2023

Farmers’ Preference and Willingness to Accept Carbon Payment Programs: Evidence from South Dakota

Pramisha Thapaliya
South Dakota State University, pramsathaps@gmail.com

FARMERS' PREFERENCE AND WILLINGNESS TO ACCEPT CARBON PAYMENT PROGRAMS: EVIDENCE FROM SOUTH DAKOTA

BY

PRAMISHA THAPALIYA

A thesis submitted in partial fulfillment of the requirements for the

Master of Science

Major in Economics

South Dakota State University

2023

THESIS ACCEPTANCE PAGE

Pramisha Thapaliya

This thesis is approved as a creditable and independent investigation by a candidate for the master's degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

Deepthi Kolady
Advisor Date

Joseph Santos
Director Date

Nicole Lounsbery, PhD
Director, Graduate School Date

ACKNOWLEDGEMENTS

I would like to thank my major advisor Dr. Deepthi Kolady for her continuous guidance, support, and mentoring from the very beginning; and for always being patient with me. My sincere thanks to the members of my advisory committee, Dr. Evert Van der Sluis and Dr. Andrea Leschewski, not only for providing your valuable time and input being part of the committee but also with respect to classroom learning and career guidance. I would also like to thank my Graduate Faculty Representative, Dr. Jose Alvarez for being part of this important work. My special gratitude to Dr. Marzieh Motallebi and Dr. Mustapha Alhassan from Clemson University, for their assistance and constructive suggestions for this research.

I would like to thank Ness School of Management and Economics, South Dakota State University for the graduate education and support during my research career. My fellow graduate students as well as friendly professors and staffs in Harding Hall have been a great part of my graduate life at Brookings. Thank you to my family and friends for your love, support, and belief in me. Finally, I would like to thank the corn and soybean farmers of South Dakota, without whom this study would not be possible.

Pramisha Thapaliya

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ABSTRACT

FARMERS' PREFERENCE AND WILLINGNESS TO ACCEPT CARBON PAYMENT PROGRAMS: EVIDENCE FROM SOUTH DAKOTA

PRAMISHA THAPALIYA

2023

Reducing greenhouse gas (GHG) emissions is crucial to mitigate the impacts of climate change. Agricultural soil carbon sequestration holds great potential in reducing GHG emissions. No-till, conservation till and cover crops are some of the widely recognized carbon-sequestering agricultural conservation practices. However, farmers need to adopt these carbon-sequestering practices to realize the potential of agricultural soil carbon sequestration. Carbon payment or market programs are voluntary mechanisms that could incentivize farmers' adoption of conservation practices that sequester carbon. However, there is limited knowledge of farmers' preferences and willingness to accept (WTA) carbon payments for enrollment in such programs. This study investigates how farmers' preferences and WTA carbon payments differ toward conservation practices, based on their current adoption behavior. This study also explores if there are different groups of farmers based on climate change perceptions and adverse weather experiences and examines how preferences and WTA for carbon market programs vary between these classes. Data for this analysis were collected through a primary mail-in survey of corn and soybean farmers in South Dakota, conducted from December 2021 to February 2022. The study employed a discrete choice experiment (DCE) and a random parameter logit (RPL) model to estimate farmers' preferences and WTA carbon payments. A latent class model (LCM) was used to assess preference and WTA heterogeneity among farmers, based on their climate change perceptions and adverse weather experiences. Our study shows that farmers' preferences and WTA carbon payments vary based on their adoption status of conservation practices and practice type. LCM results show there are four different groups of farmers based on their climate change perceptions and adverse weather experiences. There is the presence of heterogeneity in their preferences on carbon market attributes, and subsequently differences in WTA. The findings suggest that carbon market providers and policymakers should consider developing cost-effective targeted programs and policies that consider differences in farmers' preferences toward carbon payments based on their current adoption status as well as other factors including climate change perceptions and adverse weather experiences. Furthermore, tailored extension and outreach activities focusing on climate change impacts could influence farmers' perceptions and therefore change their behavior when adopting sustainable agricultural practices for mitigating the impacts of climate change.

CHAPTER I

INTRODUCTION

The Paris Agreement (2015) aims to limit global warming to below 2 degrees Celsius and preferably to 1.5 degrees Celsius, compared to the pre-industrial levels. In order to reach the goals of the Paris Agreement, 193 countries, including the US, have pledged to communicate actions they will take to limit their greenhouse gas (GHG) emissions through their nationally determined contributions (NDCs) (UNFCCC, 2015). The agriculture, forestry, and other land uses (AFOLU) sector is responsible for approximately 24% of the total global GHG emissions (IPCC, 2014). In 2021, the agricultural sector alone contributed to around 9.3% of total US GHG emissions (EPA, 2023). Hence, reducing GHG emissions is essential to mitigate the impacts of climate change. The AFOLU sector also stands out as one of the solutions to mitigate GHG emissions because it has the ability to lower emissions independently, sequester atmospheric carbon at a low cost, and supply essential resources that can facilitate emissions reductions in other sectors (Nabuurs et al., 2022). Several studies have recognized the technical potential of agricultural soil carbon sequestration in mitigating climate change impacts on agriculture (Feng et al., 2000; Lal et al., 1998; Lynne & Kruse, 2004; E. J. Pindilli et al., 2018). However, the technical potential of agricultural soil carbon sequestration to mitigate climate change can only be realized when there are economic benefits for producers (Gramig & Widmar, 2017). Voluntary carbon markets in which farmers or ranchers sell carbon credits to investors for every metric ton of sequestered carbon on their land involve market-based approaches to incentivize the adoption of production practices that facilitate agricultural soil carbon sequestration. Farmers could benefit from carbon market schemes through carbon sequestration and improved soil health while providing essential ecosystem services such as improved water quality and biodiversity (Feng et al., 2000; Sandor & Skees, 1999). In the United States, there are many initiatives to increase the adoption of climate-smart agricultural practices, including the recent Partnerships for Climate-Smart Commodities. One of its objectives is to create market and revenue streams for farmers and commodities across agriculture sector (*Partnerships for Climate Smart Commodities*, 2023). However, there are many unanswered questions regarding the enrollment of farmers in carbon payment programs. Do farmers prefer to enroll in carbon payment programs and adopt conservation practices or not? What is their willingness to accept (WTA) to switch to different practices? Do current production practices affect their preferences on carbon market programs and WTA carbon payments? Do farmers differ in terms of their preferences and WTA based on climate change perceptions and adverse weather experience? Our study aims to address these questions. Findings from this study are expected to provide important policy and market insights to policymakers and agricultural carbon market providers, as they consider cost-effective and efficient implementations of agricultural carbon payment programs.

Chapter II focuses on examining farmers' preferences and WTA carbon payments for adopting conservation management practices using a discrete choice experiment. This chapter compares the preferences and WTA carbon payments among farmers based on their current adoption status of conservation practices. Information on carbon markets, carbon market attributes and attribute levels were provided to the respondents in the survey instrument. A Random Parameter Logit (RPL) model was used to find the preferences and WTA carbon payments. The results of this chapter provide insights to policymakers and carbon market providers regarding the heterogeneity of preferences for different carbon market attributes and WTA carbon payments among farmers based on their current production practices.

Chapter III focuses on examining role of perceptions of climate change and adverse weather experiences over the preceding ten years in farmers' WTA carbon payments. Different groups of farmers are identified via Latent Class Analysis (LCA) in this chapter. Climate change perceptions, adverse weather experiences, socio-demographic characteristics and WTA carbon payments are assessed in these identified farmers' groups. The results of this chapter provide insights on the need of targeted interventions due to the existence of heterogeneity among farmers based on their climate change perceptions and adverse weather experiences.

Chapter IV summarizes results, conclusions, and policy implications from Chapters II and III.

CHAPTER II

FARMERS' PREFERENCE AND WILLINGNESS TO ACCEPT CARBON PAYMENTS FOR ADOPTING CONSERVATION MANAGEMENT PRACTICES[1]

[1] This paper is under review at the Ecological Economics Journal.

Abstract

The potential of agricultural soil carbon sequestration in reducing GHG and mitigating the impacts of climate change is widely recognized. However, there is limited knowledge of farmers' preferences and willingness to accept carbon payments to implement carbon-sequestering conservation practices. This study investigates how farmers' preferences and their willingness to accept carbon payments differ based on their current adoption behavior toward conservation practices. The data for the analysis were collected through a mail-in survey of row crop producers in South Dakota, conducted from December 2021 to February 2022. The study employed a discrete choice experiment and a random parameter logit model to estimate farmers' preferences and willingness to accept carbon payments. Our study shows that farmers' preferences and willingness to accept carbon payments vary based on their adoption status of conservation practices and practice type. The findings suggest that carbon market providers and policymakers should consider developing targeted programs and policies that incorporate differences in farmers' preferences toward carbon payments based on their current adoption status.

Introduction

The landmark Paris Agreement aims to limit global warming to below 2 degrees Celsius and preferably to 1.5 degrees Celsius, compared to the pre-industrial levels. To reach the Paris Agreement, 193 countries, including the United States, have pledged to disclose actions they will take to limit their GHG emissions through Nationally Determined Contributions (NDCs) (UNFCCC, 2015). Agriculture is associated with three of the most significant gases that contribute to global warming: Carbon Dioxide (CO_2), Methane (CH_4), and Nitrous Oxide (N_2O). The global agriculture and food system is responsible for about 21-37% of annual emissions (Lynch J et al., 2021).

Land use and land use change associated with agriculture hold great potential to mitigate the impacts of climate change through carbon sequestration, which is the storage of atmospheric carbon (Lal et al., 1998; Lynne & Kruse, 2004). Many studies have recognized the technical potential of agricultural soil carbon sequestration in mitigating climate change impacts on agriculture (Feng et al., 2000; Lal et al., 1998; Lynne & Kruse, 2004; E. J. Pindilli et al., 2018). Carbon sequestration in agricultural soils could happen by planting trees, switching cropland to grassland, transitioning from conventional to conservation tillage, planting cover crops, improving cropping systems, restoring wetlands, improving residue management, improving grazing practices, etc. (Feng et al., 2000).

The Intergovernmental Panel on Climate Change (IPCC) estimates that by 2030 global soil carbon sequestration has the technical potential to mitigate up to about 5.3

Giga tons of CO_2 per year (Smith, 2007). Soussana et al. (2019) reported that 90% of the total technical mitigation potential in agriculture could be achieved from soil organic carbon sequestration to reach the goal of the Paris Agreement to limit the increase in temperature below 1.5 degrees Celsius or well below 2 degrees Celsius above pre-industrial levels. Sperow (2020) reported that the total potential soil organic carbon increment from the adoption of activities that increase soil organic carbon, like cover crops, no-till, and others could reduce emissions by an additional 47.3 Teragrams of Carbon per year (Tg C yr^{-1}). A study conducted among German farmers shows that farmers could promote soil organic carbon and contribute to climate change mitigation if subsidies or certificates with market-based and incentive-based payment structures are implemented for switching to sustainable agricultural practices (Hermann et al., 2017).

In the United States, agriculture contributes around 10% to the nation's total GHG emissions, most of which come from the livestock sector. However, land use, land-use change, and forestry (LULUCF) activities in the United States have resulted in more removal of CO_2 from the atmosphere than emissions of CO_2 (EPA, 2020). Because of this, there are concerted efforts to increase the diffusion of climate-smart agriculture practices that improve agricultural productivity sustainably, are resilient to climate change, reduce greenhouse gas emissions or sequester carbon. The technical potential of agricultural soil carbon sequestration to mitigate climate change will only be realized in the presence where of economic benefits for producers (Gramig & Widmar, 2017).

Voluntary carbon markets in which farmers or ranchers sell carbon credits to investors for every metric ton of sequestered carbon on their land is one of the market-based approaches to incentivize the adoption of production practices that sequester carbon on agricultural soils. Farmers could benefit from carbon market programs through carbon sequestration and improved soil health while providing essential ecosystem services such as improved water quality and biodiversity (Feng et al., 2000; Sandor & Skees, 1999). Carbon payments could create a new revenue stream for farmers and incentivize more farmers to switch to climate-smart agriculture practices. Climate-smart agriculture policies would not be effective if there is a lack of farmer participation and knowledge of factors that affect farmers' decisions to participate in various climate-smart agriculture programs (Espinosa-Goded et al., 2010).

Lynne and Kruse (2004) found that Nebraska farmers with 51-99% of their cropland under conservation tillage agreed most strongly with the need to address the GHG problem, align with international climate change policy, increase both government payments and the price for stored carbon, and ask the government to certify the amount stored. Gramig et al. (2013) investigated Indiana farmers' beliefs about climate change and carbon sequestration initiatives. These findings revealed that improved understanding of climate change before the implementation of any measure is essential to drive implementation. Ma et al. (2012) assessed Michigan farmers' willingness to consider payment-for-environmental-services programs to change tillage practices and found that willingness to accept payments depends on farm and farmer characteristics, payment offers, and marginal benefit-cost criteria. Gramig and Widmar (2017) studied Indiana farmers' preference for agricultural soil carbon sequestration schemes. They found that carbon markets will not be functional if payments do not increase sufficiently and if contract terms are not acceptable to farmers. However, the study focused only on tillage practices without an option for direct carbon payments. Alhassan et al. (2019) conducted a study in South Carolina to find forestland owners' willingness to accept payment (WTA) for carbon sequestration through a contingent valuation method. Their findings showed that most of forestland owners are likely to enroll in the programs for carbon sequestration.

Limited studies have examined Midwestern crop producers' WTA carbon payments for switching to conservation practices like no-tillage, conservation tillage, and cover crops while accounting for heterogeneity in production practices. This research fills the void by examining farmers' preference and willingness to accept carbon payments among adopters and non-adopters of soil conservation practices that sequester carbon. This study's main objective is to assess South Dakota crop producers' WTA carbon payment to adopt conservation management practices. Specifically, we test the hypothesis that farmers' preferences and WTA carbon payments for switching to conservation practices vary based on their current adoption status of conservation practices.

South Dakota is a western Corn Belt state located within the Northern Great Plains climate transition zone that exhibits a distinct east-west declining average precipitation gradient, with intensive cropping operations in the east and more prevalent grassland towards the west. Focusing on South Dakota will allow us to cover a wide range of farming practices that vary based on climatic factors, an essential aspect in farmers' adoption decisions on conservation practices. Insights from the study are expected to help examine farmers' acceptance of carbon payments for agricultural soil carbon sequestration and improve the attributes of the carbon payment programs in a way that addresses heterogeneity in farmers' preferences for carbon payment programs for adopting carbon sequestering conservation practices.

Material and methods

Data

Before designing the final survey instrument, a pilot survey was conducted among nineteen producers in South Dakota, out of which data from seventeen respondents were used due to the missing data concerns. The data used for the study were collected using a mail-in survey of corn and soybean farmers in South Dakota from December 2021-February 2022. Questions related to farmers' current farm management practices, their preferences and willingness to enroll in carbon market programs, as well as farm information and farmers' perceptions were included in the survey instrument.

Based on an analysis of the pilot survey results, necessary changes were made to develop the final survey instrument. A proportionate sample of 3,000 corn and soybean farmers in South Dakota was used for the study. After sending the survey instruments, postcard reminders were also sent, to remind the producers. Out of the total of 3,000 surveys, 55 respondents couldnot be reached due to wrong addresses and 174 non-responding survey instruments were returned perhaps because those individuals were no longer farming or renting the land or were deceased. By the end of April 2022, 402 usable survey responses were received, of whom 381 answered the choice sets section of the questionnaire, yielding a response rate of 14.5%. Figure 1 shows the data collection process and timeline of this study.

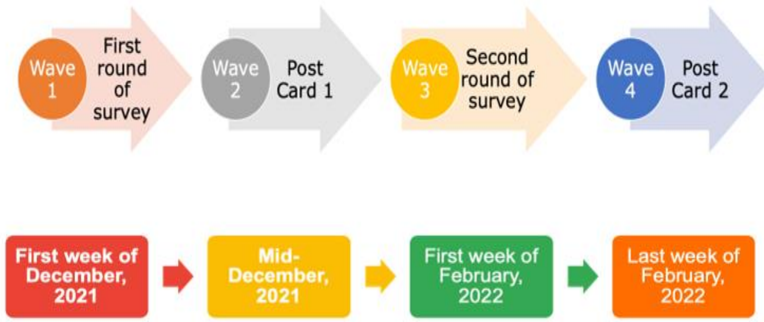

Figure 1. Data collection timeline

Discrete choice experiment design

A discrete choice experiment (DCE) is a stated preference method used extensively in consumer economics and natural resource economics to elicit preferences for non-market goods and services. The DCE simulates real-life decision-making scenarios, allows multiple attributes to be evaluated, allows hypothetical attributes (attributes not available in the market) to be included, offers respondents the option to choose among alternatives or to opt-out from the decision-making process, and allows researchers to estimate tradeoffs among different alternatives.

Some researchers have used DCE to ascertain preferences in the supply side of ecosystem services (Alhassan et al., 2019; Broch & Vedel, 2011; Christensen et al., 2011; Gramig & Widmar, 2017; Ma et al., 2012). Christensen et al. (2011) evaluated determinants of farmers' willingness to enroll in subsidy schemes for pesticide-free buffer zones in Denmark using a choice experiment. Similarly, Broch and Vedel (2011) used a DCE to assess Danish farmers' preferences for afforestation contracts. Gramig and Widmar (2017) analyzed Indiana farmers' preferences for agricultural soil carbon sequestration using a DCE. Similarly, Ureta et al. (2022) conducted a study to evaluate residents' willingness to pay for improving ecosystem services in the Santee River Basin Network through the DCE approach. CDEs are being increasingly used and has been proven effective in evaluating preferences for environmental conservation programs and decision-making. This study employs DCE as part of the stated preference methods, as it helps to elicit preferences that can be used in the absence of revealed preference data (Mangham et al., 2009). The DCE has been used to determine crop producers' preferences for carbon payments for switching to conservation practices that sequester carbon on agricultural lands.

Choice experiment attributes and attribute levels

One of the most essential steps in a discrete choice experiment is establishing attributes and attribute levels for a choice set. Based on interaction with crop producers, the study included the following five attributes in the choice experiment: tillage practice change, cover crops practice change, contract length, governance, and carbon payment ($/acre). The levels of attributes included in the study are the following: $0/acre, $5/acre, $10/acre, $15/acre, and $20/acre for carbon payments; conventional till to no-till, conventional till to conservation till, conservation till to no-till, and no change in tillage practice for tillage practice change; no change in cover crops practice and no cover crops to cover crops for cover crops practice change; ten- year contract, five-year contract and no contract for contract length; and government agency (e.g., United States Department of Agriculture (USDA)), Private (for-profit), Not-for-profit and none for the governing entity for monitoring carbon program and managing carbon payments. Price levels are allocated based on the price range of current farm conservation programs as well as proposed and implemented price levels of private carbon markets available in the United States. The respondents were given the information on agricultural soil carbon sequestration and carbon markets and shown in Appendix 1. A summary of attributes and levels included in the DCE is shown in Table 1.

Table 1. Attributes and attribute levels used in the discrete choice experiment

Attribute	**Attribute Levels**
Tillage Practice Change	No change in tillage practice
	Conservation till to no-till
	Conventional till to conservation till
	Conventional till to no-till
Cover Crops Practice Change	No change in cover crops practice
	No cover crops to cover crops
Contract Length	No contract
	Five-year contract
	Ten-year contract
Governance	None
	Not-for-profit
	Private (for-profit)
	Government (USDA)
Carbon Payment ($/ acre)	$0
	$5
	$10
	$15
	$20

The definitions of these attributes and attribute levels (provided in the survey instrument) are reported in Appendix 2.

Designing choice scenarios

The choice scenarios/tasks included in the study are designed using Ngene software. The Ngene software efficiently measures D-error value and helps in improving choice experiment design (ChoiceMetrics, 2012; Syrengelas et al., 2017). Similarly, using Bayesian priors decreases the standard error of the estimates and increases the validity of design and choice situation (SÁndor & Wedel, 2001). We used a D-efficient Multinomial Logit (MNL) model to generate the choice sets. The default-swapping algorithm was used as no choice combination needs to be rejected. It also ensures the balance in attribute levels. For the prior values, the mean and standard deviation of attributes were selected based on results from the pilot study and previous literature (Gramig & Widmar, 2017). Using the Ngene software, we generated thirty choice sets in five blocks of six choice sets. Blocking is an effective means to optimize design efficiency (Hensher et al., 2015). It also helps to reduce response fatigue.

Each respondent had six choice sets in total. Three alternatives were generated in each choice set; Option A, Option B, and Neither. Option A and Option B represented components for the carbon market payments with varying attribute levels. Neither represented the opt-out alternative, which is, not choosing any option between Options A and B. The ‘Cheap Talk Script’ was provided to respondents to motivate them to simulate real-life conditions when selecting the alternatives in choice sets. The ‘Cheap Talk Script’ is provided in Appendix 3.

Data analysis

Empirical model

The random parameters logit model in preference space was used to analyze the choice experiment data since it allows for heterogeneity among the responses. The random parameters logit model helps to estimate the heterogeneity across the evaluated attributes. So, the random utility (U_{nij}) of attribute i for individual n in situation j is

$$U_{nij} = v_{nij} + [u_{ni} + \varepsilon_{nij}], \tag{1}$$

where: v_{nij} = Deterministic portion of utility dependent upon the attributes of the carbon market alternative,

u_{ni} = Error term, which is normally distributed over individuals and attributes (but not choice sets), and

ε_{nij} = Stochastic component of utility (residual error or any unobserved variation), which is independently and identically distributed over all alternatives and choice scenarios.

The model that shows the deterministic or systematic portion of utility on choice occasion *j* is estimated using the following equation:

$$v_{nij} = \beta_p CarbonPay_{nij} + \beta_1 ConstNt_{nij} + \beta_2 ConvCt_{nij}$$

$$+ \beta_3 ConvNt_{nij} + \beta_4 Cover_{nij} + \beta_5 FiveContract_{nij}$$

$$+ \beta_6 TenContract_{nij} + \beta_7 (Not - for - profit)_{nij} + \beta_8 Private_{nij} +$$

$$\beta_9 Government_{nij} + \varepsilon_{nij}, \tag{2}$$

where *CarbonPay* is the carbon payment amount ($/acre) to producers for adopting practices that sequester carbon in the soil. All other variables are dummy coded variables. *ConvNt* represents conversion from conventional tillage to no-till, *ConvCt* represents conversion from conventional tillage to conservation till, *ConsNt* represents conversion from conservation tillage to no-till, and the reference case (*ConvNt* = *ConvCt* = *ConsNt* = 0*)* represents no change in tillage practice. *Cover* represents transition from no cover crops to cover crops practice, and the reference case (*Cover* = 0) represents no change in cover crops practice. *TenContract* represents a contract duration of ten years, *FiveContract* represents a contract duration of five years, and the reference case (*TenContract* = *FiveContract* = 0*)* represents no contract scenarios. *Government* represents USDA or government source as governing agency; *Private* represents a private market source as governing agency; *Not-for-profit* represents a non-profit agency as governing entity, and the reference case (*Government* = *Private* = *Not-for-profit* = 0*)* represents no governing agency scenario.

We used utility coefficients from equation (2) to estimate WTA values for each attribute. Mean WTA estimates are calculated by dividing the j^{th} attribute level parameter, β_j, by the negative of the carbon payment coefficient, β_p, such that $WTA_j = -\beta_j/\beta_p$. We used the Krinsky and Robb method of parametric bootstrapping to calculate 95% confidence intervals of WTA estimates (Krinsky & Robb, 1986).

In order to examine how farmers' preferences for voluntary financial incentives through carbon payments for soil carbon sequestration vary between current adopters and non-adopters of conservation practices, we categorized our survey respondents into the following categories: no-till adopters, no-till non adopters, conservation till adopters, conservation till non adopters, cover crops adopters, cover crops non adopters, and conventional till adopters, and estimated random parameter logit model separately for each of these adoption categories. Since carbon payment included in the choice experiment was for switching from the current practice to a conservation practice, categorization of survey respondents based on their adoption status also allowed us to investigate current adopters' preferences for other conservation practices. For example, no-till adopters already practice no-till, but the study elicited their preference for switching from no-cover crops to cover crops. We hope that this approach will account for heterogeneity in farmers' WTA carbon payments based on their current adoption status. Kernel density plots were used to visualize the difference in WTA carbon payments between adopters and non-adopters of different categories for switching to different conservation practices. These plots help to visualize the distribution of WTA estimates.

A Poe test (Poe et al., 2005) provides unbiased estimates of the significance of difference of two (e.g., control and treatment) distributions, and can be used to examine whether estimated WTA values are statistically different between adopters and non-adopters. However, due to differences in the number of respondents between adopters and non-adopters, use of the Poe test was not feasible in our study. Hence, we opted for pooled data analysis with interaction terms as described below. First, we pooled the data for adopters and non-adopters of each practice and generated a dummy variable that takes the value of 1 if the respondent had adopted that practice and zero, otherwise. Second, in order to test whether the preferences/utility coefficients for attributes were statistically significantly different between adopters and non-adopters, we interacted each attribute with a treatment dummy variable for each practices (no-till, conservation till, cover crops, and conventional till). To examine how preferences of conventional till growers differ from those of no-till adopters, we pooled together data for these two categories and used a dummy for no-till adoption as a treatment. Similarly, we pooled together data for conventional till growers and conservation till adopters and used a dummy variable for conservation till adoption as a treatment.

Results

Descriptive statistics of the sample

Table 2 shows the demographic information for survey respondents. The majority of the survey respondents were 65 years or older. The median age range lies within 56-64 years. This corresponds with the average age of farmers which is 56.2 years reported in the 2017 Agricultural Census data for the South Dakota (USDA, 2017). The age distribution of adopters and non-adopters of conservation practices is similar. About half of our survey respondents had a high school or associate degree followed by 48% who had a four-year college degree or higher. Among the adopters of conservation practices, cover crops adopters had the highest percentage with college degree (51%), followed by adopters of no-till (49%). Conventional till growers had the smallest percentage with college degree (27%) and the highest percentages with high school or Associate degree (63%) and less than a high school degree (5%). The average cropland acreage of our sample is substantially higher (1,467 acres) than the state average (661 acres). An examination of cropland acreage among adopters and non-adopters of conservation practices shows that conventional till growers have the smallest cropland acreage (741 acres) and is comparable to the state average (661 acres). No-till adopters have highest cropland acres (1,607 acres) followed by conservation till adopters (1,577 acres) and cover crops adopters (1,522 acres). Annual gross farm sales data are comparable to crop acreage data and differ substantially from the 2017 Agricultural Census data (USDA, 2017). For example, 43% of the survey respondents had annual gross farm sales of more than $500,000, whereas only 16% for the Census data. As per the Agricultural Census, 48% have less than $50,000 annual gross farm sales. However, in our sample, only 5% of respondents reporting having less than $50,000 in annual gross farm sales. A higher percentage of no till adopters (45%), conservation till adopters (52%), and cover crop adopters (47%) had annual gross farm sales higher than $500,000. A larger percentage of no till non-adopters (36%), conservation till non-adopters (44%), and cover crops non-adopters (42%) had gross farm sales in the range of $100,000-$499,000.

Table 2. Summary statistics of sample

Demographics	All sample	No-till		Conservation till		Conven-tional till	Cover crops		SD Census
		Adopters	Non-adopters	Adopters	Non-adopters		Adopters	Non-adopters	
	(n=402)	(n=285)	(n=99)	(n=210)	(n=164)	(n=45)	(n=218)	(n=167)	
Age									
18-25 years old	0.26%	0.36%	0%	0%	0.64%	0%	0.48%	0%	1.38%
26-35 years old	4.69%	4.74%	5.43%	5.50%	4.46%	5.00%	3.81%	6.33%	9.19%
36-45 years old	12.50%	12.77%	11.96%	12.00%	11.46%	10.00%	14.76%	9.49%	12.69%
46-55 years old	14.06%	13.50%	14.13%	15.50%	11.46%	15.00%	15.71%	10.76%	16.64%

56-64 years old	29.17%	29.20%	30.43%	31.50%	28.03%	22.50%	28.57%	31.65%	29.44%
65 years or older	39.32%	39.42%	38.04%	35.50%	43.95%	47.50%	36.67%	41.77%	30.66%
Education									
Below high school	2.09%	1.47%	4.35%	2.01%	1.91%	5.00%	1.91%	2.53%	
High school graduate or Associate degree	50.39%	49.45%	55.43%	50.75%	52.87%	62.50%	47.85%	55.06%	
College degree or higher	47.52%	49.08%	40.22%	47.24%	45.22%	32.50%	50.24%	42.41%	
Total cropland acres	1467.01	1606.84	1060.76	1577.41	1283.79	740.89	1522.12	1365.22	661.16

Annual gross farm sales									
Less than $50,000	4.91%	4.49%	6.98%	2.17%	8.70%	11.43%	3.09%	7.97%	48.37%
$50,000-$99,999	9.25%	6.12%	18.60%	5.98%	13.77%	37.14%	7.22%	11.59%	9.12%
$100,000-$499,999	42.48%	44.08%	36.05%	40.22%	44.21%	31.43%	42.27%	42.03%	26.47%
More than $500,000	43.35%	45.30%	38.37%	51.63%	33.33%	20.00%	47.42%	38.40%	16.04%
Land tenancy agreement									
1 year lease	48.50%	47.27%	54.93%	47.88%	51.26%	59.26%	46.47%	51.24%	

(2-3) years lease	36.54%	37.73%	30.99%	36.36%	35.29%	29.63%	35.88%	38.02%
(4-5) years lease	6.64%	6.82%	7.04%	8.48%	3.36%	3.70%	7.65%	4.96%
More than 5 years lease	8.31%	8.18%	7.04%	7.27%	10.08%	7.41%	10.00%	5.79%

Source: Authors’ survey and N. USDA (2017)

Farmers' preference for carbon payment programs

Table 3 shows the utility coefficient estimates from the random parameters model in preference space for adopters and non-adopters of conservation practices and the full sample for accepting carbon payments to switch to a conservation practice that sequesters soil carbon from the status quo and for other carbon payment program attributes such as governance mechanism and contract length. The presence of heterogeneity in farmers' preferences is evident from statistically significant standard deviation estimates for all the attributes in the model and justifies the use of the random parameter logit model.

Carbon payments (in $/acre) have a positive and statistically significant effect on farmers' choice of carbon payment programs. The higher the payment, the more likely participants were to choose the carbon program offered. Comparison of results for the full sample with those of the conservation practice-specific shows that other than the price/payment attribute, farmers' preference for carbon payments to switch to a conservation practice differs substantially between adopters and non-adopters of conservation practices. The last column in Table 3 shows the utility preference estimates for the full sample without considering survey respondents' current adoption status of conservation practices. Overall, the utility preference estimates for the full sample show farmers' negative preference for carbon payments to switch from their current practice and for ten-year and five-year contract lengths. Also, the utility preference estimates for the full sample shows positive preferences for government and not-for profit as governing agencies and for the opt-out option.

In the case of no-till, non-adopters (who have not adopted no-till but may be practicing conservation till or conventional till) have negative and statistically significant preference for carbon payments to switch from conservation till to no-till, conventional till to conservation till, and conventional till to no-till. Non-adopters of no-till have negative and statistically significant preferences for ten-year and five-year contracts for enrolling in carbon payment programs. Overall, these results indicate that no-till non-adopters have negative utility in participating in the carbon payment programs presented to them. As expected, adopters of no-till have negative preference for carbon payments to switch to conservation practices and for contract length attribute of the carbon payment program. Unlike non-adopters, adopters have a positive preference towards government as the agency for monitoring and evaluating the carbon payment program and for the opt-out option (Neither). The statistically significant positive utility for the opt-out option suggests that adopters of no-till do not prefer financial incentives through carbon payments and they have positive utility from opting-out. This may be because adopters might have had other reasons to adopt no-till and might have participated or might be participating in other conservation programs. Our results are consistent with the findings of Lynne and Kruse (2004) who used a qualitative survey of Nebraska farmers to gauge their preferences for carbon programs and found that farmers who had all of their cropland under conservation till were less concerned about new government programs and market pricing to bring about more carbon storage.

Table 3. Farmers' utility preference estimates for different carbon program attributes

Attributes	No Till		Conservation Till		Conventional Till	Cover Crops		Full Sample
	Adopters (N=272)	*Non-Adopters (N=91)*	*Adopters (N=205)*	*Non-Adopters (N=152)*	*Adopters (N=38)*	*Adopters (N=209)*	*Non-Adopters (N=157)*	(N=381)
Carbon Payment/ Price	0.14***	0.07***	0.10***	0.14***	0.32***	0.12***	0.12***	0.12***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.95)	(0.01)	(0.019)	(0.01)
Conservation till to no-till	-0.34	-2.60***	-0.81***	-0.64**	-2.40**	-0.41**	-1.13***	-0.73***
	(0.19)	(0.66)	(0.23)	(0.27)	(1.16)	(0.18)	(0.31)	(0.16)
Conventional till to conservation till	-0.58***	-0.66**	-0.31	-0.64***	-1.35	-0.55***	-0.84***	-0.61***
	(0.20)	(0.31)	(0.20)	(0.25)	(0.90)	(0.21)	(0.27)	(0.16)
Conventional till to no-till	-0.36**	-1.37***	-0.75***	-0.38	-3.64***	-0.31	-1.04***	-0.69***
	(0.17)	(0.37)	(0.23)	(0.23)	(1.14)	(0.18)	(0.25)	(0.15)

No cover crops to	-0.25	-0.04	-0.18	0.07	2.09***	0.04	-0.32	-0.07
cover crops	(0.14)	(0.26)	(0.16)	(0.17)	(0.73)	(0.12)	(0.22)	(0.11)
Ten-year contract	-1.32***	-1.28***	-1.11***	-1.45***	-4.09***	-1.01***	-1.29***	-1.15***
	(0.21)	(0.33)	(0.19)	(0.29)	(1.29)	(0.17)	(0.26)	(0.14)
Five-year	-0.47***	-0.94***	-0.52***	-0.58***	-1.81	-0.36**	-0.64**	-0.55***
contract	(0.16)	(0.33)	(0.19)	(0.20)	(0.96)	(0.15)	(0.25)	(0.13)
Not-for-profit	0.39	0.44	0.68***	0.25	0.32	0.66***	0.21	0.45**
	(0.22)	(0.40)	(0.25)	(0.28)	(0.88)	(0.23)	(0.30)	(0.18)
Private	-0.23	-0.15	0.00	-0.12	-2.44**	0.43	-0.73	-0.06
	(0.30)	(0.56)	(0.32)	(0.35)	(1.24)	(0.28)	(0.42)	(0.23)
Government	0.54**	0.63	0.80***	0.24	-0.98	0.83***	0.11	0.58***
	(0.24)	(0.39)	(0.25)	(0.30)	(0.93)	(0.24)	(0.33)	(0.19)
Opt-out (Neither)	1.62***	0.25	1.52***	1.63***	3.42***	1.36***	1.06***	1.33***
	(0.25)	(0.51)	(0.29)	(0.39)	(1.24)	(0.32)	(0.30)	(0.21)

Standard deviation estimates								
Conservation till	-1.33***	-1.57***	1.20***	1.11**	3.48***	0.43	1.55***	1.16***
to no-till	(0.24)	(0.53)	(0.33)	(0.44)	(1.33)	(0.36)	(0.38)	(0.22)
Conventional till	-0.98***	-0.84	0.79**	0.68	-2.83***	1.12***	1.19***	0.86***
to conservation	(0.23)	(0.44)	(0.35)	(0.39)	(0.92)	(0.25)	(0.34)	(0.27)
Conventional till	-0.43	-0.98	0.82**	-0.67	4.72***	0.26	-0.74	0.74***
to no-till	(0.28)	(0.52)	(0.38)	(0.36)	(1.18)	(0.46)	(0.46)	(0.21)
No cover crops to	0.88***	0.60	1.06***	-0.43	2.30***	-0.13	1.35***	-0.64***
cover crops	(0.24)	(0.36)	(0.23)	(0.27)	(0.74)	(0.42)	(0.23)	(0.19)
Ten-year contract	1.60***	0.57	-0.77**	1.59***	3.12***	-0.59	0.69	0.96***
	(0.26)	(0.59)	(0.31)	(0.33)	(1.03)	(0.31)	(0.35)	(0.21)
Five-year	-0.88***	0.13	-0.52	-0.41	-3.15**	-0.25	1.13***	-0.72***
contract	(0.27)	(0.52)	(0.29)	(0.46)	(1.28)	(0.27)	(0.39)	(0.22)
Not-for-profit	0.08	0.46	0.22	-0.40	-2.12***	0.38	0.45	-0.23
	(0.26)	(0.42)	(0.61)	(0.31)	(0.78)	(0.22)	(0.28)	(0.22)

Private	1.50***	1.98***	-1.45***	1.35***	4.22***	1.35***	1.08**	1.31***
	(0.23)	(0.46)	(0.32)	(0.35)	(1.12)	(0.24)	(0.51)	(0.20)
Government	-0.15	0.64**	0.23	-0.46	-1.92**	-0.56	-0.40	-0.56***
	(0.24)	(0.29)	(0.24)	(0.32)	(0.82)	(0.33)	(0.53)	(0.19)
Opt-out (Neither)	2.31***	2.99***	2.11***	2.73***	8.00***	2.71***	1.99***	2.56***
	(0.19)	(0.44)	(0.21)	(0.29)	(1.90)	(0.25)	(0.26)	(0.17)
Log likelihood	-1404.56	-420.67	-1067.98	-753.25	-151.11	-1066.73	-787.64	-1957.08
LR Chi^2	461.46	210.50	353.89	303.73	117.62	408.79	240.67	676.51
p-value (Prob > Chi^2)	0	0	0	0	0	0	0	0
Number of observations	4,836	1,578	3,663	2,661	630	3,711	2,754	6,735

Note: The figures in brackets are the estimates of standard error.

***$p \leq 0.01$(1% level of significance) and **$p \leq 0.05$ (5% level of significance)

Conservation till non-adopters (who have not adopted conservation till, but might be practicing no-till or conventional till) have negative and statistically significant preference estimates for carbon payments to switch from conservation till to no-till and conventional till to conservation till, and for ten-year and five-year contracts lengths. Non-adopters exhibit positive and statistically significant preference for “Neither”, the opt-out option. The positive and statistically significant utility for opt-put option suggest that non-adopters do not prefer the carbon payments to switch to conservation practices. This might be either because the attributes and attribute levels of the carbon program presented to them are not attractive enough or because they are happy with their current non-adoption status. Compared to this, adopters of conservation till exhibit negative and statistically significant preference for switching from conservation till to non-till and conventional till to no-till and contract lengths. Adopters of conservation till have positive and statistically significant preference estimates for not-for-profit and government as governing agencies for carbon payments and for the “Neither” option.

Non-adopters of cover crops exhibit negative and statistically significant preference estimates for switching to any of the conservation tillage-related practice and for enrolling in a ten-year or five-year contract for carbon payments. Non-adopters of cover crops have positive and statistically significant preference estimate for “Neither” option. Similar to non-adopters, adopters of cover crops also have negative and statistically significant preference estimate for switching to no-till or conservation till and for ten-year and five-year contracts for the payment program. Cover crop adopters exhibit positive and statistically significant preference estimates for the government and not-for profit as the governing agency for the carbon payment programs and for “Neither” option.

As per results in Table 3, conventional till farmers have a negative and statistically significant preference for carbon payments to switch from conservation till to no-till and from conventional till to no-till, ten-year contract for the carbon payment program, and for private firms as governing agency. Unlike any other conservation practice adopters, conventional till farmers exhibit positive preferences for carbon payments to switch from no-cover crops to cover crops. Conventional till farmers have the largest positive and statistically significant coefficient for “Neither” option suggesting that they have positive utility from opting out of the carbon programs presented.

While the results in Table 3 allow us to compare farmers’ preferences for various carbon payment programs attributes between adopters and non-adopters of various conservation practices and the full sample, they fail to tell us whether or not these preferences are statistically significantly different between adopters and non-adopters. The results from pooled models presented in Appendix 4 will help us to examine the statistical significance in differences of preference estimates. Examination of the interaction term coefficients show that there is statistically significant difference in preference estimates between adopters and non-adopters of no-till for some of the attributes (e.g., switching from conservation till to no-till, conventional till to no-till, no cover crops to cover crops, and five-year contract). The results also show that preferences of conventional till growers are different from no-till adopters (switching from conservation till to no-till, switching from conventional till to no-till, switching from no-cover crops to cover crops, and five-year contract) and conservation till adopters (switching from conventional till to no-till and switching from no-cover crops to cover crops) for some of the attributes.

Farmers' willingness to accept carbon payments

Farmers' WTA carbon payments for various attributes of carbon payment programs ($/acre), estimated using utility coefficients from Table 3, are listed in Table 4. In this section, we focus on statistically significant WTA estimates for carbon program attributes. The negative WTA values are interpreted as an indicator that farmers prefer that particular attribute and they do not need any carbon payments to select that attribute.

Table 4. Farmers' willingness to accept estimates for different carbon program attributes

Attributes	**No till**		**Conservation Till**		**Conventional Till**	**Cover Crops**		**Full Sample**
	Adopters (N=272)	*Non-Adopters (N=91)*	*Adopters (N=205)*	*Non-Adopters (N=152)*	*Adopters (N=38)*	*Adopters (N=209)*	*Non-Adopters (N=157)*	(N=381)
Conservation till to no-till	2.46 [-0.30, 5.43]	37.21** [15.66, 118.03]	8.55*** [3.61, 15.14]	4.63** [0.80, 8.98]	7.60** [0.46, 16.61]	3.53** [0.44, 7.11]	9.65*** [4.35, 16.78]	6.31*** [3.50, 9.49]
Conventional till to conservation till	4.22*** [1.32, 7.54]	9.42 [0.60, 31.12]	3.28 [-0.77, 7.96]	4.58** [1.10, 8.86]	4.26 [-1.92, 10.55]	4.80** [1.22, 9.12]	7.16*** [2.67, 13.10]	5.24*** [2.55, 8.33]
Conventional till to no-till	2.63** [0.16, 5.39]	19.53** [7.69, 63.10]	7.88*** [3.06, 14.17]	2.75 [-0.44, 6.59]	11.52*** [5.02, 24.91]	2.65 [-0.47, 6.30]	8.90*** [4.50, 15.20]	5.96*** [3.30, 9.07]

No cover crops to cover crops	1.80	0.53	1.88	-0.51	-6.62***	-0.36	2.71	0.59
	[-0.16, 4.13]	[-6.41, 14.50]	[-1.39, 6.16]	[-2.77, 2.11]	[-12.19, -2.91]	[-2.31, 1.98]	[-0.85, 7.52]	[-1.15, 2.60]
Ten-year contract	9.61***	18.30***	11.62***	10.43***	12.95***	8.71***	11.03***	9.87***
	[6.77, 12.85]	[9.38, 46.66]	[7.78, 16.79]	[6.52, 15.19]	[7.28, 21.69]	[6.01, 11.88]	[6.89, 16.52]	[7.62, 12.50]
Five-year contract	3.41***	13.38**	5.42***	4.19***	5.74**	3.12***	5.47***	4.70***
	[1.18, 5.51]	[4.05, 39.57]	[1.57, 9.64]	[1.50, 6.85]	[-0.37, 12.02]	[0.60, 5.48]	[1.31, 9.95]	[2.58, 6.83]
Not-for-profit	-2.82	-6.27	-7.11**	-1.80	-1.00	-5.75***	-1.83	-3.86**
	[-6.68, 0.34]	[-36.93, 4.32]	[-14.84, -1.86]	[-6.57, 1.99]	[-9.63, 4.48]	[-10.83, -1.78]	[-8.16, 2.81]	[-7.53, -0.83]
Private	1.71	2.17	-0.04	0.83	7.72***	-3.70	6.22	0.54
	[-2.83, 5.43]	[-23.68, 18.36]	[-7.90, 5.88]	[-4.92, 5.17]	[0.18, 14.26]	[-9.81, 0.92]	[-0.99, 12.12]	[-3.76, 4.10]
Government	-3.93**	-9.05	-8.40**	-1.75	3.11	-7.14***	-0.92	-4.98***

	[-8.32, -0.48]	[-45.05, 1.56]	[-17.06, -2.76]	[-7.01, 2.18]	[-4.54, 8.00]	[-13.03, -2.79]	[-8.04, 4.12]	[-9.16, -1.65]
Neither	-11.81*** [-15.94, -8.31]	-3.51 [-21.78, 15.83]	-16.00*** [-24.20, -10.00]	-11.73*** [-17.77, -6.56]	-10.81*** [-21.49, -4.15]	-11.76*** [-17.80, -6.48]	-9.03*** [-15.05, -4.18]	-11.43*** [-15.39, -7.96]

Note: The figures in brackets are estimates of 95% confidence interval of WTA. Confidence intervals are calculated using the Krinsky and Robb method using 5,000 repetitions.

***p $\leq$ 0.01(1% level of significance); **p $\leq$ 0.05 (5% level of significance)

It is evident from Table 4 that farmers' WTA carbon payments vary based on the current adoption status and range from negative $16.00/acre to $37.21/acre. Overall, WTA carbon payments to switch to tillage related conservation practices are higher for non-adopters than adopters and the full sample. For example, no-till non-adopters are willing to accept $37.21/acre carbon payment to switch from conservation till to no-till and $19.53/acre to switch from conventional till to no-till. Compared to this, no-till adopters' WTA carbon payment estimates are $4.22/acre and $2.63/acre to switch from conventional till to conservation till and from conventional till to no-till, respectively. Conservation till non-adopters are willing to accept $4.58/acre to switch from conventional till to conservation till and conventional till growers are willing to accept $11.52/acre to switch from conventional till to no-till. The WTA estimates for the conservation tillage practices for the full sample range from $5.24/acre to $6.31/acre. These results are consistent with (Gramig & Widmar, 2017)who reported Indiana farmers' mean marginal WTA to implement no-till as $3.21/acre and $4.79/acre, relative to conservation tillage or conventional tillage, respectively. Cover crop non-adopters are willing to accept $7.16/acre to switch from conventional till to conservation till and $8.90/acre to switch from conventional till to no-till. The differences in WTA between different categories are further confirmed by Kernel density plots, shown in Appendix 6.

The WTA estimates are higher for ten-year contract relative to five-year of contract and non-adopters have higher WTA relative to adopters for these attributes for all categories included in our analysis. Adopters of no-till (-$3.93/acre), conservation till (-$8.40/acre), and cover crops (-$7.14/acre) have negative WTA values for government, indicating that they do not need payment to accept government as governing agency for the carbon programs. Adopters of conservation till (-\$7.11/acre) and cover crops (-\$5.75/acre) also have negative WTA values for not-for profit agencies as governing bodies for carbon payment programs. The higher negative values for government relative to not-for profit agencies shows adopters of conservation till and cover crops have a stronger preference towards government than not-for profit, a finding also evident in Table 3. The high negative values for the Neither option show farmers' preference to maintain the status quo for all the groups except for no-till non-adopters (which has a statistically insignificant willingness to accept estimate). Comparison of WTA estimates of adopters and non-adopters to the whole sample shows smaller values for the latter and highlights the heterogeneity in preferences and WTA carbon payments based on adoption status.

Examination of the statistical significance of WTA estimates of the interaction terms in Appendix 5 shows that there is statistically significant difference in willingness to accept estimates between adopters and non-adopters of no-till for some of the attributes (e.g., switching from conservation till to no-till, conventional till to no-till, no cover crops to cover crops, and five years of contract). The results also show that willingness to accept estimates of conventional till growers are different from no-till adopters (switching from conservation till to no-till, switching from conventional till to no-till, switching from no-cover crops to cover crops, and fiver years contract) and conservation till adopters (switching from conventional till to no-till and switching from no-cover crops to cover crops) for some of the attributes.

Discussion

Our study shows that farmers' preferences for carbon programs differ based on whether they are adopters or non-adopters of conservation practices and the type of practice. Although their methods used are distinct, Lynne and Kruse (2004) found heterogeneity in farmers' preferences for carbon payments based on the percentage of corn-soybean acres under conservation tillage. Similar to Gramig and Widmar (2017), our study showed that WTA values are higher for non-adopters than for adopters of any given conservation practice and vary between practices. The differences in the results between using the full sample and adoption-wise sample further underscore the importance of targeted carbon payment programs that account for farmers' heterogeneity in preferences. Our finding that farmers have higher negative preference for ten-year contract and would require twice as much to enroll in a ten-year contract than in a five-year contract suggest farmers prefer shorter/no contract length than longer ones. These results are consistent with Christensen et al. (2011) and Krah et al. (2018) who found farmers dislike multi-year contracts in the context of agri-environmental policy. The negative willingness to accept values for government and not-for profit attributes by adopters of conservation practices suggest that overall adopters prefer government followed by not-for profit organization as governing agencies relative to not having any governing agency and they would rather forego carbon payments for that attribute.

The positive and statistically significant preference estimates for "Neither" option and the associated negative WTA estimates imply that most farmers, irrespective of whether they are adopters or non-adopters, in our sample prefer the status quo over the proposed changes included in the choice experiment. For the adopters, it might be because they are satisfied with the practices they are currently implementing. For the non-adopters, it might either be due to the unacceptable contract terms or governing mechanisms or simply lack of knowledge of conservation practices. If it is the latter, targeted outreach efforts could be beneficial to address the non-adoption of conservation practices to some extent. Farmers' strong preference for the opt-out option in the choice experiment indicates the challenges of using carbon payment programs to incentivize farmers to switch to carbon sequestering conservation practices on their fields. Our study shows statistically significant differences in preferences and WTA estimates of carbon payments and other carbon program attributes between adopters and non-adopters of same practice and between practices. This finding implies that for carbon market programs to become important vehicles for promoting agricultural soil carbon sequestration by farmers, carbon program providers and policymakers need to address the heterogeneity in farmers' preferences based on adoption status and practice type and design the program and outreach efforts accordingly.

Policymakers and carbon market providers need to strategize how to attract non-adopters of certain practices while making sure that adopters do not revert to non-conservation practices and develop program attributes such as contract length and governance mechanism that are acceptable to farmers. Since more knowledge leads to positive behavior towards sustainable agricultural production practices (Greiner et al., 2009; Liu et al., 2018), outreach efforts should focus on increasing knowledge and awareness toward conservation practices and carbon market programs.

Our study has some limitations. First, since we used a hypothetical choice experiment, farmers' responses might be specific to the attributes and attribute levels included in the choice experiment. Inclusion of different sets of attributes and attribute levels or expansion of attributes might lead to different results. Carbon market programs are evolving quickly in the United States. Future studies (hypothetical and non-hypothetical) that incorporate additional attributes could address this shortcoming. Second, we used dollar per acre to list carbon payments based on our interaction with various stakeholders. Our interactions with stakeholders revealed that dollar per acre is better for farmers to assess the benefits than dollar per ton of carbon. However, some of the carbon payment programs currently available in the market uses dollar per ton of carbon.

CHAPTER III

THE ROLE OF PERCEPTIONS AND ADVERSE WEATHER EXPERIENCES IN FARMERS' WILLINGNESS TO ACCEPT CARBON PAYMENTS[2]

[2] This paper is under review at the Journal of Agricultural and Resource Economics.

Abstract

Understanding factors influencing farmers' decisions to accept carbon payments aids in devising climate-smart policies. Using a Latent Class Model, we identify four groups of farmers based on their climate change perceptions and adverse weather experience and find farmers' willingness to accept carbon payments estimated using discrete choice experiment data varies between groups. Those more concerned with climate change are more likely to enroll in carbon market programs and demand smaller carbon payments than those less concerned. Findings suggest groups-specific interventions and programs could be cost effective when scaling up climate-smart agricultural practices adoption.

Introduction

The agriculture, forestry, and other land uses (AFOLU) sector is responsible for approximately 24% of total global greenhouse gas (GHG) emissions (IPCC, 2014). In 2021, the agricultural sector alone contributed around 9.3% of total US GHG emissions (EPA, 2023). Thus, reducing GHG emissions is essential for mitigating climate change impacts. In this regard, the AFOLU sector stands out because of its potential to lower emissions independently, sequester atmospheric carbon at a low cost, and supply essential resources that can facilitate emission reduction in other sectors (Nabuurs et al., 2022). The United States has developed many initiatives to increase the adoption of climate-smart agricultural practices. Several programs, such as the Agricultural Conservation Easement Program (ACEP), the Conservation Stewardship Program (CSP), the Conservation Reserve Program (CRP), the Environmental Quality Incentives Program (EQIP), Conservation Innovation Grants (CIG), Regional Conservation Partnership Program (RCPP), and the recent Partnerships for Climate-Smart Commodities were established to aid farmers, ranchers, private forest landowners, and partners in implementing climate solutions (*Climate-Smart Agriculture and Forestry*, 2023). Under its first funding pool, the Partnerships for Climate-Smart Commodities is investing as much as $2.8 billion in seventy projects to finance different initiatives, which also includes creating market and revenue streams for farmers and commodities across agriculture (*Partnerships for Climate Smart Commodities*, 2023).

Carbon markets hold significant potential for reducing GHG emissions and mitigating climate change through the removal of atmospheric carbon by paying farmers to adopt conservation practices that sequester atmospheric carbon in the soil. Previous studies have shown the technical potential of agricultural soil carbon sequestration in mitigating climate change, mainly through conservation practices like no-till, conservation-till, and cover crops (Feng et al., 2000; Lal, 2004; Lal et al., 1998; Lal et al., 2015; Lynne & Kruse, 2004; E. Pindilli et al., 2018). However, it is essential to utilize market-based mechanisms that will help farmers adopt these conservation practices to achieve agricultural soil carbon sequestration. One such approach involves carbon market programs, which have the potential to incentivize farmers to adopt conservation practices (Feng et al., 2000; Sandor & Skees, 1999).

Agri-environmental schemes will only be truly successful if they contribute to long-term changes in farmers' attitudes toward the environment and encourage them to farm in an environmentally friendly way (Lowe et al., 1999; Wilson, 1997). However, knowledge of farmers' preferences for carbon market programs and their willingness to accept carbon payments is limited (Mase et al., 2017), especially concerning farmers' perceptions about threats posed by climate change and their experiences with adverse weather.

Wuepper et al. (2023) demonstrated that agricultural economics is an integral part of behavioral economics, and that behavioral patterns are important for explaining economic agents' decision making. The way individuals interpret their experiences and form their reactions is influenced by their perceptions, which in turn inform their behavior and actions (Given, 2008). Behavioral science experiences can be helpful in informing policymakers about designing effective and appropriate agri-environmental policies and programs (Streletskaya et al., 2020). Thus, it is important to understand motivations, goals, and concerns of decision makers in designing efficient and effective policies.

According to the Intergovernmental Panel on Climate Change (IPCC), climate change perception refers to the way people relate to risks associated with the climate (IPCC, 2018). We use this definition in our study based on farmers' subjective judgments about and reactions to climate change. McFadden (1986) highlights that the perceptions or beliefs about products, generalized attitudes or values, preferences among products, decision protocols that depict preferences into choices, and behavioral intentions for choice are the critical constructs in modeling the cognitive decision process. Thus, considering latent (i.e., unobserved) variables that seek to capture attitudinal, perceptual, and socioeconomic factors is important for understanding choice behavior.

Farmers' perceptions of climate events are important determinants of their adaptation to the impacts of climate change (Arbuckle et al., 2015; Shinbrot et al., 2019; Zamasiya et al., 2017). Perceptions and experiences related to climate change might vary among farmers and result in differences in their behavior and in their preferences toward carbon market programs. Hence, knowing that farmers' behavior plays a significant role in their decision-making, only using economic incentives as a determinant and assuming farmers always make rational decisions is inadequate when designing effective and efficient policies for mitigating environmental impacts of agriculture (Dessart et al., 2019).

Understanding heterogeneity in preferences is crucial for estimating unbiased preference-based economic models and provides important information regarding the distributional effects of policy impacts and decisions on resource use (Boxall &

Adamowicz, 2002). Preference heterogeneity is important for studying a variety of factors, such as agroclimatic conditions, human capacities, and technology adoption (Feder et al., 1985). While economic factors play a significant role in farmers' willingness to participate in agri-environmental measures, preference heterogeneity is a critical factor in explaining farmer participation (Hasler et al., 2019; Lastra-Bravo et al., 2015).

Although researchers have studied heterogeneity among farmers based on a variety of factors, few studies consider heterogeneity regarding climate change risks and environmental policies (Barnes et al., 2013; Niskanen et al., 2021; Tosakana et al., 2010). Previous studies show that farmers' perceptions of climate events determine their adaptation activities, hence understanding these perceptions is critical for understanding their adaptation decision-making (Arbuckle et al., 2015; Howard & Roe, 2013; Shinbrot et al., 2019; Zamasiya et al., 2017). Similarly, farmers' experiences with climate variability and extreme events also affect their adaptation activities (Kahsay et al., 2019; Waibel et al., 2018). Howard and Roe (2013) conducted a study in Ohio and found that those farmers who believe in climate change and the potential for conservation practices in mitigating its effects were more likely to adopt best management practices (BMPs) even without incentives. A 2014 study in Vietnam also found that farmers are more likely to engage in adaptation measures if they perceive greater climate risks and believe the effectiveness of adaptation measures whereas those farmers who deny climate change risks are less likely to adapt (Dang et al., 2014).

Mase et al. (2017) showed that farmers who believe in anthropogenic climate change are more likely to recognize changes in weather patterns and are more concerned about on-farm risks like drought, extreme rainfall, insect infestations, and diseases than those less concerned about climate change. Ruto and Garrod (2009) found that environmentally-concerned farmers are relatively more receptive toward adopting agri-environmental programs than those less concerned about the environment. Furthermore, concerns regarding changes in weather patterns are a critical factor in influencing their adaptation behavior. For example, in South Dakota, a recent study showed that there is a relationship between farmers' adoption of conservation practices and their perception of severe drought and wet conditions (Etumnu et al., 2022). However, to the authors' knowledge, no study exists that explores the heterogeneity existing among farmers' preferences and their willingness to accept (WTA) payments for carbon market programs based on their climate change perceptions and their experiences with adverse weather events. Thus, the main objectives of this study are:

1) To identify different groups of farmers based on their climate change perceptions and adverse weather experiences.
2) To explore whether preferences toward carbon market programs and willingness to accept carbon payments vary between different farmer groups.

We investigate these two research objectives by employing a Latent Class Model applied to discrete choice experiment data to identify groups of farmers and estimate group-wise WTA carbon payment values. Group identification is based on the farmers' responses regarding their perceptions of anthropogenic climate change and their experiences with adverse weather conditions.

Methods: Survey Description, Latent Class Model, and Discrete Choice Experiment

Survey Description

The data used in this study were obtained from a primary mail-in survey of corn and soybean farmers in South Dakota held from late 2021 to early 2022. Before conducting the main survey, a pilot study was conducted among a small group of corn and soybean producers in South Dakota. Out of a total of 19 responses, we used 17 in our analysis due to missing data concerns. The survey consisted of sections on current farm management practices, farm operator preferences and their willingness to enroll in carbon market programs, basic farm information, farmers' perceptions of climate change, and the respondents' experiences with adverse weather conditions including excessive drought and wet situations over the preceding ten years.

Based on the responses to the pilot survey, the survey instrument was revised and sent to a representative sample of 3,000 corn and soybean farmers in South Dakota, identified using proportionate sampling. The participants were contacted four times. First, they were sent the survey instrument with stamped return envelopes in the first week of December 2021. Non-responders received post-card reminder in mid-December 2021. A second round of survey instrument mailing was done in the first week of February 2022, followed by a second post-card reminder in the last week of February 2022. By the end of April 2022, 402 usable survey responses were received, yielding a 14.5% response rate. Among those, 381 individuals provided usable responses that were utilized in this study. Table 5 shows the summary statistics of the full sample.

Table 5. Summary statistics of the full sample compared to census of agriculture data

Demographics	**Full Sample (n=402)**	**South Dakota Agriculture Census**	**US Agriculture Census**
Age			
18-25 years old	0.26%	1.38%	1.48%
26-35 years old	4.69%	9.19%	6.80%
36-45 years old	12.50%	12.69%	11.32%
46-55 years old	14.06%	16.64%	17.83%
56-64 years old	29.17%	29.44%	27.72%
65 years or older	39.32%	30.66%	33.48%
Education			
Below high school	2.09%		
High school graduate or Associate degree	50.39%		
College degree or higher	47.52%		
Total cropland acres	1467.01	661.16	268.65
Annual farm sale			
Less than $50,000	4.91%	48.37%	47.84%
$50,000-$99,999	9.25%	9.12%	10.19%
$100,000-$499,999	42.48%	26.47%	18.23%
More than $500,000	43.35%	16.04%	23.74%
Land tenancy agreement			
1 year lease	48.50%		
(2-3) years lease	36.54%		
(4-5) years lease	6.64%		
More than 5 years lease	8.31%		

Source: Authors' survey and USDA (2017)

Latent Class Model (LCM)

One of our main objectives is to identify different groups of farmer-respondents based on their climate change perceptions and adverse weather experiences. To do so, we utilized a Latent Class Model (LCM), which assumes that the observed distribution of a variable stems from a finite latent (unobserved) mix of unobserved classes of distributions of similar preferences. We used the respondents' perceived climate change concerns and adverse weather experiences as class-defining variables. Preferences are assumed to be heterogeneous between different classes or groups but homogenous within a single class or group (Colombo et al., 2009). This approach is consistent with previous studies that utilized LCA of farmers' heterogeneous preferences regarding different conservation programs (Barnes et al., 2013; Greiner, 2015; Howard & Roe, 2013; Jaeck & Lifran, 2009; Niskanen et al., 2021; Ruto & Garrod, 2009).

Grouping Farmers Based on Their Concerns about Climate Change

The farmers' perceptions about climate change were measured through five statements, each ranked on a five-point Likert scale ranging from one (strongly disagree) to five (strongly agree). Four statements elicited responses from farmers about the degree to which they perceived that climate change is happening and impacting agriculture. The remaining statement listed climate change as a natural process.

To maintain directional consistency of the five statements, the statement that listed climate change as a natural process was reverse-coded by assigning numerical values to the response options on that statement which is opposite in meaning to the other four statements on the same scale. For example, we used 1 to represent "strongly agree" and 5 to represent “strongly disagree” for the four statements, while it was the opposite for the reverse-coded statement.

Jointly, the five statements sought to capture the extent to which farmers perceive climate change as a reality. To convert the five statements to a single scale, we calculated their arithmetic means. We used Cronbach’s alpha to check the internal consistency of the scale. Table 6 describes the five statements.

Table 6. Climate change concern scale

S.N.	Climate Change Concern Statements
1.	Climate change is entirely a natural process.
2.	Climate change is due to anthropogenic (human-induced) activities.
3.	Agriculture is also contributing to climate change.
4.	Climate change is causing and will cause frequent and intense environmental disasters like floods, drought, etc.
5.	Climate change is impacting agriculture.
Overall mean of scale- 2.96	
Cronbach’s alpha- 0.8	

Grouping Farmers Based on Their Experience with Adverse Weather

Farmers’ prior experiences with adverse weather conditions were measured using one drought and one wet-related statement, each measured on a five-point Likert scale ranging from one (strongly disagree) to five (strongly agree). The statements sought to capture the respondents’ experiences with unusual drought and wet conditions on their farms over the prior ten years. For ease of analysis and interpretation, the five-point scales were converted to three points by combining ‘strongly disagree’ and ‘disagree’ to form ‘disagree’ and merging ‘strongly agree’ and ‘agree’ responses into ‘agree’.

We used both quantitative and qualitative measures to determine the optimum number of classes. Based on considerations of the former, using the Akaike Information Criterion (AIC) and Corrected Akaike’s Information Criterion (CAIC), and the latter using the significance of the predictors and sample size within each class, we finalized a latent class model with a four-class solution. Table 7 shows that while the AIC and CAIC values of the latent class model with five classes or groups are smallest, we chose the model with four classes or groups as having the best fit for optimum number of classes. This is not only because the sample size of one of the groups in the latent class model with five classes or groups would have been inadequate (representing less than 5% of the total number of respondents), but also because the class predictors were more significant in model with four classes or groups than the model with five classes or groups.

Table 7. Summary of description of latent classes

Number of Latent Classes	**Log-Likelihood**	**AIC**	**CAIC**	**McFadden Pseudo R^2**
2	-1988.03	4028.1	1.79	0.19
3	-1925.98	3934.0	1.75	0.22
4	-1892.01	3896.0	1.74	0.23
5	-1867.61	3877.2	1.73	0.24

Discrete Choice Experiment

A Discrete Choice Experiment (DCE) was conducted to elicit farmers' preferences, which is a stated preference method to study farmers' preferences for carbon market programs. Table 8 reports the attributes and their levels used in our study.

Table 8. Summary of attributes and attribute levels in the discrete choice experiment

Attribute	**Attribute Levels**
Tillage Practice Change	No change in tillage practice
	Conservation-till to no-till
	Conventional-till to conservation-till
	Conventional till to no-till
Cover Crops Practice Change	No change in cover crops practice
	No cover crops to cover crops
Contract Length	No contract
	Five-year contract
	Ten-year contract
Governance	None
	Not-for-profit
	Private (for-profit)
	Government (USDA)
Carbon Payment ($/ acre)	$0
	$5
	$10
	$15
	$20

Attribute levels were allocated based on interactions with crop producers, previous studies, and results from the pilot study. The price levels were allocated based on the price range of current farm conservation programs as well as proposed and implemented price levels of private carbon markets in the United States. Appendix A lists the definitions of these attributes and their attribute levels, as provided in the survey instrument.

The choice scenarios used in this study were designed using the Ngene software. The D-efficient Multinomial Logit (MNL) model was used to generate the choice sets, using priors from the pilot study and previous studies. A total of thirty choice sets were generated with five blocks of six choice sets. Each respondent had six choice sets with three alternatives in each choice set; Option A, Option B, and Neither (Opt-out).

The DCE data were analyzed using MNL to examine the effect of carbon market attributes on choice behavior. For the empirical analysis, we adapted the method described by Apostolidis and McLeay (2016) with minor modifications to suit our experimental design.

The random utility ($\boldsymbol{U_{nit}}$) of attribute $\boldsymbol{i}$ of individual $\boldsymbol{n}$ in choice occasion $\boldsymbol{t}$ is specified as:

$$\boldsymbol{U_{nit} = V_{nit} + e_{nit}} \tag{1}$$

In equation (1), $\boldsymbol{V_{nit}}$ is the deterministic portion of utility dependent upon the attributes of the carbon market alternative and $\boldsymbol{e_{nit}}$ is an independently and identically distributed error.

According to Lancaster (1966), the deterministic portion of utility can be expressed as:

$$V_i = \beta_0 + \sum_{k=1}^{K} \beta_k X_k \tag{2}$$

In equation (2), V_i is the sum of the group of attributes X explaining choice alternative i. β is the parameter associated with attribute levels.

In our study, the deterministic portion of utility (V_{ij}) is a linear function of price (the carbon payment), changes in conservation practices (conservation-till to no-till, conventional-till to conservation-till, conventional-till to no-till, no cover crops to cover crops), contract length (five-year contract, ten-year contract), governance mechanism (not-for-profit, private and government) and estimated using the following equation:

$$\begin{aligned} V_{ij} = {} & \beta_0 + \beta_1 CarbonPay_{ij} + \beta_2 ConstNt_{ij} + \beta_3 ConvCt_{ij} + \beta_4 ConvNt_{ij} \\ & + \beta_5 Cover_{ij} + \beta_6 FiveContract_{ij} + \beta_7 TenContract_{ij} \\ & + \beta_8 (Not - for - profit)_{ij} + \beta_9 Private_{ij} + \beta_{10} Government_{ij} \end{aligned} \tag{3}$$

The probability of an individual choosing alternative i over alternative j is expressed as:

$$P_i = Prob\left(V_i + e_i > V_j + e_j\right) \text{ } for\ all\ j \in J, where\ j \neq i. \tag{4}$$

The closed form of the logit choice probability is expressed as:

$$P_{nit} = \frac{exp\ (\beta\ X_{nit})}{\sum_{j=1}^{J} exp\ (\beta\ X_{njt})} \tag{5}$$

In the LCA, we assume that preference heterogeneity occurs discretely, where $\boldsymbol{N}$ individuals are assigned probabilities to fall into an $\boldsymbol{S}$ number of latent classes, including homogeneous respondents in each (Boxall & Adamowicz, 2002). By adjusting equation (5), we can find the conditional choice probability, which is the probability of an individual $\boldsymbol{n}$ falling in a segment or group or class $\boldsymbol{s}$ as shown in equation (6).

(6) $$\boldsymbol{P}_{\boldsymbol{ji}\,|\boldsymbol{s}} = \prod_{t(n)}^{T(n)} \frac{\boldsymbol{exp}\ (\boldsymbol{\beta'}_{\boldsymbol{s}}\ \boldsymbol{X}_{\boldsymbol{nit}})}{\sum_{j=1}^{J} \boldsymbol{exp}\ (\boldsymbol{\beta'}_{\boldsymbol{s}}\ \boldsymbol{X}_{\boldsymbol{njt}})}$$

where $\boldsymbol{t}(\boldsymbol{n})$ is a specific choice occasion from the set of choice occasions $\boldsymbol{T}(\boldsymbol{n})$ of individual $\boldsymbol{n}$ and $\boldsymbol{\beta}'$ is a class or segment-specific parameter. The unconditional choice probability could be obtained by combining this conditional choice probability with marginal membership probability

$\boldsymbol{P}_{(\boldsymbol{s})} = \frac{\boldsymbol{exp}(\boldsymbol{\lambda_s Z_n})}{\sum_{s=1}^{S} \boldsymbol{exp}(\boldsymbol{\lambda_s Z_n})}$ (where $\boldsymbol{\lambda_s}$ is the segment-specific coefficient which explains whether the variable $\boldsymbol{Z_n}$, which describes the farmer, increases the probability that individual $\boldsymbol{n}$ belongs to segment $\boldsymbol{s}$), which yields the unconditional choice probability as shown in equation (7).

(7) $$\boldsymbol{P}_{\boldsymbol{ij}} = \sum_{s=1}^{s} \boldsymbol{P}_{\boldsymbol{s}}\ \sum_{t(n)}^{T(n)} \boldsymbol{P}_{\boldsymbol{ijt}\,|\boldsymbol{s}}$$

The probabilities for an individual latent class can then be expressed as shown in equation (8) (Hu et al., 2004).

(8) $$\boldsymbol{P_{(s)}^{P}} = \frac{\boldsymbol{P_s \prod_{t(n)}^{T(n)} P_{ijt}}}{\boldsymbol{\sum_{s=1}^{s} P_s \prod_{t(n)}^{T(n)} P_{ijt\,|s}}}$$

The mean WTA estimate is calculated by using the following equation:

(9) $$\boldsymbol{Mean\,WTA_j} = \left(\boldsymbol{\frac{1}{N}}\right) \boldsymbol{\sum_{n=1}^{N} WTA_{n,j}},$$

where $\boldsymbol{Mean\,WTA_j}$ is the mean WTA for the $\boldsymbol{j}^{\text{th}}$ attribute level and $\boldsymbol{N}$ is the total number of respondents in the population. $\boldsymbol{WTA_{n,j}}$ is the individual WTA for the $\boldsymbol{j}^{\text{th}}$ attribute level, given a respondent $\boldsymbol{n}$'s class membership $\boldsymbol{s}$, in a latent class analysis with $\boldsymbol{s}$ classes, and expressed as $\boldsymbol{WTA_{n,j}} = \boldsymbol{\sum_{s=1}^{s} P_{n,s}} \left(\frac{\boldsymbol{-\beta_{s,j}}}{\boldsymbol{\beta_{s,p}}}\right)$ where, $\boldsymbol{P_{n,s}}$ is the probability that respondent $\boldsymbol{n}$ belongs to class $\boldsymbol{s}$. $\boldsymbol{\beta_{s,j}}$ is the estimated coefficient for the $\boldsymbol{j}^{\text{th}}$ attribute level for class $\boldsymbol{s}$ and $\boldsymbol{\beta_{s,p}}$ is the estimated coefficient for the price attribute for class $\boldsymbol{s}$. Data analysis for Latent Class Model (LCM) was conducted in NLOGIT® 6 software.

Results and Discussions

Latent Class Identifiers Climate Change Concern and Adverse Weather Experience

The results from the respondents' perceptions about climate change show an overall mean of 2.96 and Cronbach's alpha value of 0.8, which demonstrates the internal consistency and reliability of the scale, and indicate that the majority of the respondents exhibit relatively few concerns about the causes and impacts of climate change. Similarly, most respondents experienced both severely wet (57.74% of the respondents) and dry (64.83%) conditions on their farms over the preceding ten years. Based on these two class identifiers (climate change concern and adverse weather experience), we aim to find different latent classes or unobserved groups within our sample. We used these identifiers to detect the existence of the presence of different unobserved groups of farmers based on climate change concerns and adverse weather experiences.

Latent Classes

Out of the four groups, the largest is Group 1 (35.97%) followed by Group 2 (27.44%), Group 4 (24.80%) and Group 3 (11.78%). Figure 2 shows that Group 4 has highest concern about climate change, followed by Groups 3, 2, and 1, respectively. This result confirms the need for conducting the latent class analysis to identify different categories of farmers from the same sample based on their climate change perceptions and to examine their preferences towards carbon market programs. These results are analogous to a study by Greiner (2015), who investigated the impact of motivations and attitudes on Australian farmers' willingness to participate in biodiversity conservation contracts, in the sense that the author also demonstrated the effectiveness of a latent class model in analyzing these farmers' decision-making behavior.

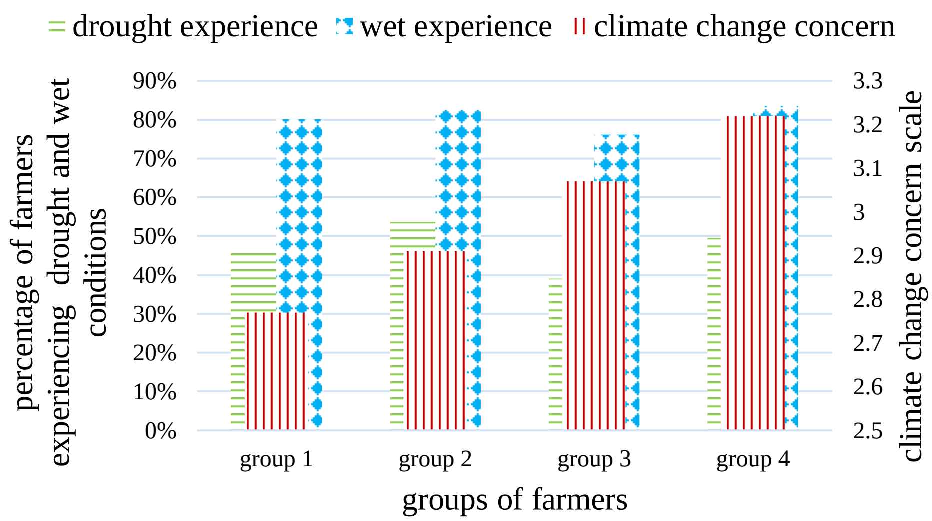

Figure 2. Climate change concerns and adverse weather experiences of respondents in different groups

While adverse weather experiences (increased or severely dry and wet experiences over the last ten years) appear relatively similar across groups, all four groups experienced more wet than dry conditions. Appendix 7 shows similar levels of adoption of various conservation practices used by farmers in different groups. For all the no-till, conservation-till, and cover crops categories, there are more adopters than non-adopters. Results in Table 9 suggest that socio-demographic characteristics of sex, education, and annual farm sales are statistically significantly different between groups at 10%. Groups of farmers who are more concerned about climate change are more likely to have higher annual farm sales.

Table 9. Sociodemographic characteristics of respondents in different latent groups

Category	**Group 1 (35.97%)**	**Group 2 (27.44%)**	**Group 3 (11.78%)**	**Group 4 (24.80%)**	**Chi-Square/ P-Value**
Age group	65+ yrs	65+ yrs	56-64 yrs	65+ yrs	20.02
	(45.19%)	(42.71%)	(40.00%)	(32.98%)	0.17
Sex	Male	Male	Male	Male	6.75
	(91.79%)	(93.75%)	(97.73%)	(98.94%)	0.08
Education	High school degree	High school degree	College degree	High school degree	11.25
	(49.63%)	(48.42%)	(62.22%)	(57.45%)	0.08
Frequency of learning about farming	1-3 times	1-3 times	1-3 times	1-3 times	9.25
	(59.09%)	(56.25%)	(62.22%)	(73.12%)	0.41
Land tenancy agreement	1 yr lease	1 yr lease	1 yr lease	1 yr lease	4.76
	(53.19%)	(46.67%)	(52.50%)	(43.75%)	0.86
Annual farm sale	$100,000-$249,999	$100,000-$249,999	$250,000-$499,999	$250,000-$499,999	23.19
	(21.01%)	(24.71%)	(20.00%)	(28.24%)	0.08
Percentage of off-farm income	(1-20) %	(1-20) %	(1-20) %	(1-20) %	10.83
	(33.60%)	(38.64%)	(39.13%)	(42.53%)	0.77

Table 10 shows the utility preference estimates of different groups obtained from the latent class logit model. Group 1, which is the largest group but with smallest concern about climate change, has a positive preference for the "none" or opt-out option and price attribute, but a negative preference for most other carbon market attributes. Similarly, Group 2 has a positive preference for the opt-out option and price attribute, but a negative preference for any kind of contract (both the ten-year and five-year contracts). Group 3's preference for the opt-out option is not significant but its price attribute is positive and statistically significant. Group 3 also has a negative preference for conversion to no-till (from both conservation-till and conventional-till), has a positive preference for a relatively short term (five-year) contract, and does not prefer a private form of governance. Group 4, which has the highest concern about climate change, has a negative preference toward the opt-out option, which means this group is interested in enrolling the cropland in a carbon market program. Hence, the group of farmers most concerned about climate change is most likely to not opt-out and enroll their land in a carbon market program. This group also has a positive preference for the price attribute but a negative preference to convert from conventional-till to conservation-till. Group 4 also has a positive preference for a non-profit and a private form of governance.

The results do not indicate a statistical difference between adopters and non-adopters of no-till and conservation-till between different groups, but our study shows a significant difference between cover crop adopters and non-adopters between different groups, as shown in Appendix 8.

Table 10. Utility preference coefficients for carbon program attributes

Attributes	**Group 1**	**Group 2**	**Group 3**	**Group 4**

None (Opt-out)	1.70***	1.29***	0.70	-1.80***
	(0.37)	(0.41)	(0.44)	(0.58)
Carbon Payment	0.11***	0.13***	0.18***	0.06**
	(0.03)	(0.03)	(0.05)	(0.03)
Conservation-till to no-till	-1.47***	-0.40	-1.71***	0.21
	(0.41)	(0.32)	(0.60)	(0.21)
Conventional-till to conservation-till	-1.68***	0.15	0.42	-0.58***
	(0.41)	(0.28)	(0.46)	(0.22)
Conventional-till to no-till	-1.18***	0.01	-3.77***	-0.16
	(0.37)	(0.28)	(0.96)	(0.22)
No cover crops to cover crops	-0.37	0.27	-0.74	-0.11
	(0.31)	(0.19)	(0.45)	(0.17)
Ten-year contract	-1.04***	-1.88***	0.99	-0.36
	(0.36)	(0.28)	(0.56)	(0.19)
Five-year contract	-0.17	-1.37***	1.46**	0.01
	(0.32)	(0.25)	(0.63)	(0.21)
Not-for-profit	-0.61	0.29	0.03	0.53**
	(0.62)	(0.38)	(0.74)	(0.26)

Private	-0.88	0.21	-4.30***	0.90***
	(0.77)	(0.46)	(1.38)	(0.32)
Government	-0.62	0.59	-0.04	0.48
	(0.71)	(0.40)	(0.74)	(0.27)
Log likelihood		-2466.38		
R-squared		0.23		
Adjusted R-squared		0.22		
Number of observations		2286		

Notes: The figures in brackets are the standard error estimates. Double and triple asterisks (**, ***) indicate statistical significance at the 5%, and 1% levels, respectively.

The results reported in Table 10 show that high levels of concern about climate change among these farmers are associated with high levels of conservation practices adoption and high levels of carbon market program participation. These findings are consistent with those of a recent study in South Dakota which showed that farmers' perceptions of extreme weather events (drought and flooding) are positively correlated with their adoption of conservation practices (Etumnu et al., 2022). The findings are also consistent with Dang et al. (2014) , who also revealed a positive correlation between farmers' perceptions of climate change risks and a likelihood to engage in adaptation measures. These findings point to the need for creating increased awareness about climate change among farmers through outreach activities for mitigation and adaptation purposes. Arbuckle et al. (2015) concluded that even farmers who do not believe in anthropogenic climate change could be motivated to engage in climate change adaptation and mitigation through outreach strategies which focus on adaptive practices. A study by Barnes et al. (2013) suggested that promoting the benefits of agri-environmental schemes could be an effective tool to increase awareness about climate change risks and encourage uptake of government and industry-supported actions.

Table 11 reports the WTA payments for converting to different conservation practices. Group 1, which is the largest of the four groups and has the smallest concern about climate change overall, requires higher payments for making change to their tillage practices. This group requires $10.06/acre to convert from conventional-till to no-till, $12.64/acre to convert from conservation-till to no-till and $13.96/acre to convert from conventional-till to conservation-till. The other groups require comparatively smaller WTA to convert their tillage practices, except for Group 3, which requires the highest amount ($18.86/acre) to convert from conventional to no-till, perhaps because this group has the strongest preference for price attributes among the four groups. These results show that there is a significant degree of heterogeneity in WTA between different groups of farmers in our study.

Table 11. Willingness to accept carbon payments ($/acre)

Groups	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**F-Statistic**

Conservation-till to no-till	12.64	3.95	8.88	-2.15	2176.87***
	(1.46)	(1.49)	(0.72)	(1.59)	
Conventional-till to conservation-till	13.96	0.24	-1.93	7.84	1140.19***
	(2.52)	(1.85)	(0.66)	(2.08)	
Conventional-till to no-till	10.06	1.72	18.86	2.78	1060.22***
	(1.48)	(2.48)	(2.37)	(1.76)	
No cover crops to cover crops	2.93	-1.36	3.56	1.34	714.62***
	(0.75)	(0.89)	(0.67)	(0.72)	
Ten-year contract	10.03	13.24	-3.47	6.86	1029.82***
	(0.84)	(2.18)	(2.34)	(1.88)	
Five-year contract	2.34	8.95	-6.28	1.12	761.11***
	(1.24)	(2.22)	(2.11)	(2.03)	
Not-for-profit	4.91	-1.83	-0.33	-7.60	2464.63***
	(1.14)	(1.08)	(0.34)	(1.32)	
Private	7.47	-0.25	21.17	-11.96	1598.18***
	(1.37)	(3.06)	(3.03)	(4.10)	
Government	4.78	-3.81	-0.19	-7.23	2060.99***
	(1.47)	(1.33)	(0.54)	(0.91)	

Notes: The figures in brackets are the estimates of standard error in the first four columns; the last column shows the F-statistic obtained from F-tests; and triple asterisks (***) indicate statistical significance at the 1% level between different groups.

Similar findings are observed for contract length. Groups 1 and 2 (with relatively small concerns about climate change) require higher WTA than Groups 3 and 4. Group 2 requires $13.24/acre and $8.95/acre for ten-year and five-year contract terms respectively. So, farmers with smaller concerns about climate change demand greater carbon payments as contract length increases. Regarding governance mechanisms, Groups 2, 3, and 4 have negative WTA for governance mechanism, except for private forms of governance for Group 3. Negative WTA indicates no carbon payments are needed for a carbon market system that utilizes a governance mechanism for oversight. Group 3 has the highest WTA for a private form of governance, $21.17/acre, and Group 4 has the highest negative WTA for all governance attributes. Group 1 has a positive WTA for all governance attributes, suggesting that farmers with relatively small concerns about climate change require some carbon payment in return for a governance mechanism. Overall, farmers with the comparatively largest concern about climate change do not need carbon payments to be governed by not-for-profit and government entities.

Our findings show that those farmers who are comparatively more concerned about climate change need smaller carbon payments. This is consistent with work by Zemo and Termansen (2021) showing that Danish farmers who strongly identified with environmental values required lower financial incentives to invest in renewable energy production and were likely to commit to more binding investment contracts. Broomell et al. (2015) also suggested that emphasizing personal experiences with climate change, including with extreme adverse weather conditions, could motivate individuals to implement actions to help mitigate climate change. Finally, our findings are consistent with Falconer and Saunders (2002), who also showed the need for tailored efforts to maximize farmers' participation in agri-environmental schemes.

Conclusions and Policy Implications

Among the respondents of our study, there are four groups of farmers with respect to their perceptions about climate change and their experiences with adverse weather conditions. Group 4 had the highest concern about climate change, followed by Groups 3, 2, and 1, respectively. All groups had similar adverse weather experiences over the last ten years, but all had more experiences with severely wet than with excessively dry conditions. The socio-demographic characteristics of the farmers in the four groups are similar.

Farmers' preferences for carbon programs and WTA carbon payments differ between the four groups. Group 1 has an overall higher WTA carbon payments associated with switching to conservation-till practices and prefers to opt-out of carbon markets. Group 2 has the highest WTA for any contract length. Group 3 does not require any payment for either a five-year or a ten-year contract, whereas Group 4, which is more concerned about climate change, has the highest negative WTA for governance and prefers to enroll in carbon market programs.

Findings from our study imply that carbon programs should incorporate heterogeneity in terms of farmers' perceptions about climate change and their experience with adverse weather in designing attributes and attribute levels. Our study shows that some groups of farmers have greater concerns about climate change than others, such that high levels of concern about climate change among farmers are associated with (a) conservation practice adoption for relatively smaller payments, (b) comparatively greater flexibility regarding different contract lengths, and (c) a relatively greater willingness to accept oversight for monitoring and verification. This information provides critical information to policymakers as they consider implementing carbon market programs in an efficient, cost-effective, and targeted manner.

Our study shows how latent class analysis could complement discrete choice models, because it can develop more nuanced conclusions in terms of farmers' decision-making based on psychological constructs such as their perceptions, preferences, motivations, and attitudes. Hence, our study provides valuable information for policymakers as they consider developing programs and policies for facilitating climate change adaptation.

Overall, our study shows heterogeneity in farmers' preferences for carbon program attributes and WTA carbon payments for switching to conservation practices. Due to the presence of heterogeneity among farmers, it is critical to incorporate these differences in the design of effective and efficient carbon market programs. Our study also shows the need for outreach, information, and extension efforts to increase awareness among agricultural producers about climate change. This increased knowledge and understanding might change behaviors related to conservation practices, increase farmers' predilection toward carbon market programs, and thus, participation in carbon sequestering activities and ultimately help mitigate climate change.

CHAPTER IV

CONCLUSIONS

In this study, we first examined South Dakota corn and soybean farmers' preferences and WTA carbon payments for adopting conservation management practices. We also evaluated the differences in preferences and WTA based on the current production practices. Second, we examined farmers' heterogeneity in preferences of carbon market attributes and WTA carbon payments based on the role of climate change perception and adverse weather experience.

Results from Chapter II show that farmers' preferences for carbon payment programs vary based on their adoption status of conservation practices and the type of practice. WTA carbon payments are higher for non-adopters than adopters of any given conservation practice and vary between practices. Since the result of the adoption-wise sample is different from the full sample, it is essential to develop tailored carbon payment programs that account for heterogeneity based on current production practices along with targeted outreach efforts. Furthermore, policymakers and carbon market providers need to formulate strategies to attract non-adopters of conservation practices while making sure that current adopters do not revert to non-conservation practices. Carbon market attributes like governance and contract length need to be developed based on farmers' preferences.

Results from Chapter III show that there exist different classes of farmers with respect to climate change perception and adverse weather experience. The preferences for carbon market attributes and WTA carbon payments differ significantly between these classes. Those farmers who have higher concern on climate change prefer to enroll in carbon payment programs, need comparatively less WTA to switch to conservation practices, do not need payment for governance mechanisms and give importance to reduced risk for their preference to enroll. As higher concern on climate change shows the preference for enrollment in carbon payment programs along with need for less WTA, awareness, extension and outreach activities regarding the impacts of climate change needs to be conducted for cost-effective and efficient carbon payment programs.

Thus, we can conclude that while formulating carbon payment programs for farmers, heterogeneity based on the current production practices and climate change concern needs to be considered. Targeted outreach and intervention efforts would be effective to increase the adoption of carbon sequestering agricultural conservation practices.

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APPENDIX

Appendix 1. Information on agricultural soil carbon sequestration and carbon markets

Carbon sequestration refers to the capture of atmospheric carbon. Through carbon sequestration, carbon is kept out of the atmosphere and thus does not contribute to the rise of atmospheric greenhouse gas concentrations, which is contributing to global warming and climate change. Agricultural soil carbon sequestration helps to capture carbon in the soil through the implementation of conservation practices such as no-till, conservation till, cover crops, etc.

There is strong evidence that the adoption of practices such as no-till, conservation till, and cover crops improve soil health. Agricultural producers who use these practices also mitigate greenhouse gas emissions from agricultural production through agricultural soil carbon sequestration. Producers who switch to practices such as no-till, conservation-till, or cover crops can enroll in carbon market programs and can receive carbon credits as long as they meet the terms and conditions set by the carbon market firm/broker/aggregator.

Carbon credits can be awarded per ton of carbon sequestered or on a per-acre basis. Thus, carbon markets offer an additional revenue source for producers who are willing to switch to more conservation-oriented practices such as no-till, conservation till, and cover crops. There is an emerging carbon marketplace that brings agricultural producers and buyers of carbon credits together. However, attributes and attribute levels of the carbon market program vary between carbon market programs.

Appendix 2. Definition of Carbon Market Program Attributes and Levels

1. Tillage Practice Change: refers to switching from current tillage practices such as from conventional-till to conservation-till or from conventional-till to no-till and from conservation-till to no-till.

No change in tillage practice: continue the current tillage practice.

2. Cover Crops Practice Change: refers to switching from not growing cover crops to growing cover crops.

No change in cover crop practice: continue the current practice with respect to cover crops.

3. Contract Length: required duration of enrollment in carbon market program or scheme to receive carbon payment.

No contract: no contract length specified.

4. Governance: means the authority who will do verification and monitoring of carbon sequestered (stored) on the agricultural soil through the adoption of conservation practices. Government (USDA), private (for-profit), not-for-profit, and none are the options included in the study.

None: no governance

5. Carbon Payment ($/acre): the dollar amount a producer receives per acre for sequestering (i.e., storing) carbon on agricultural soil by switching current farm management practices to conservation practices such as no-till, conservation-till, and cover crops. $0/acre, $5/acre, $10/acre, $15/acre, and $20/acre are the payment levels included in the study.

Appendix 3. Cheap talk script

Please read the following instructions before proceeding with the survey carefully.

Imagine you are in a scenario to choose a carbon market program in real life. On this page and next pages, you will see **six (6) choices/decision scenarios for carbon market participation.** Each choice scenario includes a description of different carbon market attributes and a choice set that is comprised of Option 1, Option 2, and Neither. In each choice scenario, please indicate the decision you would make based on your preferences.

You may decide NOT TO CHOOSE either combination by selecting NEITHER. When you are faced with a choice scenario, assume the available options are the only options you have and select one of the following options: Option 1 or Option 2. Please do not compare options between questions.

Before answering, note that prior research shows that people often overstate/understate the amount they are willing to accept when answering survey questions like this. ***I request that you think carefully and respond to each of the following six questions exactly as you would if you were deciding in real-life conditions and were going to face the consequences of your decision: which is to accept the carbon payments you selected if you decide to change your practices.***

Appendix 4. Farmers' utility preference estimates for different carbon program attributes - pooled data

Table A1. Farmers' utility preference estimates for different carbon program attributes - pooled data

Attributes	**No Till Adopters and Non-Adopters**	**Conservation Till Adopters and Non-Adopters**	**Cover Crops Adopters and Non-Adopters**	**Conventional Till Producers and No Till Adopters**	**Conventional Till Producers and Conservation Till Adopters**
Price	0.12***	0.11***	0.12***	0.12***	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Conservation till to no-till	-1.58***	-0.51**	-0.82***	-0.25	-0.78***
	(0.31)	(0.22)	(0.25)	(0.18)	(0.21)
Conservation till to no-till*Treatment	1.25***	-0.31	0.18	-1.04*	-0.48
	(0.34)	(0.29)	(0.31)	(0.54)	(0.59)
Conventional till to conservation till	-0.50**	-0.74***	-0.56**	-0.49***	-0.44**
	(0.26)	(0.23)	(0.23)	(0.19)	(0.22)

Conventional till to conservation	-0.26	0.22	-0.20	-0.13	0.30
till*Treatment	(0.33)	(0.30)	(0.29)	(0.62)	(0.52)
Conventional till to no-till	-1.10***	-0.40**	-0.75***	-0.29*	-0.74***
	(0.29)	(0.20)	(0.21)	(0.16)	(0.21)
Conventional till to no-till*Treatment	0.63**	-0.37	0.29	-1.17*	-1.59**
	(0.31)	(0.27)	(0.26)	(0.68)	(0.75)
No cover crops to cover crops	0.38*	0.09	-0.06	-0.13	-0.20
	(0.21)	(0.15)	(0.16)	(0.12)	(0.16)
No cover crops to cover	-0.66***	-0.20	-0.03	1.12***	0.99**
crops*Treatment	(0.25)	(0.19)	(0.19)	(0.42)	(0.42)
Ten-year contract	-1.46***	-1.03***	-1.22***	-1.06***	-1.06***
	(0.30)	(0.20)	(0.21)	(0.17)	(0.18)
Ten-year contract*Treatment	0.29	-0.22	0.20	-0.83	-0.79
	(0.34)	(0.26)	(0.26)	(0.53)	(0.54)
Five-year contract	-0.93***	-0.46**	-0.62***	-0.40***	-0.50***
	(0.28)	(0.19)	(0.19)	(0.13)	(0.18)

Five-year contract*Treatment	0.61**	-0.02	0.25	-1.41***	-0.62
	(0.30)	(0.25)	(0.24)	(0.54)	(0.59)
Not-for-profit	0.23	0.32	0.33	0.49**	0.80***
	(0.31)	(0.24)	(0.25)	(0.21)	(0.25)
Not-for-profit*Treatment	0.17	0.23	0.19	-0.43	-0.20
	(0.33)	(0.30)	(0.30)	(0.58)	(0.52)
Private	-0.21	0.17	-0.66**	0.00	-0.17
	(0.39)	(0.30)	(0.33)	(0.26)	(0.34)
Private*Treatment	0.04	-0.26	1.08***	0.13	-0.02
	(0.43)	(0.37)	(0.38)	(0.70)	(0.75)
Government	0.39	0.41	0.38	0.56***	0.88***
	(0.32)	(0.25)	(0.26)	(0.22)	(0.26)
Government*Treatment	0.14	0.30	0.21	-0.83	-0.75
	(0.35)	(0.31)	(0.31)	(0.57)	(0.58)
Neither	1.17***	1.30***	1.31***	1.59***	1.19***
	(0.22)	(0.22)	(0.22)	(0.27)	(0.29)

Standard deviation estimate					
Conservation till to no-till	0.94***	0.84***	-1.22***	0.93***	0.93**
	(0.28)	(0.24)	(0.23)	(0.28)	(0.38)
Conservation till to no-till*Treatment	0.44**	0.41	-0.23	0.59	-1.17
	(0.21)	(0.34)	(0.33)	(0.50)	(0.73)
Conventional till to conservation till	-0.28	0.97***	1.17***	0.85***	1.32***
	(0.38)	(0.26)	(0.22)	(0.31)	(0.33)
Conventional till to conservation	-0.97***	0.53*	-0.31	-1.88***	-0.37
till*Treatment	(0.28)	(0.32)	(0.42)	(0.62)	(0.74)
Conventional till to no-till	0.81**	0.56*	-0.51	0.51*	0.79*
	(0.35)	(0.29)	(0.31)	(0.30)	(0.43)
Conventional till to no-till*Treatment	0.12	-0.56*	-0.23	-0.54	2.88***
	(0.24)	(0.30)	(0.41)	(0.78)	(0.94)
No cover crops to cover crops	-0.63***	-0.53***	0.70***	0.35	0.99***
	(0.23)	(0.20)	(0.19)	(0.28)	(0.22)

No cover crops to cover crops*Treatment	-0.08	0.71***	-0.13	-0.35	-0.50
	(0.25)	(0.20)	(0.19)	(0.38)	(0.43)
Ten-year contract	1.11***	0.96***	0.72***	1.05***	0.26
	(0.24)	(0.22)	(0.21)	(0.25)	(0.32)
Ten-year contract*Treatment	0.51	0.34	-0.21	-0.08	0.99*
	(0.48)	(0.25)	(0.27)	(0.47)	(0.54)
Five-year contract	0.44*	-0.66***	-0.23	-0.16	-0.02
	(0.26)	(0.23)	(0.25)	(0.86)	(0.27)
Five-year contract*Treatment	0.24	0.25	-0.02	-0.32	2.07***
	(0.26)	(0.25)	(0.37)	(0.48)	(0.61)
Not-for-profit	0.08	-0.31	0.33	0.03	0.62***
	(0.36)	(0.37)	(0.24)	(1.05)	(0.23)
Not-for-profit*Treatment	0.06	0.02	-0.09	1.76**	0.66
	(0.19)	(0.25)	(0.23)	(0.77)	(0.48)
Private	1.16***	0.95***	-1.29***	1.16***	1.84***
	(0.23)	(0.29)	(0.20)	(0.33)	(0.35)

Private*Treatment	0.77**	1.40***	-0.21	-1.34**	0.79
	(0.32)	(0.39)	(0.27)	(0.64)	(0.51)
Government	-0.43**	0.28	0.41**	0.19	0.64***
	(0.21)	(0.24)	(0.16)	(0.34)	(0.24)
Government*Treatment	0.73***	0.62***	0.87***	1.89***	-0.77**
	(0.19)	(0.20)	(0.30)	(0.52)	(0.35)
Neither	2.40***	2.40***	2.52***	2.42***	2.68***
	(0.17)	(0.18)	(0.19)	(0.20)	(0.22)
Log likelihood	-1840.79	-1827.90	-1854.59	-1575.62	-1225.87
LR Chi^2	649.73	646.59	651.15	544.00	461.49
p-value (Prob > Chi^2)	0	0	0	0	0
Number of observations	6,414	6,324	6,465	5,466	4,293

Significance level: ***p<0.01, **p<0.05, *p<0.1.

Appendix 5. Farmers' willingness to accept estimates for different carbon program attributes - pooled data

Table A2. Farmers' willingness to accept estimates for different carbon program attributes - pooled data

Attributes	**No Till Adopters and Non-Adopters**	**Conservation Till Adopters and Non-Adopters**	**Cover Crops Adopters and Non-Adopters**	**Conventional Till Producers and No Till Adopters**	**Conventional Till Producers and Conservation Till Adopters**
Conservation till to no-till	13.42***	4.59**	7.13***	1.98	8.20***
	[8.12, 19.68]	[0.68, 8.89]	[2.92, 11.80]	[-0.83, 4.91]	[3.69, 14.18]
Conservation till to no-till*Treatment	-10.66***	2.78	-1.53	8.34*	5.10
	[-17.27, -4.88]	[-2.33, 8.11]	[-6.85, 3.78]	[-0.23, 17.25]	[-7.56, 18.24]
Conventional till to conservation till	4.28**	6.70***	4.81**	3.93**	4.69**
	[0.02, 8.72]	[2.51, 11.52]	[0.91, 9.08]	[0.91, 7.35]	[0.22, 10.04]

Conventional till to conservation till*Treatment	2.17	-2.02	1.76	1.02	-3.17
	[-3.29, 7.86]	[-7.63, 3.46]	[-3.20, 6.88]	[-9.12, 10.79]	[-14.84, 7.72]
Conventional till to no-till	9.31***	3.63*	6.47***	2.33*	7.78***
	[4.43, 14.80]	[0.07, 7.62]	[2.77, 10.73]	[-0.25, 5.18]	[3.28, 13.77]
Conventional till to no-till*Treatment	-5.36**	3.36	-2.49	9.41*	16.73**
	[-11.03, -0.16]	[-1.54, 8.30]	[-7.28, 2.00]	[-1.44, 20.77]	[1.20, 35.18]
No cover crops to cover crops	-3.25*	-0.84	0.48	1.05	2.10
	[-6.60, 0.19]	[-3.34, 1.90]	[-2.16, 3.43]	[-0.79, 3.24]	[-1.07, 6.31]
No cover crops to cover crops*Treatment	5.64***	1.80	0.24	-9.00***	-10.43**
	[1.55, 9.88]	[-1.68, 5.36]	[-3.17, 3.59]	[-16.33, -2.44]	[-20.93, -1.81]
Ten-year contract	12.40***	9.32***	10.55***	8.54***	11.23***
	[7.56, 17.81]	[5.76, 13.36]	[7.08, 14.46]	[5.83, 11.65]	[7.66, 15.91]
Ten- year contract*Treatment	-2.47	2.01	-1.73	6.65	8.37
	[-8.42, 3.18]	[-2.81, 6.79]	[-6.31, 2.69]	[-1.86, 15.47]	[-2.93, 20.97]
Five- year contract	7.95***	4.16**	5.36***	3.18***	5.23***
	[3.37, 12.81]	[0.83, 7.45]	[2.13, 8.64]	[1.13, 5.16]	[1.63, 9.07]

Five- year contract*Treatment	-5.21**	0.20	-2.15	11.37**	6.58
	[-10.72, -0.08]	[-4.33, 4.84]	[-6.42, 2.02]	[2.75, 20.90]	[-5.85, 20.25]
Not-for-profit	-1.92	-2.93	-2.89	-3.97**	-8.43***
	[-7.60, 2.99]	[-7.83, 1.34]	[-7.67, 1.22]	[-7.86, -0.71]	[-16.21, -3.04]
Not-for-profit*Treatment	-1.41	-2.12	-1.66	3.44	2.08
	[-7.01, 4.23]	[-7.66, 3.22]	[-6.76, 3.44]	[-5.87, 12.60]	[-9.26, 13.51]
Private	1.82	-1.57	5.67**	-0.01	1.82
	[-5.00, 8.07]	[-7.60, 3.47]	[0.14, 10.76]	[-4.58, 3.70]	[-6.10, 8.29]
Private*Treatment	-0.37	2.37	-9.33***	-1.02	0.21
	[-7.79, 6.96]	[-4.23, 9.19]	[-16.38, -2.87]	[-12.11, 10.43]	[-16.12, 16.55]
Government	-3.34	-3.74	-3.28	-4.54**	-9.28***
	[-9.44, 1.84]	[-9.10, 0.68]	[-8.52, 1.08]	[-8.94, -1.04]	[-18.07, -3.48]
Government*Treatment	-1.19	-2.72	-1.82	6.66	7.94
	[-7.22, 4.80]	[-8.42, 2.78]	[-7.21, 3.54]	[-2.34, 16.31]	[-4.09, 21.60]
Neither	-9.94***	-11.75***	-11.35***	-12.81***	-12.55***
	[-14.13, -6.28]	[-16.19, -7.89]	[-15.56, -7.69]	[-17.84, -8.49]	[-19.81, -6.76]

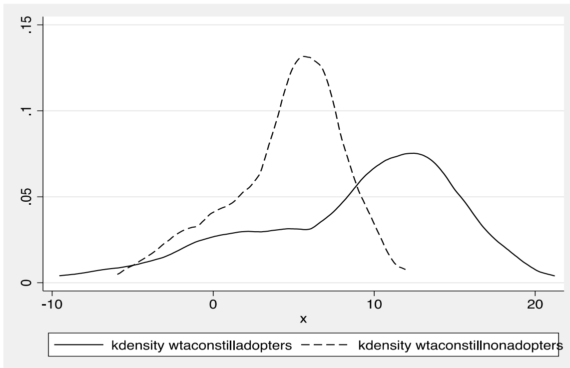
Note: The figures in brackets are estimates of 95% confidence interval of WTA. Confidence intervals are calculated using the Krinsky and Robb method using 5,000 repetitions

*Significance level: ***p<0.01, **p<0.05, *p<0.1*

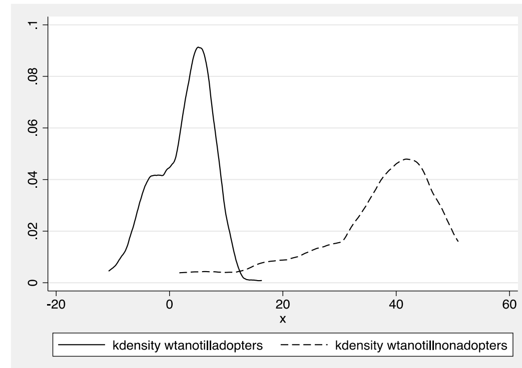
Appendix 6. Kernel density plots demonstrating differences in WTA estimates for carbon payments

Figure A1. Kernel density plots demonstrating differences in WTA estimates for carbon payments between adopters and non-adopters

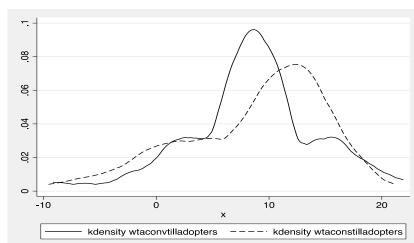
a. Willingness to accept to convert from conservation till to no till



Conservation till adopters vs non-adopters

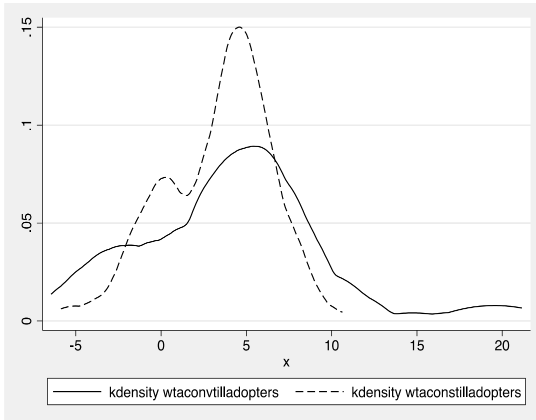


No till adopters vs non-adopters

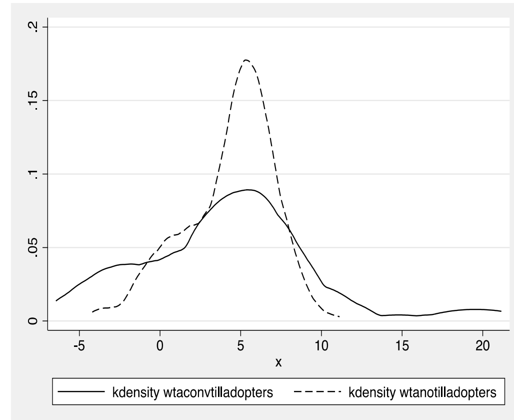


Conventional till vs conservation till adopters

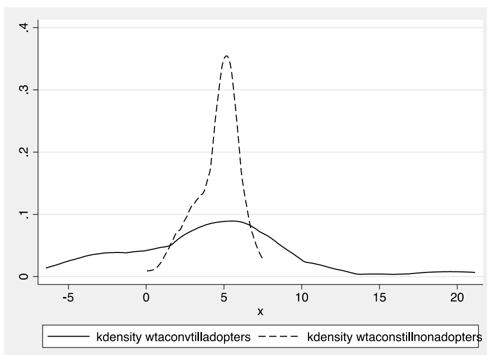
b. Willingness to accept to convert from conventional till to conservation till



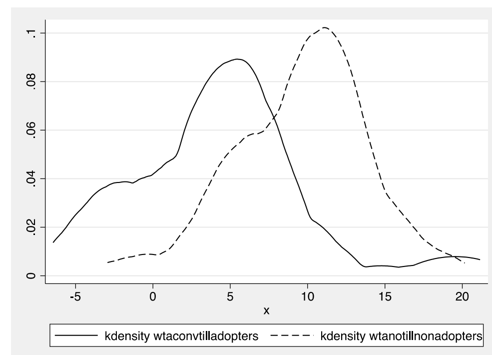
Conventional till vs. conservation till adopters



Conventional till vs. no till adopters



Conventional till vs. conservation till non-adopters



Conventional till vs. no till non-adopters

Appendix 7. Adverse weather experience of respondents in different classes

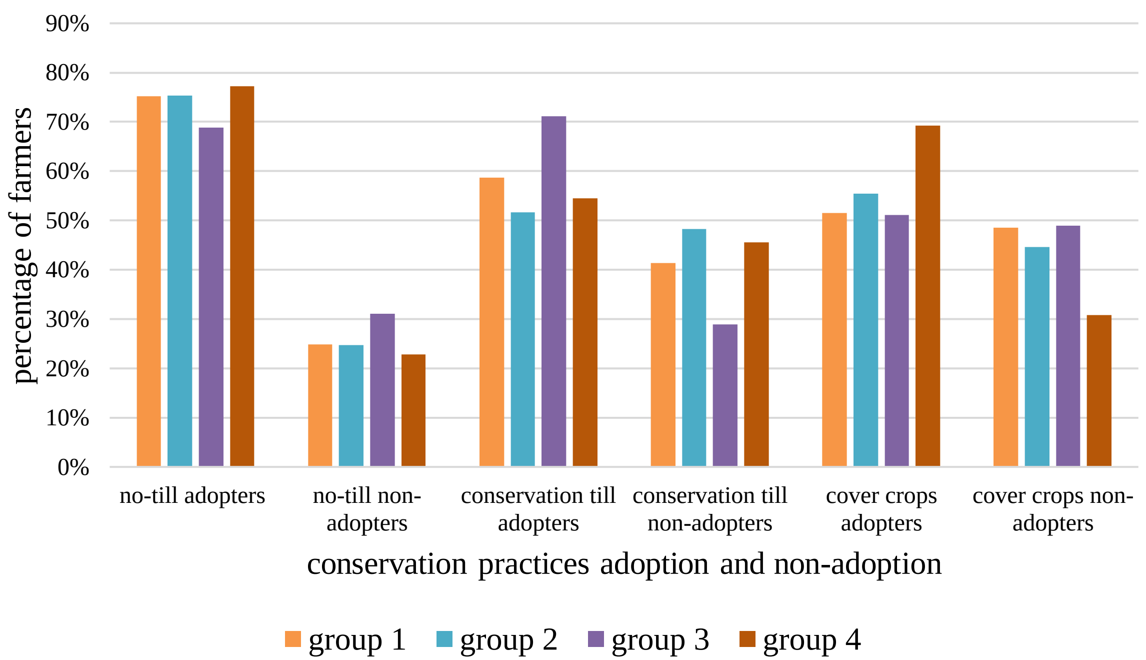


Figure A 2. Conservation Practices Adoption and Non-adoption in Different Groups

Appendix 8. Statistical difference Between Adopters and Non-Adopters in Different Groups

Table A 3. Statistical Difference Between Adopters and Non-Adopters in Different Groups

Categories	**Group 1**	**Group 2**	**Group 3**	**Group 4**
No-till non-adopters	24.81%	24.73%	31.11%	22.83%
No-till adopters	75.19%	75.27%	68.89%	77.17%
Pearson chi2		1.1313		
P-value		0.770		
Conservation-till non-adopters	41.35%	48.31%	28.89%	45.56%
Conservation-till adopters	58.65%	51.69%	71.11%	54.44%
Pearson chi2		5.0550		
P-value		0.168		
Cover crops non-adopters	48.55%	44.57%	48.89%	30.77%
Cover crops adopters	51.45%	55.43%	51.11%	69.23%
Pearson chi2		8.0055		
P-value		0.046		