MIDWEST FARMERS' DECISION-MAKING IN CONSERVATION AGRICULTURE ADOPTION

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food, and Resource Economics—Doctor of Philosophy

2021

ABSTRACT

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Conservation Agriculture (CA) adoption can alleviate the environmental consequences of conventional agricultural production while maintaining yields. A better understanding of farmers' decision-making in CA adoption is needed to inform policy design that encourages adoption. In the absence of the CA adoption market, experimental methods provide an essential alternative to investigate decision-makers' preference. Therefore, this dissertation leverages a Discrete Choice Experiment (DCE) to analyze farmers' decision-making to shed light on policy design as well as to inform methodological issues associated with DCE approach.

The first chapter evaluates farmers' Willingness-to-Accept (WTA) CA practices and assesses the factors affecting the WTA. In addition to the payment to compensate the expenses or efforts of taking a CA practice, a substantial payment is needed to incentivize farmers leaving the status quo and committing to a CA program. Internal factors, such as farmers' characteristics and experience with CA practices, as well as external factors, i.e., policy design in terms of information framing and the decision time window, both have impacts on the WTA. These findings provide a practical guide for cost-efficient policy design.

The traditional DCE approach for stated preference evaluation builds on an essential assumption that decision-making is reference independent, i.e., independent of irrelevant alternatives. The second chapter develops a new framework to relax and test this assumption by incorporating behavioral realism into modeling. I found that decision-makers use behavioral strategies, i.e., reference dependence, in decision making, and that different sources of

information are evaluated differently as reference points. These findings, on the one hand, set caveats for modeling DCE data based on independence of irrelevance assumption, and on the other hand, indicate a more cost-efficient policy design tool that nudges desired behaviors through shaping the reference point.

Three decision-making strategies could describe the decision making in a DCE: reference independence, reference dependence, and attributes non-attendance. This last chapter explicitly discusses which strategy is adopted and how such strategies evolve in repeated choice tasks. I found that decision-makers use behavioral strategies to make decisions. As decision-makers collect information over the repeated choice scenarios, they are shifting from the current choice set to the path as the reference point. Failing to account for the reference dependence behavior in choice modeling could misidentify the attended attributes as non-attended. This finding suggests that the reference dependence model can be a guiding choice for DCE modeling. Again, this chapter implies that discrete choice modeling without accounting for behavioral realism will fail to reveal the true preference.

ACKNOWLEDGEMENTS

First and foremost, a huge THANK YOU to my adviser, Dr. Jinhua Zhao, for encouraging me to explore my curiosities, find ways to improve, conquer the challenges, and explore career possibilities. His keen insights about research, learning, and communication continuously inspire my work and life way beyond the research.

I am deeply grateful for my wonderful committee members: Dr. Frank Lupi, for providing advice and critical opportunities to grow my stated preference research capability; Dr. Vincenzina Caputo, for sharing her expertise and passion in choice experiment research; Dr. Joseph Herriges and Dr. Jeffrey Wooldridge for offering critical advice on econometrics for my dissertation and beyond.

I am also thankful to the AFRE department for giving me this Ph.D. research opportunity and providing the best resource with the fabulous research talents, fellow graduate students, and departmental staff. I also thank my NSF CNH collaborators, Dr. Adam Reimer, Dr. Bruno Basso, Dr. Diana Stuart, Dr. G. Philip Robertson, and Dr. Sandy Marquart-Pyatt, for working together in the interdisciplinary team to support my research dataset and make a better planet through environmental research.

In addition, I would like to thank my friends for all the time we spent together. I could never go so far without you all being there for me.

Finally, to my mom and dad, for your love, understanding, and sacrifices, for modeling me living with no regret, being kind, optimistic, and fearless. I developed my dissertation on the topic of regret minimization in decision-making, and I love that topic a lot because that is also the motto my mom and dad taught me many years as I was growing up.

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CHAPTER 1. INTRODUCTION

Nitrogen leakage from farming systems brings significant ecological consequences, such as aquatic and marine eutrophication and greenhouse gas. Conservation Agriculture (CA) practices and tools have been developed to reduce nitrogen leakage while sustaining yields, but the adoption rates remain strikingly low. To encourage CA adoption, a policy with a payment vehicle is needed to fill the gap between social benefits and individual farmers' inputs. This dissertation aims to analyze U.S. Midwest farmers' decision-making on CA adoption to facilitate policy design.

To understand farmers' CA adoption decision-making, it is essential to understand farmers' preferences over program payments and requirements. A critical challenge of CA adoption decision-making analysis is the lack of an existing market implementing a similar policy to reveal farmers' preferences. Experimental methods provide an essential alternative for eliciting individual preference confronting such a challenge. However, a key concern when employing experimental methods, such as Discrete Choice Experiments (DCE), is the incentive compatibility of the experiment. An experimental mechanism is considered incentive-compatible only if the participants' behavior in the experiment is consistent with their behavior in real life. Failing to incorporate behavioral realism in DCE modeling will conclude with preference evaluation that departures from the real preference and affect the policy effectiveness. Therefore, this dissertation discusses how to design and model the DCE to reveal the real preference better.

Besides preference evaluation, understanding the factors that affect the preference is critical to improving policy efficiency. Examining the internal relationship between farmers' characteristics and willingness to adopt a CA program will help identify the farmers who are more willing to adopt a program given the same payment incentive. Learning the external relationship between policy framing and farmers' decision will inform how to frame a policy in a way that incentivizes adoption better. There have been numerous literature justifying the internal and external factors' impacts on decision behavior, however, the studies that examine the relationship in the CA adoption scenario are too limited to guide policy design.

To inform CA policy design, Chapter 2 evaluates two external factors of a policy design—the framing of a policy and a decision-making window. Through designing a two-by-two treatment DCE and examining the interaction effects of the two external factors, my analysis examines how these two factors interactively influence farmers' decision-making. Negative framing and a decision-making window with learning opportunity tend to reduce farmers' Willingness-to-Accept (WTA) of the CA program. In addition to external factors, my analysis also estimates the effects of farmers' social demographic factors, attitudes, and sources of information on CA adoption. The results in this chapter provide empirical support for better designing of a CA policy.

Both Chapter 3 and Chapter 4 build on the same experiment that evaluates Midwest farmers' CA adoption but go beyond empirical analysis to investigate the decision-making strategies in a DCE through developing and examining models that relax the independence of irrelevant alternative assumption imposed on the DCE modeling framework. The assumption is that a respondent's utility from choosing a particular alternative is independent of the other alternatives in the choice set. This assumption validates modeling DCE behavior through a Random Utility Maximization (RUM) framework. Chapter 3 develops a Random Regret Minimization (RRM) model that relaxes the assumption imposed on the RUM framework. It allows behavioral decision-making strategies where decision-makers base their choice on a wish to avoid the situation where the non-chosen alternative(s) perform(s) better than the chosen one. The analysis suggests that (1) decision-making is within as well as across choice sets dependent; (2) different sources of information are evaluated differently as reference points; and (3) the extent of individuals relying on the behavioral decision strategy is associated with their characteristics. These findings challenge basing on RUM framework to model DCE. In the meantime, policymakers can make use of the reference dependence behavior to improve policy cost-efficiency by setting a reference point to nudge desired behavior.

Chapter 4 extends from Chapter 3 to further assess the decision-making strategies and the changing patterns of these strategies over repeated choice scenarios in a DCE. Through examining the decisions in a DCE survey of four repeated choice scenarios, this study verifies that the reference dependence strategy is used and reveals an adaptive pattern of the dependence strategy. Decision-makers shift from the current choice set- dependent to path-dependent as they gradually collect information through repeated choices. The attributes that are otherwise identified as non-attended under an attribute non-attendance framework are attended in a path-dependent manner. These findings suggest that incorporating reference dependence behavior and correctly identifying the reference points in DCE modeling are important for preference evaluation. In the meantime, designing an experiment that perfectly matches the real-world decision scenario from the perspective of reference points will enable the DCE approach to evaluate real preference better.

In summary, this dissertation provides empirical supports on CA policy design and discusses the modeling issues of the DCE approach. By properly framing the intention of a policy and setting the decision window, the policy adoption rate can be increased. Targeting the policy based on farmers' characteristics can also improve policy cost efficiency. Meanwhile, my thesis models and justifies behavioral decision strategies, such as reference dependence, loss aversion, and changing patterns of decision strategies in a DCE. These findings set caveats on using DCE to reveal preference as well as provide modeling solutions. These behavioral strategies can also be carefully used to facilitate policy design.

CHAPTER 2. FARMERS' DECISION ON NITROGEN APPLICATION: TESTING INFORMATION TREATMENT EFFECT AND COMMITMENT COST THEORY

2.1. Introduction

Nitrogen (N) leakage from farming systems brings significant ecological consequences, including water pollution and greenhouse gas emissions (e.g., Fenn et al., 1998; Syswerda, 2009; EPA, 2011). Global N fertilizer use has increased by approximately ten folds since 1950 (Robertson et al., 2000). However, most crops only take up to 50% of the nitrogen applied, with the other 50% leaking to the environment (Syswerda, 2009; Smil, 1999). Therefore, Conservation Agriculture (CA)[1] practices and tools have been developed to reduce N application and leakage, but their adoption rates remain strikingly low (Ribaudo et al., 2011; Osmond et al., 2015). The main reason for the low adoption of CA is the divergence between social benefits and individual interests: the incremental costs associated with adopting CA accrue at the farm level, while the beneficial environmental effects are captured by the society (Ma et al., 2012). A policy that motivates the CA adoption with production regulation, taxes, or payment incentives are needed to fill the gap.

A large body of empirical literature on CA adoption has been developed to facilitate policy design, but there is still no universal conclusion on how sociological, economic, and technical factors collectively shape farmers' decisions (Knowler and Bradshaw, 2007; Prokopy et al., 2008; Baumgart-Getz et al., 2012). Among these factors, the financial incentive has been found to be the most crucial motive for CA adoption, though it is not the single factor (e.g., Cary and Wikinson, 1997; Chouinard et al., 2007; Stuart et al., 2012; Honlonkou, 2004; Claassen and

[1] Conservation Agriculture (CA) is a term defined by the Food and Agricultural Organization of the United Nations to package the concepts of "resource-saving agricultural crop production that strives to achieve acceptable profits together with high and sustained production levels while concurrently conserving the environment".

Horan 2000). Internal factors associated with farmers and farms such as farmers' education levels (e.g., Okoye, 1998), farm size and profitability (e.g., Lambert et al., 2007), household income (e.g., Somda et al., 2002), farmers' sources of information and attitude toward environmental issues (e.g., Mase et al., 2015; Napier and Camboni, 1993; Traoré et al., 1998; Reimer et al., 2012; Stuart et al. 2012) all have impacts on CA adoption. Besides these internal factors, external factors associated with the proposed programs such as information communication (Opdam et al., 2015; Hong and Zinkhan, 1995; Chernev, 2004; Florack and Scarabis, 2006) can also shape CA adoption. External factors study can directly contribute to improving policy cost-efficiency, but the related research regarding CA adoption is far from sufficient to inform policy design.

To shed light on policy design, this paper studies farmers' CA adoption focusing on two external factors—the framing of a policy and the decision window, and investigates how these two factors jointly affect the decision-making. I perform a discrete choice experiment (DCE) with two-by-two interacted treatments to understand farmers' CA adoption in the Midwestern U.S.

Tversky and Kahneman (1981) has shown that framing can affect decision-making and lead to violations of classic axioms of rational choice. In environmental economics, some works suggest that disclosing environment externalities to the consumers can be effective at shifting conservation preferences (Thaler and Sunstein, 2008), while other research demonstrates that disclosing potential environmental benefits can encourage conservation behavior among the general public (Opdama et al., 2015; Maibach et al., 2008; Myers et al. 2012; Krantz and Monroe 2016; Stevenson et al., 2018). However, to my best knowledge, none of this previous literature has studied the effect of framing from the environmental service providers' perspective, even though environmental service provider is the basis of managing environmental issues. Understanding these psychological phenomena from farmers' perspective can help researchers, practitioners, and policymakers design a more cost-effective policy to encourage CA adoption, and in parallel, help elucidate the motives for shifting farm management. This paper studies how the framing of the goal of policy affects environmental service providers' decisions. Two versions of framing are discussed and compared in this study: positive policy framing emphasizes the positive environmental contribution as well as the N efficiency of CA adoption, and negative policy framing focuses on the damaging environmental externalities of no-action.

The decision window is another essential factor in policy design. In stated preference experiments, it is commonly assumed that decision-making is in a static setting without uncertainty. Real-world choices, however, are more often made in dynamic settings with uncertainty. Under a dynamic scenario, individuals can delay decisions to obtain further knowledge or even reverse the choice (Arrow and Fisher 1974; Dixit and Pindyck, 1994). Zhao and Kling (2001, 2004) investigate the quasi-option value concept to explain consumers' Willingness-to-Pays (WTP) divergence between static and dynamic welfare measures. They found that committing to a decision at the moment of transaction may represent a "commitment cost" for the individual because the individual has to give up the opportunity to learn more about the value of an option if a decision is made today.

Decision-making in dynamic settings has been investigated from the WTP perspective in environmental economics (e.g., Arrow and Fisher, 1974; Corrigan et al., 2008), finance (e.g., Dixit and Pindyck, 1994), and consumer behavior (e.g., Castaño et al., 2008; Bazzani et al., 2017). However, this concept has rarely been investigated from the Willingness-to-Accept (WTA) perspective, i.e., the services/goods providers' perspective. The uncertainty of decision-making can manifest in different ways for consumers and producers. The uncertainty for consumers arises as they do not have complete information about the product, whereas producers have more knowledge of what to expect. Meanwhile, once a decision is made, consumers can immediately explore all the attributes of the product they have purchased, while producers, on the other hand, may take a longer time to explore the choice's impacts as production proceeds. As such, this paper makes the first try to investigate the learning effect on farmers' CA adoption decisions by providing two decision-making windows. The static decision window only gives decision-makers one time to enroll in the program. In contrast, the dynamic decision window offers a second chance to vote and thus allows for information collection and learning.

The paper is organized as follows: section 2 introduces the survey design, survey procedure, and the survey sample characteristics; model specification and estimation procedure are presented in section 3; empirical application results are reported in section 4; I close the discussion and point out directions for future research in section 5.

2.2. Survey and Data

2.2.1. Survey and Experimental Design

The target population of the research is corn growers in the Midwestern U.S., specifically Michigan, Iowa, and Indiana. I chose corn growers because corn is the most widely planted crop in the U.S. and the largest user of nitrogen fertilizer in terms of application rates per acre, total acres treated, and overall applications[2]. The Midwest was chosen because corn production is most centered in this region, with Iowa ranking first in sales of corn (McCurry, 2014). The survey distribution was through mailing, and the survey participants and mailing addresses were

[2] According to ERS 2012, around 50% of N fertilizer in the US is applied to corn, 11% to wheat, 10% to turf, and 3% to cotton.

drawn from farmers growing corn in 2013 from the Farm Service Agency (FSA)[3] address book. Two focus groups with a total of 20 farmers were conducted in 2015 to derive an understanding of people's views on CA practices. These sessions were also used to test early versions of the questionnaire. A pilot study with a sample of 300 was conducted in 2015 to estimate the range of the payment as well as to test the design of the questionnaire. For the final survey, 1600 corn growers were randomly drawn from each state with 4,800 corn growers in total. I used a modified Tailored Design Method survey design (Dillman et al., 2014), with two questionnaire mailings and a reminder mailing. An initial contact containing a cover letter, survey questionnaire, and $2 cash incentive was sent out in March 2016, followed by a reminder card one week later. A second questionnaire mailing without incentives was sent out in April 2016 to those who had not responded.

To test the effects of framing and the decision window on decision-making, I designed a two-by-two treatment survey and used a between-subject approach following Lusk and Schoeder (2004), in which each survey respondent will be assigned to one of the four treatment designs. I am interested in how these two factors jointly affect decision-making because in real choice-making these two factors may interact with each other. For testing the decision window effect, the respondents from the no-delay option group were notified that whether the program will be implemented depends on their one-time vote. In contrast, the respondents from the delay option group were informed that they would have a second chance to vote one year later if the program does not pass this year so that they can collect more information to make a decision. This information was highlighted right before each choice question to ensure the information is effectively delivered. For framing effect testing, the negative information group's questionnaire

[3] FSA is the payment services agency within USDA. FSA has records for every farmer who receives any form of payment (direct payments, crop insurance subsidies, disaster payments, conservation payments, etc) through USDA.

starts with introducing fertilizer leakage's consequence to the environment. In contrast, the positive information treatment group's questionnaire begins by introducing the nitrogen efficiency and environmental benefit of CA adoption. The details of the two treatments are listed in Figure 2.1 – Figure 2.4. The static/dynamic decision time treatments and two information treatments combine into four treatment groups shown in Table 2.1. I randomly assigned the respondents to one of the four treatment groups.

Figure 2.1. Positive Information Treatment

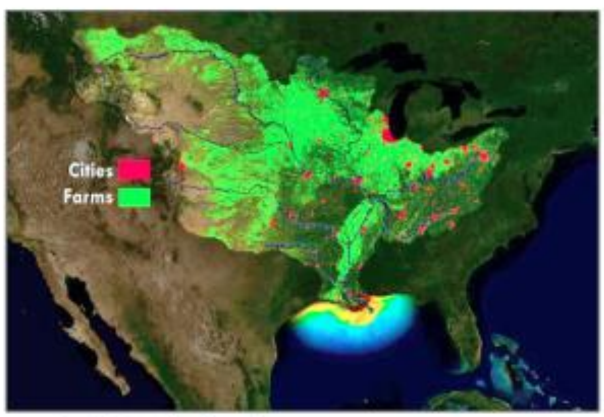
Increasing Nitrogen Efficiency and Improving Farmer Profitability

Farmers have made significant gains in improving nitrogen (N) efficiency in corn operations, and N efficiency can be further enhanced by emerging technologies and improvements in field-based modeling. Expanding agricultural production to meet growing global demand and making agricultural production more environmental friendly will require farmers to **optimize fertilizer** use through improved **use of new practices** and more **efficient application**. Through greater efficiency in nitrogen use, farmers can not only save money but also protect the environment by decreasing losses of N to water and air. New programs may also be able to help. In the case of N, good stewardship is what is best for your bottom line.

Figure 2.2. Negative Information Treatment

Effects of Nitrogen on the Environment

Nitrogen (N) is a crucial component of crop production. However, N lost from farming operations **contributes to pollution of the environment**. In surface waters, N contributes to algal growth, damaging both **water quality** and natural ecosystems both near farm fields and many miles downstream. Ecosystem eutrophication (over-fertilization) and hypoxia (lack of dissolved oxygen) in coastal areas is a major problem, including in the Gulf of Mexico. Excess soil N can also lead to **air pollution**. N can enter the atmosphere as nitrogen oxides (NO_x) that contribute to smog and acid rain. Nitrous oxide (N_2O) is also a greenhouse gas that contributes to climate change. By weight, N_2O is 300 times more powerful than CO_2 at warming the atmosphere. According to the US Environmental Protection Agency (EPA), seventy percent of all US emissions of N_2O are from agriculture.



Hypoxia in the Gulf of Mexico (photo courtesy of NOAA)

Figure 2.3. Dynamic Decision Context

Note: This program is not expected to reduce corn yield with appropriate application rates
Expected N savings are based on average application rate of 170 lbs/acre with no practice adoption
*The program chosen by the majority of respondents will be implemented immediately. If no program is implemented for now, you will be provided with **new information** about N application and **given another chance to decide one year later**.*

	Program 1	Program 2	Do not participate
Fall application prohibited	Yes	No	I would not participate in these programs
Sidedress application required	No	Yes	
Winter cover crops required	Yes	Yes	
Expected Nitrogen savings	25%	40%	
Annual payment level	$180/acre	$180/acre	
I would choose ... (check only one)	☐	☐	☐

+

Figure 2.4. Static Decision Context

Note: This program is not expected to reduce corn yield with appropriate application rates
Expected N savings are based on average application rate of 170 lbs/acre with no practice adoption
The program chosen by the majority of respondents will be implemented immediately. If the majority of respondents choose "not to participate," no program will be implemented.

	Program 1	Program 2	Do not participate
Fall application prohibited	Yes	Yes	I would not participate in these programs
Sidedress application required	No	Yes	
Winter cover crops required	Yes	No	
Expected Nitrogen savings	25%	25%	
Annual payment level	$180/acre	$100/acre	
I would choose ... (check only one)	☐	☐	☐

Table 2.1. Treatment Groups

	Positive Information	Dynamic Decision Window
Treatment 1 (PD)	✓	✓
Treatment 2 (PS)	✓	×
Treatment 3 (ND)	×	✓
Treatment 4 (NS)	×	×

The main body of the mail survey consists of four parts and a preamble. Before the start of the choice experiment, the preamble provides definitions of the terms referred to in the choice setting and asks whether the survey respondents have heard of these terms to ensure they clearly understand the proposed practices. Part I contains four choice experiment tasks with two hypothetical alternatives and an "opt-out" alternative, i.e., SQ, to avoid forced-choice (Batsell and Louviere, 1991; Carson et al., 1994). The SQ alternative represents each respondent's perceived status quo of CA adoption. Part II collects information about farmers' current farming behaviors and will be used to represent farmers' individual specific SQ. Part III collects farmers' opinions about farming and the environment. Part IV gathers socio-demographic information. Data from Part III and Part IV will be used to investigate farmers' opinion and social-demographic factors' impact on CA adoption. An example survey is attached in Figure 2.5.

Within the choice set, each hypothetical alternative is described by three CA practices, an expected nitrogen saving, and a payment vehicle. The three CA practices are avoidance of fall nitrogen application, i.e., *Fall*, side-dressing N fertilizer, i.e., *Side*, and covering crops in winter, i.e., *Winter*. I chose these three because they are the most efficient methods of improving N use efficiency without adding operation costs, as compared to other alternatives (Osmond et al., 2015; Christianson et al., 2014). Hypothetical alternatives' expected N savings are calculated using the Systems Approach to Land Use Sustainability (SALUS) model (Basso et al. 2012) and the specific formula is reported in Table 2.2. SQ alternative's expected N saving is calculated using the same formula with everyone's stated status quo practices levels. The assumption is notified at the top of each decision scenario. Note that the survey respondents may not perceive hypothetical and SQ alternatives in the same way because SQ is the endowment alternative and the practice levels are not saliently presented in the choice scenario. The range of the payment is based on Natural Resources Conservation Service (NRCS) payment levels for N management, and is adjusted based on focus group study and pilot survey estimation.

Attributes and attributes levels are defined in Table 2.3. The three proposed CA practices will potentially reduce N usage by 5% to 50% without affecting yields if adequately handled. This point is noted before each choice set in the questionnaire. In the meantime, such a program carries benefits as well as costs and risks to the farmer. The benefits include program participation payment, nitrogen fertilizer saving, and soil protection. According to Schnitkey (2015), the gross revenue of corn growing per acreage is $804, with a net return of $194, and the associated cost of fertilizer is $161. Therefore, even without the payment program, there is still an incentive for CA adoption in a hope to save fertilizer cost. On the other hand, side-dressing fertilizer and covering crops in winter add to farm management costs. Prohibiting fertilizer application in fall and covering crops in winter are perceived to be risky by many farmers due to challenges in managing the timing of spring planting operations (Arbuckle and Roesch-McNally, 2015).

Table 2.2. Expected Nitrogen Savings

Winter Cover Crops Required	Fall Application Prohibited	Sidedress Application Required	Nitrogen Savings
Yes	Yes	Yes	50%
No	Yes	Yes	25%
Yes	No	Yes	40%
Yes	Yes	No	25%
Yes	No	No	10%
No	Yes	No	10%
No	No	Yes	25%

Table 2.3. Attributes and Levels of the Choice Design

Attributes	Levels
Winter Cover Crops Required	Yes, No
Fall Application Prohibited	Yes, No
Sidedress Application Required	Yes, No
Expected Nitrogen Savings	0%, 10%, 25%，40%，50%
Annual Payment/Acre	\$0, \$5, \$20, \$40, \$100, \$180

A Bayesian design that minimizes D-error based on priors from the pilot survey was used to create the choice sets with variation in attributes levels. First, an orthogonal fractional factorial design generated by SAS was used for the pilot survey. Next, a conditional logit model was applied to analyze the pilot survey data, and the estimates served as the priors for the final design. Lastly, a Bayesian efficiency design that minimizes D-error based on priors from the pilot survey and contains 24 choice sets, is generated using Ngene software (Choice Metrics, 2012). I used a block design with six blocks containing four choice sets for each to avoid fatigue effects. Respondents were randomly assigned to one of these blocks. The order of presentation and allocation to respondents of the various choice sets is randomized. Examples of the choice tasks are attached in Figure 2.3 and Figure 2.4.

2.2.2. Hypothesis Testing

Hypothesis testing is conducted to investigate if there is a significant difference between treatments for WTA. The two-by-two treatments combine four hypotheses tests. Hypothesis 1 and hypothesis 2 are introduced to test the effect of decision window conditional on a specific framing approach; hypothesis 3 and hypothesis 4 are added to test information treatment conditional on decision window setting. The subscripts of WTA, i.e., P, N, D, S, represent "positive", "negative", "dynamic", and "static" respectively.

Hypothesis 1:

$$H0_1: WTA_{PD} - WTA_{PS} = 0$$
$$H1_1: WTA_{PD} - WTPA_{PS} \neq 0$$

Hypothesis 2:

$$H0_2: WTA_{ND} - WTA_{NS} = 0$$
$$H1_2: WTA_{ND} - WTA_{NS} \neq 0$$

Hypothesis 3:

$$H0_3: WTA_{PD} - WTA_{ND} = 0$$
$$H1_3: WTA_{PD} - WTA_{ND} \neq 0$$

Hypothesis 4:

$$H0_4: WTA_{PS} - WTA_{NS} = 0$$
$$H1_4: WTA_{PS} - WTA_{NS} \neq 0$$

2.2.3. Data

The survey experiment achieved a response rate of 31%. After removing returns with more than 10% of the questions incomplete, I have 1,140 usable returns of the survey, with response rates as 30%, 26%, 22%, respectively, for Michigan, Iowa, and Indiana.

Table 2.4 reports the farmer characteristics by the four treatments. 97% of respondents are male. 94% survey respondents are above 35 years old, with about 30% for each age group (35-54, 55-64, 65 and above). 96% of farmers have above high school or higher education (96%).

Half respondents have more than 36 years of experience with farming. About 63% of the respondents are full-time farmers working off-farm less than 49 days a year. 59% of respondents operate small to medium farms (less than 500 acres), with 64% of farmers obtained product values more than $100,000 in the year 2015. About 61% of respondents have ever enrolled in a conservation program.

I also reported the respondents' statistics by the treatment group to generate an idea about the randomization of the sample. A chi-square test, as reported in Table 2.3, was conducted to see if there are any unbalanced characteristics associated with the treatment group. The results suggest that the null hypothesis of equality between the socio-demographic characteristics across treatment samples cannot be rejected at the 5% significance level for all variables except for conservation group enrollment. This result confirms that the randomization is successful in equalizing the characteristics of respondents across treatments.

Table 2.4. Sample Characteristics in Percentage (%) by Treatment Sample

Sample	PD (n=286)	PS (n=279)	ND (n=284)	NS (n=291)	All (n=1,140)
State					
IA	36	32	34	32	33
IN	26	30	27	32	29
MI	38	38	40	36	38
Pearson chi2(6) = 3.6579 Pr = 0.723					
Gender					
Female	4	3	3	3	3
Male	96	97	97	97	97
Pearson chi2(3) = 0.6667 Pr = 0.881					
Age					
Between 18-34	7	4	6	5	6
Between 35-54	27	29	29	28	28
Between 55-64	32	32	30	31	31
Above 64	34	35	36	36	35
Pearson chi2(9) = 3.5161 Pr = 0.940					
Education					
Elementary School	5	4	5	2	4
High School or Some College	48	50	48	53	50
University	47	46	48	45	47
Pearson chi2(6) = 4.5376 Pr = 0.604					
Years of farming experience					
Less than 37 years	50	45	50	47	48
Longer than 36 years	50	55	50	53	52
Pearson chi2(3) = 1.6459 Pr = 0.649					
Days off-farm					
Great than 50 days/year	37	39	36	37	37
Less than 49 days/year	63	61	64	63	63
Pearson chi2(3) = 0.4826 Pr = 0.923					
Acres of farm operated in 2015					
Less than 100 acres	42	44	39	40	41
Between 100 - 500 acres	32	33	36	35	34
Greater than 500 acres	27	23	25	26	25
Pearson chi2(6) = 2.5865 Pr = 0.859					
Total values of products sold in 2015					
Less than $100,000	44	32	34	36	36
$100,000 - $499,999	35	42	42	43	41
$500,000 - $999,999	13	14	14	12	13
Greater than $1,000,000	8	11	10	9	10
Pearson chi2(9) = 9.7982 Pr = 0.367					
Annual Household Income					
Low (up to $25,000)	12	13	10	11	12

Table 2.4 (cont'd)

Medium ($25,000-$100,000)	66	62	62	68	65
High (above $100,000)	22	25	28	21	24
Pearson chi2(6) = 5.4099 Pr = 0.492					
Conservation program enrollment					
Never enrolled	54	62	67	60	61
Ever enrolled	46	38	33	40	39
Pearson chi2(3) = 9.7944 Pr = 0.020					

2.3. Estimation Procedures

The choice experiment approach was initially developed by Louviere and Hensher (1982) and Louviere and Woodworth (1983) and constructed upon the Random Utility Theory (Lancaster 1966; McFadden 1974). In a random utility framework, the researcher observes some attributes of the alternatives, but other components of the individual utility are unobservable and treated as stochastic from the researcher's perspective. In the empirical specification, the utility function is composed of the attributes that describe the alternative, as well as an alternative specific constant that represents the opt-out, i.e. SQ alternative, and a stochastic term. The utility for individual *i* from alternative *j* within choice task *t* can be expressed as:

(1) $U_{ijt} = V_{ijt} + \varepsilon_{ijt}$

where V_{ijt} is the systematic portion of the utility function which depends on the experimentally designed attributes for alternative *j*, and ε_{ijt} represents the unobserved random/stochastic term. Assumptions regarding the functional form of V_{ijt} and the distribution of ε_{ijt} are required in order to transform the random utility model into a choice model.

To capture unobserved preference heterogeneity and correlation across repeated choices, this paper uses a Random Parameter Logit Model with Error Component (RPL-EC) and the utility is specified in WTA space for the estimation (Scarpa and Alberini 2005; Scarpa, Ferrini, and Willis, 2005; Hess and Rose, 2009; Thiene and Scarpa, 2009; Scarpa et al., 2008). To account for preference heterogeneity, this paper assumes the attribute' coefficients, except for that of *Pay*, follow random normal distributions. Fixing the payment coefficient ensures that the estimated WTAs are normally distributed, and all respondents have a positive coefficient for *Pay'*s parameter (Train, 1999). It is worthwhile to mention that the SQ alternative is experienced by respondents, while the hypothetical alternatives can only be conjectured. As such, the utilities of hypothetical alternatives are more correlated within themselves than with the SQ option. Besides, as the SQ alternative is familiar to respondents, it is likely to have a smaller individual valuation error. With these considerations, an error component stochastic term was included in the model to account for the systematic effects associated with the SQ and the hypothetical alternatives. The advantage of specifying the model in WTA space is that the coefficients can directly be interpreted as marginal WTA values. Besides, WTA space estimation is a more feasible approach when comparisons across treatments are made than that based on marginal utilities, i.e., preference space estimation (Caputo, Scarpa, and Nayga, 2017).

The utility of RPL-EC model in WTA space for a respondent *i* choosing alternative *j* at choice task *t* is specified as:

$$(2)\ U_{ijt} = \alpha\big(Pay_{ijt} - \theta_{1i}^{h} * Winter_{ijt} - \theta_{2i}^{h} * Fall_{ijt} - \theta_{3i}^{h} * Side_{ijt} - \theta_{4i}^{h} * Nitrogen_{ijt} - \theta_{5i}^{h} * SQ_{ijt} + \eta_{ijt}\big) + \varepsilon_{ijt} \ \ when\ j = 1\ or\ 2$$

$$or$$

$$= \alpha\big(Pay_{ijt} - \theta_{1i}^{sq} * Winter_{ijt} - \theta_{2i}^{sq} * Fall_{ijt} - \theta_{3i}^{sq} * Side_{ijt} - \theta_{4i}^{sq} * Nitrogen_{ijt} - \theta_{5i}^{sq} * SQ_{ijt} + \eta_{ijt}\big) + \varepsilon_{ijt} \quad when\ j = sq$$

where Pay_{ijt} represents the payment farmers receive from the proposed program; $Winter_{ijt}, Fall_{ijt}, Side_{ijt}$ are three proposed practices with *1* indicating that this practice is required, and 0, otherwise; $Nitrogen_{ijt}$ is the expected nitrogen saving in percentage; SQ_{ijt} is a dummy variable with value *1* indicating the SQ alternative and *0*, otherwise; α is the payment parameter; $\boldsymbol{\theta}$ are the coefficients of the estimated WTA values; error component η_{ij} is normally distributed with zero mean for the hypothetical alternatives, and $\eta_{ij} = 0$ for the SQ alternative; and ε_{ijt} is the unobserved error term which follows a Gumbel distribution. Note that here I estimated the model with panel structure, assuming that the error components are the same for all choice sets by the same individual following the suggestion by Scarpa et al., 2007. Also note that, in addition to setting the SQ constant term dummy SQ_{ijt} to identify SQ alternative's constant contribution to utility, here I allow the preferences for the same attribute to be different between hypothetical and SQ alternatives by separately specifying $\boldsymbol{\theta}^{\boldsymbol{h}}$ and $\boldsymbol{\theta}^{\boldsymbol{sq}}$. A formal testing of the assumption that $\boldsymbol{\theta}^{\boldsymbol{h}}$ = $\boldsymbol{\theta}^{\boldsymbol{sq}}$ is reported in the later empirical analysis.

Moreover, I allowed the taste parameters to be interdependent by assuming the coefficients of attributes follow a multivariate normal distribution. With this setting, I allowed the preferences for the proposed practices to be correlated. For example, I might expect some correlation between preferences for Winter and Side. The multivariate normal distribution has vector mean μ, and variance-covariance matrix $\Omega = C'C$, where *C* is the Cholesky matrix. The significance of any element of Cholesky matrix C will support the dependence across tastes.

It is worth to mention that an SQ constant term was included in equation (2) to explore the potential divergence between hypothetical alternatives and SQ alternative. Leaving the status quo situation has been justified to decrease utility in many DCE applications (e.g., Lehtonen et al. 2003; Hanley, Wright, and Alvarez-Farizo 2006). However, a crucial question for these findings is whether the SQ constant term is capturing the average effect on utility of all factors not included in the model, or whether the SQ constant term is associated with a behavioral decision strategy, such as misperceived sunk costs or regret aversion (e.g., Meyerhoff and Liebe, 2009). Therefore, this study relates each farmer's SQ alternative with the stated status quo values provide in the survey to capture the heterogeneity of farmers' status quo values following Rose et al., 2008. In this way, the SQ constant term captures the pure effect of staying at status quo because the individual specific status quo situations have been controlled in the data.

To test the external treatment's effect, I pooled the data and specified an extended utility function including a set of dummy variables following de-Magistris 2013, and Bazzani 2017. The data was pooled based on one of the two treatments so that the dummy variables can test the other treatment's effect conditional on the pooled treatment. The extended utility function is specified as follows:

$$(3)\ U_{ijt} = \alpha\ \ [Pay_{ijt} - \theta_{1i}^{h} * Winter_{ijt} - \theta_{2i}^{h} * Fall_{ijt} - \theta_{3i}^{h} * Side_{ijt} - \theta_{4i}^{h} * Nitrogen_{ijt}$$

$$- \theta_{5i}^{h} * SQ_{ijt} - \ \gamma_1\big(dTreat \times Winter_{ijt}\big) - \gamma_2\big(dTreat \times Fall_{ijt}\big)$$

$$- \gamma_3\big(dTreat \times Side_{ijt}\big) - \gamma_4\big(dTreat \times Nitrogen_{ijt}\big) - \gamma_5\big(dTreat \times SQ_{ijt}\big)$$

$$+ \eta_{ij}\big] + \varepsilon_{ijt}\ \ when\ j = 1\ or\ 2$$

$$or$$

$$= \alpha\ \ [Pay_{ijt} - \theta_{1i}^{sq} * Winter_{ijt} - \theta_{2i}^{sq} * Fall_{ijt} - \theta_{3i}^{sq} * Side_{ijt} - \theta_{4i}^{sq} * Nitrogen_{ijt} - \theta_{5i}^{sq}$$

$$* SQ_{ijt} - \ \gamma_1\big(dTreat \times Winter_{ijt}\big) - \gamma_2\big(dTreat \times Fall_{ijt}\big)$$

$$- \gamma_3\big(dTreat \times Side_{ijt}\big) - \gamma_4\big(dTreat \times Nitrogen_{ijt}\big) - \gamma_5\big(dTreat \times SQ_{ijt}\big)$$

$$+ \eta_{ij}\big] + \varepsilon_{ijt}\ \ when\ j = sq$$

where $dTreat$ is a dummy variable indicating the treatment group, i.e., information or decision window; $\boldsymbol{\gamma}$ represent the respective treatment effect on the specific attribute. Note that dummy variables are included within the brackets and minus signs are specified such that the coefficients can be directly interpreted as the difference in WTAs. A total of four extended utility functions are estimated based on the four different dimensions of pooled data.

To understand survey respondent characteristics' impact on WTA, I ran an Ordinary Least Square model by specifying the individual posterior estimates of WTA as the dependent variables and the respondent characteristics as the independent variables following Train, 2009:

(4) $WTA_{Xi} = \beta_0 + \beta X_i + \varepsilon_i$

where WTA_{Ai} represents the individual $i's$ WTA for attribute A estimated from equation (2); X_i represents the respondent's characteristics such as social-demographic factors, opinions, and information sources.

2.4. Results

This section discusses the estimation results of the RPL-EC models in WTA-space and the extended utility RPL-EC models to test the treatment effects. The relations between farmers' WTA and their social demographic characteristics, attitude, and source of information are also examined.

2.4.1. WTA Estimation

I started with investigating the assumption that $\boldsymbol{\theta^h} = \boldsymbol{\theta^{sq}}$ through running two specifications of RUM model. The RPL-EC model estimation results in WTA space are reported in Table 2.5 with RUM assuming $\boldsymbol{\theta^h} = \boldsymbol{\theta^{sq}}$ and RUM' lifting the assumption. All signs of the RUM estimations are as expected except that of *Nitrogen*, and the estimations of *Fall, Side*, *Nitrogen* are not significant. All signs of the RUM' estimations are as expected with *Winter, Side* and *SQ* being significant. The unexpected signs and insignificant estimations of RUM imply that restricting

$\boldsymbol{\theta}^{\boldsymbol{h}} = \boldsymbol{\theta}^{\boldsymbol{sq}}$ might fail to capture the true underlying decision criteria. Furthermore, the likelihood ratio test was conducted to evaluate the nested structure of RUM and RUM'. The test rejected RUM in favor of RUM' with the likelihood ratio statistic being 122. This rejection again suggests that the preferences over the same attribute in the hypothetical and SQ alternative are not the same. Therefore, the following analysis will build on RUM' specification.

The RUM' results imply that all three CA practices are unfavored, payment and nitrogen saving are favored, and leaving the status quo is unfavored. The statistical significance of the estimated standard deviation parameter indicates heterogeneity in respondents' preferences. Moreover, the significance of the error component for the alternative specific constants justifies the hypothesis of correlation across the hypothetical alternatives.

The WTA estimations for $Winter$ are most significant among the three CA practices in both hypothetical and SQ alternatives, i.e., \$87/acre and \$91/acre. This finding is consistent with my expectation as covering winter crops is most costly and time-consuming. WTA estimations for *Fall* are small and insignificant. With respect to WTA of *Side*, the estimation is small and insignificant in hypothetical alternative, however, is significant and relatively high in SQ alternative, i.e., \$151/acre.

N saving has a positive impact on preferring an alternative: a 10% expected nitrogen saving decreases the WTA of a hypothetical alternative by \$13/acre and the WTA of an SQ alternative by \$29/acre. Although the estimations are not significant. Referring to the costs of fertilizer for corn, which is approximately \$161/acre (Schnitkey, 2015), the scale of estimation in the bonus gained from expected fertilizer saving is reasonable. However, we should be cautious in interpreting the parameters of $Nitrogen_{ijt}$. Here $Nitrogen_{ijt}$ is the expected nitrogen saving calculated by assuming the farmer currently does not take any of the CA practices and applies

170lb/acre fertilizer on the land. It is not the actual nitrogen saving that will occur after the proposed practices are adopted. We should cautiously interpret the coefficient of $Nitrogen_{ijt}$ to be the effect of the information related with expected nitrogen saving, rather than the effect of nitrogen saving. In addition to that, a crucial point to note here is as $Nitrogen_{ijt}$ is highly correlated with the three CA practices, $Nitrogen_{ijt}$'s parameters will be likely to tradeoff with other attributes' parameters and will be challenging to be significantly identified if sample size is not sufficiently large. In light of these two points, we did not find $Nitrogen_{ijt}$ shows as significant impacts as we might expect.

Shifting farmers away from the status quo significantly brings up the WTA by about $145/acre, which implies farmers' unwillingness to commit to a CA program. Program acceptance aversion is a significant issue in conservation program promotion. In addition to the SQ dummy term, SQ and hypothetical alternatives also diverge in each attribute's preference/WTA. Generally, the scales of WTAs for the SQ alternatives are larger and more significant than for the hypothetical alternatives. That means that if a farmer has adopted a certain practice in the SQ, he/she needs higher incentive to stay at SQ, or lower incentive to switch to the CA program because he/she will gain policy payment by simply committing to the proposed program without changing the practices he/she has adopted.

It is worth mentioning that sample size can be a limitation from which this research suffers. On one hand, lifting the assumption of $\boldsymbol{\theta}^{\boldsymbol{h}} = \boldsymbol{\theta}^{\boldsymbol{sq}}$ increases the required sample size to identify the model parameters as the number of parameters doubled. On the other hand, the alternatives' expected N saving follows a formula of the three CA practices and is thus highly correlated with *Winter*, *Fall*, and *Side*. This high correlation raises the required sample size to power the identification of parameters.

Table 2.5. WTA Space Estimations

	RUM	RUM'
Mean Values		
$Winter^h$	77***[a]	87***
	(14.3)[b]	(17.3)
$Fall^h$	1	1
	(8.7)	(9.9)
$Side^h$	13	2
	(20.6)	(23.7)
$Nitrogen^h$	39	-128
	(84.2)	(98.6)
$Winter^{sq}$		91***
		(30.4)
$Fall^{sq}$		28
		(20.9)
$Side^{sq}$		151***
		(52.9)
$Nitrogen^{sq}$		-292
		(208)
SQ	-90***	-145***
	(4.9)	(10.5)
Standard Deviations		
$Winter^h$	117***	93***
	(37.7)	(25.2)
$Fall^h$	6	3
	(16.2)	(4.9)
$Side^h$	32	4
	(45.8)	(5.3)
$Nitrogen^h$	69	151
	(122)	(119)
$Winter^{sq}$		107***
		(25.5)
$Fall^{sq}$		42
		(39.2)
$Side^{sq}$		147***
		(23.8)
$Nitrogen^{sq}$		301*
		(174)
η_{ijt}	114***	108***
	(13.3)	(11.7)
Model Statistics		
Log-Likelihood	-4495	-4434
AIC/N	2.09	2.07
BIC/N	2.10	2.08
N	4300	4300

a. p-value with *** 1%, ** 5%, * 10%.
b. Standard error is reported in the bracket.

2.4.2. Treatment Effect Testing

To examine the treatment effect, I started with rerunning the RUM' model based on each treatment group. The results in Table 2.6 show that the individual treatment group's estimations are consistent with the findings based on the pooled sample in the previous section: the WTAs for the same attributes in an SQ alternative are higher than that in a hypothetical alternative. In PS and NS groups, the parameters of *Side* and *Nitrogen* are extremely high and trading off with each other, which again brings attention to the high correlation between *Nitrogen* and the three CA practices. Comparing the WTAs among the treatment groups, I found that the WTA estimations are relatively lower for the ND group, and relatively higher for the PS group.

To continue, I formally tested the difference in WTAs by running the extended utility equation (3) to make pairwise comparisons. The results are reported in Table 2.7. To test the decision time window's impact with hypothesis $\mathrm{H0}_1$, I pooled the positive information observations to run equation (3). As the extended part for the treatment dummy parameters $\boldsymbol{\gamma}$ are also included in the WTA space, the estimated parameters can be directly interpreted as the difference in dollar amount of WTA. Likewise, I separately pooled negative information treated observations, delayed option available observations, and delayed option unavailable observations to test $\mathrm{H0}_2$, $\mathrm{H0}_3$, and $\mathrm{H0}_4$ respectively. With respect to the three CA practices, ND group generates the lowest WTA estimations and PS group generates the highest WTA estimations. With respect to N saving and staying at SQ, ND group produces the highest WTA estimations and PS group produces the lowest WTA estimations. The scale of the difference in WTA between treatment groups is substantial referring to the scale of WTAs; however, the estimation of the difference is not significant. The statistical insignificance holds us from claiming a winner among the treatment groups. However, it is worth mentioning again that sample size is a limitation of this work to identify the parameters significantly. On that note, this treatment testing suggests that negative information framing combined with a dynamic decision window has the potential to reduce program costs as compared with the other three treatments.

In summary, information framing treatment and decision window setting may have impacts on decision-making. Negative information framing combined with a dynamic decision scenario is most promising in reducing the program's WTA. Positive information framing combined with a static decision scenario may prevent people from adoption. That being said, people are more effectively nudged by the negative consequence of taking no action to conduct good deeds as compared with the positive contributions they could have made. Meanwhile, people feel more confident to commit to a program immediately if they are provided with the option to delay decisions to collection information rather than being pushed to make a decision immediately. These findings are merely based on raw WTAs comparison and are not statistically justifiable due to the sample size limitation.

Table 2.6. WTA Space Estimations by Treatment Sample

Sample	PD	PS	ND	NS
Mean Values				
$Winter^h$	45[a]	90.4***	62.7**	77.1**
	(72.2)[b]	(30.8)	(28.0)	(32.7)
$Fall^h$	-3.49	14.2	-14.7	-0.902
	(22.2)	(17.5)	(20.8)	(19)
$Side^h$	0.66	13.7	-18.5	4.63
	(52.8)	(42.3)	(49.7)	(44.7)
$Nitrogen^h$	-153	-132	-113	-95
	(220)	(175)	(208)	(186)
$Winter^{sq}$	106***	134**	73.6**	144**
	(38.9)	(54.8)	(36.1)	(66.2)
$Fall^{sq}$	-69	57.2	9.29	79.3*
	(49.7)	(37.1)	(38.5)	(46.2)
$Side^{sq}$	71.2	250***	64.7	308***
	(124)	(95.1)	(96)	(117)
$Nitrogen^{sq}$	579	-745**	103	-884**
	(501)	(369)	(379)	(458)
SQ	-153***	-123***	-161***	-143***
	(24.7)	(17.6)	(22.8)	(19.4)
Standard Deviations				
$Winter^h$	61	116***	73*	91**
	(77.8)	(42.1)	(37.1)	(40.1)
$Fall^h$	7.9	32	14	5.3
	(9.1)	(29.7)	(100)	(4.7)
$Side^h$	2.7	25	24	7.0
	(7.5)	(37.1)	(106)	(9.5)
$Nitrogen^h$	179*	154	116	106
	(107)	(137)	(89.5)	(95.7)
$Winter^{sq}$	121***	131***	84***	160**
	(10.7)	(21.2)	(23.3)	(63.2)
$Fall^{sq}$	82	74	13.9	82.2**
	(92.2)	(57.5)	(12.8)	(33.4)
$Side^{sq}$	85	185***	78	327***
	(39.6)	(57.5)	(69.3)	(118)
$Nitrogen^{sq}$	741	866***	123	895**
	(637)	(289)	(95.4)	(394)
η_{ijt}	102***	94***	93***	108***
	(17.1)	(15.2)	(16.5)	(13.7)
Model Statistics				
Log-Likelihood	-1094	-1101	-1121	-1100
AIC/N	2.08	2.07	2.07	2.07
BIC/N	2.12	2.12	2.12	2.12
N	1064	1072	1092	1072

a. p-value with *** 1%, ** 5%, * 10%.
b. Standard error is reported in the bracket.

Table 2.7. Hypothesis Tests

	Winter	Fall	Side	Nitrogen	SQ
$H0_1: WTA_{PD} - WTA_{PS} = 0$					
$WTA_{PD} - WTA_{PS}$	-30.2[a]	-19.4	-36.1	136	12.1
s.d.	(41.3)[b]	(24.2)	(59.1)	(243)	(14.2)
$H0_2: WTA_{ND} - WTA_{NS} = 0$					
$WTA_{ND} - WTA_{NS}$	-20.2	-17.1	-49.2	140	13.8
s.d.	(40.5)	(24.4)	(58.5)	(240)	(40.5)
$H0_3: WTA_{PD} - WTA_{ND}$					
$WTA_{PD} - WTA_{ND}$	39.2*	6.31	15.9	-51.8	-1.63
s.d.	(22.1)	(15.8)	(43.3)	(260)	(15.3)
$H0_4: WTA_{PS} - WTA_{NS} = 0$					
$WTA_{PS} - WTA_{NS}$	11.3	8.38	0.722	-33.5	2.10
s.d.	(38.1)	(22.8)	(54.4)	(224)	(13.1)

a. p-value with *** 1%, ** 5%, * 10%.
b. Standard error is reported in the bracket.

2.4.3. Farmers Internal Factors' Effects

Besides the external factors' impacts on decision-making as discussed above, I further tested farmers characteristics' impacts on decision-making. As the WTA estimations are larger and more significant for the SQ alternative, I ran the posterior estimations of equation (4) separately on the SQ alternative's WTAs for *Winter*, *Fall*, *Side*, *Nitrogen*, and *SQ*.

As reported in Table 2.8, the F values show that farmers' characteristics have impacts on WTA_{Winter}, WTA_{Side}, and $WTA_{Nitrogen}$, but do not have significant impacts on WTA_{Fall}, and WTA_{SQ}. Looking further into the factors, I found that states, gender, education, days off-farm, experience with conservation programs, and trust in neighbors and media as farming information sources all have impacts on WTA_{Winter}, WTA_{Side}, and $WTA_{Nitrogen}$. Generally, Iowa farmers need higher compensation than Michigan farmers; male, higher educated, full-time, conservation program experienced, trusting neighbors more and media less farmers need more compensation to enroll in the proposed program.

Table 2.8. Farmer Characteristics' Impacts on WTA of the SQ Alternative

Factors	Winter	Fall	Side	Nitrogen	SQ
State					
IA	-3[a]	4	38***	34	6
	(10.1)[b]	(3.7)	(10.6)	(32.3)	(7.2)
IN	22	2	24	25*	17
	(18.4)	(5.7)	(13.6)	(14.5)	(10.1)
Gender					
Male	28***	10	22	57*	39
	(11.2)	(9.2)	(17.8)	(31.1)	(25.6)
Age					
Senior (>59 years)	9	3	-6	7	6
	(8.8)	(3.1)	(4.9)	(9.2)	(5.7)
Education					
College Degree or Above	-8	-3	2	-26*	14**
	(8.1)	(2.0)	(3.8)	(14.1)	(6.22)
Days off Farm					
Full-time (less than 50 days off farm)	-8	-6	29**	15	3
	(6.3)	(5.4)	(12.3)	(11.6)	(4.2)
Farm Value					
High Product Value (>$499,999)	3	7	5	-11	2
	(3.8)	(6.1)	(3.9)	(7.3)	(4.2)
Conservation Program					
Has Experience with Conservation Program	25*	31	-20	5	-12
	(13.3)	(22.6)	(15.2)	(6.2)	(7.5)
Information Source					
Trust in Neighbor > 2.5[c]	14*	-1	21*	-38	-10
	(7.4)	(1.5)	(10.9)	(27.0)	(7.2)
Trust in Extension > 2	6	1	2	3	-2
	(8.2)	(2.0)	(3.4)	(5.2)	(3.2)
Trust in Private Sector > 3	1	3	4	2	4
	(3.2)	(4.8)	(2.8)	(3.3)	(4.1)
Trust in Media > 2	-27***	-5	7	-8	1
	(7.2)	(5.3)	(5.7)	(6.2)	(1.5)
Trust in Online Calculator > 1	-2	-9	-4	-7	6
	(3.4)	(7.8)	(3.4)	(6.3)	(5.7)
Constant	79***	19	138*	-304	-152***
	(31.6)	(12.8)	(81.7)	(259)	(35.2)
N	686	686	686	686	686
F	3.13	1.44	4.52	3.74	1.25
Prob > F	0.0002	0.1312	0.0000	0.0000	0.2298
R-squared	0.0418	0.0329	0.0702	0.0548	0.0214

a. p-value with *** 1%, ** 5%, * 10%.
b. Standard error is reported in the bracket.
c. The median value for a 1-5 liker scare question is used to generate the binary variable.

2.5. Conclusions

This chapter investigated corn growers' decision-making for CA adoption through conducting a survey experiment analysis. I estimated the corn growers' WTAs to commit to CA programs and examined the external and internal factors' impacts on the WTAs.

Incentives are effective at encouraging farmers to adopt CA practices. The costs come in two parts: one is the direct practice costs that compensate the added expenses or efforts of taking a particular practice, the other is the program enrollment cost that compensates for leaving the status quo. Among the three CA practices, covering crops in winter is relatively significant and expensive. This is consistent with the difficulty level of adopting each practice. Besides that, the unwillingness to change from the status quo also plays a critical part in the compensation. This unwillingness to leave the status quo can be due to 1) the endowment effect wherein people ascribe more values to the status quo merely because they have been endowed with it; 2) concern of the incurred transaction cost; 3) aversion or distrust of a regulated/government program; 4) aversion of commitment; 5) risk aversion where people avoid making changes to take any risk; or 6) protest of the survey. Understanding the reasons for unwillingness to leave the status quo will inform policymakers taking actions to remove the associated concerns and thus improving policy cost efficiency. These tasks are out of the scope of this dissertation and are suggested for future research directions.

Two factors effectively reduce the necessary compensations of CA adoption. One is the farmers' experience with CA practices in the status quo. On one hand, taking CA practices in the status quo will naturally lower the utility level of staying at status quo, making people more likely to commit to a CA program. On the other hand, the WTAs for the same CA attributes are generally higher and more significant in the SQ alternative than in the hypothetical alternatives.

This greater WTAs for the SQ alternative further lowers the CA-taken-farmers' utility level of staying at SQ. This finding raises the importance of building CA experience among farmers. The other factor that reduces necessary compensation is the expected N savings, even though this expected N saving might depart from the actual N saving depending on the survey respondents' SQ fertilizer application. This indicates the importance of including the expected nitrogen saving as part of the program design to incentivize adoption.

Furthermore, this study tested the interaction effect of the policy design from two dimensions, i.e., the information framing and a decision time window. The two-by-two treatment test suggests that the negative information framing combined with a dynamic decision scenario is the most promising design in terms of improving the CA programs' cost efficiency. However, further research with sufficient sample size should be conducted to provide statistical evidence for these findings.

Finally, farmers' characteristics also showed impacts on program enrollment. Targeting the program among factors with program-favor features can potentially increase the adoption rate without increasing the policy budget. Understanding the reasons and causal effects of why each factor contributes to their decision will also generate insights on how to encourage participation.

Figure 2.5. Survey Sample

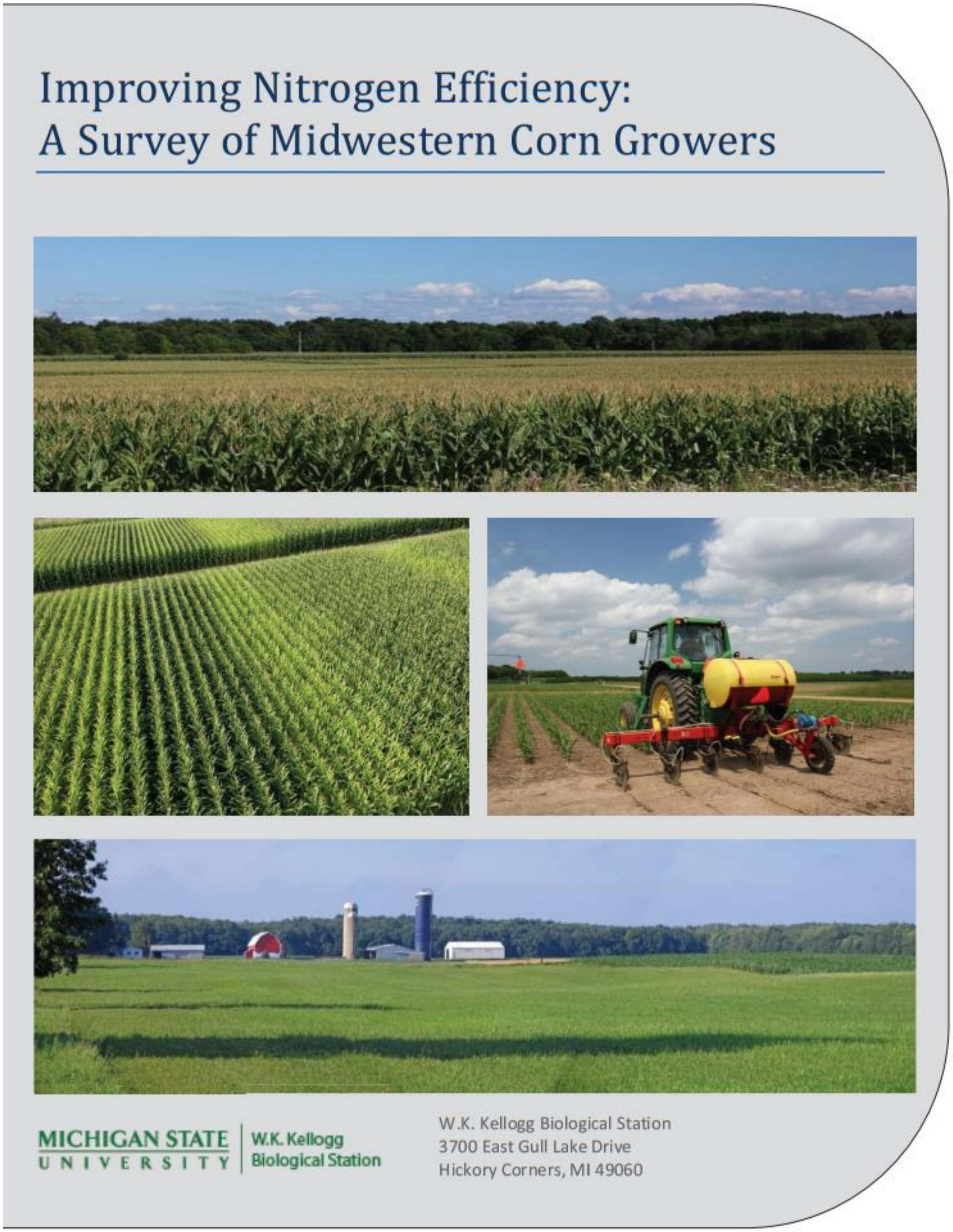
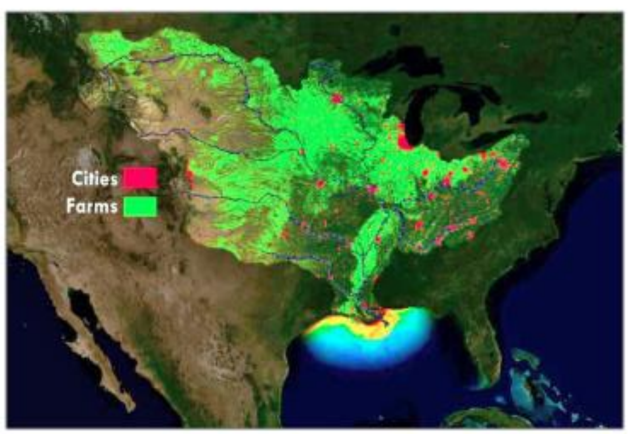


Figure 2.5 (cont'd)

Effects of Nitrogen on the Environment

Nitrogen (N) is a crucial component of crop production. However, N lost from farming operations **contributes to pollution of the environment**. In surface waters, N contributes to algal growth, damaging both **water quality** and natural ecosystems both near farm fields and many miles downstream. Ecosystem eutrophication (over-fertilization) and hypoxia (lack of dissolved oxygen) in coastal areas is a major problem, including in the Gulf of Mexico. Excess soil N can also lead to **air pollution**. N can enter the atmosphere as nitrogen oxides (NO_x) that contribute to smog and acid rain. Nitrous oxide (N_2O) is also a greenhouse gas that contributes to climate change. By weight, N_2O is 300 times more powerful than CO_2 at warming the atmosphere. According to the US Environmental Protection Agency (EPA), seventy percent of all US emissions of N_2O are from agriculture.



Hypoxia in the Gulf of Mexico (photo courtesy of NOAA)

Figure 2.5 (cont'd)

Scenario Introduction

Suppose hypothetically the US government is starting a 10 year program that encourages farmers to improve N use efficiency on their farmland. Participation in this program is voluntary and farmers could enroll any part of their farm. Farmers who participate will receive a payment in exchange for adopting N efficiency practices.

Below we ask you to make choices about several different scenarios. For each scenario, you are asked to choose between participating and not participating in two different programs. One scenario will be randomly chosen for evaluation. Therefore, **you should not compare the scenarios when making choices**. In each scenario, your task is simply to choose whether to participate or not.

For the randomly chosen scenario, the most-selected program will be implemented immediately if the majority of respondents decide to participate. If no program is implemented, **you will be provided with another chance one year later to decide again in which programs you would like to participate**. Further, we will make **new information** available obtained from ongoing research about best N practices.

Your input on policy designs is very important. While these program designs are hypothetical, your honest answers will be critical in informing future policies. **When answering the following questions, please respond as if this were a real option.**

Figure 2.5 (cont'd)

These programs are NOT intended to impact yield. The goal of these programs is to increase efficiency in N application so that less fertilizer is needed without affecting yield. For these scenarios, please assume that crop and N prices will stay steady at current prices. Your participation in these scenarios does not prohibit your participation in other existing cost share programs.

Definitions

Please keep these definitions in mind when reading through the policy scenarios on the following pages:

Fall Application Prohibited: A ban on fall application of synthetic fertilizers, such as anhydrous ammonia, following fall harvest with the purpose of providing N for next year's crop.

Side-dress Application Required: Application of N fertilizer following corn emergence in the spring (typically between 4 and 8 weeks after planting). This program component requires at least one post-emergence application of nitrogen.

Winter Cover Crops Required: Crops planted to provide cover following harvest of the primary crop, intended to prevent erosion, improve soil health, and supply nutrients. The specific plant species selected is up to you.

Expected Nitrogen savings: Percentage of N application rate (based on agronomic models) you will not need to apply with the given practices, based on an average application rate of 170 lbs N/acre.

Annual Payment Level: This payment per acre will be provided annually in a single payment with enrollment in the program. There is no cap, so you can enroll as many acres as you want.

Which of these practices have you previously heard of?

Fall N Application ☐
Side-dress N Application ☐
Winter Cover Crops ☐

Please mark all answers clearly, with a pen or pencil, as indicated below.

Example: ☐ ☑ ☐ or ☐ ☒ ☐

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Figure 2.5 (cont'd)

Scenario #1

Note: This program is not expected to reduce corn yield with appropriate application rates
Expected N savings are based on average application rate of 170 lbs/acre with no practice adoption
The program chosen by the majority of respondents will be implemented immediately. If no program is implemented for now, you will be provided with ***new information*** *about N application and* ***given another chance to decide one year later****.*

	Program 1	**Program 2**	**Do not participate**
Fall application prohibited	Yes	No	I would not participate in these programs
Sidedress application required	No	Yes	
Winter cover crops required	Yes	Yes	
Expected Nitrogen savings	25%	40%	
Annual payment level	$180/acre	$180/acre	
I would choose ... (check only one)	☐	☐	☐

1. **How sure are you about your choice?**
   - ☐ 5 . . . . . Very certain
   - ☐ 4 . . . . . Certain
   - ☐ 3 . . . . . Somewhat certain
   - ☐ 2 . . . . . Slightly certain
   - ☐ 1 . . . . . Not at all certain

Figure 2.5 (cont'd)

Scenario #2

Note: This program is not expected to reduce corn yield with appropriate application rates
Expected N savings are based on average application rate of 170 lbs/acre with no practice adoption
*The program chosen by the majority of respondents will be implemented immediately. If no program is implemented for now, you will be provided with **new information** about N application and **given another chance to decide one year later**.*

	Program 1	Program 2	Do not participate
Fall application prohibited	Yes	No	I would not participate in these programs
Sidedress application required	Yes	No	
Winter cover crops required	Yes	Yes	
Expected Nitrogen savings	50%	10%	
Annual payment level	$40/acre	$5/acre	
I would choose ... (check only one)	☐	☐	☐

2. How sure are you about your choice?

☐ 5 . . . . . Very certain
☐ 4 . . . . . Certain
☐ 3 . . . . . Somewhat certain
☐ 2 . . . . . Slightly certain
☐ 1 . . . . . Not at all certain

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Figure 2.5 (cont'd)

Scenario #3

Note: This program is not expected to reduce corn yield with appropriate application rates
Expected N savings are based on average application rate of 170 lbs/acre with no practice adoption
*The program chosen by the majority of respondents will be implemented immediately. If no program is implemented for now, you will be provided with **new information** about N application and **given another chance to decide one year later**.*

	Program 1	Program 2	Do not participate
Fall application prohibited	No	Yes	I would not participate in these programs
Sidedress application required	Yes	Yes	
Winter cover crops required	No	Yes	
Expected Nitrogen savings	25%	50%	
Annual payment level	$5/acre	$100/acre	
I would choose ... (check only one)	☐	☐	☐

3. How sure are you about your choice?

☐ 5 . . . . . Very certain
☐ 4 . . . . . Certain
☐ 3 . . . . . Somewhat certain
☐ 2 . . . . . Slightly certain
☐ 1 . . . . . Not at all certain

Figure 2.5 (cont'd)

Scenario #4

Note: This program is not expected to reduce corn yield with appropriate application rates
Expected N savings are based on average application rate of 170 lbs/acre with no practice adoption
*The program chosen by the majority of respondents will be implemented immediately. If no program is implemented for now, you will be provided with **new information** about N application and **given another chance to decide one year later**.*

	Program 1	Program 2	Do not participate
Fall application prohibited	Yes	Yes	I would not participate in these programs
Sidedress application required	No	Yes	
Winter cover crops required	Yes	No	
Expected Nitrogen savings	25%	25%	
Annual payment level	$100/acre	$20/acre	
I would choose ... (check only one)	☐	☐	☐

4. How sure are you about your choice?

☐ 5 . . . . . Very certain
☐ 4 . . . . . Certain
☐ 3 . . . . . Somewhat certain
☐ 2 . . . . . Slightly certain
☐ 1 . . . . . Not at all certain

5. **If you chose not to participate IN ANY OF THE SCENARIOS, which of the following best describes the most important reason for your choice (check one)?**

- Payment is too low
- Timing of the proposed practices does not fit my operation
- I do not have the capacity (equipment, data, or knowledge) to participate
- Too much risk of yield loss
- Do not want to participate in government programs
- N does not lead to environmental damage
- Other, please explain ______

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Figure 2.5 (cont'd)

We would like to ask you some questions about why you made your choices the way you did.
When answering the questions on this page, think back to the four scenarios collectively.

6. When you were deciding whether to participate in the program, how much influence did each of the characteristics have in your decision? Please indicate below.

	Not at all important	*A little important*	*Somewhat important*	*Very important*	*Extremely important*
Fall application	☐	☐	☐	☐	☐
Side-dress nitrogen application	☐	☐	☐	☐	☐
Winter cover crops	☐	☐	☐	☐	☐
Expected nitrogen savings	☐	☐	☐	☐	☐
Annual payment level	☐	☐	☐	☐	☐

7. Thinking about everything you read in the scenarios, did the questions asked overall make you feel that we were trying to influence your decision one way or another?

- No — Continue to next page
- Yes — Please see questions below, then continue to next page
  - Strongly pushed me to choose a program
  - Weakly pushed me to choose a program
  - Let me make up my own mind
  - Weakly pushed me to reject a program
  - Strongly pushed me to reject a program

Figure 2.5 (cont'd)

Now we would like to ask you some questions about your farm operation and use of fertilizers. On the following pages, you will see questions about your farm operation, use and timing of nitrogen fertilizers, sources of information you consult about fertilizers, and your views of farming and the environment. These questions will help us get a better sense of you and your operation.

Farm Characteristics

8. In 2014, how many acres of cropland did you:

Own and operate		acres
Lease ***from*** others		acres
Lease ***to*** others		acres

8. Thinking back over the last three years of planting and harvest, please provide the following information about your most recent harvests *on your largest corn field*.

2012 Corn Acreage Planted		acres
2012 Corn Average Yield		bushels/acre
2013 Corn Acreage Planted		acres
2013 Corn Average Yield		bushels/acre
2014 Corn Acreage Planted		acres
2014 Corn Average Yield		bushels/acre

10. Which type of tillage did you use in 2014 on your largest corn field?

Conventional (such as moldboard), less than 15% residue remaining on surface .... ○

Reduced tillage (such as chisel plow), 15-30% residue remaining on surface .... ○

Conservation tillage (such as ridge, mulch, or no-till), more than 30% residue remaining on surface ...... ○

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Figure 2.5 (cont'd)

Fertilizer Practices

11. In each year, how much nitrogen do you typically apply to corn? ☐ lbs of N/acre

12. In 2015, what nitrogen fertilizers did you apply to your largest corn field?

Type of Fertilizer	Number of Applications	Season of Application (check all that apply)				Total Lbs of N per Acre
		Fall	Pre-planting	At-planting	Post-planting	
Anhydrous Ammonia . . .	☐	☐	☐	☐	☐	#/acre
Urea (granular) . . .	☐	☐	☐	☐	☐	#/acre
UAN 28/32 . .	☐	☐	☐	☐	☐	#/acre
Manure	☐	☐	☐	☐	☐	#/acre
Other . . . . . . ☐	☐	☐	☐	☐	☐	#/acre

13. Which of the following practices do you use when you apply nitrogen on corn? (check all that apply)

Practice	On your largest corn field in 2015	In the past, but not in 2015
Winter cover crops	☐	☐
Side-dress N application	☐	☐
Soil or plant nitrate testing . . .	☐	☐
Variable rate N application . . .	☐	☐
Slow-release fertilizer products	☐	☐
Imagery (such as aerial photography, on-the-go sensors, etc.)	☐	☐

Figure 2.5 (cont'd)

Conservation Programs

14. Have you *ever* participated in any of the following federal conservation programs?

- Conservation Reserve Program (CRP) . . . . ☐
- Environmental Quality Incentives Program (EQIP) . . . . . ☐
- Conservation Stewardship Program (CSP) . . . . ☐
- Other ____________ . . . . ☐

15. We would like your opinions about modern farming practices. Please indicate your agreement with the following statements.

	Strongly Disagree	Somewhat Disagree	Neither Agree or Disagree	Somewhat Agree	Strongly Agree
Modern farming relies too heavily upon fertilizers	☐	☐	☐	☐	☐
Modern farming relies too heavily upon insecticides, herbicides, and fungicides	☐	☐	☐	☐	☐
Farmers often apply too much fertilizer	☐	☐	☐	☐	☐
The pollution effects of nitrogen fertilizer are quite unimportant compared to their benefits	☐	☐	☐	☐	☐
I am concerned that herbicide resistant weeds will become a problem in my area	☐	☐	☐	☐	☐
When prices of nitrogen fertilizer are high, I use less	☐	☐	☐	☐	☐
I use the same amount of nitrogen regardless of price	☐	☐	☐	☐	☐
Increased use of sustainable farming practices would help maintain our natural resources	☐	☐	☐	☐	☐
Other ____________	☐	☐	☐	☐	☐

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Figure 2.5 (cont'd)

Farmers and the Environment

16. We would like to understand your views of farming and the environment. Please indicate the degree to which you agree or disagree with the following statements:

	Strongly Disagree	*Disagree*	*Neither Agree or Disagree*	*Agree*	*Strongly Agree*	*Don't Know*
Good farming requires using all available acreage as efficiently as possible to maximize yields	☐	☐	☐	☐	☐	☐
To protect the rural landscape, farmers must move away from conventional agricultural practices to approaches that mimic ecological processes	☐	☐	☐	☐	☐	☐
Modifications to my farm that increase production, such as removal of grasslands, fencerows, or grass field buffers, have little impact on the environment	☐	☐	☐	☐	☐	☐
Programs to protect soil and water resources should emphasize approaches that primarily benefit agricultural production	☐	☐	☐	☐	☐	☐
As a result of modern agricultural practices, farmers must exert more effort now to protect the environment than was necessary in the past	☐	☐	☐	☐	☐	☐
The primary role of farms is the production of food and related agricultural products; the protection of the environment is separate from this purpose	☐	☐	☐	☐	☐	☐
Good farming results from placing equal importance on the management of both agricultural and natural areas of my farm	☐	☐	☐	☐	☐	☐
A successful farmer is someone who continuously evaluates the environmental impact of their farm and adopts new approaches to protect the environment	☐	☐	☐	☐	☐	☐

Figure 2.5 (cont'd)

Sources of Information

17. How often do you receive information about nitrogen fertilizers from the following sources? (check all that apply)

	Never	*Rarely*	*Occasionally*	*Frequently*	*Very freq.*
Other farmers, friends, neighbors	☐	☐	☐	☐	☐
Farm magazines/media	☐	☐	☐	☐	☐
My fertilizer consultant/agronomist . . .	☐	☐	☐	☐	☐
My fertilizer supplier/salesman	☐	☐	☐	☐	☐
County extension/university specialist .	☐	☐	☐	☐	☐
My seed supplier	☐	☐	☐	☐	☐
My farm cooperative	☐	☐	☐	☐	☐
Online N calculator	☐	☐	☐	☐	☐

18. How much do you *trust* these sources when it comes to fertilizer recommendations?

	Not at all	*Slightly*	*Moderately*	*Very much*	*Totally*
Other farmers, friends, neighbors	☐	☐	☐	☐	☐
Farm magazines/media	☐	☐	☐	☐	☐
My fertilizer consultant/agronomist . . .	☐	☐	☐	☐	☐
My fertilizer supplier/salesman	☐	☐	☐	☐	☐
County extension/university specialist .	☐	☐	☐	☐	☐
My seed supplier	☐	☐	☐	☐	☐
My farm cooperative	☐	☐	☐	☐	☐
Online N calculator	☐	☐	☐	☐	☐

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Figure 2.5 (cont'd)

About You

19. In what year were you born? ☐

20. In what year did you begin farming? ☐

21. What is your gender? Male ☐ Female ☐

22. Which category below best describes your formal years of education (check one)?

- Less than 9^{th} grade . . . . . ○
- 9^{th} to 12^{th} grade . . . . ○
- High school diploma . . . . ○
- Some college, no degree ○
- Associate degree . . . . ○
- Bachelor degree . . . . ○
- Graduate degree . . . . ○

23. How many days did you work off the farm in 2015? Indicate days in which you worked at least 4 hours per day in an off-farm job. Include work on someone else's farm for pay.

- None . . . . ○
- 1-49 days . . . . ○
- 50-99 days . . . . ○
- 100-199 days . . . . ○
- 200 days or more . . . . ○

24. Please indicate the total value of *farm products sold* as part of your operation in 2015:

- Less than $100,000 . . . . . ○
- $100,000 - $499,999 . . . . ○
- $500,000 - $999,999 . . . . ○
- Greater than $1,000,000 . ○

25. Please indicate your *household income* in 2015:

- Less than $25,000 . . . . . . ○
- $25,000 - $49,999 . . . . . . ○
- $50,000 - $99,999 . . . . . . ○
- Greater than $100,000 . . ○

Figure 2.5 (cont'd)

Please use the space below to provide any additional comments or concerns you would like to share regarding nitrogen fertilizer management in corn production systems:

Thank you for completing this survey! Make sure to return it in the pre-addressed and stamped envelope!

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REFERENCES

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CHAPTER 3. REGRET MINIMIZATION IN DECISION-MAKING: IMPLICATIONS FOR CHOICE MODELING AND POLICY DESIGN

3.1. Introduction

Discrete Choice Experiment (DCE) is a survey-based economic approach (developed by Louviere and Hensher, 1982, and Louviere and Woodworth, 1983) for eliciting individual preferences. It is increasingly used in non-market valuation to elicit environmental preferences (Louiviere et al., 2000; Kanninen, 2007; Carson and Groves, 2007). Respondents are provided with hypothetical choice scenarios, and each choice scenario contains multiple alternatives, usually more than two, including a Status Quo (SQ) or an opting-out alternative. Each alternative is described by a combination of attributes. The respondents are asked to choose one alternative from each choice scenario in order to elicit their preferences of the goods to be valued. Compared with the binary-alternative (referendum) contingent valuation method, DCE provides more information from a single choice due to its multiple-alternatives setting. Besides, the DCE allows value examination of individual attributes, in addition to the value of the whole package estimated with the contingent valuation method.

Disregarding the advantages of the DCE method, an essential issue with this stated preference method is incentive compatibility. A mechanism is incentive compatible if truth revelation is best for all participants (Myerson, 1979). DCE applications have long implicitly assumed this approach is truth revelation (e.g., Louviere and Woodworth, 1983). However, increasing studies investigate the hypothetical bias of the experimental approach, where the hypothetical scenarios may fail to generate the same responses as the real scenarios do, and discuss experimental design solutions to reduce the hypothetical bias (e.g., Carlsson and Martinsson, 2001; Lusk and Schroeder, 2004; Carson and Groves, 2007; Taylor et al., 2010;

Rakotonarivo et al., 2016). However, there has been limited research studying how the multiple-alternatives choice scenario setting may departure an experiment's preference revelation away from the true preference regardless how cautiously the experiment is designed to incentivize decision-making compatible with real-world behavior. Vossler et al. (2012) suggests that a single binary DCE combined with a consequentiality condition is incentive compatible. Anderson et al. (2007) finds that a multiple price list auction provides simple incentives for truthful revelation, and this auction mechanism collapses to a binary choice under certain conditions. Carson and Groves (2007) suggests that expending the choice set to multiple alternatives and/or repeated choice tasks would violate incentive compatibility property of DCE.

Besides incentivizing decision-makers to behave consistently in experimental and real-world settings, a more fundamental issue is how to model the decision behaviors to reveal the decision-makers' true preference in that specific setting, no matter it is an experimental setting or a real-world setting. The Random Utility Maximization (RUM) framework, where the DCE approach has been built on, may fail to depict the true decision behavior because it makes a naïve assumption that decision-making is rational and ignores the critical alternative behavioral decision realism. New models have been developed to relax these assumptions (e.g., Swait, 2001; Arentze and Timmermans, 2007; Kivetz et al., 2004; Zhang et al., 2004), but these models are mostly less interpretable than the RUM framework. An exception is Random Regret Minimization (RRM), which has been recently proposed by Chorus (2008, 2010) to incorporate the behavioral features while still inheriting the RUM interpretable estimation framework.

This paper develops a new Random Regret Minimization model, i.e., Path Dependent Random Regret Minimization (P-RRM) model, that relaxes the assumptions imposed on traditional RUM and RRM. Thereby, we can understand the decision rules through hypothesis testing. Similar to the existing RRM models, this P-RRM model allows for reference dependence and loss aversion behavior. Different from the existing RRM models, this P-RRM allows for different impacts from the status quo and hypothetical alternatives as Reference Points (RPs). Meanwhile, this P-RRM model allows for reference dependence behavior not only within but also across choice sets.

Finally, this paper uses a Willingness-To-Accept (WTA) context DCE data on Conservation Agriculture (CA) practice adoption among corn growers in the Midwest U.S. to examine the model empirically[4]. These findings also have applications in analyzing decision making outside of the environmental economics area. This study rejects the assumption that decision making is choice set independent, supporting reference-dependent behavior. Besides, I found that hypothetical alternatives, individual status quo, and previous choice sets can all affect decision making as RP. This finding implies that mimicking the real choice scenario, in terms of composition of alternatives, can be a guiding approach way to support the incentive compatibility of DCE. Lastly, due to reference-dependent behavior, policymakers can nudge their desired choice by strategically altering the choice set composition.

3.2. Methodology Foundations

RUM is the dominant estimation strategy in the context of DCE. The fundamental assumption of RUM is that the utility derived from an alternative is a function of its attributes with the objective of utility maximization. This RUM framework presumes that decision-makers evaluate each alternative independently to maximize utility. However, there has been rich evidence of reference-dependent decision making, where people make choices based on pairwise comparison

[4] Conservation Agriculture (CA) is a term defined by the Food and Agricultural Organization of the United Nations to package the concepts of “resource-saving agricultural crop production that strives to achieve acceptable profits together with high and sustained production levels while concurrently conserving the environment”.

and classify the comparison outcomes as losses or gains. The loss aversion emotion leaves individuals more sensitive to losses than to gains generated from the bilateral comparison (see Prospect Theory, Kahneman & Tverskey, 1979; Regret Theory, Bell, 1982; Fishburn, 1982; Loomes and Sugden, 1982). Therefore, the utility (or regret, as more often named in regret minimization literature) of an alternative relies on attributes of its own as well as the referred alternatives.

Whether the reference-dependent behavior disturbs the incentive compatibility property of DCE depends on if the RP is endogenous of the choice experiment. If the RP is endogenous of the choice experiment, the decision making will be contingent on the experiment design. In such a case, DCE will be incentive-compatible only if the experiment provides the exactly same choice set as the real decision scenario does. An example of exogenous RP is a consumer's choice is affected by the prices experienced outside the DCE, such as previous shopping (Caputo et al., 2018; Tonsor, 2018). An example of endogenous RP is an individual's evaluation of a specific alternative is contingent on the whole choice sets design, which is the case I will discuss in the paper.

RRM (Chorus, 2008, 2010) is developed to incorporate this endogenous choice set reference behavior. Decision making is endogenous of the experiment because the choice sets composed of the experiment are the RPs. RRM inherits two critical points from Regret Theory and Prospect Theory. One is reference-dependent, which indicates that decision making is based on a binary comparison of the chosen alternative and forgone alternatives. The other is loss aversion, which implies that decision-makers do not want their foregone alternative to perform better than their chosen alternative. Under the RRM framework, losses and gains are generated from the binary comparison, and a new utility function form is developed to measure the asymmetry of weighting in those losses and gains. Besides that, RRM models are similar to their RUM counterparts and can be estimated with the existing econometric models for RUM.

Due to the advantages in capturing behavior features with no extra estimation requirement by following the framework of RUM, RRM has gained wide attention from literature in fields such as transportation, marketing, and environmental economics (e.g., Hensher et al., 2013; Thiene et al., 2012; Chorus and Bierlaire, 2013; Chorus et al., 2014; Boeri et al., 2014; Adamowicz, Glenk, and Meyerhoff 2014). Comparison studies between RRM and RUM have been conducted, and model performance difference between the two models, in terms of statistical criteria, is small and dataset dependent (see Chorus, 2014 for a review of comparison between the two models). However, in terms of choice probability or market share prediction, the difference can be large and lead to a substantial difference in policy implications (Chorus et al., 2014). Therefore, choosing between the models has a notably practical impact.

Besides model comparison and selection, another research direction is to incorporate different decision paradigms within a single model. Hess et al. (2012) and Boeri et al. (2014) use a Latent Class Model (LCM) to allow individuals to apply heterogeneous information processing strategies. Chorus et al. (2013) uses a hybrid model to allow attributes to be processed by different decision rules. Van Cranenburgh et al. (2015) and Chorus (2014) generalize the classical RRM and RUM models by allowing a parameter to decide between RRM and RUM. Other RRM related works include model adaptation to choice scenarios including SQ alternative, i.e., opt-out, (Thiene et al., 2012; Hess et al., 2014), welfare analysis (e.g., Dekker & Chorus, 2018), and choice set efficiency design (Van Cranenburgh et al., 2018).

Despite the fruitful development of RRM in the past decade, some fundamental issues are still unsolved. To begin, even though RRM was developed to fill the gap between RUM assumptions and decision behavior realism, there is not a framework designed to investigate the realism of decision behavior. This study extends the RRM framework to examine the realism of decision behavior by constructing a framework that nests the RUM and RRM assumptions in a single model. Specifically, I relaxed the assumptions that decision making is both within and across choice sets dependent. I discussed how the relaxation of the assumptions affects the incentive property of DCE and choice modeling analysis.

To continue, the existing RRM literature does not discuss how to handle SQ alternative in choice modeling. A direct approach is to replace the SQ alternative with individual perceived values or homogeneous no-action if perceived values are not available. This approach does not treat SQ alternatives differently than other alternatives. However, RRM literature with an SQ setting based on this approach results in weaker performance in terms of statistical power (Thiene et al., 2012; Hess et al., 2014; Chorus, 2012). This phenomenon limits the application of the RRM framework in more expansive research fields. This paper, for the first time, develops a framework to handle SQ alternative by distinguishing SQ alternative from hypothetical alternatives in regret generation. This new framework will not only improve model performance but also help to understand the decision mechanism in the presence of SQ choice.

Finally, RRM does not provide direct welfare analysis implications as RUM does (e.g., WTP estimation), due to RRM's utility function specification. This is the first paper to quantify the impacts of accounting for behavioral factors on welfare analysis and policy implementation through a simulation approach. I found that relaxing the decision-making assumptions leads to a remarkable difference in estimations of the alternative's chosen probability.

Note that this paper's empirical analysis is based on a Willingness-To-Accept (WTA) context as opposed to a Willingness-To-Pay (WTP) context on which almost all the other RRM literature is based. To my knowledge, the only relevant work examining reference dependence behavior in the context of WTA is Tonsor (2018), which examines producer decisions within a DCE. This study completes the literature in understanding the roles behavioral strategies (e.g., reference-dependent, regret aversion) play in a WTA scenario.

The remainder of the paper is organized as follows. Section 3 constructs models to account for different decision rules and discusses how to use hypothesis tests to examine the underlying assumptions. The survey and data used for empirically examining the models are introduced in section 4. Empirical estimation results and hypothesis tests are reported in section 5. Section 6 discusses the implications of incorporating behavioral factors for policy design and discrete choice experiments. The paper closes with a summary and discussion of the findings and future directions in section 7.

3.3. Models

This section discusses how to model discrete choices under different decision rule assumptions. There are three components of DCE: choice scenario and sets of alternatives, a function that describes the observed utility, and an error term that describes the unobserved utility and the associated distribution. In this paper, I am interested in adding regret minimization behavior to the choice modeling by modifying the function that describes the observed utility or regret.

To start, I introduced the existing models, which are Random Utility Maximization (RUM), Random Regret Minimization (RRM), and Generalized Random Regret Minimization (G-RRM). Next, I discussed how to model the regret minimization behavior in a DCE with the SQ setting. I am interested in understanding whether the SQ alternative has an equal contribution as the hypothetical alternative does in serving as an RP. Third, I developed a new RRM model that relaxes all the assumptions imposed by the existing DCE modeling and discussed how to investigate the underlying behavioral rules with this new model.

3.3.1. Traditional DCE Modeling

Presume a regular choice scenario: a decision-maker, i, faces a choice scenario, *s*, with *J* alternatives, each being described in terms of M attributes x_{isjm}. RUM (McFadden, 1974) postulates that utility from alternative *j* is independent of alternatives *k*, i.e., independent of choice set composition. A decision-maker will choose the alternative with the highest utility from the given choice set. The random utility of each alternative is described by a linear combination of the observable attributes plus a random error term ε_{isj}. The random error term represents the inability of researchers to observe all the factors determining a decision-maker's utility, i.e., the unobserved heterogeneity among decision-makers. An individual *i*'s utility from choosing alternative *j* with taste parameters β_m can be described as follows:

(1) $U_{isj} = V_{isj} + \varepsilon_{isj}$

$$= \sum_m \beta_m^h \cdot x_{isjm} + \beta_0 \cdot sq_{isj} + \varepsilon_{isj} \quad when\ j = 1\ or\ 2$$

Or

$$= \sum_m \beta_m^{sq} \cdot x_{isjm} + \beta_0 \cdot sq_{isj} + \varepsilon_{isj} \quad when\ j = sq$$

An SQ constant term $\beta_0 \cdot sq_{isj}$ is added to capture the status quo effect. sq_{isj} is a dummy variable: $sq_{isj} = 1$ when *j* is the SQ option and $sq_{isj} = 0$ otherwise. Here I assume individuals' preferences over attributes for hypothetical alternatives and SQ alternative are different, and therefore I separately specify the corresponding preference parameters as $\boldsymbol{\beta^h}$ and $\boldsymbol{\beta^{sq}}$. I name this framework as RUM' to mark this difference. When $\boldsymbol{\beta^h} = \boldsymbol{\beta^{sq}}$, RUM' will reduced to conventional RUM. Under the assumption that error term ε_{isj} follows independent and identically distributed, *i.i.d*. Extreme Value Type I with variance equaling $\pi^2/6$, multinomial logit (MNL) model can be used for estimation (McFadden, 1974). The choice probability for alternative *j* is: $Pr_{isj} = exp(V_{isj})/\sum_{k=1}^{J} exp(V_{isk})$.

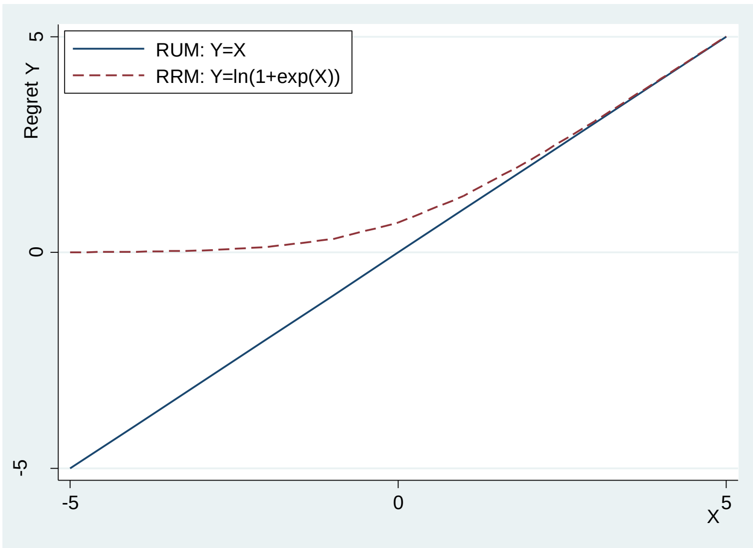
For the same choice scenario, RRM framework (Chorus, 2008, 2010) postulates that a decision-maker *i* will choose the alternative with the lowest regret from the given choice set, and the regret is composed of a systematic regret R_{isj} described by the observed attribute x_{isjm} and an *i.i.d* random error ε_{isj}. Regret is generated when the considered alternative is outperformed by the competing alternatives within the choice set with respect to any attribute. Note that this setting presumes that an individual's belief about an outcome can create an instance of loss aversion, regardless of whether a tangible change has occurred or not (Kőszegi and Rabin, 2006). Following the work of Quiggin (1994), Chorus (2010) defines the regret for alternative *j* attribute *m* by bilaterally comparing with alternative *k* as follows: ${R_{ij}}^{mk} = ln\,(1 + exp\left[\beta_m \cdot \left(x_{ikm} - x_{ijm}\right)\right])$[5]. Figure 3.1 illustrates the regret as a function of loss $X = \beta_m \cdot \left(x_{ikm} - x_{ijm}\right)$ as compared with RUM. This function of regret posits that individuals respond more to loss (X > 0) than to gain (X < 0) due to the convexity of the log function. This setting also presumes that individuals' sensitivity to loss increases as loss does. Lastly, the sum of attribute-level regrets, i.e., *m*, with all RPs, i.e., *k*, will be an individual's observable regret from choosing alternative *j*: $R_{ij} = \sum_m \sum_{k\neq j}^{J} ln\,(1 + exp\left[\beta_m \cdot \left(x_{ikm} - x_{ijm}\right)\right])$. An individual *i*'s regret from choosing

[5] An alternative regret minimization model is defined in Chorus (2008) as follows: max{$0, \beta_m \cdot \left(x_{jm} - x_{im}\right)$}, where β_m is the preference parameter of attribute m. This formulation implies that gain generates zero weight in formulating regret: when a considered alternative outperforms its competing alternative, i.e., $\beta_m \cdot \left(x_{jm} - x_{im}\right) < 0$, the regret is zero.

alternative *j* from choice scenario *s* will be the observable regret plus a random error defined as follows:

$$(2)\ U_{isj} = R_{isj} + \varepsilon_{isj} = \sum_{m}\sum_{k\neq j}^{J} \ln\left(1 + \exp\left[\beta_m \cdot \left(x_{iskm} - x_{isjm}\right)\right]\right) + \beta_0 \cdot sq_{isj} + \varepsilon_{isj}$$

Figure 3.1. RUM and RRM Comparison



Note that the minimization of regret is mathematically equivalent to maximizing the negative of the regret defined in equation (2). As a result, the SQ constant term parameter β_0 has the opposite sign of that from the conventional RUM model. Assuming that $-\varepsilon_{isj}$ follows i.i.d Extreme Value Type I, multinomial logit can be used for model estimation with the probability of choosing alternative *j* over other alternatives defined as follows: $Pr_{isj} = exp(-R_{isj})/\sum_{k=1}^{J} exp(-R_{isk})$. Note that in the case of a single binary choice where a choice set contains two alternatives, RRM reduces to linear RUM (see Chorus, 2010, for a formal proof).

RRM framework posits a non-substitution behavior. That is, the ratios of preference parameters can no longer measure the marginal rates of substitution. As such, a decrease in one attribute may not be compensated by an equal increase in another attribute. In addition, an alternative with in-between attribute values generates lower regret than those with more extreme attribute values, in which some attributes have very high values while others have very low values.

With two frameworks, i.e., RUM and RRM, available for choice modeling, the question is how to choose between the two frameworks. Therefore, Generalized Random Regret Minimization (G-RRM) model (Chorus, 2014) is constructed to nest RRM and RUM as special cases and allow the model itself to test the underlying decision rule(s).

The G-RRM model replaces "*1*" in equation (2) with a regret weight parameter "γ"[6]. The G-RRM is defined as follows:

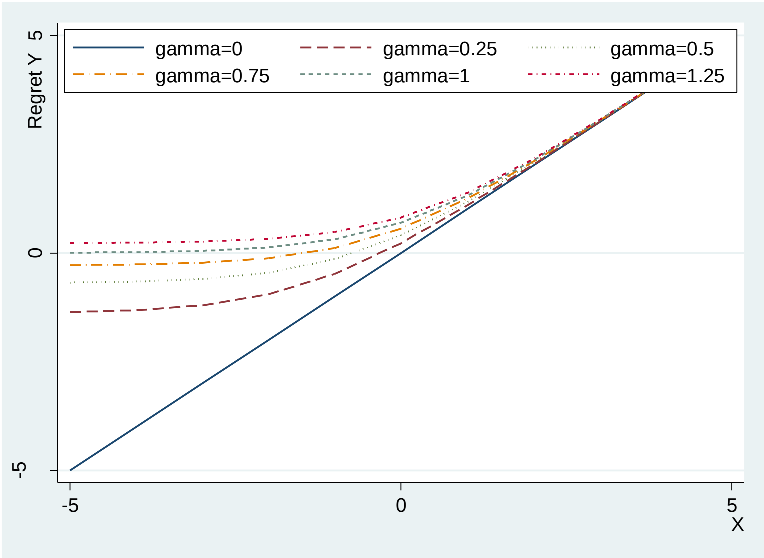
$$(3)\ U_{isj} = R_{isj} + \varepsilon_{isj} = \sum_{m} \sum_{k \neq j}^{J} ln\left(\gamma + exp\left[\beta_m \cdot \left(x_{iskm} - x_{isjm}\right)\right]\right) + \beta_0 \cdot sq_{isj} + \varepsilon_{isj}$$

γ $(0 \leq \gamma \leq 1)$ is a regret weight parameter that depicts the curvature of the regret function. Figure 3.2 describes how the regret function responds to the change of regret weight parameter γ. When $\gamma = 1$, equation (3) will be the conventional RRM model defined in equation (2); when $\gamma = 0$, the G-RRM model generates the same prediction as a RUM model does (see Appendix A and Chorus, 2014 for a formal proof). As γ approaches zero, the asymmetry on loss and gain vanishes; as γ increases, so does the asymmetry. Note that γ is arbitrarily set to be between 0 and 1 because the curvature of the regret line is getting less sensitive to the value of γ as γ increases. Removing the upper bound of γ is likely to confound the estimation of β with γ since β is

[6] By replacing γ with γ_m, I can assume different curvatures for the attributes as proposed in Chorus (2014). In this paper, I assume a single curvature for the regret function.

trading off with γ with respective to estimation (Chorus, 2014). Lastly, let $\gamma = \alpha_0 + \alpha_1 X$, where X is an individual characteristic, I can measure the relationship between regret weight and individual factors (Chorus, 2014).

Figure 3.2. Regret Function Conditional on Regret Weight (gamma)



3.3.2. DCE Modeling in the Presence of SQ Alternative

An essential setting of DCE is the existence of a baseline alternative SQ, i.e., opt-out alternative. This setting avoids forced choice of the proposed alternatives and thus guarantees proper welfare measures (Hanley et al., 2001). There has been substantial literature discussing the importance of including an SQ alternative specific constant term in DCE modeling to account for the endowment effect—the fact that people demand more to give up an object they process than they would be willing to acquire it (Thaler, 1980; Samuelson and Zeckhauser, 1988; Adamowicz et al., 1998). However, there is no literature investigating the role of an SQ alternative in DCE when there exists reference dependence behavior. This paper will discuss this issue.

As has been discussed in the RRM section, giving up a hypothetical alternative that outperforms the considered alternative for a particular attribute can generate a loss feeling. Similarly, foregoing the SQ that performs better than the considered alternative for a particular attribute can generate loss as well. Prior studies have recognized that decision-makers may have their SQ as a critical RP (Kahneman & Tverskey, 1979; Tversky & Kahneman, 1981, 1986, 1991). The question is how to measure the impact of SQ as RP in DCE.

To examine the role of SQ option as RP in DCE, this paper sets SQ as an RP and allows the SQ to generate an impact that is different from the hypothetical alternatives. The rationale of allowing the difference is SQ is endowed by the decision-makers and thus serves as an internal reference, whilst hypothetical alternatives are imposed by choice set design and therefore serves as an external reference. Furthermore, different from the studies that examine reference effects by asking the respondents of their reference prices before decisions are made (Mazumdar et al., 2005; Caputo et al., 2018), this study asks the respondents' SQ after decisions are made. This is consistent with real-world settings since, in most cases, there is no chance of explicitly reminding decision-makers of their SQ before they make a choice. Lastly, different from the existing works that focus on the cost variable as the single reference element (e.g., Caputo, et al., 2018), this paper investigates the contributions of all attributes that describe the SQ as the reference of decision making.

After differentiating SQ and hypothetical alternatives' roles as RP, individual *i*'s regret from choosing alternative *j* is specified as follows. I named the model as G'-RRM to indicate its modification from the previous G-RRM model.

(4) $U_{isj} = R_{isj} + \varepsilon_{isj} = \sum_{k \neq sq \text{ or } j} \sum_m \ln\left(\gamma + exp\left[\beta_m^h \cdot \left(x_{iskm} - x_{isjm}\right)\right]\right) + \sum_m ln\left(\gamma + exp\left[\beta_m^{sq} \cdot \left(x_{issqm} - x_{isjm}\right)\right]\right) + \beta_0 \cdot sq_{isj} + \varepsilon_{isj}$

Assuming that $-\varepsilon_{isj}$ follows i.i.d Extreme Value Type I, an MNL model can be used for model estimation. The hypothesis of G'-RRM model is, preference parameters $\boldsymbol{\beta^h}$ and $\boldsymbol{\beta^{sq}}$ based on comparison with different RPs can be different. That is, for a considered hypothetical alternative, the exact same difference in one attribute generating from comparing with hypothetical alternative and SQ alternative does not generate the same amount of regret. Again, when $\gamma = 0$, G'-RRM reduces to RUM. A formal proof is provided in Appendix B.

Similar to G-RRM framework, $let\ \gamma = \alpha_0 + \alpha_1 X$, where X is individual information, I can measure the relationship between regret weight and personal factors.

3.3.3. DCE Modeling in the Presence of Path Dependence Behavior

As decision making is reference-dependent, a natural question is whether decision making is path-dependent. That is, the information delivered from the previous choice sets affects the current choice set's decision when survey participants are making repeated choices in a single survey.

When a decision-maker faces a choice scenario *s*, where $s \geq 2$, the previous choice scenarios *1, ..., s-1* including the chosen alternative in the prior choice scenarios, i.e., $X_{it\check{j}}$ $(t = 1, \ldots, s-1)$, constructs the path. To test the path dependence behavior, I chose the chosen alternative in the previous choice scenario s-1, $X_{is-1\check{j}}$, as the RP from the path. If there exists any path-dependent behavior, the chosen alternative would be the most critical RP. Therefore, a Path Dependent Random Regret Minimization (P-RRM) model is defined as follows:

$$(5)\ U_{isj} = R_{isj} + \varepsilon_{isj} = \sum_{k \neq sq\ or\ j} \sum_{m} \ln\left(\gamma + exp\left[\beta_m^h \cdot \left(x_{iskm} - x_{isjm}\right)\right]\right)$$

$$+ \sum_{m} ln\left(\gamma + exp\left[\beta_m^{sq} \cdot \left(x_{issqm} - x_{isjm}\right)\right]\right)$$

$$+\sum_{m} ln\left(\gamma + exp\left[\beta_m^l \cdot \left(x_{is-1\check{j}m'} - x_{isjm}\right)\right]\right) + \beta_0 \cdot sq_{isj} + \varepsilon_{isj}$$

Assuming that $-\varepsilon_{isj}$ follows i.i.d Extreme Value Type I, a multinomial logit can be used for model estimation. Similar to the previous RRM models, the P-RRM model presumes that losses and gains as a result of comparison with last round's chosen alternative will generate asymmetry in loss and gain. Again, when $\gamma = 0$, P-RRM will reduce to RUM. A formal proof is provided in Appendix C.

3.3.4. Hypothesis Testing

With models (1) – (5), we are back to the question: what is the underlying decision rule of decision making in DCE? Specifically, among models (1) – (5), which model best describes the decision making?

The relationship map of the models is shown in Figure 3.3. RUM is nested in RUM' defined in equation (1) when $\boldsymbol{\beta^h} = \boldsymbol{\beta^{sq}}$. RUM, RRM, G-RRM, and G'-RRM defined in equations (1) – (4) are nested in P-RRM defined in equation (5) as special cases. If $\boldsymbol{\beta^l} = \boldsymbol{0}$ in equation (5), P-RRM will reduce to G'-RRM. If $\boldsymbol{\beta^h} = \boldsymbol{\beta^{sq}}$ in equation (4), G'-RRM will reduce to G-RRM. If $\gamma = 0$ in equation (3), (4) or (5), the corresponding models will reduce to RUM. Therefore, through hypothesis testing on the parameters of P-RRM, we can understand whether decision making is regret minimization or utility maximization, and what is(are) the RP(s). The hypotheses are listed below:

Hypothesis 1: Survey respondents have same preferences over attributes for SQ alternative and hypothetical alternatives in RUM framework.

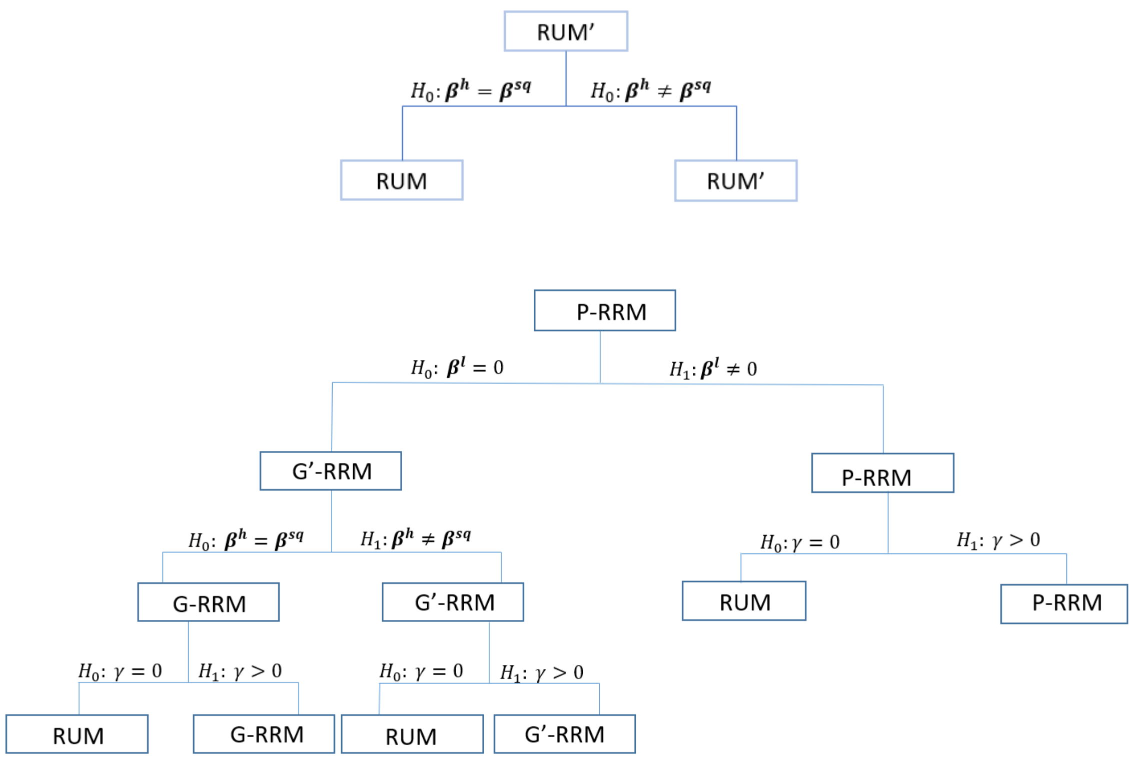
Hypothesis 2: Survey respondents have same preferences over attributes for SQ alternative and hypothetical alternatives in G-RRM framework.

Hypothesis 3: decision making is utility maximization. To test this hypothesis, I need to test whether P-RRM, G'-RRM and G-RMM will reduce to RUM through testing whether $\gamma = 0$ in equation (3), (4) and (5).

Hypothesis 4: SQ alternative and hypothetical alternative have the same impacts as RP. To test this hypothesis, I need to test if $\boldsymbol{\beta^h} = \boldsymbol{\beta^{sq}}$ in equation (4).

Hypothesis 5: decision making is path independent. To test this hypothesis, I need to test if $\boldsymbol{\beta^l} = \mathbf{0}$.

Figure 3.3. Nesting Stucture of Models



3.4. Survey and Data

As an empirical illustration of the approach, I used data from a choice experiment that elicits farmers' preferences for a CA program. The objective of the CA program is to incentivize farmers to adopt CA practices to reduce nitrogen fertilizer leakage into the environment. To understand farmers' willingness to adopt these CA practices, a mail survey with $2 cash incentives was conducted amongst corn growers in the Midwestern U.S., specifically in Michigan, Iowa, and Indiana in 2016. Mailing addresses for the survey are randomly drawn from the Farm Service Agency (FSA).[7] With a response rate of 27%, I have 1,294 completed surveys.

The survey contains four repeated choice experiment tasks, with each described by two hypothetical alternatives and an SQ alternative. Each alternative is described by a payment vehicle and three CA practices plus an expected nitrogen saving. The payment level is suggested by a focus group study among farmers and adjusted after a pilot study of this survey, which was conducted in 2015. Attributes and attribute levels are defined in Table 2.2. The first three attributes are the CA practices with a "Yes" indicating requirement imposed. Expected nitrogen saving is decided by the combination of the three CA practices calculated by agronomy and environmental experts. Besides the choice tasks, the survey contains questions about the respondents' SQ so that the SQ alternative can be linked with individual stated SQ values. The survey asks respondents' SQ CA practices after the choice tasks to avoid the questions affecting decision making. The individual status quo CA adoption levels as well as associated expected Nitrogen saving levels will be incorporated into the dataset for the later empirical estimation. A Bayesian efficiency design that minimizes D-error based on priors from the pilot survey and contains 24 choice sets is generated using Ngene software (Choice Metrics, 2012). I used a block

[7] FSA is the payment services agency within USDA. FSA has records for every farmer who received any form of payment (direct payments, crop insurance subsidies, disaster payments, conservation payments, etc) through USDA. This FAS address book covers over 90% of farmers that the CA program is targeted at.

design with six blocks containing four choice sets for each to avoid fatigue effects. A respondent was randomly assigned to one of the blocks. The order of presentation and allocation to respondents of the various choice sets is randomized. A sample of the survey is attached in Figure 2.5.

Beyond discrete choice questions, this dataset also contains information about farmers' social demographic status, attitude toward the environment policy, different resources for information, as well as farms' characteristics. For this paper, this information can be used to test their relationship with the regret weight parameter that describes decision-makers' asymmetry weighting on loss and gain. Details of this survey design and administration can be found in Chapter 2 of this dissertation.

The sample characteristics by the state are summarized in Table 3.2. After excluding the incomplete response, with which more than 10% of the questions incomplete, the response rate is highest in Michigan, i.e., 27%, and lowest in Indiana, i.e., 21%. Opting out rate, i.e., the percentage of farmers choosing SQ alternative among the three alternatives, reaches its highest level in Iowa, i.e., 43. Through examining the follow-up questions of the survey[8], I found that the Conservation tillage rate is significantly lower in Michigan than that in the other two states, while the reduced tillage rate is highest in Michigan. Conservation program enrollment is relatively higher in Iowa. The distributions of age, gender, farming experience, and days off farms are generally consistent across the three states. Iowa has a higher percentage of farmers who completed associate or higher-level degrees. Both farm product values and household incomes are higher in Iowa. Iowa and Indiana have more large farm owners in the sample. The status quo CA adoptions are diverging across states: Iowa has the lowest rates of covering crops

[8] For further details of the questions, see Figure 2.5 for a survey sample.

in the winter whilst having the highest rate of fertilizer application in the fall; Indian has the highest rate of fertilizer side-dressing.

Table 3.1. Sample Characteristics by State

Variable names and codes	IA	IN	MI	All states
Survey response rate (%)				
	24	21	27	24
Alternative chosen (%)				
Alternative 1	29	33	30	31
Alternative 2	28	30	31	30
Status quo	43	37	39	40
Tillage type (%)				
Conventional tillage: less than 15% residue remaining on surface	5	2	12	7
Reduced tillage: 15-30% residue remaining on surface	50	53	65	56
Conservation tillage: more than 30% residue remaining on surface	45	45	23	37
Conservation program enrollment (%)				
Ever participated in the past	43	37	38	39
Age (%)				
Between 18-34	4	5	5	5
Between 35-54	28	25	28	27
Between 55-64	34	32	34	33
Above 64	34	38	33	35
Farming experience (%)				
Average or above experience	35	37	38	37
Gender (%)				
Male	97	95	98	97
Education (%)				
Some college, no degree, or lower	53	58	64	58
Associate degree, or higher	47	42	36	42
Days off farm per year (%)				
Less than 100 days	67	68	68	68
Greater than 100 days	33	32	32	32
Total values of products sold in 2015 (%)				
Less than $100,000	30	33	44	36
$100,000 - $499,999	44	39	38	41
$500,000 - $999,999	15	14	12	13
Greater than $1,000,000	11	14	6	10
Annual Household Income (%)				
Low income (up to $25,000)	11	8	14	12
Medium income ($25,000-$100,000)	62	66	66	64
High income (above $100,000)	27	26	20	24
Acres of farm operated in 2015 (%)				
Less than 100 acres	17	17	17	17
Between 100 - 500 acres	43	38	49	44

Table 3.1 (cont'd)

Greater than 500 acres	40	45	34	39
Certainty about the decision (%)				
Uncertain	5	8	5	6
Somewhat certain	28	29	29	29
Certain	67	63	66	65
Winter crops covered (%)				
Adopted	18	23	24	22
Fall application (%)				
Adopted	31	6	9	15
Side-dress application applied (%)				
Adopted	32	53	47	44

3.5. Results

Models based on equation (1) – (5) are estimated with MNL using Python Biogeme. With a nesting structure, I tested the assumptions imposed on different models. Estimation results of RUM, RUM', G-RRM, and G'-RRM based on the whole sample that includes the first choice set are reported in columns (1) – (4) in Table 3.2. Estimation results of G'-RRM and P-RRM based on the subsample, which excludes the first choice set, are reported in columns (5) and (6) in Table 3.2[9]. Here I excluded the first choice set because there is no previous choice set to refer to for path-dependence model. Hypothesis test results are summarized in Table 3.3. Note that I have incorporated SQ alternatives with individual stated SQ values.

[9] I reran the G'-RRM with the subsample data for comparison purpose.

Table 3.2. Estimation Results

Sample	(1) Set = 1, 2, 3, 4	(2) Set = 1, 2, 3, 4	(3) Set = 1, 2, 3, 4	(4) Set = 1, 2, 3, 4	(5) Set = 2, 3, 4	(6) Set = 2, 3, 4
	RUM	RUM'	G-RRM	G'-RRM	G'-RRM	P-RRM
β^h_{winter}	-0.643***[a]	-0.718***	-0.234*	0.845**	0.646***	0.241*
	(0.120)[b]	(0.145)	(0.135)	(0.407)	(0.148)	(0.145)
β^h_{fall}	-0.0118	0.00343	-0.00669	0.0253	-0.0689	-0.91***
	(0.0733)	(0.0821)	(0.0368)	(0.0463)	(0.0479)	(0.139)
β^h_{side}	-0.108	-0.0133	-0.0455	-0.864	0.734***	0.569
	(0.173)	(0.196)	(0.102)	(0.549)	(0.129)	(0.827)
$\beta^h_{nitrogen}$	0.324	1.06	0.145	-0.158	0.505*	1.69**
	(0.707)	(0.813)	(0.411)	(0.338)	(0.278)	(0.881)
β^h_{pay}	0.00840***	0.00827***	0.00300***	0.00178	0.00174	0.00162***
	(0.000455)	(0.000472)	(0.00111)	(0.00816)	(0.00132)	(0.000251)
β^{sq}_{winter}		-0.752***		-2.18**	-2.14***	-2.20***
		(0.434)		(1.02)	(0.236)	(0.315)
β^{sq}_{fall}		-0.231***		-0.00678	-0.000682	0.00422
		(0.173)		(0.0159)	(0.0195)	(0.185)
β^{sq}_{side}		-1.26		2.02**	-2.07***	-2.16***
		(0.434)		(0.945)	(0.210)	(0.241)
$\beta^{sq}_{nitrogen}$		2.44		-0.304	0.703*	1.25**
		(1.72)		(0.639)	(0.385)	(0.544)
β^{sq}_{pay}		0[c]		0.0247	0.0319***	0.0195***
		-		(0.0512)	(0.0128)	(0.00247)
β^l_{winter}						-3.44***
						(0.197)
β^l_{fall}						-2.73***
						(0.203)
β^l_{side}						-2.24***
						(0.210)
$\beta^l_{nitrogen}$						3.29**
						(1.78)
β^l_{pay}						0.00181***
						(0.000226)
β_0	0.751***	1.2***	-0.753***	-0.83	-0.946***	-1.28***
	(0.0499)	(0.0759）	(0.0497)	(0.616)	(0.155)	(0.291)
γ			0.0699	0.369	0.350**	0.114***

Table 3.2 (cont'd)

			(0.379)	(0.932)	(0.117)	(0.0224)
$\hat{\mathcal{L}}$	-4495	-4434	-4495	-4414	-3278	-2965
AIC/N	2.09	2.07	2.09	2.06	2.04	1.85
BIC/N	2.10	2.09	2.10	2.08	2.06	1.88
N	4300	4300	4300	4300	3225	3225

a. *** $p \leq 1\%$, ** $p \leq 5\%$, * $p \leq 10\%$.
b. Robust standard error is reported in the bracket.
c. β_{pay}^{sq} is not identifiable since the status quo payment is constant at zero.

Table 3.3. Hypothesis Test Results

Equ	Null hypothesis	Alternative hypothesis	Unrestricted $\hat{L}$	Restricted $\hat{L}$	LR test	t-value	d.f.	p-value
(1)	$\beta^h = \beta^{sq} \rightarrow RUM$	$\beta^h \neq \beta^{sq} \rightarrow RUM'$	-4495	-4434	122		5	0
(3)	$\gamma = 0 \rightarrow RUM$	$\gamma > 0 \rightarrow G - RRM$				0.18	4292	0.85
(4)	$\gamma = 0 \rightarrow RUM$	$\gamma > 0 \rightarrow G' - RRM$				0.40	4287	0.69
(4)	$\gamma = 0 \rightarrow RUM$	$\gamma > 0 \rightarrow G' - RRM$				2.99	3212	0
(5)	$\gamma = 0 \rightarrow RUM$	$\gamma > 0 \rightarrow P - RRM$				5.10	3207	0
(4)	$\beta^h = \beta^{sq} \rightarrow G - RRM$	$\beta^h \neq \beta^{sq} \rightarrow G' - RRM$	-4414	-4495	162		5	0
(5)	$\beta^l = 0 \rightarrow G' - RRM$	$\beta^l \neq 0 \rightarrow P - RRM$	-2965	-3278	626		5	0

First of all, the signs of the preference parameters for RUM and RUM' as reported in columns (1) and (2) of Table 3.2 are generally as expected. Covering crops in winter, i.e., *Winter*, avoiding fertilizer application in fall, i.e., *Fall*, and side-dressing fertilizer, i.e., *Side*, all decrease utility, while saving nitrogen, i.e., *Nitrogen*, and payment, i.e., *Pay*, both increase utility. The SQ constant term is positive, indicating that maintaining SQ is preferred. These findings are also consistent with each practice's current adoption proportion. Based on the follow-up questions in the survey, 22%, 85%, and 44% of the respondents have ever met the requirements of covering crops in winter, avoiding fertilizer application in fall, and side-dressing fertilizer in the past. The null hypothesis that individuals have same preferences over attributes for hypothetical alternatives and SQ alternative is rejected in Table 3.3. People do not take hypothetical and SQ alternatives with the same weights either because their preferences over the two types of alternatives' attributes are not the same, or because the SQ alternative's attributes values are not salient in the choice scenarios and cannot be processed similarly.

To continue, I investigated whether decision making is utility maximization or alternatively regret minimization through hypothesis testing. Specifically, I investigated whether G-RRM, G'-RRM, and P-RRM reduce to RUM through testing if $\gamma = 0$ or $\gamma > 0$ for the corresponding models. The regret weight parameter γs are respectively 0.0699 and 0.369 for G-RRM and G'-RRM as reported in columns (3) and (4), and 0.224 and 0.112 for G'-RRM and P-RRM as reported in columns (5) and (6). The null hypothesis that $\gamma = 0$ is rejected in G'-RRM and P-RRM which run on the sub-sample at 1% significance level, however, is not rejected in G-RRM and G'-RRM which run on the whole sample. These findings imply that regret minimization is a reasonable assumption for decision making modeling when people start to make repeated choices.

As decision making is reference-dependent and regret minimizing in repeated choice scenario, I examined what are the RPs and the relative contributions of these RPs. I started with testing whether SQ and hypothetical alternatives have the same impacts as RPs. Specifically, I tested the hypothesis that $\boldsymbol{\beta^h} = \boldsymbol{\beta^{sq}}$. G-RRM is the restricted model of G'-RRM with $\boldsymbol{\beta^h} = \boldsymbol{\beta^{sq}}$. The likelihood ratio test, as reported in row six of Table 3.3 rejects this hypothesis at the 1% significance level, implying that hypothetical alternatives do not share the same impacts with SQ alternatives as RP. Therefore, it is reasonable to estimate $\boldsymbol{\beta^h}$ and $\boldsymbol{\beta^{sq}}$ separately in DCE that includes an SQ alternative. Besides, the Akaike information criterion (AIC) and Bayesian information criterion (BIC) suggest that G'-RRM is slightly better than RUM' in terms of minimizing information loss.

Next, let's take a closer look at the implications of the G'-RRM model. I'll focus on G'-RRM running on the subsample because reference dependence behavior is only significant in repeated choice scenario of our sample and the results are easy to be compared with that from the P-RRM model. As reported in column (5) of Table 3.2., $\boldsymbol{\beta^{sq}}$ have all signs, except that of *Fall*, as expected and generally statistically significant. $\boldsymbol{\beta^h}$ only have signs significant and as expected for attributes *Nitrogen*. This raises the concern of identifying parameters for hypothetical alternatives in G'-RRM. I will further check this issue after path dependence behavior is incorporated. Generally, the G'-RRM model implies that both SQ and hypothetical alternatives can play as RP, but hypothetical alternatives might have weaker impacts.

Lastly, the P-RRM estimation is reported in column (6) of Table 3.2. Note that G'-RRM is the restricted model of P-RRM with $\boldsymbol{\beta^l} = \boldsymbol{0}$. The likelihood ratio test of the nesting structure of G'-RRM and P-RRM is reported in the last row of Table 3.3. The likelihood ratio test rejects G'-RRM in favor of P-RRM, implying the existence of path-dependent behavior. Meantime, P-

RRM significantly outperforms G'-RRM in terms of likelihood value $\hat{L}$, AIC and BIC. These findings justify that incorporating the last round chosen alternative is vital for correctly modeling the choice behavior.

Taking a closer look at the parameters of the P-RRM model, I found that the signs and scales of $\boldsymbol{\beta^l}$ that represent the last round reference-dependent behavior are consistent with those from the previous models for all attributes. Besides, the estimations for $\boldsymbol{\beta^{sq}}$ are significant with expected signs for all attributes except for *Fall*, and the estimations for $\boldsymbol{\beta^h}$ are significant with expected signs for all attributes except for *Winter* and *Side*. The scales of parameter for the same attribute among three RPs are highest for the last round chosen alternative and lowest for the hypothetical alternative, except that *Pay* has higher weight when SQ alternative is referred. It is worth mentioning this work's sample might not be large enough to power all the parameters to be significantly identified if the associated preferences are significant. One reason is due to the nature of the research, correlations between Nitrogen saving and adopting CA practices are relatively high, i.e., 0.4 - 0.8. This high correlation among attributes significantly raises the required minimal sample size for statistical identification. Some parameters in RUM and RUM' are also not significantly and correctly identified. Meantime, P-RRM further raises the required sample size as the number of parameters triples as compared with the RUM model. Last, if the last round's chosen alternative is SQ, the estimation is going to confound the last round's chosen alternative with this round's SQ alternative since the respondent's status quo level is unchanged over choice sets. This again increases the required sample size for parameter identification.

Taking all the above findings and challenges together, the P-RRM model reveals a solid decision pattern. That is, when there is no previous choice experience, decision-makers' SQ is the most critical RP for decision making. When there is a path, decision making is both current choice set and path-dependent: decision-makers' last round chosen alternative, SQ alternative, and hypothetical alternatives can all play as RP to influence the decision making, though the same attribute might have different weights as different types of RP. For the same attribute, the last round chosen alternative has the highest weight as a RP and the hypothetical alternative has the lowest weight. The limitation of this work is we need a larger sample to comprehensively understand the roles of SQ and hypothetical alternatives in a path-dependence choice scenario.

It is worth mentioning that I have related the individual-specific status quo with SQ alternative. This approach, as compared with treating the SQ alternative as homogeneous among survey respondents, is recommended in DCE literature because it addresses the problem of heterogeneity of SQ and can increase model explanatory power (Kataria et al., 2012; Glenk, 2011; Artell et al., 2013; Barton and Bergland, 2010; Banzhaf et al., 2001). On the one hand, this explains why SQ plays as a more important RP as compared with the hypothetical alternative. On the other hand, there raises the concern of endogeneity since the individual specific SQ might be correlated with the error term of the utility function. The potential endogeneity of individual specific SQ is a general problem if it is a problem of the DCE literature in the presence of the SQ setting. This is out of the scope of this paper's discussion and is left for future discussion.

Finally, I examined the relationship between individual characteristics and regret weight by defining $\gamma \quad = \alpha_0 + \alpha_1 X$ for P-RRM using the subsample of choice sets (2) – (4), where X is individual information with dummy coding. Table 3.4 reports the factors that influence the regret weight by running γ separately on each factor, i.e., X. Besides experience with conservation tillage or conservation programs, and gender, all factors are associated with regret weight. People who have higher education, longer days off-farm, higher farm product value, higher household income, or larger farm are less regret minimization oriented. Farmers who are older, more certain about their decisions, or have more farming experience, are more regret minimization oriented.

Table 3.4. Factors Influencing Regret Profundity

	Par	Est
Tillage type	α_0	1.07***[a] (0.037)[b]
Conservation tillage	α_1	-0.126 (0.184)
Conservation program enrollment	α_0	0.78*** (0.183)
Ever participated in the past	α_1	-0.193 (0.208)
Age	α_0	0.286*** (0.0819)
55 or older	α_1	0.0312*** (0.00709)
Farming experience	α_0	0.321*** (0.238)
Average or above	α_1	0.0672*** (0.00279)
Gender	α_0	1.02*** (0.312)
Male	α_1	-0.202 (0.923)
Education	α_0	1.25*** (0.422)
Associated degree or higher	α_1	-0.326*** (0.0721)
Days off farm per year (%)	α_0	0.82*** (0.281)
Greater than 100 days	α_1	-0.132*** (0.0298)
Total values of products sold in 2015	α_0	0.92*** (0.363)
$500,000 or above	α_1	-0.37*** (0.0675)
Annual Household Income	α_0	0.96*** (0.395)
High income	α_1	-0.32*** (0.0286)
Acres of farm operated in 2015 (acres)	α_0	0.79*** (0.274)
Greater than 500 acres	α_1	-0.293*** (0.0712)
Certainty about the decision (%)	α_0	0.424*** (0.106)
Certain	α_1	0.175*** (0.0547)

a. *** $p \leq 1\%$, ** $p \leq 5\%$, * $p \leq 10\%$.
b. Robust standard error is reported in the bracket.

3.6. Implications

The discussion above rejects the choice set independent assumption imposed on conventional RUM models. This section investigates how such reference-dependent behavior affects welfare analysis and policy design based on DCE and discusses the implications for DCE.

3.6.1. The Implications for Policy Design

As decision making is reference-dependent, policymakers can influence decisions by manipulating the RP of a policy. Below I used a simulation approach to show how differently composing the alternatives of a program affects the same target program's participation rate. This will inform policymakers to increase policy efficiency.

Presume a policy scenario which is exactly the same as the scenario in the survey design. There are four choice tasks with two hypothetical alternatives plus an SQ alternative for each. One alternative is the target program that the policymaker aims at maximizing the adoption rate, and the other alternative is the nudge program that the policymaker adds to the choice set to give the decision-maker an alternative option and potentially nudge the desired behavior. The decision-makers do not know which is the target program and which is the nudge program, and they make decisions to minimize their regret. I will show how to choose the nudge program to increase the target program's adoption.

According to the survey's case, the target program is to adopt all three CA practices with an expected nitrogen saving of 50%. Excluding the target program (Yes, Yes, Yes) and no-action program (No, No, No), I have six different nudge programs as candidates. The first step is to decide the payment level for each of the candidate nudge programs. The objective is to set the payment at the level that is reasonable to decision-makers but still low enough such that the nudge program will not be chosen even when the target program's payment (X) is as low as $60[10]. That is, the nudge program's payment is set at the level that either the target program or SQ will be chosen. I refer to the WTA estimation based on RUM models and run a few simulations to decide the nudge program's payment levels, and the results are listed in Table 3.5. Next, I predicted 10,000 simulated decisions based on estimations with RUM' models and P-RRM models conditional on different nudge programs using software R. It is important to note that I constructed the choice makers' values of SQ and the previous chosen alternative based on the survey respondents' actual values[11] .

With simulation, the program adoption rate predicted with G'-RRM represents the true adoption rate. The program adoption rate estimated with RUM represents the prediction that fails to account for reference dependence behavior. The target program's adoption rate, P_{target}, is depicted in Figure 3.4. As the nudge program is designed at the payment level such that it will not be chosen, the staying at SQ rate equals to $1 - P_{target}$.

[10] I chose $60 by referring to the range of WTA estimations based on RUM model.
[11] As there are 1,249 respondents, I randomly replicated their stated status quo to generate 10,000 decisions.

Table 3.5. Candidate Nudge Programs

Program No.	Target	1	2	3	4	5	6
winter	Yes	Yes	No	No	Yes	No	Yes
fall	Yes	No	Yes	No	Yes	Yes	No
side	Yes	No	No	Yes	No	Yes	Yes
nitrogen	50%	10%	10%	25%	25%	25%	40%
Pay ($)	X	85	5	15	60	20	65

Figure 3.4. Target Program's Adoption Rates Conditional on Different Nudge Programs

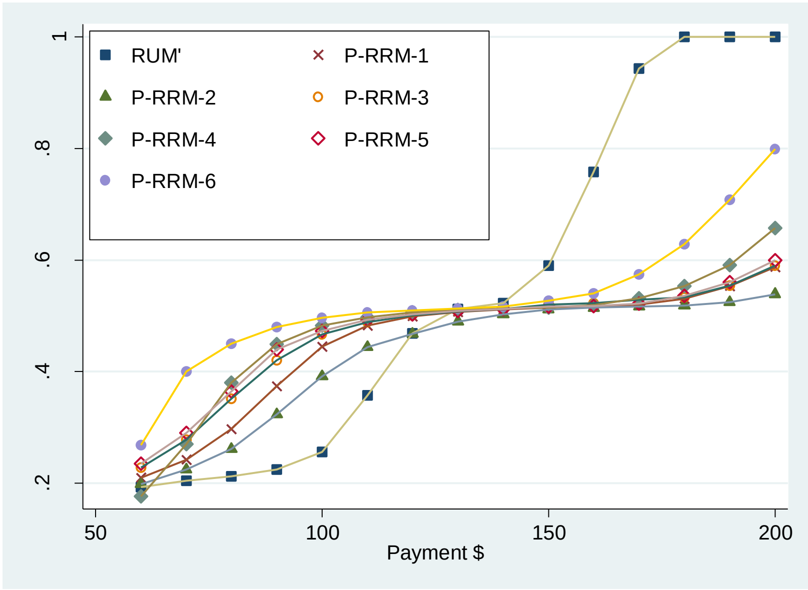


Figure 3.4 shows how the target program's adoption rate changes with the payment and the nudge program's setting—generally, the target program's adoption rate increases as payment increases. However, the increasing patterns differentiate under different model assumptions. In the meantime, the adoption curvature does not follow a sigmoid pattern, which is due to the distribution of survey respondents' status quo. Under the simulation with P-RRM assumption, the adoption is most sensitive when payment is either below $100 or above $160; under the simulation with RUM' assumption, the adoption is most sensitive when payment is between $100 and $170. The different patterns reflect the difference in decision behavior assumptions.

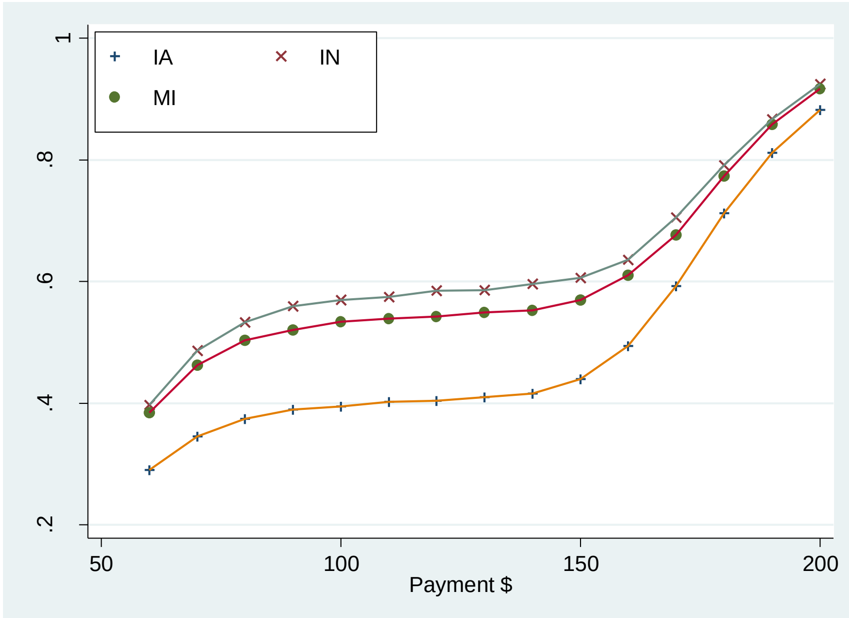
The reason is, when the payment is low, the target program is attractive to “easy adopters” whose SQs have met most of the target program’s requirements. For this group of growers, small increases in payment can be effective in encouraging adoption because their SQs are not favorable enough to compensate for the regret of losing the small payment from enrolling in the target program. As the payment increases above $100, the target program begins to attract “difficult adopters” whose SQs are not meeting the requirement of the target program. For this group of growers, the regret generated from comparing SQ with the target program, for the three CA practices, is so large that a large increase in payment is needed to compensate for the regret associated with the CA practices to shift a grower’s choice from SQ to the target program. Lastly, as payment increases above $150, loss emotion of meeting the program’s requirement has been compensated by payment, and payment regains its ability to promote adoption. Payment not working well in the mediocre payment range explains the RRM framework’s underlying assumption: alternatives with in-between attribute values generate lower regret than those with more extreme attribute values because attributes are not linearly substitutable as assumed in the utility maximization framework.

For the adoption rate, the program adoption can reach 100% as long as payment is high enough, i.e., $180, according to the RUM’ model. However, the same amount of payment cannot reach the same adoption rates based on the P-RRM prediction. Similarly, the adoption rates predicted with P-RRM, when payment is low, are not as low as those predicted with RUM. The difference again explains the difference in decision behavior assumptions: with the RUM’ model, the utility will increase as long as any attribute gets better; with the P-RRM model, decision making depends on the bundle of attributes that do not have short slabs rather than on a single attribute that excels. Therefore, increasing payment's contribution to decreasing regret is bounded after payment no longer generates regret.

The next question is whether policymakers can promote the program's adoption through nudge programs and how to select the nudge program. As shown in Figure 3.4, program 6 is most effective in encouraging adoption, while program 2 works the least effective. Referring to the design of nudge programs in Table 3.5, I found that the nudge programs with CA attribute levels similar to that of the target program will nudge the target program's adoption better. Note that for the target program, the gains are from bilateral comparison with respect to payment, and the losses are from the bilateral comparison with respect to the three CA practices. We want the nudge program to be designed at the levels that the CA practices are similar to that of the target program, such that regret generated from comparing the target program with the nudge program is minimized. In this way, the target program's adoption will be promoted.

Finally, I examined the program adoption rate by the state for policy reference purposes. Table 3.1 shows that the SQ levels are diverging among states: the rates of covering crops in winter and side-dressing fertilizer are lower in Iowa, and the rate of fall application is higher in Iowa. Consistent with the survey data, the target program's adoption rate is always lower in Iowa, given the same payment as shown in Figure 3.5.

Figure 3.5. Target Program's Adoption Rate by State with Program 6 as the Nudge



In summary, as decision-makers use a behavioral strategy for decision making, a small amount of payment is most effective in attracting people who can easily meet the policy requirement. Otherwise, a large amount of payment is needed to shift the decision-makers from a feeling of loss to a feeling of gain due to committing the program requirements. On the other hand, policymakers can make use of the behavioral strategy to promote program adoption by carefully designing the nudge program.

3.6.2. The Implications for Discrete Choice Experiment

The existence of choice set dependent behavior set caveats on how to choose discrete choice modeling framework to correctly describe the true decision behavior. In a choice set with multiple alternatives, i.e., greater than two alternatives, the preference evaluation will be contingent on the choice set composition. The problem with a multiple-choice setting is that the evaluation of a considered alternative will not only depend on its attributes but also depend on the other hypothetical alternatives provided in the choice set as RP. As a result, DCE will no longer reveal the preferences for another decision scenario unless the experiment design perfectly imitates the real decision scenario's choice set composition. Furthermore, if the real-world decision is a single binary choice, a single binary choice setting will be the necessary condition for accurate preference estimation of the stated preference approach.

Similarly, as preference evaluation is contingent on the choice set composition, WTP/WTA will also be contingent on the hypothetical alternatives provided in the choice set. As we know, due to the linear additive form of the utility function of RUM, the RUM model can give direct WTA estimation by taking the ratio of marginal utility of an attribute to the marginal utility of the cost attribute. However, due to the feature of asymmetry in loss and gain of RRM, WTA cannot be directly calculated. To give a direct comparison to welfare analysis between the models, I used a searching approach to estimate the program's median WTAs that make decision-makers indifferent between the proposed plan and their status quo. Specifically, I used the preference estimates from RUM' and P-RRM to simulate 10,000 decisions with their values of SQ and previously chosen alternatives randomly drawn from the respondents of the survey. I used program 2 and program 6 as the nudge programs for P-RRM model prediction. Lastly, I gradually increased the objective program's payment from $0 until the payment is high enough to incur a 50% adoption rate. The objective program's requirement and median WTAs predicted based on different models are reported in Table 3.6.

Table 3.6. WTA ($) Indifferent Between Target and SQ Programs

Winter	Fall	Side-dress	Nitrogen Saving	RUM'	P-RRM-Nudge 2	P-RRM-Nudge 6
No	No	No	0%	101	143	159
Yes	No	No	10%	191	268	242
No	Yes	No	10%	88	68	88
No	No	Yes	25%	92	71	58
Yes	Yes	No	25%	159	162	142
No	Yes	Yes	25%	99	78	75
Yes	No	Yes	40%	141	154	131
Yes	Yes	Yes	50%	135	132	107

I found that WTAs of achieving a 50% objective program's adoption are different across models. Given that RUM' fails to take account of choice set dependent decision behavior, using RUM' for welfare analysis would give a biased estimation. Besides, WTAs estimation depends on the design of the nudge program. Consistent with previous findings, program 6 is generally more efficient than program 2 in nudging desired behaviors concerning reducing WTAs. Note that nitrogen saving itself can reduce farming costs, and nitrogen saving is decided by the combination of practices that have been taken—as such, taking all three practices incurs lower WTA than taking a single or two practices.

3.7. Conclusions

Based on a DCE survey studying farmers' WTA the CA program, this study formally tests the decision behavior assumptions imposed on RUM and RRM frameworks. This study is among the first few literature investigating regret behavior using the RRM framework in environmental economics (e.g., Boeri et al., 2012; Thiene et al., 2012). Meanwhile, the findings have general implications in fields outside environmental economics. This is also the first paper investigating the RRM framework in a WTA scenario.

First, decision making is choice set composition as well as path-dependent. The hypothetical alternatives, the decision-makers' SQ, and the chosen alternative from the last choice scenario can all play as the RPs of decision making. Among the three, the last round's chosen alternative is the most important if the current choice scenario is not the first choice scenario. When the decision-makers are first exposed to the choice set where there is no last round of information delivered, SQ is the most critical RP. As survey respondents gradually collect information over repeated choices, the decision making shows a path-dependent pattern. That is, decision making evolves from the current choice set dependent to across choice sets dependent. Moreover, attributes' impacts depend on their positions of being hypothetical, SQ, or last round's chosen.

The existence of the path dependence decision raises the issue of a proper interpretation of DCE analysis results. The gap between the survey and real-world decision scenarios can produce significant bias in decision prediction and WTP/WTA estimation. This work reveals a new perspective of the concern with DCE method's incentive compatibility which has long been discussed in DCE literature.

The policy implication of these findings is that, by manipulating the nudge program proposed together with the target program, the target program's adoption rate can increase. Setting the nudge program close to the target program is most efficient in nudging desired choices. A future research avenue is to study which approach works best in boosting a target program's adoption: expanding the choice set by proposing the target program with a nudge program or proposing a single binary choice.

There are several issues left with future discussions. First and foremost, we need to be cautious that these conclusions are based on an experimental study, whether the decision-makers adopt similar decision strategies in the real choice scenario remains further examined. Next, how the path dependence behavior evolves over repeated choice remains further investigation. So far, I only take the last round's chosen alternative to represent the information delivered from the previous choices. However, how the other information collected from the earlier choices works together to influence decision making remains to be discussed. To continue, due to the sample size limitation, it is difficult to distinguish the effects of different attributes that work as different kinds of RPs as the model complexity increases. Future work is necessary to understand each attribute's role and the underlying reasons for the difference in these attributes' roles. Furthermore, relating the individual-specific status quo with SQ alternative solves the problem of individuals' heterogeneity of the SQs as well as raises the issue of endogeneity of individual SQs in discrete choice modeling. An avenue for further research would be discussing the endogeneity of the SQ setting in DCE. Lastly, a nudge program has been justified to be effective in promoting the target program's adoption in policy that is brought about through. As such, future research should be enacted to investigate whether a single alternative policy or a target alternative combined with a nudge alternative will work better in achieving the desired results.

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CHAPTER 4. REGRET MINIMIZATION, PATH DEPENDENCE, AND ATTRIBUTE NON-ATTENDANCE IN DISCRETE CHOICE EXPERIMENTS

4.1. Introduction

Discrete Choice Experiment (DCE), developed by Louviere and Hensher (1982) and Louviere and Woodworth (1983), is a popular stated preference approach to elicit environmental preferences (Louiviere et al., 2000; Kanninen, 2007). A hypothetical decision-making scenario is introduced through a survey experiment. The survey consists of repeated choice scenarios. Each choice scenario consists of multiple alternatives, with each described by a combination of attributes. Through observing respondents' choice in the DCE, estimation models such as Random Utility Maximization (RUM) (McFadden, 1974) are constructed to estimate respondents' preferences over the individual attributes.

The workhorse estimation model of DCE, i.e., RUM, is based on the notion of rational agents making choices to maximize expected utilities. However, recent developments in behavioral economics have identified a range of alternative decision strategies that challenge the rational decision assumption that endorses the RUM framework. These decision strategies include attribute cancellation/exclusion when attributes are in common levels (e.g., Layton and Hensher, 2010), reduced attention to a subset of attributes (e.g., Houston and Sherman, 1995), imposing thresholds of acceptable levels on attributes (e.g., Swait, 2001; Hensher and Rose, 2012), and reference dependence around a recent or past experience (e.g., Chorus, 2008, 2010; Caputo, Lusk, and Nayga, 2018, 2020). In sum, there are two major categories of behavioral decision strategies—reduced attention and reference dependence. Previous research shows these strategies are context specific (Gilovich et al., 2002), whereas there is a lack of research directly investigating and comparing the performances of these alternative strategies within a single study.

This paper examines the interlinkage and implications of these two major behavioral strategies, namely reduced attention and reference dependence, in the hope of making up the absence of DCE literature that investigates the relationship between the two approaches. To account for these two strategies within discrete choice modeling, I followed the frameworks of Attribute non-Attendance (ANA) (see, Hensher et al., 2005 for an initial introduction) and Random Regret Minimization (RRM) (see, Chorus et al., 2008 for an initial introduction), and developed a model to examine these two strategies within a single framework.

Specifically, ANA literature describes an information processing strategy—wherein respondents ignore specific attributes in comparing alternatives—in a DCE setting. The idea of ANA can be traced back to the lexicographic heuristic strategy (Tversky, 1969), which assumes that choices are made based on the essential attributes while ignoring all other information. The drivers for ANA behavior can be either subjective ignorance or unconscious ignorance—decision-makers intentionally eliminate the irrelevant/unimportant attributes to simplify choice tasks, or they unconsciously ignore the attributes due to inattention.

RRM (Chorus, 2008, 2010) argues that decision making is based on pairwise comparison of the chosen and foregone alternatives (Bell, 1982; Fishburn, 1982; Loomes and Sugden, 1982). Rooted in Regret Theory (RT), it posits that the foregone alternative performing better or worse than the chosen alternative gives people a feeling of loss or gain from that decision. The regret aversion emotion leaves individuals more sensitive to loss than to gain generated from the bilateral comparison. Its consistency with real behavior has made RT a popular alternative of utility maximization for choice analysis (e.g, Loomes and Sugden, 1983, 1987; Machina, 1987; Quiggin, 1994; Hey and Orme, 1994; Starmer, 2000; Hart, 2005).

This paper investigates the relationship between ANA and RRM in a single framework and how the relationship evolves across the repeated choice scenarios in the DCE setting. The empirical analysis uses data from a Willingness-To-Accept (WTA) DCE survey on incentives to adopt Conservation Agriculture (CA)[12] practices among corn growers in the Midwest U.S. I showed that the reference-dependent regret minimization model matches respondents' behavior better than the utility maximization framework in terms of statistical criteria. I also found a decision-maker's choice in the previous choice scenario of the survey, if the choice set is not the first one, is an important Reference Point (RP) of decision making. Specifically, decision-makers shift the RP from the current choice set's alternatives to the previously chosen alternatives as they collect information through making repeated choices. Lastly, I found evidence of ANA behavior in DCE under both RUM and RRM frameworks, but this behavior vanishes after this path dependence behavior is accounted for.

Before going into the details of model development, which will be presented in the next section, I will first take the space to introduce the frameworks of ANA and RRM as well as to discuss the rationales of developing a new model based on these two frameworks.

To begin with, RRM (Chorus, 2008, 2010) describes a simplifying decision strategy of reference dependence. It assumes a decision-maker chooses the alternative with the lowest regret from the given choices and follows a similar framework of RUM for econometric modeling. RRM distinguishes from RUM in that RRM adopts a non-linear function form for the observed part of utility (or regret), as opposed to the linear combination function form adopted by RUM. It, therefore, captures the asymmetrical weighting in loss and gain. Due to the advantages in

[12] Conservation Agriculture (CA) is a term defined by the Food and Agricultural Organization of the United Nations to package the concepts of "resource-saving agricultural crop production that strives to achieve acceptable profits together with high and sustained production levels while concurrently conserving the environment".

capturing behavior features with no additional requirement of estimation, RRM has gained wide attention from literature in fields such as transportation, marketing, and environmental economics (e.g., Hensher et al., 2013; Thiene et al., 2012; Chorus and Bierlaire, 2013; Boeri et al., 2014; Adamowicz et al., 2014).

Notwithstanding the contribution of the RRM framework in incorporating reference-dependent behavior within discrete choice modeling, the RRM literature does not explicitly discuss the roles of different information plays as reference points. Chapter 3 of this dissertation addresses this issue explicitly. There is a multitude of information delivered in the survey with the potential of playing as an RP. The information includes the hypothetical alternatives described in the choice set, the Status Quo (SQ) of the decision-maker, as well as the information acquired from the previous choice set(s). Different RPs may contribute to regret generation with different weights. Besides, if information learned from the previous choice set(s) serves as a significant RP, the reference strategy will be dynamic because details of the previous choices are accumulated across the repeated choice sets. This paper will explicitly discuss the roles of different RPs and explore the dynamic pattern of reference dependence behavior.

To continue, ANA is another simplifying strategy that captures the reduced attention behavior. Decision making is based on a lexicographic heuristic, and only important attributes are given attention. One type of ANA behavior is that an attribute is always ignored regardless of its value. Another type of ANA behavior is based on the Elimination by Aspects (EBA) rule (Tversky, 1972). This rule starts by setting a cutoff value for each attribute, and then all attributes below the cutoffs are eliminated and thus ignored. The later type coincides with the reference dependence strategy. Under the RRM framework, the attribute(s) of the considered alternative performing better than that of the forgone alternative generate(s) zero regret and thus will be statistically eliminated. Under such circumstances, an attribute contributing no regret will statistically be identified as ignored if it is modeled with the ANA framework. This phenomenon brings up the necessity of accounting for reference dependence behavior in the ANA framework to avoid accidentally identifying reference dependence behavior as ANA behavior.

There are two primary methods to identify the ANA information processing strategy—stated ANA, which asks respondents which attributes have been ignored, and inferred ANA, which identifies ANA behavior through statistical inference without directly asking (Caputo et al., 2018). Whilst the stated approach is straightforward, it suffers the problem of inconsistency between stated and actual behaviors. On the one hand, the stated ignored attribute is not necessarily totally ignored. On the other hand, if the question of ignorance is asked at the end of the serial choice sets, there is no guarantee that ignorance behavior has not changed across repeated choices. If the question of ignorance is inserted right after each choice set, the question itself is likely to influence the following choice sets' decisions. Therefore, there is growing interest in identifying the role of ANA through model inference (e.g., Caputo et al., 2013; Scarpa et al., 2010; Hess and Hensher, 2010; Hensher and Greene, 2010; Hole, 2011). This approach assumes multiple latent classes, which represent a different combination of attended attributes. The most popular latent class model is the Equality-Constrained Latent Class model (ECLC). ECLC assumes that the ignored attributes' parameters in a latent class are restricted to zeros and that the other attributes' parameters are either the same or different across classes (Scarpa et al., 2009; Caputo et al., 2013). This paper follows the inferred ANA framework to identify ANA behavior.

Despite the popularity of examining ANA behavior using stated or inferred approaches in empirical DCE literature, there are several problems unsolved within the ANA framework. One problem, as pointed by Hess et al. (2013), is if there exists substantial preference heterogeneity that is not related to ANA, then setting a restriction to zero for parameters of the latent class model will produce results that confound non-attendance and taste heterogeneity. Besides, there lacks of discussion about the changing patterns of ANA behavior over repeated choices in both stated and inferred ANA literature. That is, ANA behavior is assumed to be respondents heterogeneous, but for each individual decision-maker, ANA behavior is assumed to be unchanged across choice sets. Moreover, an inferred ANA behavior could be due to the failure of modeling alternative strategies rather than due to true ANA behavior. To the best of my knowledge, all existing ANA literature builds on the utility maximization framework rather than the alternative. This paper solves the above problems by allowing for reference dependence behavior within the inferred ANA framework and discusses the changing pattern of ANA behavior, if there are any.

The remainder of the paper is organized as follows. Section 2 introduces models to account for different decision rules and discusses how to test these decision rules with these models. The survey and data used for empirically examining the models are introduced in section 3. Empirical estimation results are reported in section 4. Section 5 discusses the implications of incorporating behavioral factors for DCE.

4.2. Econometric Frameworks and Hypothesis Testing

There are three components of a DCE: a choice scenario composed of several alternatives, a decision rule defined by a function that describes the observed utility, and an error term that describes the unobserved utility and the associated distribution. This study focuses on identifying the underlying decision rule through model development and hypothesis testing. In this section, I discussed the models I developed to explore the decision rule.

I began by introducing the traditional discrete choice modeling approach, i.e., RUM. I then discussed the RRM framework and the associated innovations as well as the ANA framework. I concluded by introducing an integrated framework to test the decision strategy.

4.2.1. Random Utility Maximization (RUM)

Assume the following choice scenario: a decision-maker, i, faces a choice scenario, s, composed of J alternatives, with each alternative, j, being described in terms of the attribute, m, i.e., x_{isjm}. Utility Maximization Theory (McFadden, 1974) postulates that utility from alternative j is independent of other alternatives within the choice set, and the alternative with the highest utility will be chosen. The utility of each alternative is described by a linear combination of observable attributes. A random error term is added to the utility to represent the inability to capture all factors that determine a decision-maker's utility. As such, an individual i's utility from choosing alternative j in choice scenario s with taste parameters β_m can be described as follows:

(1) $U_{isj} = V_{isj} + \varepsilon_{isj}$

$$= \sum_{m} \beta_m^h \cdot x_{isjm} + \beta_0 \cdot sq_{isj} + \varepsilon_{isj} \quad when\ j = 1\ or\ 2$$

Or

$$= \sum_{m} \beta_m^{sq} \cdot x_{isjm} + \beta_0 \cdot sq_{isj} + \varepsilon_{isj} \quad when\ j = sq$$

Note that the RUM model restricts $\beta_{sm} = \beta_m$ and $\beta_{s0} = \beta_0$ by assuming that preferences are consistent over repeated choice scenarios. An SQ constant term $\beta_0 \cdot sq_{isj}$ is added to capture the status quo effect with $sq_{isj} = 1$ when j is the SQ alternative and $sq_{isj} = 0$ otherwise. Here I assume individuals' preferences over attributes for hypothetical alternatives and SQ alternative are different, and therefore I separately specify the corresponding preference parameters as $\boldsymbol{\beta^h}$ and $\boldsymbol{\beta^{sq}}$. I name this framework as RUM' to mark this difference. When $\boldsymbol{\beta^h} = \boldsymbol{\beta^{sq}}$, RUM' will reduced to conventional RUM. Under the assumption that the error term ε_{isj} follows an independent and identically distributed, i.e. i.i.d., Extreme Value Type I with variance equaling $\pi^2/6$, a multinomial logit (MNL) model can be used for model estimation (McFadden, 1974). The choice probability for alternative j is: $Pr_{isj} = exp(U_{isj})/\sum_{k=1}^{J} exp(U_{isk})$.

4.2.2. Random Regret Minimization (RRM)

RRM framework, based on Regret Theory (RT) (Bell, 1982; Fishburn, 1982; Loomes and Sugden, 1982), assumes that decision making depends not only on the performance of the considered alternative but also on that of the foregone alternatives. The regret aversion emotion leaves individuals focusing on the loss rather than the gain generated from the bilateral comparison. As the counterpart of the RUM framework, RRM postulates that a decision-maker will choose the alternative with the lowest regret from the given choice set, and the regret is composed of a systematic regret described by observed attributes and an i.i.d random error.

Regardless of the RUM or RRM framework, there exists a decision strategy for decision-makers irrespective of the researchers' model assumption. The researchers' task is to identify the underlying decision rule.

4.2.2.1. Random Regret Minimization (RRM)

A utility function is needed to translate the observable attributes into comparable levels of regret as well as to account for the regret minimization assumption. Chorus (2010) defines attribute-level regret as ${R_{isj}}^{m} = \sum_{k \neq j}^{J} ln\,(1 + exp[\beta_m \cdot (x_{iskm} - x_{isjm})])$ [13] where $J \geq 3$. That is, for an individual *i* in choice set *s*, the regret of alternative *j* for attribute *m* is determined by bilaterally comparing alternative *j* with every other referred alternative *k*. The regret is a function of loss based on the comparison, i.e., $X = \beta_m \cdot (x_{iskm} - x_{isjm})$. A non-linear log function form is used to represent that individuals respond more to loss (X>0) than to gain (X<0). This paper will focus on the case when $J \geq 3$, because when $J = 2$, RRM reduces to linear RUM (see Chorus, 2010, for a formal proof). Figure 3.1 plots regret over the loss, i.e., $X = \beta_m \cdot (x_{iskm} - x_{isjm})$ and explicitly illustrates how the non-linear function form of RRM captures the asymmetrical weights in loss and gain as opposed to the linear function form of RUM. Note that this figure can also plot regret over the loss for the RUM framework because the regret function reduces to ${\mathrm{R}_{\mathrm{isj}}}^{m} = \sum_{k \neq j}^{J} \beta_m \cdot (x_{iskm} - x_{isjm})$ when "1" is replaced with "0", and the corresponding model produces equal estimates as a RUM framework does (see, Chorus, 2014, for a formal proof).

With attribute-level regret defined, an individual *i*'s regret from choosing alternative *j* from choice set *s* can be defined as follows:

$$(2)\ U_{isj} = R_{isj} + \varepsilon_{isj} = \sum_{m=1}^{M} \sum_{k \neq j}^{J} \ln\,(1 + \exp[\beta_m \cdot (x_{iskm} - x_{isjm})]) + \beta_0 \cdot sq_{isj} + \varepsilon_{isj}$$

Minimizing the regret is mathematically equivalent to maximizing the negative of the regret defined in equation (2). As such, the SQ constant term parameter, β_0, has the opposite sign of the conventional RUM model as defined in equation (1). An MNL regression can be used to estimate the parameters of RRM in equation (2).

[13] An alternative regret minimization model is defined in Chorus (2008) as follows: $\max\{0, \beta_m \cdot (x_{jm} - x_{im})\}$, where : β_m is the preference parameter of attribute m. This formulation implies that rejoice gains zero weight in formulating regret: when a considered alternative outperforms its competing alternative, i.e., $\beta_m \cdot (x_{jm} - x_{im}) < 0$, the regret is zero.

4.2.2.2. Random Regret Minimization in the Presence of Status Quo (G'-RRM)

An essential setting of DCE is the existence of a baseline alternative (also referred as "status quo", "opt out" or "do nothing" alternative). This setting avoids forced choice and thus guarantees proper welfare measures (Hanley et al., 2001). This setting calls the issues of the endowment effect—the fact that people demand more to give up an object than they would be willing to acquire it (Thaler, 1980) and status quo bias—the fact that a preference for the current state biases the decision-makers against foregoing the current status (Samuelson and Zeckhauser, 1988). Hence, the inclusion of an SQ specific constant term as I defined in the model specification is important.

Besides the endowment effect and status quo effect, the inclusion of an SQ alternative also incurs the behavior of reference dependence since SQ can also play as an RP. As discussed in the RRM section, giving up a hypothetical alternative that performs better than the considered one can generate emotions of regret. Similarly, leaving the SQ that performs better than the considered alternative can cause regret as well. The only difference is that SQ serves as an internal reference point since it has been endowed with the decision-makers; in contrast, the hypothetical alternatives serve as an external reference point since they are introduced in the choice set design. This difference makes it reasonable to differentiate the impacts of SQ and hypothetical alternatives in serving as RPs. Chapter 3 explicitly investigates the contributions of SQ as RP and discusses the importance of differentiating the contribution of SQ alternatives from hypothetical alternatives. I, therefore, followed that framework and defined a G'-RRM model that describes the regret function as follows:

$$(3)\ U_{isj} = R_{isj} + \varepsilon_{isj} = \sum_{k \neq sq\ or\ j} \sum_{m=1}^{M} \ln\left(\gamma + exp\left[\beta_m^h \cdot \left(x_{iskm} - x_{isjm}\right)\right]\right)$$

$$+\sum_{m=1}^{M} ln\left(\gamma + exp\left[\beta_m^{sq} \cdot \left(x_{issqm} - x_{isjm}\right) \right]\right) + \beta_0 \cdot sq_{isj} + \varepsilon_{isj}$$

This model differentiates from the RRM model in that it allows for different preference estimates for the comparisons with hypothetical and SQ alternatives, i.e., $\boldsymbol{\beta^h}$ and $\boldsymbol{\beta^{sq}}$. Additionally, it introduces a new parameter γ, where $0 \leq \gamma \leq 1$, such that it allows the model to be reduced to a traditional utility maximization framework if the underlying behavior is utility maximization when $\gamma = 0$[14].

4.2.2.3. Random Regret Minimization in the Presence of Path Dependence (P-RRM)

If decision making is reference-dependent, it is necessary to explore all possible RPs comprehensively. As I discussed above, both hypothetical and SQ can play as RP. The next question is whether the previous choice set(s) can also contribute as an RP if the decision-makers are making repeated choices in the survey. Specifically, when a decision-maker faces a choice scenario s, where $s \geq 2$, it is possible that the path, i.e., previous choice scenarios *1, 2,…, s-1*, will also play as an RP. To account for this path dependence behavior, Chapter 3 develops a Path Dependent Random Regret Minimization (P-RRM) model where the chosen alternative from the previous choice scenario s-1 plays as the RP from the path. I, therefore, followed this work and defined the P-RRM as follows:

$$(4)\ U_{isj} = R_{isj} + \varepsilon_{isj} = \sum_{k \neq sq\ or\ j} \sum_{m=1}^{M} \ln\left(\gamma + exp\left[\beta_m^{h} \cdot \left(x_{iskm} - x_{isjm}\right) \right]\right)$$

$$+\sum_{m=1}^{M} ln\left(\gamma + exp\left[\beta_m^{sq} \cdot \left(x_{issqm} - x_{isjm}\right) \right]\right)$$

$$+\sum_{m=1}^{M} ln\left(\gamma + exp\left[\beta_m^{l} \cdot \left(x_{is-1\check{j}m}, - x_{isjm}\right) \right]\right) + \beta_0 \cdot sq_{isj} + \varepsilon_{isj}$$

[14] See Appendix B for a formal proof.

The innovation of this P-RRM model from the previous RRM models is that it sets an additional part of regret generated from comparison with the last round chosen alternative, which is described by $x_{is-1\check{j}m}$ for each attribute m.

4.2.3. Attributes Non-Attendance (ANA)

Besides regret minimization behavior, ANA is another simplifying strategy for decision making. It assumes that decision-makers strategically ignore some of the attributes when evaluating the alternative provided in the choice tasks. The unattended attributes will be given zero/reduced weights in assessing the alternatives. ANA strategy is not necessarily exclusive to but can coincide with the reference dependence strategy. Under such a circumstance, decision-makers set the forgone alternative as the RP and eliminate the attribute(s) which perform(s) better, i.e., generate(s) no regret, for the considered alternative rather than for the forgone alternative.

To explore the incidence of ANA behavior, I followed an Equality Constrained Latent Class (ECLC) framework (Scarpa et al., 2009) to account for heterogeneous attention behaviors. The ECLC model assumes that the population of the respondents can be divided into a set number (Q) of classes with heterogeneous preferences. An individual belongs to each class with a certain probability where the probability belonging to each class sums up to one. Following the RUM framework for discrete choice modeling, the probability of individual *i* choosing alternative *j* when *i* belongs to class q can be described as follows:

$$(5)\ Pr\left(y_{ij} = 1 \,\middle|\, class\ q\right) = \frac{exp\ (U_{ij}|class\ q)}{\sum_{j=1}^{J} exp\ (U_{ij}|class\ q)}$$

The probability that an individual belongs to a certain class q is given as:

$$(6)\ Pr\ (class\ q) = \frac{exp\ (s_q)}{\sum_{q=1}^{Q} exp\ (s_q)}\ with\ s_Q = 0$$

where $s_q \in (-\infty, \infty)$ is the class parameter to be estimated and s_Q is normalized to zero to secure identification of the model (Greene and Hensher, 2003). The probability that alternative j is chosen from J alternatives is a weighted average over the Q classes with weight Pr $(class\ q)$:

$$(7)\ Pr\left(y_{ij} = 1\right) = \sum_{q=1}^{Q} Pr\left(y_{ij} = 1 \mid class\ q\right) \times Pr\ (class\ q)$$

Different from the standard latent class model, which is intended to explore preference heterogeneity, the ECLC model is based on classes embedding different forms of attendance to attributes. Hence, the preference coefficients of the unattended attribute(s) belonging to a particular class are(is) restricted to zero(s). A stepwise approach (Lagarde, 2013) is used in this paper to avoid too many classes being generated. That is, I started with one single class with all attributes being attended. I then added additional classes with one attribute of each class not being attended. Furthermore, I kept the classes with non-zero probability from the previous step and added additional classes with one more attribute not being attended. I continued the process to exhaust the combination of all ANA classes.

The existing ECLC framework of identifying heterogeneous attention classes is built on the RUM framework. Hence, the utility function U_{ij} in equation (5) is defined as equation (1). But this does not restrict the ECLC framework from being extended to the RRM framework. That being said, I can take the regret function defined in equations (2) – (4) into equation (5) to conduct ECLC estimation.

4.2.4. Decision Rule Testing

To investigate the decision rule of DCE, I started with separately running each model, i.e., RUM, RRM, G’-RRM, and P-RRM, and I then allowed ANA behavior in each of these models. The null hypothesis of running each model is that this model has captured the underlying decision rule.

Furthermore, to explore the changing pattern of the decision rule over repeated choice sets of DCE, I separately ran each model over every single choice set and compared the corresponding performance over repeated choices. The null hypothesis is that the decision strategy does not change over repeated choices. The alternative hypothesis is that the decision strategy changes over repeated choices. The rationale of changing strategy is that survey respondents collect information from the repeated choices, and they may unconsciously or strategically use this information to make better decisions as well as reduce decision making cognitive burden. If the decision strategy is dynamic, failing to capture such behavior will produce inconsistent estimations over different choice sets.

If there exists a dynamic decision-making strategy, one possible change is the general decision rule, and the other possible change is the information processed under each decision rule. For instance, decision-makers might switch from utility maximization strategy to simplifying strategies such as regret minimization and ANA because the information acquired from the previous choices could help with simplifying the decision. Besides the decision rule, decision-makers might also change the information processed, such as the RPs or the attended attributes. In the section on empirical analysis, I will explicitly investigate these decision patterns.

4.3. Survey and Data

As an empirical illustration of the approach, I used data from a choice experiment that elicits the farmer’s preferences for a CA program. The objective of the CA program is to encourage farmers to adopt CA practices to reduce nitrogen fertilizer leakage into the environment. To understand farmer's willingness to adopt these CA practices, a mail survey with $2 cash incentives was conducted amongst corn growers in the Midwestern U.S., specifically in Michigan, Iowa, and Indiana in 2016. Mailing addresses for the survey were randomly drawn from the Farm Service Agency (FSA)[15]. With a response rate of 27%, there are 1,294 completed surveys.

The survey contains four repeated choice experiment tasks, with each described by two hypothetical alternatives and one SQ alternative. Each alternative is described by a payment vehicle and three CA practices plus an expected nitrogen saving. The payment level is suggested by a focus group study among farmers and adjusted after a pilot study of this survey, which was conducted in 2015. Attributes and attribute levels are defined in Table 2.2. The first three attributes are the CA practices that the program requires with a "Yes" indicating requirement imposed. Expected nitrogen saving is decided by the combination of the three CA practices calculated by agronomy and environmental experts. Besides the choice tasks, the survey contains questions about the respondents' status-quo so that the SQ alternative can be linked with individual stated status quo values. To be compatible with a real decision scenario, the survey asks respondents' status quo CA practices after the choice tasks to avoid the questions affecting decision making. The individual status quo CA adoption levels as well as associated expected Nitrogen saving levels will be incorporated into the dataset for the later empirical estimation. A Bayesian efficiency design that minimizes D-error based on priors from the pilot survey and contains 24 choice sets is generated using Ngene software (Choice Metrics, 2012). I used a block design with six blocks containing four choice sets for each to avoid fatigue effects. A respondent was randomly assigned to one of the blocks. The order of presentation and allocation to

[15] FSA is the payment services agency within USDA. FSA has records for every farmer who receives any form of payment (direct payments, crop insurance subsidies, disaster payments, conservation payments, etc) through USDA.

respondents of the various choice sets is randomized. A sample of the survey is attached in Figure 2.5.

Beyond discrete choice questions, this dataset also contains information about farmers' social demographic status, attitude toward the environment policy, different resources for information, as well as farms' characteristics. Further details of this survey can be found in Chapter 2.

Sample characteristics by the state are summarized in Table 3.2. After excluding the incomplete responses, the response rate is highest in Michigan, i.e., 27%, and lowest in Indiana, i.e., 21%. Opting out rate, i.e., the percentage of farmers choosing SQ alternative among the three alternatives, reaches its highest level in Iowa, i.e., 43%, and lowest in Indiana, i.e., 37%. The conservation tillage rate is significantly lower in Michigan than that of the other two states, while the reduced tillage rate is highest in Michigan. Conservation program enrollment is relatively higher in Iowa. The distributions of age, gender, farming experience, and days off-farms are generally consistent across the three states. Iowa has a higher percentage of farmers who completed Associate or higher-level degrees. Both farm product values and household incomes are higher in Iowa. Iowa and Indiana have more large farm owners. The status quo CA adoptions are diverging across states: Iowa has the lowest rates of covering crops in the winter and side-dressing fertilizer but has the highest rate of avoiding fertilizer application in the fall.

4.4. Empirical Estimation Results

To test the decision rules, I ran MNL models with RUM', G'-RRM, and P-RRM specifications using Python Biogeme. I also examined these models separately on every single choice set to identify the decision strategy changing pattern over repeated choice scenarios.

4.4.1. RUM', G'-RRM and P-RRM Estimations

The estimation results of RUM', G'-RRM, and P-RRM are reported in Table 4.1 - 4.3. For the RUM' model[16], the signs and the scales of the preference parameters are generally as expected. The three CA practices, i.e., covering crops in the winter (*Winter*), avoid applying fertilizer in the fall (*Fall*), and side-dressing fertilizer (*Side*), all reduce utility, nitrogen-saving (*Nitrogen*) and payment (*Pay*) both increase utility, and leaving status quo (SQ) decreases utility. Note that β_{pay}^{sq} is constant as 0 because the SQ alternative has no variation with \$0 payment. The sensitivity with respect to attributes in SQ is stronger and more significantly than that in hypothetical alternatives. In addition to the sensitivity, SQ alternative also adds a positive constant term to the alternative's utility. Checking the scales of the parameters, I found that *Winter* is the least favored, followed by *Side* and *Fall*. This is consistent with the difficulty of adopting each practice, as suggested by the agronomy experts as well as the actual adoption rate claimed in the survey. 22%, 85%, and 44% of the survey respondents have met the requirements of *Winter*, *Fall*, and *Side*, respectively. This finding persists after running the RUM' model on every single choice set separately.

To continue, I checked the G'-RRM model, which allows for within choice set reference dependence behavior. Here instead of estimating γ in Equ (3), I set γ = 1 following the RRM framework because regret minimization behavior has been verified in Chapter 3 and measuring regret extent, i.e. γ, is out of the scope of this chapter. I did the same for P-RRM modeling defined in Equ (4). Note that with G'-RRM, I allowed hypothetical alternatives and SQ alternatives to make different contributions to regret generation. Compared with the RUM' model, the G'-RRM's estimations of preference parameters $\boldsymbol{\beta^{sq}}$ are consistent except for

[16] I used RUM' in this chapter because the RUM model with the assumption that $\boldsymbol{\beta^{sq}} = \boldsymbol{\beta^{h}}$ is rejected in chapter 3.

attribute *Fall*, but the estimations of $\boldsymbol{\beta^h}$ are only consistent for *Nitrogen* and *Pay*. Specifically, when referring to an *SQ* alternative, *Winter* and *Side* significantly contribute to increasing regret level, and *Nitrogen* and *Pay* significantly contribute to decreasing regret level. However, this is not true for *Winter*, *Fall*, and *Side* when referring to the hypothetical alternatives. Further checking the performances of this same model on each single choice set, I found similar results. One reason for the unexpected signs of β^h_{winter} and β^h_{side} could be that the model confounds the estimations of $\boldsymbol{\beta^h}$ with that of $\boldsymbol{\beta^{sq}}$ due to the restriction of the sample size. As SQ is a more critical RP, $\boldsymbol{\beta^{sq}}$ is more likely to be significantly identified when the sample size is small. Lastly, comparing the statistical criteria, I found that G'-RRM slightly outperforms RUM' in terms of the likelihood value $\hat{\mathcal{L}}$, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC).

Furthermore, I allowed decision making to be path-dependent by incorporating the last round's chosen alternative into choice modeling. As there is not a last round's chosen alternative information for the first choice set, I tested this model based on choice sets 2, 3, and 4. I found that the last round chosen alternative is the most important RP. It produces expected signs of estimates, and the estimations are all significant at the 1% level. SQ alternative produces consistent estimations for all attributes except for *Fall*. Hypothetical alternative produces consistent estimations for all attributes except for *Winter* and *Side*. Besides, the scales of estimations for the same attribute are largest for the last round chosen alternative and smallest for the hypothetical alternative. The expected signs, scale of estimations, significance of estimations for the last round chosen alternative persist in each single choice set. Besides that, this P-RRM model significantly outperforms RUM and SQ-RRM in terms of the likelihood value $\hat{\mathcal{L}}$, AIC, and BIC. These findings raise the necessity of accounting for path dependence decision behavior in a DCE.

In summary, after comparing the estimations of models RUM', G'-RRM, and P-RRM, I found that the last round's chosen alternative is a more reasonable RP if the current choice set is not the first one. Besides the last round's chosen alternative, the SQ alternative contributes to regret generation in terms of the attributes *Winter*, *Side*, *Nitrogen*, and *Pay*. The hypothetical alternative contributes to regret generation in terms of the attributes *Fall*, *Nitrogen*, and *Pay*. There are a few confounding estimates regarding the signs and significance levels considering the SQ and hypothetical alternatives as RPs. A possible explanation is the increase in model complexity significantly increases the minimal sample size required for statistical identification. Restricted by the sample size, only the most important parameters are significantly identified.

Table 4.1. RUM' Estimations

Sample	**Set = 1, 2, 3, 4**	**Set = 1**	**Set = 2**	**Set = 3**	**Set = 4**
β^h_{winter}	-0.718***[a]	-0.969***	-0.842***	-0.437	-0.609**
	(0.145)[b]	(0.312)	(0.283)	(0.296)	(0.302)
β^h_{fall}	0.00343	-0.222	-0.0309	0.175	0.117
	(0.0821)	(0.179)	(0.166)	(0.157)	(0.172)
β^h_{side}	-0.0133	-0.222	-0.154	0.344	-0.0522*
	(0.196)	(0.429)	(0.376)	(0.402)	(0.403)
$\beta^h_{nitrogen}$	1.06	2.75	1.71	-0.892	0.615
	(0.813)	(1.8)	(1.55)	(1.64)	(1.7)
β^h_{pay}	0.00827***	0.00648***	0.00773***	0.00828***	0.00941***
	(0.000472)	(0.00108)	(0.000961)	(0.00097)	(0.000909)
β^{sq}_{winter}	-0.752***	-0.722	-0.853*	-0.475	-0.915*
	(0.249)	(0.518)	(0.476)	(0.506)	(0.51)
β^{sq}_{fall}	-0.231	0.00952	-0.25	-0.298	-0.275
	(0.173)	(0.357)	(0.326)	(0.357)	(0.35)
β^{sq}_{side}	-1.26***	-0.904	-1.51*	-1.01	-1.41
	(0.434)	(0.899)	(0.825)	(0.89)	(0.883)
$\beta^{sq}_{nitrogen}$	2.44	0.242	3.8	1.35	3.48
	(1.72)	(3.6)	(3.26)	(3.5)	(3.49)
β^{sq}_{pay}	-	-	-	-	-
β_0	1.2***	1.02***	1.15***	1.15***	1.3***
	(0.0759)	(0.161)	(0.16)	(0.148)	(0.153)
Model Statistics					
$\hat{\mathcal{L}}$	-4434	-1109	-1108	-1112	-1085
AIC/N	2.07	2.08	2.08	2.18	2.04
BIN/N	2.08	2.13	2.13	2.14	2.09
N	4300	1075	1075	1075	1075

a. *** $p \leq 1\%$, ** $p \leq 5\%$, * $p \leq 10\%$.
b. Robust standard error is reported in the bracket.

Table 4.2. G'-RRM Estimations

Sample	Set = 1, 2, 3, 4	Set = 1	Set = 2	Set = 3	Set = 4
β^{h}_{winter}	0.435***[a]	0.623***	0.283	0.787***	0.384
	(0.121)[b]	(0.218)	(0.225)	(0.312)	(0.213)
β^{h}_{fall}	-0.134**	-0.237	-0.093	-0.0517	-0.0316
	(0.0589)	(0.273)	(0.107)	(0.0929)	(0.106)
β^{h}_{side}	0.58***	-0.777***	0.496**	0.81***	0.497**
	(0.0866)	(0.171)	(0.205)	(0.195)	(0.157)
$\beta^{h}_{nitrogen}$	0.738***	0.0875	0.821	0.284	0.762
	(0.22)	(0.331)	(0.593)	(0.463)	(0.417)
β^{h}_{pay}	0.00498***	0.00416***	0.00395***	0.00531***	0.00597***
	(0.000374)	(0.00077)	(0.000789)	(0.000767)	(0.000687)
β^{sq}_{winter}	-1.95***	-2.07***	-1.74***	-2.3***	-1.85***
	(0.154)	(0.287)	(0.294)	(0.354)	(0.298)
β^{sq}_{fall}	0.033	0.263	-0.0257	-0.00537	0.00402
	(0.042)	(0.453)	(0.11)	(0.0176)	(0.0202)
β^{sq}_{side}	-1.79***	-1.77***	-1.59***	-2.08***	-1.81***
	(0.117)	(0.229)	(0.253)	(0.238)	(0.236)
$\beta^{sq}_{nitrogen}$	1.1***	0.144	1.14	0.453	1.16
	(0.383)	(0.531)	(1)	(0.765)	(0.782)
β^{sq}_{pay}	0.037***	0.00989***	0.0327**	0.0402***	0.0384**
	(0.00638)	(0.0038)	(0.0152)	(0.00813)	(0.00839)
β_0	-2.13***	-1.63***	-2.13***	-2.08***	-2.33***
	(0.0656)	(0.131)	(0.146)	(0.112)	(0.115)
Model Statistics					
$\hat{\mathcal{L}}$	-4418	-1122	-1110	-1097	-1073
AIC/N	2.06	2.11	2.09	2.06	2.02
BIN/N	2.05	2.16	2.14	2.11	2.07
N	4300	1075	1075	1075	1075

a. *** $p \leq 1\%$, ** $p \leq 5\%$, * $p \leq 10\%$.
b. Robust standard error is reported in the bracket.

Table 4.3. P-RRM Estimations

Sample	**Set=2, 3, 4**	**Set=2**	**Set=3**	**Set=4**
β^{h}_{winter}	1.12***[a]	-0.257	1.72***	0.201
	(0.114)[b]	(0.213)	(0.247)	(0.242)
β^{h}_{fall}	-0.838***	-0.871***	-1.01***	-0.906***
	(0.105)	(0.172)	(0.162)	(0.177)
β^{h}_{side}	0.94***	0.107	-0.0363	0.185
	(0.103)	(0.293)	(0.27)	(0.192)
$\beta^{h}_{nitrogen}$	0.825***	-0.302	0.254	0.255
	(0.227)	(0.648)	(0.569)	(0.393)
β^{h}_{pay}	0.00637***	0.00543***	0.00708***	0.00717***
	(0.000416)	(0.000856)	(0.00088)	(0.000802)
β^{sq}_{winter}	-1.7***	1.63***	-1.76***	1.31***
	(0.173)	(0.32)	(0.409)	(0.397)
β^{sq}_{fall}	-0.192	0.0186	0.00922	0.0658
	(0.119)	(0.213)	(0.14)	(0.184)
β^{sq}_{side}	-1.46***	-1.06***	-1.8***	-1.3***
	(0.158)	(0.36)	(0.281)	(0.296)
$\beta^{sq}_{nitrogen}$	1.86***	-0.24	0.297	0.368
	(0.59)	(0.56)	(0.67)	(0.581)
β^{sq}_{pay}	0.0285***	0.0345*	0.0275***	0.0403***
	(0.00799)	(0.0192)	(0.00782)	(0.0162)
β^{l}_{winter}	-2.07***	-2.31***	-2.72***	-2.6***
	(0.111)	(0.21)	(0.22)	(0.202)
β^{l}_{fall}	-1.79***	-2.01***	-2.19***	-1.7***
	(0.111)	(0.211)	(0.202)	(0.243)
β^{l}_{side}	-1.86***	-2.32***	-2.42***	-2.45***
	(0.116)	(0.249)	(0.213)	(0.194)
$\beta^{l}_{nitrogen}$	2.63***	4.96***	1.65	1.21
	(0.654)	(1.22)	(1.73)	(1.52)
β^{l}_{pay}	0.0025***	0.00277***	0.00316***	0.00227***
	(0.000437)	(0.000758)	(0.000835)	(0.000906)
β_0	-2.3***	-2.36***	-2.24***	-2.42***
	(0.0863)	(0.168)	(0.136)	(0.151)
Model Statistics				
$\hat{\mathcal{L}}$	-4198	-997	-971	-990
AIC/N	1.96	1.88	1.84	1.87
BIC/N	1.98	1.95	1.91	1.95
N	4300	1075	1075	1075

a. *** $p \leq 1\%$, ** $p \leq 5\%$, * $p \leq 10\%$.
b. Robust standard error is reported in the bracket.

4.4.2. RUM', G'-RRM, and P-RRM Estimations Accounting for the ANA Behavior

In this section, I explored the ANA behavior under different models and explored the behavior's changing pattern over repeated choices. I allowed for ANA behavior with RUM', G'-RRM, and P-RRM modeling based on the ECLC framework. The unattended attribute's parameter is restricted to zero. To figure out a proper number of classes for the ANA model, I followed a stepwise approach (Lagarde, 2013) by starting with one class that all attributes are attended, and then added additional classes that only one attribute of each class is not attended. Furthermore, I kept the classes with non-zero probability from the previous step and continued to add additional classes with more attributes not being attended until I exhausted the combination of all ANA classes. After this stepwise approach, I found that only five classes are common scenarios. That is, I have the first class with all of the five attributes attended and the other four classes with one of *Winter*, *Fall*, *Side*, and *Nitrogen* non-attended. Further checking the probability of each class, I found that *Fall* non-attended is the only class with significant non-zero probability. Therefore, I proceeded with the model examination with only two classes, i.e., all attended and only *Fall* non-attended.

With the number of classes defined, I ran RUM', G'-RRM, and P-RRM defined in Equ (1) – (3) with $\gamma = 1$ and two latent classes to examine the ANA behaviors. The attributes' estimated coefficients are reported in Table 4.4 - 4.6. Note that the class probability parameter s_q for all attributes attended (AA) class is fixed at zero for identification. I found that the model that accounts for the ANA behaviors are generally consistent with the model that does not account for ANA behaviors with respect to parameter estimation. Checking the class probability for the RUM'-ANA model, I found that the class that *Fall* is unattended is significant with high probability starting from choice set 2. It is worth to mention that after the ANA behavior is accounted for, the estimation of *Fall*'s parameter is still insignificant for the sign is not as expected. One explanation is that *Fall* is not important for people's decision making; a second explanation is that the sample size is too small to identify *Fall*'s parameter after the *Fall* non-attended observations are excluded; a third explanation is that *Fall* is assessed in a way not correctly specified by this model. Checking the class probability for the G'-RRM model in Table 4.4, I found that the class that *Fall* is non-attended is still close to 100%, and the associated estimation is significant on any single choice set. Finally, I explored the ANA behaviors with the P-RRM-ANA model. I no longer observed any significant or greater than zero probability of ANA class after controlling for the path dependence behavior. The last round chosen alternative plays a significant role in regret generation with correct signs. Note that ANA models that do not account for path dependence—RUM-ANA and G'-RRM-ANA—indicate that ANA behavior emerges starting from the second or the third choice set. However, after controlling for path dependence behavior, ANA behavior no longer persists. β^l for all the five attributes are significantly identified with correct signs. Meanwhile, *Fall* is correctly and significantly identified for all three positions, i.e., $\beta^h_{fall}, \beta^{sq}_{fall}, and\ \beta^l_{fall}$. The findings above imply that it is not that respondents gradually lost attention or some attributes are not important, but that respondents gradually shifted their RPs to process each attribute and alternative. This changing pattern of ANA behavior across choice sets manifests the importance of accounting for the path dependence behavior in discrete choice modeling. Attributes can be mistakenly interpreted as insignificant when they are actually important if the actual underlying decision rule is not accounted for.

Finally, I found that the statistical performances of the three models—RUM, G'-RRM, and P-RRM—do not change after accounting for ANA behavior. The likelihood value, AIC, and

BIC of ANA models all stay basically the same as the models without controlling for ANA behavior. This again justifies the unnecessity of controlling for ANA behavior.

To conclude, the findings above show that the inferred ANA approach is sensitive to model specification. Imposing model structures that best describe the underlying decision strategies is the prerequisite of correctly identifying ANA behaviors. After path dependence behavior is accounted for, I no longer observed evidence of ANA behavior. Besides, reference dependence behavior is consistent over repeated choices. Decision-makers gradually shift their RP from the current choice set to the previously chosen alternative as they gradually collect information from the path.

Table 4.4. RUM' Estimations with Inferred ANA

Sample	Set = 1, 2, 3, 4		Set = 1		Set = 2		Set = 3		Set = 4	
Class	AA	ANA-Fall	AA	ANA-Fall	AA	ANA-Fall	AA	ANA-Fall	AA	ANA-Fall
β^{h}_{winter}	-0.453***	-0.453***	-0.665***	-0.665***	-0.497***	-0.497***	-0.484***	-0.484***	-0.772***	-0.772***
	(0.0521)	(0.0521)	(0.0766)	(0.0766)	(0.114)	(0.114)	(0.0997)	(0.0997)	(0.136)	(0.136)
β^{h}_{fall}	0.141***	0	-0.0254	0	0.258***	0	0.152***	0	0.0844	0
	(0.0336)	-	(0.0937)	-	(0.101)	-	(0.0953)	-	(0.0805)	-
β^{h}_{side}	-0.361***	-0.361***	-0.206	-0.206	-0.36*	-0.36*	-0.275**	-0.275**	-0.283	-0.283
	(0.102)	(0.102)	(0.165)	(0.165)	(0.192)	(0.192)	(0.185)	(0.185)	(0.111)	(0.111)
$\beta^{h}_{nitrogen}$	1.55***	1.55***	1.42**	1.42**	0.693	0.693	1.39***	1.39***	1.87***	1.87***
	(0.298)	(0.298)	(0.618)	(0.618)	(0.876)	(0.876)	(0.664)	(0.664)	(0.448)	(0.448)
β^{h}_{pay}	0.00826***	0.00826***	0.00652***	0.00652***	0.00764***	0.00764***	0.00818***	0.00818***	0.00931***	0.00931***
	(0.000392)	(0.000392)	(0.001)	(0.001)	(0.000615)	(0.000615)	(0.000796)	(0.000796)	(0.000864)	(0.000864)
β^{sq}_{winter}	-0.366**	-0.366**	-0.793***	-0.793***	-0.459***	-0.459***	-0.266	-0.266	-0.478**	-0.478**
	(0.188)	(0.188)	(0.235)	(0.235)	(0.178)	(0.178)	(0.188)	(0.188)	(0.196)	(0.196)
β^{sq}_{fall}	-0.0537	0	-0.0228	0	0.333	0	-0.219	0	-0.0912	0
	(0.108)	-	(0.187)	-	(0.6)	-	(0.196)	-	(0.127)	-
β^{sq}_{side}	-0.569***	-0.569***	-0.997***	-0.997***	-0.787**	-0.787**	-0.63***	-0.63***	-0.642**	-0.642**
	(0.0757)	(0.0757)	(0.24)	(0.24)	(0.213)	(0.213)	(0.16)	(0.16)	(0.179)	(0.179)
$\beta^{sq}_{nitrogen}$	0.683	0.683	1.07	1.07	1.11	1.11	0.267	0.267	0.53	0.53
	(0.612)	(0.612)	(0.936)	(0.936)	(0.965)	(0.965)	(0.699)	(0.699)	(0.669)	(0.669)
β^{sq}_{pay}	0	0	0	0	0	0	0	0	0	0
	-	-	-	-	-	-	-	-	-	-
β_0	1.2***	1.2***	1.06***	1.06***	1.07***	1.07***	1.12***	1.12***	1.26***	1.26***
	(0.114)	(0.114)	(0.146)	(0.146)	(0.173)	(0.173)	(0.189)	(0.189)	(0.112)	(0.112)
ANA Class Estimations										
Class Par[a]	0[b]	38.7***	0	0.136	0	1.59**	0	33.5***	0	1.3***

Table 4.4 (cont'd)

	-	(0.00000319)	-	(2.12)	-	(0.153)	-	(0.00000116)	-	(0.0000272)
Class Prob	0%	100%	47%	53%	17%	83%	0%	100%	21%	79%
Model Statistics										
l		-4422		-1108		-1109		-1111		-1084
AIC/N		2.06		2.08		2.08		2.09		2.04
BIC/N		2.08		2.14		2.14		2.15		2.09
N		4300		1075		1075		1075		1075

a. Latent class parameter s in Equ (6).
b. Latent class parameter, i.e., s, for the all attributes attended (AA) class is fixed at zero.

Table 4.5. G'-RRM Estimations with Inferred ANA

Sample	**Set = 1, 2, 3, 4**		**Set = 1**		**Set = 2**		**Set = 3**		**Set = 4**	
Class	AA	ANA-Fall	AA	ANA-Fall	AA	ANA-Fall	AA	ANA-Fall	AA	ANA-Fall
β^{h}_{winter}	0.86***	0.86***	0.704***	0.704***	0.229*	0.229*	1.01***	1.01***	0.611***	0.611***
	(0.158)	(0.158)	(0.127)	(0.127)	(0.128)	(0.128)	(0.271)	(0.271)	(0.293)	(0.293)
β^{h}_{fall}	-0.38***	0	-0.119	0	1.12	0	-2.04	0	8.66	0
	(0.119)	-	(0.288)	-	(1.8)	-	(2.45)	-	(24.26)	-
β^{h}_{side}	-0.545***	-0.545***	-0.618***	-0.618***	-0.192	-0.192	-1.07***	-1.07***	-0.723***	-0.723***
	(0.116)	(0.116)	(0.11)	(0.11)	(0.13)	(0.13)	(0.11)	(0.11)	(0.0874)	(0.0874)
$\beta^{h}_{nitrogen}$	1.92***	1.92***	-0.811	-0.811	1.96***	1.96***	3.29***	3.29***	3.21***	3.21***
	(0.188)	(0.188)	(0.561)	(0.561)	(0.453)	(0.453)	(0.484)	(0.484)	(0.363)	(0.363)
β^{h}_{pay}	0.0075***	0.0075***	0.00616***	0.00616***	0.00614***	0.00614***	0.00815***	0.00815***	0.00846***	0.00846***
	(0.00037)	(0.00037)	(0.000732)	(0.000732)	(0.000586)	(0.000586)	(0.000577)	(0.000577)	(0.000679)	(0.000679)
β^{sq}_{winter}	-1.98***	-1.98***	-2.03***	-2.03***	-1.84***	-1.84***	-2.24***	-2.24***	-1.88***	-1.88***
	(0.199)	(0.199)	(0.209)	(0.209)	(0.237)	(0.237)	(0.323)	(0.323)	(0.373)	(0.373)
β^{sq}_{fall}	-0.132	0	0.15	0	6.88	0	10	0	-10	0
	(0.173)	-	(0.512)	-	(10.3)	-	(1.80e+308)	-	(1.80e+308)	-
β^{sq}_{side}	-1.8***	-1.8***	-1.77***	-1.77***	-1.49***	-1.49***	-2.01***	-2.01***	-1.72***	-1.72***
	(0.0916)	(0.0916)	(0.157)	(0.157)	(0.226)	(0.226)	(0.186)	(0.186)	(0.138)	(0.138)
$\beta^{sq}_{nitrogen}$	5.52***	5.52***	0.734	0.734	9.51***	9.51***	7.52***	7.52***	5.96***	5.96***
	(0.234)	(0.234)	(0.731)	(0.731)	(0.808)	(0.808)	(0.563)	(0.563)	(0.659)	(0.659)
β^{sq}_{pay}	7.03***	7.03	6.39**	6.39**	5.47***	5.47***	3.05***	3.05***	2.94***	2.94***
	(2.97)	(2.97)	(3.40)	(3.40)	(0.0786)	(0.0786)	(0.0741)	(0.0741)	(0.0713)	(0.0713)
β_0	-1.26***	-1.26***	-0.862***	-0.862***	-1.28***	-1.28***	-1.27***	-1.27***	-1.45***	-1.45***
	(0.0539)	(0.0539)	(0.0952)	(0.0952)	(0.101)	(0.101)	(0.0935)	(0.0935)	(0.0953)	(0.0953)
ANA Class Estimations										
Class Par[a]	0[b]	21.7***	0	32.2***	0	48.5***	0	2.45**	0	33.7***
	-	(1.12)	-	(0.0153)	-	(0.0183)	-	(1.27)	-	(0.158)

Table 4.5 (cont'd)

Class Prob	0%	100%	0%	100%	0%	100%	8%	92%	0%	100%
Model Statistics										
$\hat{\mathcal{L}}$	-4410		-1123		-1066		-1083		-1072	
AIC/N	2.06		2.11		2.01		2.04		2.02	
BIC/N	2.07		2.17		2.06		2.09		2.07	
N	4300		1075		1075		1075		1075	

a. Latent class parameter s in Equ (6).
b. Latent class parameter, i.e., s, for the all attributes attended (AA) class is fixed at zero.

Table 4.6. P-RRM Estimations with Inferred ANA

Sample	**Set = 2, 3, 4**		**Set = 2**		**Set = 3**		**Set = 4**	
Class	AA	ANA-Fall	AA	ANA-Fall	AA	ANA-Fall	AA	ANA-Fall
β^{h}_{winter}	1.33***	1.33***	1.15***	1.15***	1.8***	1.8***	1.27***	1.27***
	(0.169)	(0.169)	(0.143)	(0.143)	(0.217)	(0.217)	(0.448)	(0.448)
β^{h}_{fall}	-1***	0	-1.05***	0	-1.05***	0	-0.997***	0
	(0.0749)	-	(0.14)	-	(0.138)	-	(0.148)	-
β^{h}_{side}	0.167	0.167	0.251	0.251	0.11	0.11	0.283*	0.283*
	(0.111)	(0.111)	(0.183)	(0.183)	(0.249)	(0.249)	(0.154)	(0.154)
$\beta^{h}_{nitrogen}$	0.243	0.243	-0.199	-0.199	-0.0288	-0.0288	0.115	0.115
	(0.259)	(0.259)	(0.592)	(0.592)	(0.516)	(0.516)	(0.104)	(0.104)
β^{h}_{pay}	0.00336***	0.00336***	0.00137	0.00137	0.00354***	0.00354***	0.00478***	0.00478***
	(0.000693)	(0.000693)	(0.00129)	(0.00129)	(0.000983)	(0.000983)	(0.000898)	(0.000898)
β^{sq}_{winter}	-1.5***	-1.5***	-1.56***	-1.56***	-1.88***	-1.88***	-1.14	-1.14
	(0.301)	(0.301)	(0.291)	(0.291)	(0.383)	(0.383)	(0.978)	(0.978)
β^{sq}_{fall}	-0.0611	0	-0.0297	0	-0.0265	0	-0.0246	0
	(0.106)	-	(0.208)	-	(0.158)	-	(0.128)	-
β^{sq}_{side}	-1.4***	-1.4***	-1.04***	-1.04***	-1.85***	-1.85***	-1.39***	-1.39***
	(0.119)	(0.119)	(0.29)	(0.29)	(0.21)	(0.21)	(0.167)	(0.167)
$\beta^{sq}_{nitrogen}$	2.17*	2.17*	6.14***	6.14***	1.55	1.55	0.27	0.27
	(1.27)	(1.27)	(1.19)	(1.19)	(2.66)	(2.66)	(0.251)	(0.251)
β^{sq}_{pay}	5.32***	5.32***	7.53	7.53	3.66***	3.66***	2.63***	2.63***
	(0.0959)	(0.0959)	(1.80e+308)	(1.80e+308)	(0.193)	(0.193)	(0.107)	(0.107)
β^{l}_{winter}	-2.44***	-2.44***	-2.14***	-2.14***	-2.68***	-2.68***	-2.44***	-2.44***
	(0.111)	(0.111)	(0.143)	(0.143)	(0.207)	(0.207)	(0.245)	(0.245)
β^{l}_{fall}	-1.96***	0	-2.38***	0	-2.18***	0	-1.67***	0
	(0.177)	-	(0.186)	-	(0.217)	-	(0.269)	-
β^{l}_{side}	-2.4***	-2.4***	-2.27***	-2.27***	-2.4***	-2.4***	-2.35***	-2.35***

Table 4.6 (cont'd)

	(0.114)	(0.114)	(0.232)	(0.232)	(0.22)	(0.22)	(0.225)	(0.225)
$\beta^{l}_{nitrogen}$	0.506	0.506	1.29	1.29	1.0525	1.0525	0.264	0.264
	(0.838)	(0.838)	(1.03)	(1.03)	(0.915)	(0.915)	(0.424)	(0.424)
β^{l}_{pay}	0.0149***	0.0149***	0.0164***	0.0164***	0.0155***	0.0155***	0.0162***	0.0162***
	(0.00129)	(0.00129)	(0.00185)	(0.00185)	(0.00211)	(0.00211)	(0.00156)	(0.00156)
β_0	-1.35***	-1.35***	-1.37***	-1.37***	-1.22***	-1.22***	-1.55***	-1.55***
	(0.0688)	(0.0688)	(0.116)	(0.116)	(0.0948)	(0.0948)	(0.0948)	(0.0948)
ANA Class Estimations								
Class Par[a]	0[b]	-25.3***	0	-0.53	0	-59.3***	0	-38.8***
	-	(0.00000126)	-	(0.83)	-	(0.00000588)	-	(0.00000257)
Class Prob	100%	0%	63%	37%	100%	0%	100%	0%
Model Statistics								
$\hat{\mathcal{L}}$	-2959		-985		-965		-987	
AIC/N	1.85		1.86		1.83		1.88	
BIC/N	1.88		1.94		1.91		1.95	
N	3225		1075		1075		1075	

a. Latent class parameter s in Equ (6).
b. Latent class parameter, i.e., s, for the all attributes attended (AA) class is fixed at zero.

4.5. Conclusions

There is increasing literature incorporating behavioral strategies into discrete choice modeling. This study discusses how the respondents in a DCE use these behavioral strategies to make decisions, how such strategies evolve over repeated choice tasks, and how failing to identify these strategies leads to confounding conclusions.

One behavioral strategy developed in the DCE literature is ANA. Respondents strategically or unconsciously ignore some attributes in a choice task to reduce cognitive burdens of decision making. Another behavioral strategy is RM. Respondents use RP to cancel out shared attributes and make choices depending on the net gain or loss from the bilateral comparisons between alternatives. The asymmetric weights on gain and loss leave some attributes of certain alternatives appearing to be non-attended. This paper, for the first time, discusses the relation of RM with ANA.

The empirical analysis is based on a DCE survey conducted in the Midwest states of Michigan, Iowa, and Indiana on farmers' WTA of a government-paid fertilizer management program. This is among the first few literatures investigating RM or ANA behaviors in a WTA choice scenario as well as in environmental economics. However, the findings have general implications in fields outside the environmental economics literature. In addition, even though the proposed government program in the survey provides public benefits, the adoption of this program from the perspective of survey respondents, i.e., corn growers, is still an individual decision. So, the behavior identified in this paper will also apply to other private good decision-making scenarios.

The first finding is that decision making is choice set composition as well as path dependent. The hypothetical alternatives, the information carried in the SQ alternative, and the last round's chosen alternative can all play as the RPs of decision making. Among these three, the last round's chosen alternative is the most important. When the decision-makers are first exposed to the choice set where there is no last round of information delivered, the SQ is the most important RP. As survey respondents gradually collect information over repeated choices, the decision-making shifts to path dependence. That is, decision making evolves from the current choice set dependent to across choice sets dependent. Moreover, the RPs are attributes specific. For instance, *Winter* and *Fall* contribute to regret generation in all referred scenarios, but Side only contributes to regret in the SQ and the last round chosen referred scenarios.

To continue, although I found evidence of ANA behavior based on RUM' and G'-RRM specifications, I no longer observed this behavior once I allowed respondents to condition their current decision on their choices in the previous choice scenario(s) in the extended RRM model, i.e, P-RRM. For instance, the RUM' model shows significant ANA behavior starting from the choice set 2. This inferred ANA behavior can be interpreted as reduced attention over repeated choices due to the fatigue effect, as discussed in previous ANA literature. However, after I accounted for the last round's chosen alternative in choice modeling, ANA turns no longer significant. This implies that the attributes that are otherwise interpreted to be non-attended might be, in fact, attended in a path-dependent regret minimization manner. Thus, ANA behavior can be the result of model misspecification rather than a true decision strategy.

Finally, this study suggests that P-RRM can be a guiding choice in DCE modeling. I showed that the reference-dependent regret minimization model matches respondent behavior better than RUM'. Meanwhile, P-RRM captures the behavior strategies that are otherwise identified as ANA in a more informative manner. More importantly, this reference-dependent behavior brings a new perspective to evaluate the incentive compatibility property of the DCE method. Discrete choice researchers need to account for the across choice sets dependent decision behaviors in the DCE survey design. Otherwise, the preference estimation from the DCE would be survey design dependent and cannot be adapted to general decision-making predictions.

There are several issues left with future discussions. First, we need to be cautious that these conclusions are based on an experimental study. Whether the decision-makers adopt similar decision strategies in a real choice scenario remains further examination. Second, the rejection of the ANA strategy in favor of the path-dependent RM strategy is built on a four-choice sets survey with five attributes. Whether there exists an ANA behavior in a survey that includes more choice tasks and/or more attributes remains further investigation. It is also worth mentioning that the conclusions are based on an ECLC model, which restricts the coefficients of non-attended attributes to be zeros. It is possible that the non-attended class's attributes have discounted but non-zero weights. Whether survey respondents use ANA strategies and under what circumstance they use these strategies are left for further research. Last, among the information gained from the previous choice sets, I defined the last round's chosen alternative as the RP. Future work is needed to examine the role of other previously delivered information.

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CHAPTER 5. CONCLUSIONS

As global nitrogen fertilizer use has increased dramatically in the past decades, and most crops only take a small proportion of the nitrogen applied, nitrogen leakage from the farming system has brought significant ecological consequences. CA practices and tools have been developed to reduce nitrogen leakage, but the adoption rates are strikingly low. For instance, agronomists have developed three corn growing CA practices, i.e., coving crops in the winter, forbidding applying fertilizer in the fall, and side-dressing fertilizer, to effectively reduce nitrogen usage by up to 50% without affecting yields. However, according to this thesis's survey conducted among Midwest corn growers, only 11%, 85%, and 32% of corn growers, respectively, have applied each of the three practices in at least one of the past three years. A policy to incentivize CA adoption is needed to fill the gap between social benefits and farmers' inputs associated with CA adoption. To guide policy design, this thesis discusses farmers' CA adoption decisions in a paid-to-participate program through conducting a DCE.

This thesis finds that payment incentives are critical and effective to encourage CA adoption, and the necessary amount of payment is associated with the difficulty level of adopting each practice. In addition to the payment directly associated with compensating the adoption of each practice, a significant amount of money is needed to compensate farmers' unwillingness to change behaviors from their status quo. Removing the concerns of committing to a CA program, if the concerns are clearly studied, can potentially increase the adoption rate without increasing the policy costs. In addition, payment has its sweet point as well as limitation in incentivizing adoption. As shown in Chapter 3, a small amount of payment can effectively attract "easy" adopters who have experience with the CA practices or are more sensitive to payment; however, a very large amount of payment will still not work well in attracting the last few “hard” adopters, who do not want to commit to a program regardless of how high the payment is. Future researchers can work on solving an optimal policy adoption target to balance the adoption rate, policy cost, and social welfare to improve policy efficiency.

A couple of factors associated with the policy design as well as farmers are found to affect the WTA. For instance, I found that emphasizing the environmental consequences of not taking CA practices works better than emphasizing the benefits and contributions of enrolling in a CA program. Giving farmers the opportunity to delay the decision-making and collect more information can nudge CA adoption effectively compared to forcing farmers to make decisions immediately. A reference number of expected nitrogen savings provided in the policy can also effectively reduce the WTA. Besides, as people use behavioral strategies, i.e., reference dependence, to reduce the cognitive burden of making decisions, when it comes to proposing a policy, a nudge program can be carefully designed and combined with the target program to increase the target program’s adoption rate. In addition to the policy design, targeting the policy to farmers with “willing-to-adopt” characteristics can also play a critical role in increasing policy efficiency.

Going beyond empirical analysis, this thesis investigates the fundamental assumptions of DCE modeling. The DCE modeling traditionally relies on the RUM framework, which assumes rational decision-making. This thesis investigates alternative decision strategies through developing a behavioral decision framework that nests rational decision-making as a special case. An adaptive decision pattern that gradually shifts the reference dependence points is justified in the DCE composed of repeated choice scenarios. This finding sets caveats for constructing DCE modeling without controlling behavioral strategies and inspires future researchers to explore better DCE design and modeling strategies.

As this thesis's decision-making analysis is built on an experimental approach, whether the decision-makers adopt similar decision strategies in the real-world choice scenario remains to be examined further. Meanwhile, even though the behavioral DCE modeling specification makes DCE possible to reveal the preference better, the complexity of modeling introduces parameter identification issues given the limited sample size. This may restrict the application of the behavioral DCE framework concerning the sample size. Lastly, as nudging can effectively increase policy adoption due to the behavioral decision pattern, future research can be carried out on quantifying the impacts of nudging to generate more specific policy suggestions.

APPENDICES

APPENDIX A. G-RRM REDUCES TO RUM WHEN $\boldsymbol{\gamma = 0}$[17]

Given a choice set of J alternatives, the probability of choosing an alternative generated by G-RRM ($\gamma = 0$) with preference parameters $\boldsymbol{\beta}$, and SQ specific constant term parameter $\boldsymbol{\beta_0}$ will be equal to that generated by RUM with preference parameters $\boldsymbol{J\beta}$ and SQ specific constant term parameter $-\boldsymbol{\beta_0}$.

Proof: first when $\gamma = 0$, ln $(\gamma + \exp\left[\beta_m \cdot \left(x_{km} - x_{jm}\right)\right]$= ln $(0 + \exp\left[\beta_m \cdot \left(x_{km} - x_{jm}\right)\right]$=$\beta_m \cdot \left(x_{km} - x_{jm}\right)$. So, the regret of alternative j can be written as:

$$\mathrm{R_j} = \sum\nolimits_m \sum\nolimits_{j \neq k}^{J} \beta_m \cdot \left(x_{km} - x_{jm}\right) + \beta_0 \cdot sq_j$$

$$= \sum\nolimits_m \sum\nolimits_{k \neq j}^{J} \left(\beta_m \cdot x_{km} - \beta_m \cdot x_{jm}\right) + \beta_0 \cdot sq_j$$

$$= \sum\nolimits_m \sum\nolimits_{k \neq j}^{J} \beta_m \cdot x_{km} - (J-1) \sum\nolimits_m \beta_m \cdot x_{jm} + \beta_0 \cdot sq_j$$

$$= \sum\nolimits_m \sum\nolimits_{k=1}^{J} \beta_m \cdot x_{km} - \sum\nolimits_m \beta_m \cdot x_{jm} - (J-1) \cdot \sum\nolimits_m \beta_m \cdot x_{jm} + \beta_0 \cdot sq_j$$

$$= \sum_m \sum_{k=1}^{J} \beta_m \cdot x_{km} - J \cdot \sum_m \beta_m \cdot x_{jm} + \beta_0 \cdot sq_j$$

So, the probability of alternative j is chosen will be:

$$\mathrm{Pr_j} = \frac{exp\left(-R_j\right)}{\sum_{t=1}^{J} \exp(-R_t)}$$

$$= \frac{\exp\left(-\sum_m \sum_{k=1}^{J} \beta_m \cdot x_{km} + J \cdot \sum_m \beta_m \cdot x_{jm} - \beta_0 \cdot sq_j\right)}{\sum_{t=1}^{J} \exp\left(-\sum_m \sum_{k=1}^{J} \beta_m \cdot x_{km} + J \cdot \sum_m \beta_m \cdot x_{tm} - \beta_0 \cdot sq_t\right)}$$

$$= \frac{\exp\left(J \cdot \sum_m \beta_m \cdot x_{jm} - \beta_0 \cdot sq_j\right)}{\sum_{t=1}^{J} \exp\left(J \cdot \sum_m \beta_m \cdot x_{tm} - \beta_0 \cdot sq_t\right)}$$

This probability is equal to that generated by RUM with preference parameters of $\boldsymbol{J\beta}$.

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[17] Chorus, 2014 gives a formal proof of how G-RRM reduces to RUM when γ=0.

APPENDIX B. G'-RRM REDUCES TO RUM WHEN $\boldsymbol{\gamma = 0}$

Given a choice set of J alternatives, the probability of choosing an alternative generated by G'-RRM ($\gamma = 0$) with preference parameters $\boldsymbol{\beta^{sq}}, \boldsymbol{\beta^{h}}$ and SQ specific constant term parameter $\boldsymbol{\beta_0}$ will be equal to that generated by RUM with preference parameters $(\boldsymbol{J-1})\boldsymbol{\beta^{h}} + \boldsymbol{\beta^{sq}}$, and SQ specific constant term parameter $-\boldsymbol{\beta_0}$.

Proof: first, when $\gamma = 0$, $\ln\left(\gamma + exp\left[\beta_m^h \cdot \left(x_{km} - x_{jm}\right)\right]\right) = \beta_m^h \cdot \left(x_{km} - x_{jm}\right)$ $where\ k = 1\ or\ 2$, $\ln\left(\gamma + \exp\left[\beta_m^{sq} \cdot \left(x_{sqm} - x_{jm}\right)\right]\right) = \beta_m^{sq} \cdot \left(x_{sqm} - x_{jm}\right)$. So, the regret of alternative j can be written as:

$$\mathrm{R_j} = \sum\nolimits_{k \neq sq\ or\ j} \sum\nolimits_m \beta_m^h \cdot \left(x_{km} - x_{jm}\right) + \sum\nolimits_m \beta_m^{sq} \cdot \left(x_{sqm} - x_{jm}\right) + \beta_0 \cdot sq_j$$

$$= \sum\nolimits_{k \neq sq\ or\ j} \sum\nolimits_m \beta_m^h \cdot x_{km} + \sum\nolimits_m \beta_m^{sq} \cdot x_{sqm} - \sum\nolimits_{k \neq sq\ or\ j} \sum\nolimits_m \beta_m^h \cdot x_{jm} - \sum\nolimits_m \beta_m^{sq} \cdot x_{jm} + \beta_0 \cdot sq_j$$

$$= \sum\nolimits_{k \neq sq} \sum\nolimits_m \beta_m^h \cdot x_{km} + \sum\nolimits_m \beta_m^{sq} \cdot x_{sqm} - \sum\nolimits_m \left(\sum\nolimits_{k \neq sq} \beta_m^h \cdot x_{jm} + \beta_m^{sq} \cdot x_{jm}\right) + \beta_0 \cdot sq_j$$

$$= \sum\nolimits_{k \neq sq} \sum\nolimits_m \beta_m^h \cdot x_{km} + \sum\nolimits_m \beta_m^{sq} \cdot x_{sqm} - \sum\nolimits_m \left((J-1)\beta_m^h + \beta_m^{sq}\right) \cdot x_{jm} + \beta_0 \cdot sq_j$$

So, the probability of alternative j is chosen will be:

$$\mathrm{Pr_j} = \frac{exp\left(-R_j\right)}{\sum_{j=1}^{J} \exp\left(-R_j\right)}$$

$$= \frac{\exp\left(-\sum_{k \neq sq} \sum_m \beta_m^h \cdot x_{km} - \sum_m \beta_m^{sq} \cdot x_{sqm} + \sum_m \left((J-1)\beta_m^h + \beta_m^{sq}\right) \cdot x_{jm} - \beta_0 \cdot sq_j\right)}{\sum_{t=1}^{J} \exp\left(-\sum_{k \neq sq} \sum_m \beta_m^h \cdot x_{km} - \sum_m \beta_m^{sq} \cdot x_{sqm} + \sum_m \left((J-1)\beta_m^h + \beta_m^{sq}\right) \cdot x_{tm} - \beta_0 \cdot sq_t\right)}$$

$$= \frac{\exp\left(\sum_m \left((J-1)\beta_m^h + \beta_m^{sq}\right) \cdot x_{jm} - \beta_0 \cdot sq_j\right)}{\sum_{t=1}^{J} \exp\left(\sum_m \left((J-1)\beta_m^h + \beta_m^{sq}\right) \cdot x_{tm} - \beta_0 \cdot sq_t\right)}$$

This probability is equal to that generated by RUM with preference parameters $(\boldsymbol{J-1})\boldsymbol{\beta^{h}} + \boldsymbol{\beta^{sq}}$, and SQ specific constant term parameter $-\boldsymbol{\beta_0}$.

APPENDIX C. P-RRM REDUCES TO RUM WHEN $\gamma = 0$

Given a choice set of J alternatives, the probability of choosing an alternative generated by P-RRM ($\gamma = 0$) with preference parameters $\boldsymbol{\beta^l}$, $\boldsymbol{\beta^{sq}}, \boldsymbol{\beta^h}$ and SQ specific constant term parameter $\boldsymbol{\beta_0}$ will be equal to that generated by RUM with preference parameters $(\boldsymbol{J-1})\boldsymbol{\beta_m^h} + \boldsymbol{\beta_m^{sq}} + \boldsymbol{\beta_m^l}$, and SQ specific constant term parameter $-\boldsymbol{\beta_0}$.

Proof: first, when $\gamma = 0$, $\ln\left(\gamma + exp\left[\beta_m^h \cdot (x_{ikm} - x_{ijm})\right]\right) = \beta_m^h \cdot (x_{km} - x_{jm})$, $\ln(\gamma + \exp\left[\beta_m^{sq} \cdot (x_{sqm} - x_{jm})\right] = \beta_m^{sq} \cdot (x_{sqm} - x_{jm})$, and $\ln\left(\gamma + exp\left[\beta_m^l \cdot (x_{lm} - x_{jm})\right]\right) = \beta_m^l \cdot (x_{lm} - x_{jm})$, . So, the regret of alternative j can be written as:

$$
\begin{aligned}
\mathrm{R_j} &= \sum_{k\neq sq}\sum_m \beta_m^h \cdot (x_{km} - x_{jm}) + \sum_m \beta_m^{sq} \cdot (x_{sqm} - x_{jm}) + \sum_m \beta_m^l \cdot (x_{lm} - x_{jm}) + \beta_0 \cdot sq_j \\
&= \sum_{k\neq sq}\sum_m \beta_m^h \cdot x_{km} + \sum_m \beta_m^{sq} \cdot x_{sqm} + \sum_m \beta_m^l \cdot x_{lm} - \sum_{k\neq sq}\sum_m \beta_m^h \cdot x_{jm} - \sum_m \beta_m^{sq} \cdot x_{jm} \\
&\qquad - \sum_m \beta_m^l \cdot x_{jm} + \beta_0 \cdot sq_j \\
&= \sum_{k\neq sq}\sum_m \beta_m^h \cdot x_{km} + \sum_m \beta_m^{sq} \cdot x_{sqm} + \sum_m \beta_m^l \cdot x_{lm} - \sum_m \left(\sum_{k\neq sq} \beta_m^h \cdot x_{jm} + \beta_m^{sq} \cdot x_{jm} + \beta_m^l \cdot x_{jm}\right) \\
&\qquad + \beta_0 \cdot sq_j \\
&= \sum_{k\neq sq}\sum_m \beta_m^h \cdot x_{km} + \sum_m \beta_m^{sq} \cdot x_{sqm} + \sum_m \beta_m^l \cdot x_{lm} - \sum_m ((J-1)\beta_m^h + \beta_m^{sq} + \beta_m^l) \cdot x_{jm} + \beta_0 \cdot sq_j
\end{aligned}
$$

So, the probability of alternative j is chosen will be:

$$
\begin{aligned}
\mathrm{Pr_j} &= \frac{exp(-R_j)}{\sum_{j=1}^J \exp(-R_j)} \\
&= \frac{\exp\left(-\sum_{k\neq sq}\sum_m \beta_m^h \cdot x_{km} - \sum_m \beta_m^{sq} \cdot x_{sqm} - \sum_m \beta_m^l \cdot x_{lm} + \sum_m ((J-1)\beta_m^h + \beta_m^{sq} + \beta_m^l) \cdot x_{jm} - \beta_0 \cdot sq_j\right)}{\sum_{t=1}^J \exp\left(-\sum_{k\neq sq}\sum_m \beta_m^h \cdot x_{km} - \sum_m \beta_m^{sq} \cdot x_{sqm} - \sum_m \beta_m^l \cdot x_{lm} + \sum_m ((J-1)\beta_m^h + \beta_m^{sq} + \beta_m^l) \cdot x_{tm} - \beta_0 \cdot sq_t\right)} \\
&= \frac{\exp\left(\sum_m ((J-1)\beta_m^h + \beta_m^{sq} + \beta_m^l) \cdot x_{jm} - \beta_0 \cdot sq_j\right)}{\sum_{t=1}^J \exp\left(\sum_m ((J-1)\beta_m^h + \beta_m^{sq} + \beta_m^l) \cdot x_{tm} - \beta_0 \cdot sq_t\right)}
\end{aligned}
$$