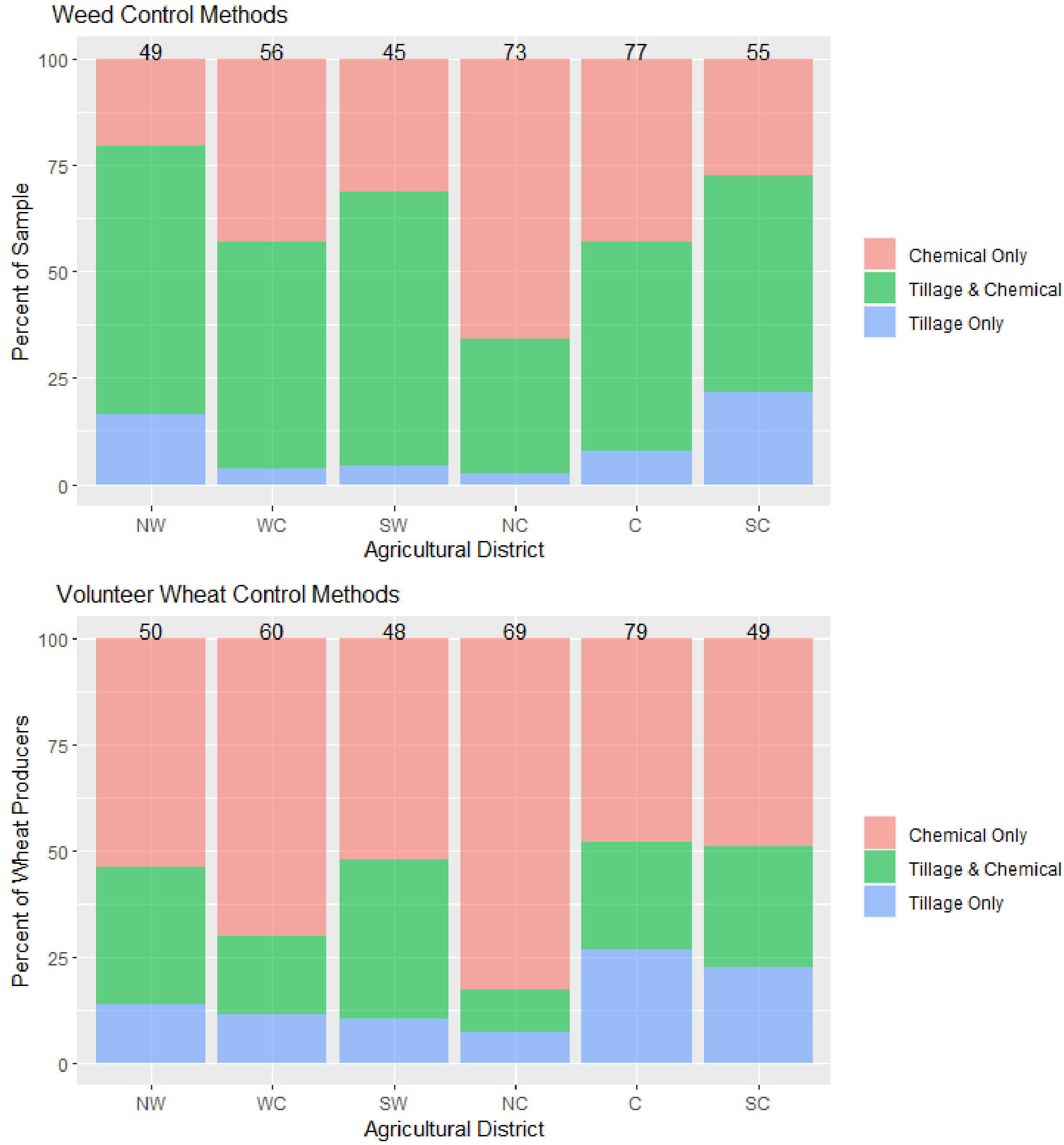

Figure A.7 Weed and Volunteer Wheat Control Methods

Figure A.7 indicates that most of the respondents in our sample use a combination of tillage and chemical to control weeds. The largest portions of chemical only applications, which are indicative of no-till, occur in the North Central and Central districts. The percentages of tillage used to control volunteer wheat is small in most regions, indicating volunteer wheat is controllable with chemical and that wheat planting may have a small impact no-till adoption.

Appendix A, Section 2: Additional Charts and Survey Information

Section 2 of Appendix A discusses charts and information provided by recipients which were not discussed in the text. The results are deemed interesting and applicable to the project but do not add to the discussion in the paper. We first cover government program enrollment and then cover the expected and experienced adoption costs of cover crop and no-till. We finish this section by looking at adoption rates of cover crop and no-till through time.

One question in our survey asked if the producer is or has been involved in government contracts. Government contracts operate similarly to carbon credit contracts and acceptance may signal producers which are less constrained by contractual agreements. Of the 299 respondents that answered the question, the Conservation Reserve Program (CRP) was the most popular with 235 enrollees. This was followed by 120 and 77 respondents receiving payments from the Environmental Quality Incentives Program (EQIP) and the Conservation Stewardship Program (CSP) respectively.

Figure A.8 indicates that most producers who have already adopted cover crop primarily believe cover crop planting costs fall between $20.00 and $50.00 per acre. On the other hand, perceived cost for non-adopters is inconclusive. The largest bin indicates that a sizable portion of non-adopters believe they could adopt cover crops for $0-$10 per acre. However, 48 respondents indicated cost larger than $50 per acre.

Results of no-till costs indicate no-till adoption costs more than $10 per acre. This is heavily lead by producers that have already adopted and is reciprocated by producers that have not adopted. On the opposite end of the spectrum, around 50 respondents each noted that no-till adoption would cost $5-$10 per acre or that no-till is less expensive than tillage.

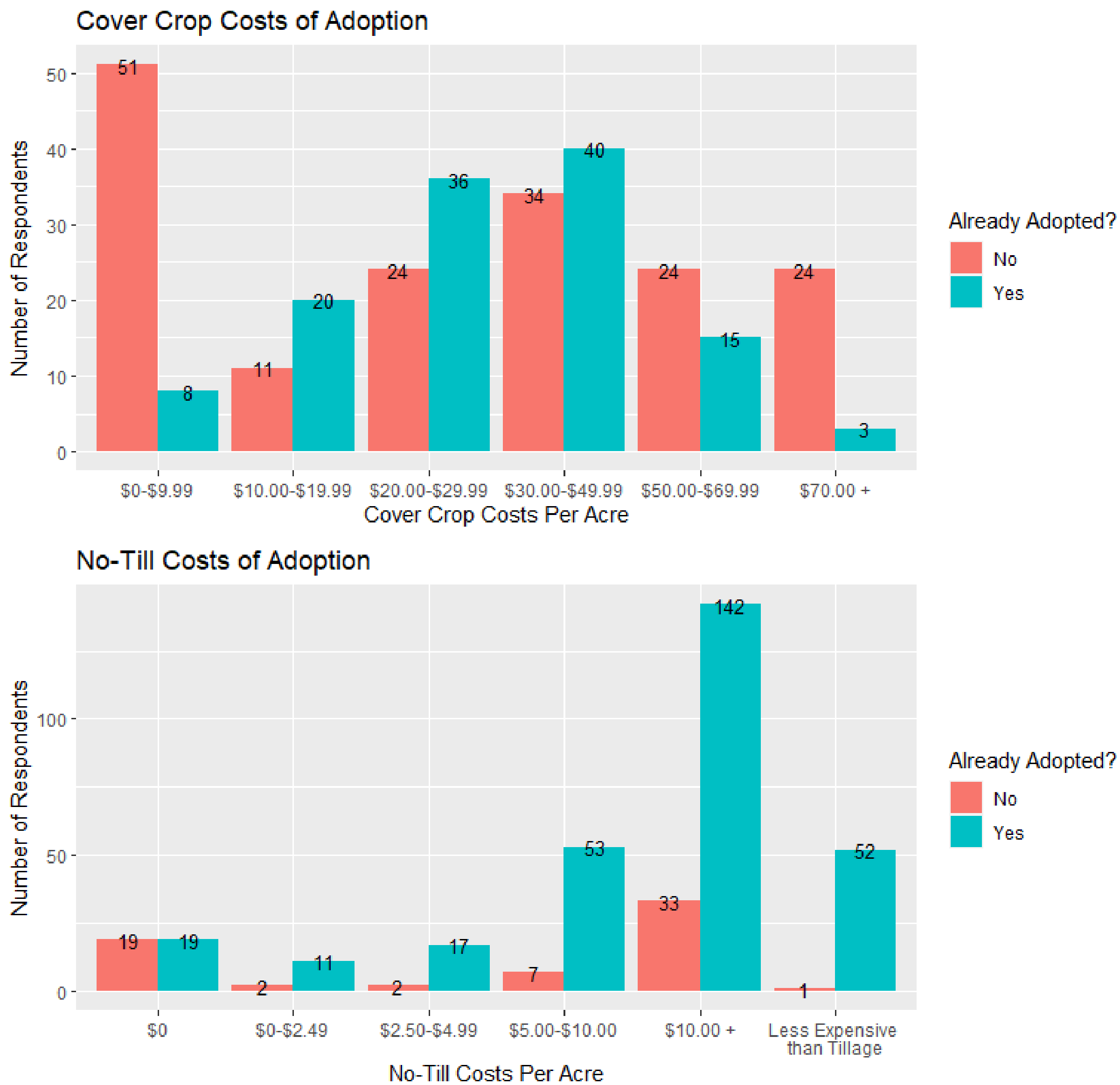

Figure A.8 Adoption Costs by Practice and Adoption Status

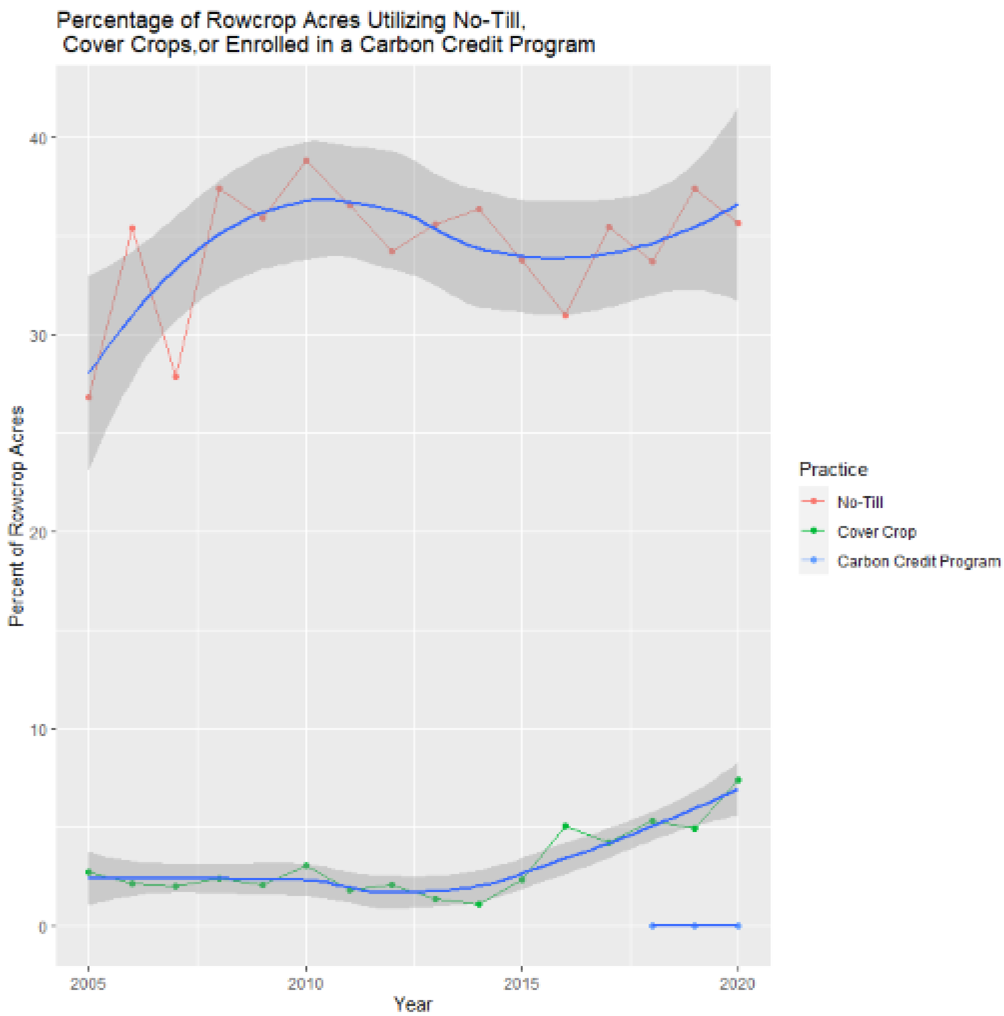

Figure A.9 Adoption Rates for Western and Central District by Year

We graph adoption curves in Figure A.9 by combining data from our survey on CCP adoption and data from the Operational Tillage Information System (OpTIS) developed by Dagan Inc.®. Results show the adoption rates for our entire sample. As enrollment rates of CCP are not publicly available, we estimate enrollment numbers by calculating the number of acres which use no-till and cover crop for each respondent enrolled in a carbon credit program. We then estimate adoption rates by spreading the number of acres enrolled evenly across the years CCPs have been available. Adoption rates for cover crop and no-till adoption are calculated using the OpTIS data.

The adoption trends indicate that no-till adoption may have stagnated in Kansas. The convex hump likely depicts disadoption which is pointed out by Sawadgo and Plastina (2022). Cover crop adoption trends indicate that the percentage of acres utilizing cover crop has increased by ~0.5% per year since 2013. Conversely, we estimate the percentage of carbon credit enrollees to be between 0% and 1%.

Appendix A, Section 3: Full Choice Sets for Choice Experiments

Table A.1 Full Choice Sets for Cover Crop Choice Experiment

Attributes	Contract A	Contract B	Option C
Block 1			
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	1 Year 100% $60.00	10 Years 66% $24.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 33% $60.00	1 Year 100% $36.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 33% $18.00	5 Years 66% $18.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	1 Year 100% $6.00	1 Year 100% $18.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 33% $6.00	10 Years 66% $36.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 66% $36.00	1 Year 66% $6.00	I would not accept Contract A or Contract B

Table A.2 Continued

Block 2			
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 100% $36.00	5 Years 33% $36.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 66% $60.00	10 Years 33% $18.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 66% $24.00	10 Years 66% $18.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	1 Year 33% $36.00	10 Years 100% $60.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 100% $24.00	1 Year 33% $60.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	1 Year 66% $18.00	1 Year 33% $36.00	I would not accept Contract A or Contract B
Block 3			
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	1 Year 33% $24.00	5 Years 33% $6.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 66% $24.00	5 Years 100% $24.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 33% $6.00	1 Year 33% $24.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 100% $18.00	10 Years 100% $6.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 66% $6.00	5 Years 66% $60.00	I would not accept Contract A or Contract B

Table A.3 Full Choice Sets for No-Till Choice Experiment

Attributes	Contract A	Contract B	Option C
Block 1			
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 66% $6.00	5 Years 100% $6.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 66% $12.00	10 Years 33% $3.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 66% $9.00	1 Year 66% $1.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 66% $6.00	10 Years 66% $3.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	1 Year 100% $1.00	1 Year 100% $3.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 33% $1.00	10 Years 66% $9.00	I would not accept Contract A or Contract B

Table A.3 Continued

Block 2			
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	1 Year 33% $9.00	10 Years 100% $12.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	1 Year 66% $3.00	1 Year 33% $9.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	1 Year 33% $6.00	5 Years 33% $1.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 33% $3.00	5 Years 66% $3.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 100% $3.00	10 Years 100% $1.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	5 Years 100% $6.00	1 Year 33% $12.00	I would not accept Contract A or Contract B
Block 3			
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 100% $9.00	5 Years 33% $9.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 33% $1.00	1 Year 33% $6.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 66% $1.00	5 Years 66% $12.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	1 Year 100% $12.00	10 Years 66% $6.00	I would not accept Contract A or Contract B
Length of Contract **Portion of Acreage to Enroll** **Payment $/Acre/Year**	10 Years 33% $12.00	1 Year 100% $9.00	I would not accept Contract A or Contract B

Appendix A, Section 4: Random Parameters Logit Results

Table A.4 Random Parameters Logit Estimation Results

Variable	**Cover Crop** Coefficients (Standard Error)	**No-Till** Coefficients (Standard Error)
Random Parameters		
33% of Cropland	0.01	-1.32***
	(0.18)	(0.25)
66% of Cropland	-1.04***	-1.02***
	(0.27)	(0.35)
100% of Cropland	-3.60***	-2.76***
	(0.43)	(0.43)
5-Year Contract	-0.88***	-0.56
	(0.26)	(0.35)
10-Year Contract	-3.04***	-2.56***
	(0.49)	(0.42)
Nonrandom Parameters		
Payment	0.10***	0.51***
	(0.01)	(0.05)
Distributions of Random Parameters (Std.Dev)		
33% of Cropland	1.56***	1.66***
	(0.26)	(0.24)
66% of Cropland	1.59***	1.52***
	(0.28)	(0.34)
100% of Cropland	2.98***	3.04***
	(0.33)	(0.39)
5-Year Contract	1.38***	1.25*
	(0.38)	(0.71)
10-Year Contract	3.19***	2.38***
	(3.19)	(0.43)
Statistics on Fit and Observations		
Log Likelihood	-1085.34	-1308.22
Restricted Log Likelihood	-2104.94	-2087.36
McFadden Pseudo R-Squared	0.48	0.37
AIC	2192.7	2636.4
Halton Draws	500	500
N (Choice Situations)	1916	1900
Panels (Respondents)	343	341

Appendix B - Producer Response to Groundwater Quality Concerns: Are Concerned Producers Irrigating Less?

Appendix B contains two sections which supply supplemental information to Essay 2, "Producer Response to Groundwater Quality Concerns: Are Concerned Producers Irrigating Less?" The two sections are:

Section 1: Marginal Effects of Water Quality Concern Estimation and Discussion
Section 2: Water Quality Effected Crop Choice Results and Discussion

Appendix B, Section 1: Marginal Effects of Water Quality Concerns

To explore the marginal impact of water quality concerns we interact our measures of well yield and water quality concerns. We then estimate the marginal impact of increases in water quality concern while holding the levels of well yield concern constant. We avoid reporting the results of this analysis in the main paper as we do not see clear trends at each level of concern. This may indicate that using interaction terms spreads our sample too thin to estimate the marginal effects of interactions. We instead report the results in this appendix as we do deem the information interesting to researchers and useful for future applications which attempt to separate well yield and water quality concerns or measures.

Regression results which interact concerns over well yield and water quality concerns are listed in Table B.1. We avoid explaining the coefficients of our main and interaction effects at this moment and instead save it for the marginal effects discussion as interaction terms of two categorical variables are difficult to interpret without graphs.

Table B.1 Regression Results Using Interaction Terms for Concerns

	Total Margin	Extensive Margin	Intensive Margin
Variables			
Well Yield Concern (WYC)			
Level 2	-5.67*	-7.79***	0.23
	(3.20)	(1.81)	(0.18)
Level 3	-15.96***	-14.71***	-0.06
	(4.41)	(2.50)	(0.25)
Level 4	-23.18***	-21.15***	0.48*
	(4.26)	(2.42)	(0.25)
Irrigation Quality Concern (IQC)			
Level 2	-0.67	-6.10***	0.36*
	(3.70)	(2.10)	(0.21)
Level 3	23.73***	18.91***	0.67
	(7.30)	(4.14)	(0.42)
Level 4	7.60	3.98	1.00**
	(8.29)	(4.71)	(0.48)
WYC*IQC			
Level 2,2	-13.97***	3.64	-1.02***
	(4.61)	(2.62)	(0.27)
Level 2,3	-25.73***	-10.69**	-1.33***
	(8.23)	(4.67)	(0.47)
Level 2,4	-10.55	-10.02*	-0.51
	(10.54)	(5.98)	(0.61)
Level 3,2	-0.004	1.55	0.37
	(5.68)	(3.22)	(0.33)
Level 3,3	-13.85	-5.29	-0.81*
	(8.56)	(4.86)	(0.49)
Level 3,4	14.61	0.75	0.47
	(9.99)	(5.67)	(0.57)
Level 4,2	18.87***	21.33***	-0.63*
	(5.67)	(3.22)	(0.33)
Level 4,3	-26.78***	-16.06***	-1.48***
	(8.52)	(4.84)	(0.49)
Level 4,4	11.59	15.50***	-1.69***
	(9.39)	(5.33)	(0.54)

Table B.1 Continued

Growing Season Water Deficit	1.57***	-0.08	0.14***
	(0.19)	(0.11)	(0.01)
Degree Days 10C-34C	-3.13***	-0.60***	-0.24***
	(0.31)	(0.18)	(0.02)
Degree Days 34C and Above	-0.06	0.06	0.02*
	(0.19)	(0.11)	(0.01)
Soil Organic Carbon (0-150 cm)	-0.14	-0.54***	0.03**
	(0.22)	(0.13)	(0.01)
Saturated Hydraulic Conductivity	0.14***	-0.14***	0.02***
(ksat)	(0.03)	(0.02)	(0.002)
Basic pH	3.42	6.40***	-0.37***
	(2.13)	(1.21)	(0.12)
LEPA	171.99***	150.79***	12.22***
	(1.60)	(0.91)	(0.12)
Center Pivot	162.18***	149.34***	11.63***
	(2.77)	(1.57)	(0.18)
Flood	143.02***	122.56***	12.96***
	(4.03)	(2.28)	(0.24)
Other System	176.70***	158.58***	11.78***
	(2.84)	(1.61)	(0.18)
Corn Share			1.89***
			(0.09)
Soybean Share			1.36***
			(0.11)
Alfalfa Share			2.40***
			(0.13)
Sorghum Share			0.09
			(0.15)
Other Crops Share			1.07***
			(0.09)
Controls			
Year Dummies	Yes	Yes	Yes
County Dummies	Yes	Yes	Yes
Observations	19,743	19,743	19,743

We first investigate the total effect of both concerns on each margin. Results can be found in Table B.2. Table B.2 shows that on the total margin, total water use declines for all combinations of concern except for the pairings of moderate well yield concern and major water quality concern and moderate or major water quality concern when no concern over well yield is present.

In this discussion, we focus on the interaction effects when moderate well yield concern and major water quality concerns are present. At this level, water use increases on the intensive margin by 1.42 inches/acre. Even though the extensive margin indicates a decrease of 10 acres, additional application on the intensive margin results in an increase of total water use in comparison to a producer with no concern over well yield or water quality.

Table B.2 Total Effects of Well Yield and Water Quality Concern

Level WYC, IQC	Total Margin	Extensive Margin	Intensive Margin
Level 1,1 (Base)	0	0	0
Level 1,2	-0.67	-6.10***	0.36*
	(3.70)	(2.10)	(0.21)
Level 1,3	23.73***	18.91***	0.67
	(7.30)	(4.14)	(0.42)
Level 1,4	7.60	3.98	1.01**
	(8.29)	(4.71)	(0.48)
Level 2,1	-5.67*	-7.79***	0.23
	(3.20)	(1.81)	(0.18)
Level 2,2	-20.31***	-10.25***	-0.43***
	(2.47)	(1.40)	(0.14)
Level 2,3	-7.67**	0.44	-0.44**
	(3.62)	(2.05)	(0.21)
Level 2,4	-8.62	-13.82***	0.72**
	(6.42)	(3.64)	(0.37)
Level 3,1	-15.96***	-14.71***	-0.06
	(4.41)	(2.50)	(0.25)
Level 3,2	-16.63***	-19.26***	0.67***
	(2.86)	(1.62)	(0.16)
Level 3,3	-6.09**	-1.09	-0.21
	(3.07)	(1.74)	(0.18)
Level 3,4	6.24	-9.98***	1.42***
	(4.41)	(2.50)	(0.25)
Level 4,1	-23.18***	-21.15***	0.48*
	(4.26)	(2.42)	(0.25)
Level 4,2	-4.98	-5.93***	0.21
	(3.10)	(1.76)	(0.18)
Level 4,3	-26.23***	-18.30***	-0.33*
	(3.14)	(1.78)	(0.18)
Level 4,4	-3.98	-1.67	-0.21
	(2.91)	(1.65)	(0.17)

Table B.3 presents the marginal effects of water salinity concern at each level of well yield concern. Figure B.1 graphs the marginal effects for ease of interpretation. Figure B.1 shows that the marginal effects of major water quality concern indicate an increase in water use on the total margin as concern over well yield increases. We find that producers with major water quality concern apply 22.21 or 19.19 more-acre feet of water per well on average when well yield concern is moderate or major, respectively.

On the extensive margin we see fluctuations in the slope of water quality concern at each level of well yield concern. Of the most interest is the large jump in the number of acres watered at minor and major well yield concern. These results again show that producers with the highest level of water quality concern are watering the most acreage per well. Thus, increases in water use due to major water quality concern are driven by larger irrigated acreages.

On the intensive margin, we start by looking at low and moderate concern. Although the marginal effects are statistically significant, each one is less than inch making them economically insignificant when looking for evidence of the “washing” or “waning” effects. When major quality concern is present, the results supply evidence that producers are irrigating 1.50 more inches/acre when well concern is moderate. This result may indicate that producers use a “washing effect” when major quality concerns and moderate well yield concerns are present. At the fourth level of well yield concern, we find that producers retract irrigation intensity, irrigating less than producers with no concern. Using the results from the extensive margin, we conjecture that these producers are irrigating a larger quantity of acres and thus decrease irrigation on the intensive margin rather than the extensive margin.

Table B.3 Average Marginal Effects of Water Quality Concern holding Well Yield Concern Constant

			Marginal Effect of Water Quality		
			Minor Concern	Moderate Concern	Major Concern
Well Yield Concern	Total Margin	No Concern	-0.67	23.73***	7.60
		Minor Concern	-14.64***	-2.00	-2.95
		Moderate Concern	-0.67	9.87**	22.21***
		Major Concern	18.19***	-3.05	19.19***
	Extensive Margin	No Concern	-6.10***	18.91***	3.98
		Minor Concern	-2.47	8.22***	-6.04
		Moderate Concern	-4.55*	13.62***	4.73
		Major Concern	15.22***	2.85	19.48***
	Intensive Margin	No Concern	0.20	0.58	0.45
		Minor Concern	-0.44***	-0.60***	0.72*
		Moderate Concern	0.57**	-0.07	1.50***
		Major Concern	-0.39	-0.78***	-0.78***

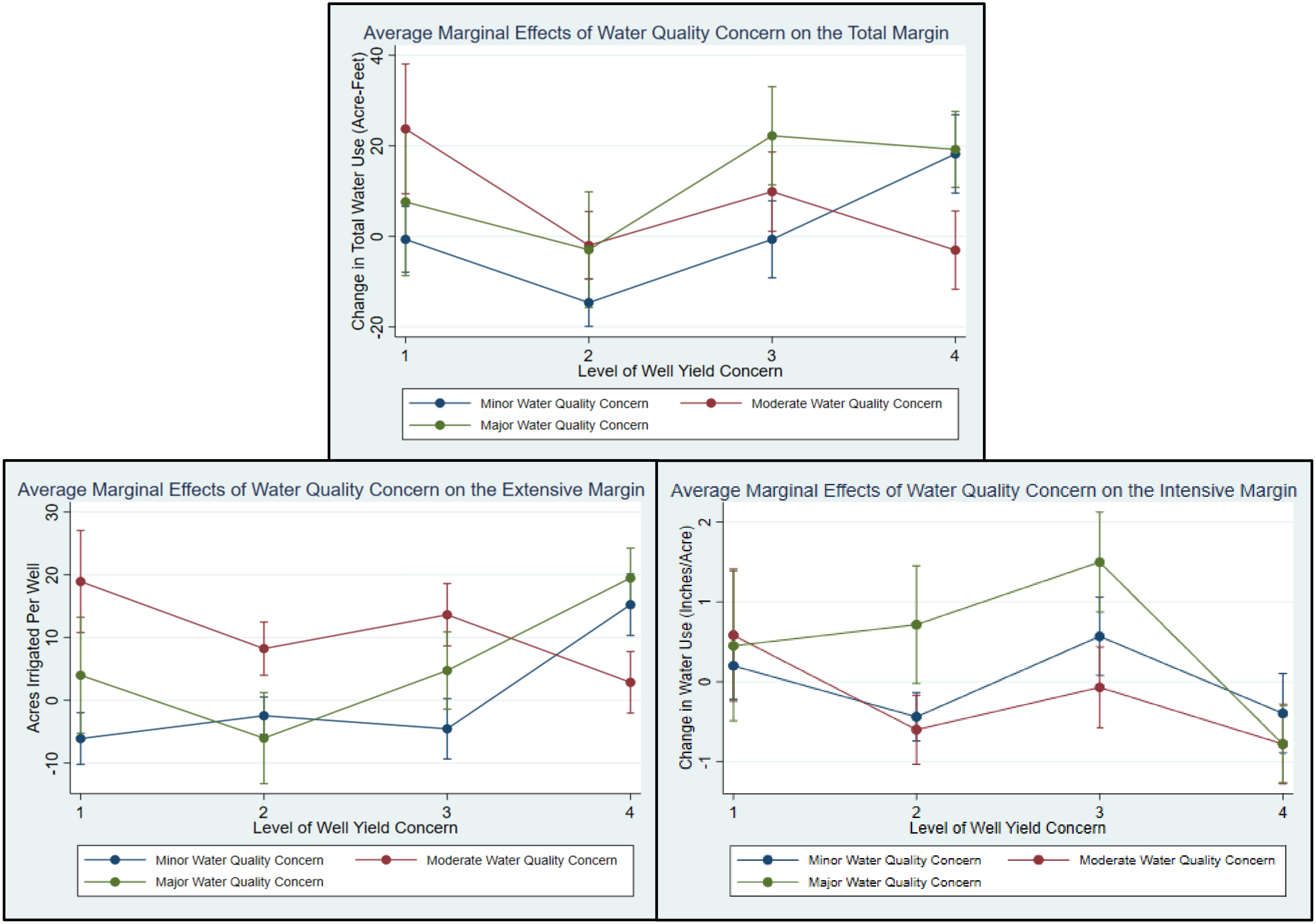

Figure B.1 Marginal Response to Water Quality Concerns

Appendix B, Section 2: Water Quality Effected Crop Choice Results and Discussion

To explore the impacts of crop choice on water use decision making, we re-estimate our primary regression but add in a dummy variable which indicates whether the producer expressed water quality concerns having had a moderate or major effect on crop choice. Using this variable, we separate the effects of changes in crop choice from water quality concerns. Regression Results are listed in Table B.4.

Comparing the results in Table B.4 to our main results in Table 2.2, it is no surprise that coefficients change slightly with the largest changes occurring to the coefficients on moderate or major water quality concern. The positive coefficient on major quality concern gets smaller as our dummy variable absorbs a portion of the increases in total water use and acres irrigated on the total and extensive margins. Thus, results indicate that producers that are changing crop choice irrigate more acres per well and use more water on average.

We find that on the intensive margin the amount of irrigation per acre is not significant from a producer with no crop change, thus it is difficult to hypothesize which crops are switching. To look at how producers are changing their crop choice we use the same specification as our crop choice estimations and again introduce the dummy indicating whether producers have changed their crop choice. Results are listed in Table B.5.

Table B.5 indicates that the dummy for changes in crop choice is not statistically different from no concern for every crop besides corn. Interestingly in the corn estimation, we find that the dummy for changes in crop choice indicate corn is planted on 4.63% more acres per field in comparison to producers that indicated no changes or minor changes to crop choice. The resulting positive coefficient is surprising as we would expect producers with concerns over water quality to switch to more saline tolerant crops (i.e., less corn and alfalfa). However, including the control variable does change the impact of major water quality concern which now indicates that producers with major quality concerns plant 2.43% less of their fields in corn on average.

Contemplating both coefficient estimates and the changes in the estimations from Table 2.4, we determine that producers who are changing their crop choice likely planted much more corn than an average producer before crop changes took place. Even after changing crop choice due to water quality, these producers still plant 4.63% more corn on average. Additionally, changes in crop choice due to quality concerns are likely to only affect water use when producers are planting substantial portions of their irrigated acreage in corn.

Table B.4 Regression Results including Crop Choice Dummy

	Total Margin	Extensive Margin	Intensive Margin
Variables			
Well Yield Concern (WYC)			
Level 2	-15.46***	-7.93***	-0.37***
	(2.08)	(1.19)	(0.12)
Level 3	-12.24***	-13.64***	0.37***
	(2.27)	(1.29)	(0.13)
Level 4	-17.03***	-13.07***	-0.13
	(2.27)	(1.29)	(0.13)
Irrigation Quality Concern (IQC)			
Level 2	-3.98**	-0.87	-0.10
	(1.75)	(1.00)	(0.10)
Level 3	-1.32	6.00***	-0.47***
	(2.14)	(1.22)	(0.12)
Level 4	10.24***	9.02***	0.08
	(2.48)	(1.41)	(0.14)
Dummy for Water Quality	4.63**	2.27*	-0.13
Effected Crop Choice	(2.19)	(1.24)	(0.13)
Growing Season Water Deficit	1.52***	-0.12	0.14***
	(0.19)	(0.11)	(0.01)
Degree Days 10C-34C	-3.02***	-0.60***	-0.23***
	(0.31)	(0.18)	(0.02)
Degree Days 34C and above	-0.02	0.09	0.02*
	(0.19)	(0.11)	(0.01)
Soil Organic Carbon (0-150 cm)	-0.26	-0.62***	0.03**
	(0.22)	(0.12)	(0.01)
Saturated Hydraulic Conductivity (ksat)	0.10***	-0.14***	0.02***
	(0.03)	(0.02)	(0.002)
Basic pH	3.15	7.19***	-0.40***
	(2.03)	(1.20)	(0.12)

Table B.4 Continued

LEPA	171.28***	150.12***	12.23***
	(1.60)	(0.91)	(0.12)
Center Pivot	162.16***	149.20***	11.66***
	(2.77)	(1.58)	(0.18)
Flood	143.19***	122.53***	12.95***
	(4.03)	(2.29)	(0.24)
Other System	176.76***	158.33***	11.81***
	(2.84)	(1.62)	(0.18)
Corn Share			1.90***
			(0.09)
Soybean Share			1.37***
			(0.11)
Alfalfa Share			2.40***
			(0.13)
Sorghum Share			0.06
			(0.15)
Other Crops Share			1.08***
			(0.09)
Controls			
Year Dummies	Yes	Yes	Yes
County Dummies	Yes	Yes	Yes
Observations	17,752	17,752	17,752

Table B.5 Regression Results for Crop Choice including Crop Choice Dummy

Variable	Corn	Soybean	Wheat	Sorghum	Alfalfa
Well Yield Concern					
Level 2	0.56	-2.15***	-2.08***	1.18***	-2.54***
	(1.03)	(0.68)	(0.51)	(0.36)	(0.42)
Level 3	4.56***	-0.50	-1.43***	0.23	-0.83*
	(1.12)	(0.75)	(0.56)	(0.39)	(0.45)
Level 4	-3.11***	0.27	-0.53	1.53***	-0.44
	(1.12)	(0.74)	(0.56)	(0.39)	(0.46)
Irrigation Quality Concern					
Level 2	-5.14***	2.91***	-0.17	-0.34	2.44***
	(0.87)	(0.58)	(0.43)	(0.30)	(0.35)
Level 3	-5.08***	0.16	-0.37	0.25	0.64
	(1.06)	(0.70)	(0.52)	(0.37)	(0.43)
Level 4	-2.43**	1.13	-0.07	-1.15***	0.03
	(1.22)	(0.81)	(0.61)	(0.43)	(0.50)
Dummy for Water Quality	4.27***	0.16	0.46	0.09	0.44
Effected Crop Choice	(1.08)	(0.72)	(0.54)	(0.38)	(0.44)
Growing Season Water Deficit	-0.11	0.0001	0.05	-0.02	0.01
	(0.09)	(0.06)	(0.54)	(0.03)	(0.04)
Degree Days 10C-34C	0.86	-1.29**	-1.67***	0.81***	-1.12***
	(0.90)	(0.60)	(0.45)	(0.31)	(0.36)
Degree Days 34C and above	-0.05	0.10	0.07	0.001	0.11***
	(0.10)	(0.07)	(0.05)	(0.04)	(0.04)
Soil Organic Carbon (0-150 cm)	-0.19*	-0.17**	-0.09*	-0.004	0.24***
	(0.11)	(0.07)	(0.05)	(0.04)	(0.04)
Saturated Hydraulic Conductivity (ksat)	-0.18***	-0.08***	-0.03***	0.003	0.18***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Basic pH	-0.61	-1.68***	1.41***	1.42***	0.20
	(1.04)	(0.69)	(0.52)	(0.36)	(0.42)

Table B.5 Continued

LEPA	47.47***	11.01***	11.05***	3.79***	4.86***
	(0.79)	(0.53)	(0.39)	(0.28)	(0.32)
Center Pivot	43.04***	12.91***	15.23***	5.67***	6.61***
	(1.37)	(0.91)	(0.68)	(0.48)	(0.56)
Flood	41.89***	16.62***	11.51***	5.75***	4.34***
	(1.99)	(1.33)	(0.99)	(0.70)	(0.81)
Other System	37.98***	10.30***	11.41***	3.42***	3.87***
	(1.41)	(0.94)	(0.70)	(0.49)	(0.57)
Lagged Corn Price	-1.50				
	(3.83)				
Lagged Soybean Price		3.59***			
		(1.12)			
Lagged Wheat Price			4.25***		
			(1.13)		
Lagged Sorghum Price				-4.18**	
				(1.67)	
Lagged Alfalfa Price					3.67**
					(1.85)
Year Dummies	Yes	Yes	Yes	Yes	Yes
County Dummies	Yes	Yes	Yes	Yes	Yes
Observations	17,752	17,752	17,752	17,752	17,752