Enrollment Restrictions and the Adoption of Conservation Practices in the U.S. Corn Belt

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Abstract

Payments for environmental services (PES) can incentivize the adoption of conservation practices. However, concerns arise regarding limited additional environmental benefits when the prevailing cost-share programs could pay for practices that would be adopted without financial incentives. To reduce the problem of non-additionality, we explore the impact of enrollment restrictions in PES programs to improve the design of conservation programs. Using a mixed-mode survey of 424 farmer respondents in the Boone and North Raccoon River watersheds in Iowa, we examine the influence of enrollment restrictions on farmers' preferences for conservation practices using a discrete choice experiment and a random parameters logit model. Our findings indicate prospective farmer participants favor conservation contracts with enrollment requirements on new, additional practices. We evaluate three contracts with per-acre payments similar to those in Iowa's Environmental Quality Incentives Program, comparing willingness-to-accept with and without specific enrollment requirements. Simulation outcomes reveal decreased mean willingness-to-accept for cover crops, no-till, and split nitrogen application contracts—by 55%, 69%, and 52% – with enrollment restrictions, respectively. In addition, participation supply curves also demonstrate higher enrollment, though this is especially true for low compensation levels, and enrollment gains shrink as the proportion of farmers who are ineligible for the conservation contract rises.

Keywords: Agri-environmental policy; Enrollment restrictions; Additionality; Conservation practices; Willingness-to-accept; Choice experiment

JEL Codes: Q53, Q15, Q58

Introduction

Agricultural production contributes significantly to non-point source pollution in surface waterways throughout the United States. It is estimated that agricultural crop and livestock production accounts for 92% of the total nitrogen (N) and 80% of the total phosphorus (P) loadings in Iowa waterways (IDALS and CALS, 2017), leading to dead zones and harmful algal blooms in the Gulf of Mexico (Rabalais et al., 2007; Diaz and Rosenberg, 2008; Scavia et al., 2017). Achieving a goal of agricultural sustainability in the United States relies largely on farmers' voluntary conservation efforts (Reimer, 2015). Agricultural conservation practices are those farming operations designed with the goal to improve environmental performance with respect to soil health, water quality, air quality, wildlife habitat, and greenhouse gas emissions. U.S. federal and local governments have developed multiple conservation programs that provide cost shares or subsidies to incentivize farmers to adopt key conservation practices. These programs, especially those funded by U.S. Department of Agriculture (USDA), such as the Environmental Quality Incentive Program (EQIP), Conservation Stewardship Program (CSP), and Conservation Reserve Enhancement Program (CREP), are leading policy instruments for curbing nutrient loading. Unlike the Conservation Reserve Program (CRP) that incentivizes retirement of environmentally sensitive cropland from production, programs like EQIP or CSP are dubbed as the working lands program that provides financial supports for conservation practices during or after crop production. Between 2000 and 2020, USDA funding for agricultural conservation programs has increased from $3.5 billion to more than $6.5 billion annually, with working lands programs such as EQIP capturing a larger share (U.S. Department of Agriculture, Economic Research Service., 2022).

However, researchers have long been concerned about the effectiveness of conservation payments (Fleming et al., 2018; Jack et al., 2008; Duke et al., 2013). Lack of additionality ('Paying for Nothing') may well be one of the most serious design problems in current payments for ecosystem services (PES) programs (Howard, 2020; Bottazzi et al., 2018; Engel et al., 2016). The effectiveness of conservation payments depends partly on whether they induce a change in farmers' behaviors (Fleming et al., 2018). From an environmental externality perspective, when a voluntary incentive contract induces a behavioral change that leads to improved environmental quality, these changes are described as "additional" (Alberini and Segerson, 2002). If the supported practice, and improvement to environmental quality, would have been realized without the payment, no net environmental gain should be attributed to the payment. In recent years, this issue has received increasing attention as low additionality greatly compromises the effectiveness of conservation programs (Plastina et al., 2018; Mezzatesta et al., 2013; Cisneros et al., 2022). In a government conservation program, payments made for non-additional practices expend budget resources but do not contribute to improving environmental quality (Pannell and Claassen, 2020; Mason and Plantinga, 2013). In an offset credit market, without additionality, carbon credits could be awarded for projects that would have happened anyway, even without the incentive of receiving credits. This would undermine the effectiveness of the carbon credit system in driving real emissions reductions (Ruseva et al., 2017). Furthermore, over a dozen non-governmental organizations (NGOs) and private company initiatives are offering farmers payments for the generation of agricultural carbon credits via adoption of conservation practices, and all programs have additionality restrictions that require new, additional practices as opposed to existing practices (Plastina and Wongpiyabovorn, 2021).

It is challenging to completely eliminate non-additionality in conservation payment programs (Horowitz and Just, 2013; Mason and Plantinga, 2013; Fleming et al., 2018). To address this, Claassen et al. (2014), for example, proposes prioritizing practices that are less likely to be implemented without payment support. However, this may not be cost-effective if these practices are more costly or produce fewer environmental benefits. Furthermore, Alpizar et al. (2013) design three payment selection rules based on environmental benefit, additionality, and reward, respectively, and only find significantly increased contributions for an additionality rule that offers incentives to those with relatively low contributions. In the context of a carbon credit market, Vegh and Murray (2020) highlights the importance of an additionality principle, which serves as a cornerstone to guarantee the authenticity of emissions reductions. The additionality principle ensures that issued credits or allowances are exclusively granted for emissions reductions that wouldn't have taken place without the market incentive. The principle not only ensures market transparency but also stimulates innovation by compelling participants to adopt practices they otherwise might not have embraced.

In practice, enrollment restrictions in conservation programs refer to criteria or conditions set by policymakers to determine the eligibility of participants for these programs. These restrictions are designed to target specific groups or individuals who have not yet adopted certain conservation practices, with the aim of encouraging additional adoption beyond existing practices. By imposing enrollment restrictions, the government seeks to ensure that the program's benefits are directed toward those who need the most encouragement to adopt conservation practices. For example, both EQIP and CSP provide financial assistance for new practice adoption. EQIP extends assistance by covering up to 75% of the USDA-estimated cost for new adoption through cost-sharing, and CSP provides support amounting to 10% of this cost in the form of Additional Activity Payments (AAPs) (Wongpiyabovorn and Plastina, 2023). Ideally, enrollment restrictions disqualify potential applicants whose enrollment would be costly to the funder but would not generate additional benefits.

It is an open question, however, whether the eligibility requirement will engage, discourage, or have no significant effects on agricultural producers, especially for prospective adopters. From the perspective of neoclassical economics, farmers are assumed to make decisions based on maximizing their utility and profits, irrespective of the program's enrollment criteria. On the other hand, behavioral economics challenges this assumption and suggests that the design of government policy, 'choice architecture' (Thaler and Sunstein, 2009), can trigger specific psychological mechanisms that influence individual's decisions (Thaler and Sunstein, 2009; Oullier et al., 2010). When governments introduce enrollment requirements in conservation programs, it sends a clear message that it aims to target resources toward those who have not yet adopted conservation practices. This signal conveys the government's commitment to achieving additionality, incentivizing new conservation behaviors that go beyond the status quo. Farmers, as potential program participants, may interpret this signal as an indication that the program is designed to maximize environmental benefits by focusing on those who need the most encouragement to adopt sustainable practices.

In the context of governmental signaling, farmers could perceive enrollment criteria as an effective approach to achieve greater conservation outcomes (Darnall and Carmin, 2005). They may believe that the government's commitment to additionality implies better monitoring and enforcement of the program, as well as a more targeted and efficient use of financial resources. This perception of effectiveness may lead farmers to trust that their participation will indeed contribute to significant environmental improvements. Consequently, they are more likely to support and engage in voluntary conservation programs, as demonstrated by Canales et al. (2023), since they perceive the government as a capable and reliable partner in addressing their environmental concerns and needs. In contrast, in scenarios where enrollment requirements are absent, our data shows that some respondents questioned the role of government and expressed their concerns about the inefficiencies in government programs, as reflected by the comments in the questionnaires, such as "We waste too much money on administrative cost. It has gotten out of control, just like everything related to government" and "Less government, less regulations, let invisible hand and free market work."

Moreover, behavioral economics highlights the importance of "social norms" in shaping pro-environmental behavior (Dessart et al., 2019; Allcott, 2011). Additionality requirements can possibly influence potential participants by signaling a collective commitment to conservation efforts. Prospective farmers may conform to these norms and participate in the program to align with the actions of early adopters and community peers. For example, some respondents acknowledged that farmers will adopt more sustainable practices over time as they become more aware of the benefits and as societal norms evolve. One respondent mentioned, “I have seen many changes in my years. I feel others will become common in the future. Hopefully, by choice no government.” Another respondent expressed a similar sentiment, saying, “Expect we will be forced to do these practices in the future...Believe we are learning to apply good stewardship practices with time.” Further, enrollment restrictions can create a sense of competition among farmers for limited program slots. The competitive nature of restricted programs may encourage more farmers to participate to secure a spot, as they perceive the opportunity as valuable and exclusive. This increased competition may result in a “bandwagon effect” (Rohlfs, 2003), where farmers anticipate their peers to enroll and feel compelled to follow suit to avoid missing out on potential benefits or incentives. In summary, while a standard view of the farmer as merely a profit-maximizing agent may predict that the existence or absence of enrollment restrictions should have no impact on participation by current non-adopters (who would be eligible in both cases), there are behavioral theories that suggest this prediction is worth exploring.

Using a mixed-mode mail and online survey of 424 farmer respondents residing in the Boone and North Raccoon River watersheds in Iowa, we administer a discrete choice experiment where farmers choose among a set of voluntary conservation contracts. We include a between-subjects treatment where some contracts stipulate enrollment requirements while others do not. We then estimate a random parameters logit model that both relaxes the independence of irrelevant alternatives (IIA) assumption in other choice models and allows for preference heterogeneity on unobservables (Train, 2009). This model provides a framework to test whether enrollment restrictions influence farmer behavioral responses. In the model, we allow the required practice attributes of a contract and alternative-specific constants (ASCs) to differ by our exogenously varied inclusion/exclusion of enrollment restrictions. We further use parameter estimates to uncover farmer-specific minimum willingness-to-accept (WTA) and participation supply curves for specific conservation contracts to assess the implications of introducing enrollment restrictions.

Our results show that farmers generally dislike adding conservation practices on their fields. More importantly, the coefficient on the status quo ASC is positive for baseline contracts (i.e., contracts without enrollment restrictions) and significantly negative for enrollment-restricted contracts. This implies that prospective adopters are much more likely to enroll in a contract when told the contract contains enrollment requirements. We then conduct six different policy simulations comparing WTA and participation supply curves of a baseline program to an enrollment-restricted program. We find that enrollment-restricted contracts reduce estimated WTAs substantially. Similarly, predicted participation rates are significantly higher in enrollment-restricted contracts, despite the fact that a portion of farmers are ineligible to enroll. This suggests that, under the right circumstances, enrollment requirements can be effective tools to increase program participation rates for a target population. This issue is even more important as many NGOs and private companies use some form of enrollment restrictions or additionality requirements in their carbon credits programs.

This study makes at least two important contributions to the literature of agri-environmental policy design and behavioral economics. First, this study extends the limited research on the design of enrollment criteria in agricultural conservation programs. In recent years, a growing literature has emphasized additionality and baseline eligibility settings in carbon offset markets (Richards and Huebner, 2012; Gren and Aklilu, 2016), but few studies look into additionality-related enrollment requirements for government conservation programs. Most previous work, such as Claassen et al. (2018) and Plastina et al. (2018), focus primarily on estimating additionality in U.S. agricultural conservation programs using propensity score matching while neglecting how to design effective policy tools to alleviate non-additionality.

Second, this paper contributes to understanding farmers' behavioral responses to enrollment-restricted conservation programs. Though Alpizar et al. (2013) find negative spillovers by those who are excluded from a conservation policy, it is still unclear whether the eligibility requirements will engage, discourage, or have no significant effects on prospective enrollees whose eligibility is not impacted by the restrictions. Our results suggest that introducing proper additionality requirements in conservation programs could reduce WTA and increase program participation. Achieving environmental improvements with limited funding is a key challenge for agri-environmental programs (Duke et al., 2013; Messer and Allen III, 2018). Our findings could have important policy implications for the design of agri-environmental payment programs, especially when program budgets are tight.

Data and Survey Design

Survey Design

Following Dillman's Tailored Survey Design framework (Dillman et al., 2014), we designed a mixed-mode online and paper survey of Iowa farmers' conservation practice choices. We sent questionnaires to a sample of 2,400 Iowa farmers purchased from Dynata who reside in the Boone and North Raccoon HUC-8 watersheds, two primary agricultural watersheds in Iowa with substantial crop acreage. Figure 1 presents a map with both the Boone and North Raccoon River watersheds highlighted and overlaying Iowa counties and major cities. Specifically, we drew 1,083 farmers from the Boone River watershed and 1,317 farmers from the North Raccoon River watershed. The sample was screened to include crop farmers who operate at least 100 acres of land.

We conducted one online focus group interview with 14 farmers, as well as an online pilot survey with 20 randomly selected farmers from the Boone and North Raccoon River watersheds. These focus group discussions and pilot survey responses were instrumental in identifying key elements of the choice experiment, especially the three important in-field conservation practices, cover crops, no-till/strip-till, and split N application, the focus in our study. Cover crops are planted in the fall and able to survive the winter to provide soil cover to cultivated cropland that would otherwise be left bare and susceptible to erosion. The live roots of cover crops can absorb excess nutrients from the soil left after the growing season, thus reducing nutrient runoff and leaching into groundwater. Strip-till, a reduced-tillage system that combines no-till and narrow 6–12-inch tilled strips, covers at least 90 percent or more of the soil surface with crop residue after planting, leaving the soil undisturbed from harvest to planting. Strip-till is commonly regarded by focus group participants as comparable to no-till, thus we used "No-Till or Strip-Till (leaving more than 90% residue)" as one of the conservation contract requirements. Split N application is a nutrient management strategy that divides total nitrogen application into two or more treatments to improve N uptake and nutrient efficiency. These practices reduce nutrient loading into waterways (Triana et al., 2021) and potentially reduce emissions of greenhouse gases such as carbon dioxide and nitrous oxide (Preza-Fontes et al., 2022). Indeed, the USDA regards all three practices as "climate-smart practices" (USDA, 2022), and the three practices are internally compatible and can be implemented together to mitigate nutrient loss and enhance soil quality, thereby delivering more environmental benefits.

We administered the survey in two rounds from March 2019 to December 2019. In the first round, we began by sending an invitation letter, which included a $2 cash incentive, with a link to an online survey to 1,800 sampled farmers. In April, we sent a follow-up to non-respondents with a survey packet that included a cover letter, a paper survey, and a postage-paid return envelope. Finally, we mailed a reminder card to non-respondents several weeks after the survey packet. We sent the second survey in December 2019 and January 2020 to a different random sample of 600 farm owner-operators who included 83 in the Boone River watershed and 517 in the North Raccoon River watershed. This second survey questionnaire is identical to the first survey except that we appropriately updated questions regarding past and future management decisions—we updated past management years from 2018 in the first survey to 2019 in the second, and we updated future management years from 2019 in the first survey to 2020 in the second. Data collection for the second survey finished before the onset of COVID-19 restrictions and lockdowns. Of the 2,400 sampled farmers, we classified 420 farmers as ineligible as most reported that they did not intend to operate a farm in the years that were the focus of our survey. Finally, we received 568 completed surveys out of the 1,980 eligible respondents, generating a response rate of 28.7%.

Choice Experiment Design

Before presenting the choice scenario question, respondents were asked to specify the practices they had actually used or intended to use in the current growing season. Based on this information, we characterize farmers who mentioned using any of the three practices as "early adopters," while those who didn't are classified as "future adopters." In the choice experiment section, we presented each respondent with two stated-preference discrete choice questions. These questions asked the respondent to consider a field where runoff is the greatest concern for them and presented them with hypothetical conservation contracts.

We designed two categories of hypothetical programs—an additionality-based program with stipulated enrollment restrictions and a baseline program—and randomly assigned respondents to one group. In the baseline group, each choice scenario asked respondents to choose among three options: two hypothetical conservation contracts and a status quo option of neither contract (Figure 3). The two programs vary in five attributes: length of the contract in years (two or four years); requirement on no-till or strip-till ("not required" or "must be used throughout the length of the contract"); cover crops ("not required" or "must be used throughout the length of the contract"); split N application ("not required" or "must be used throughout the length of the contract"); and annual per-acre payment. We described the payment attribute as an EQIP-style per-acre cost-share, with offered payment levels of \$10/acre, \$40/acre, \$70/acre, \$100/acre, and \$130/acre in our design.

Choice scenarios presented to farmers in the enrollment-restricted group are identical in their number, attribute makeup, and design. They differ, however, in that the survey stated, "the funding is only available to encourage additional, new acres of conservation practices." Restricted programs only support practices that were not already in use by the farmer in the most recent year.[1] Each respondent in the restricted program group views the full set

[1] An enrollment restriction that more precisely excludes non-additional conservation practices would focus on planned implementation of practices in the upcoming year as the basis for exclusion. However, this is difficult to do in practice since farmers could lie about their intentions for the upcoming year. Our focus on past practices to determine enrollment eligibility is more in line with actual enrollment restrictions that exist in this space.

of two conservation contracts in each choice, but is only able to select contracts for which they are eligible (meaning the practices they did not use during the past growing season). There is nuance in the approach to implementing enrollment restriction between online and mail surveys. In the online survey, we filtered out ineligible options based on respondents' answers on used practices. In the mailed version, we prompted respondents to confirm their eligibility for specific practices, drawing from their prior responses about conservation usage. Additionally, we provided reminders to guide them in choosing from eligible options before indicating their contract preferences. Our experiment design includes 20 different choices selected to maximize D-efficiency (Scarpa and Rose, 2008), which we efficiently grouped into 10 choice blocks of two choices each. Because we could phrase each choice block using language for the enrollment restriction group or the unrestricted group, we constructed a total of 20 (10×2) versions of the questionnaire. [2]

Methodology

Discrete Choice Model

The random utility maximization (RUM) model (McFadden, 1974) is widely used to link the deterministic model with a statistical model of human behavior. RUM models posit that an individual chooses the alternative that gives the highest utility among alternatives, and modern variants of the model allow preference parameters to vary from one individual to another, capturing random taste and scale (i.e., error) variation among individuals.

Assume that farmer i faces a choice among J alternatives denoting the two hypothetical conservation contracts and the status quo, $J = \{1, 2, 3\}$, and chooses the alternative that

[2] While every respondent was presented with two choice questions, our sample includes less than two choice responses per respondent. This disparity comes from two sources. First, respondents may have elected to answer only one of the two choice questions. Second, and more common, in the enrollment restriction group there are some choices where farmers were ineligible for both conservation contracts. In these cases, farmers were shown all contracts, but since there was only one viable choice (the status quo alternative), these choices cannot be included in our analysis.

gives the highest utility. The utility, U_{ijt}, that farmer i derives from alternative j in choice situation t is:

$$
\begin{aligned}
U_{ijt} &= V_{ijt} + \epsilon_{ijt} && (1)\\
&= \beta_i' X_{ijt} + \epsilon_{ijt}, && (2)
\end{aligned}
$$

where V_{ijt} is the observable indirect utility from observable attributes of option j; X_{ijt} is a vector of contract attributes and ASCs for alternative j; β_i is a vector of farmer i's latent preference parameters for these attributes; and, ϵ_{ijt} is the error term that captures the unobserved element of the utility with a type-I extreme value distribution. We adopt a random parameters logit (RPL) framework to model unobserved preference heterogeneity, in which each farmer's preference parameter is a draw from a continuous preference distribution with mean μ and standard deviation σ (to be estimated), denoted as $f(\mu, \sigma)$. Under this framework, the probability that farmer i will select alternative j from a set of J alternatives in choice situation t is given by

$$
P_i(j_t) = \frac{e^{V_{ijt}}}{\sum_{j=1}^{J} e^{V_{ijt}}}. \tag{3}
$$

In the choice experiment setting, each individual faces T choices. We define the choice sequence that includes farmer i's choice in each time t as $\mathcal{J} = \{j_1, \ldots, j_T\}$. The joint probability of observing farmer i's choice sequence is given by

$$
\begin{aligned}
P_i(j_1, \ldots, j_T) &= \int_{\beta_i} \prod_{t=1}^{T} P_t(j_t|\beta_i) f(\mu, \sigma) d\beta_i && (4)\\
&= \int_{\beta_i} \prod_{t=1}^{T} \left[\frac{e^{V_{ijt}}}{\sum_{j=1}^{J} e^{V_{ijt}}}\right] f(\mu, \sigma) d\beta_i, && (5)
\end{aligned}
$$

We can consider the unconditional probability as a weighted average of the standard logit probability evaluated at different values of β, with weights derived from the density of

β. Since the integral does not have an analytical solution, we approximate the solution through simulation using the expectation maximization (EM) algorithm (Train, 2009). Each simulation in our EM algorithm uses 500 Halton draws. We assume all attributes and ASCs have a normal preference distribution except for contract payment, which we model as fixed.

To further specify the model, choice attributes include characteristics of the offered contracts and an ASC for the status quo option of rejecting both offered contracts. We allow for heterogeneity in preference for the required practice contract attributes and ASCs by contract type (enrollment-restricted or unrestricted).[3] The following gives the observable indirect utility for farmer i from contract j:

$$\begin{aligned}
V_{ij} = {} & \beta_{i1} Length + \beta_2 Payment + \\
& I(N) * \Big[\beta_{iN3} I(CoverCrop) + \beta_{iN4} I(NoTill) + \beta_{iN5} I(SplitN) + \beta_{iN6} SQ\Big] + \\
& I(R) * \Big[\beta_{iR3} I(CoverCrop) + \beta_{iR4} I(NoTill) + \beta_{iR5} I(SplitN) + \beta_{iR6} SQ\Big],
\end{aligned} \tag{6}$$

where $Length$ indicates the number of years the proposed contract will cover; $NoTill$, $CoverCrop$, and $SplitN$ are indicator variables for whether the proposed contract requires no-till/strip-till, winter cover crops, and split N application, respectively; $Payment$ denotes the annual cost-share payment in the proposed contract; SQ is an indicator variable for the status quo ASC; and, $I(R)$ and $I(N)$ are indicator variables for whether the choice involved contracts designed with and without enrollment restrictions, respectively.

Welfare Estimates and Policy Simulations

We use our discrete choice model estimates to conduct a counterfactual analysis, which allows for assessment of policy effectivenss. We model farmers' minimum WTA using compensating variation, which measures the incremental change in income that makes individual i indif-

[3]Models that allow contract length and program payment attributes to vary by enrollment restriction yield virtually identical results to those presented here.

ferent to an exogenous change (Haab and McConnell, 2002). In our study, the compensating variation for a conservation contract is the amount of money paid that leaves a farmer at a utility level equal to the status quo state. Thus, this WTA measure is the minimum amount of money a farmer will accept to opt-in to a program. Using the farmer behavioral model described above, we generate individual-specific preference parameters for each attribute of the conservation contracts (as well as parameters for ASCs). We condition these farmer-specific parameters on farmers' choices in the survey and simulate them using 500 Halton draws to populate preference values for all random contract attributes and ASCs. Using these individual preference parameters, we estimate each farmer's minimum WTA for a specified contract. Let $\widehat{V_{ij}}$ and $\widehat{V_{iSQ}}$ denote the estimated utility of the non-payment attributes of the offered contract and the status quo alternative, respectively, for farmer i. In this setting, the following formula gives the minimum WTA of individual i for program j:

$$WTA_{ij} = -\frac{\widehat{V_{ij}} - \widehat{V_{iSQ}}}{\widehat{\beta_2}}, \tag{7}$$

where $\widehat{\beta_2}$ is the estimated preference parameter on contract payment from Equation 6. When calculating the WTA, the estimated utilities $\widehat{V_{ij}}$ and $\widehat{V_{iSQ}}$ are contingent on the nature of the contracts being examined. Specifically, when evaluating enrollment-restricted contracts, both $\widehat{V_{ij}}$ and $\widehat{V_{iSQ}}$ are computed using the preference parameters corresponding to those restricted attributes. In contrast, for simulations that examine contracts without such enrollment restrictions, the estimated utilities $\widehat{V_{ij}}$ and $\widehat{V_{iSQ}}$ are derived using only the preference parameters for the unrestricted contract attributes.

In the policy simulation, we follow EQIP payment-rate lists and consider six specified conservation contracts where we offer cost-share payments of: \$40/acre for cover crops; \$10/acre for no-till or strip-till; \$9/acre for split N application; \$50/acre for a bundle of cover crops and no-till or strip-till; \$49/acre for a bundle of cover crops and split N application; and, \$19/acre for a bundle of split N application and no-till or strip-till. Each contract requires implementation of the specified practices for four years with offered annual cost-share payments. When simulating responses to cost-share contracts, we assume that any farmer whose estimated WTA is below the offered cost-share payment will accept the contract.

Results

Descriptive Summary

Table 1 presents summary statistics of demographic and socioeconomic characteristics of farmers in baseline and enrollment-restricted groups. We received 568 completed surveys, of which 424 farmers have valid responses for the choice experiment and do not have missing demographics or socioeconomic characteristics. From these 424 responses, 259 received baseline versions of the survey, whereas 165 received enrollment-restricted versions of the survey. Among the respondents, 368 answered two choice questions and 56 answered only one choice question, generating a total of 792 choice cases in the data set. In the sample, 96% of the farmers are male, 40% have a bachelor's degree, and nearly half have an annual gross income over $250,000. The average respondent is 59 years old, has nearly 34 years of farming experience, and owns about 310 acres of farmland. In addition, rented farmland accounts for 64% of operated farmland. Demographics are very similar between the baseline and restricted groups, and t-test results show that the differences are neither economically nor statistically significant.

Table 2 shows farmers' conservation practices used for the previous season. In the questionnaire, before the choice question on hypothetical conservation programs, we asked farmers to indicate which practices they used (or intended to use) on the field during that year's growing season. This question determines eligibility status for a future enrollment-restricted program, as the restricted program only supports practices that were not already in use in the most recent growing season. Table 2 shows that future farmers, who did not use any of the three conservation practices (cover crops, no-till or strip-till, and split N application), account for roughly half of respondents, and early adopters, who used at least one of these practices, account for the other half. If the addtionality-based program could help motivate more future farmers to adopt at least one of these conservation practices, then the program will contribute to generating greater levels of environmental benefits. Among the three practices, there are remarkable differences in the adoption rate. Cover crops are the least popular conservation practice, with only a 14% participation rate. Split N application is the most prevalent and recognized practice—nearly one-third of farmers implement it, which is reasonable considering that split N application can improve N uptake and enhance optimum yields (Du et al., 2019), thus directly influencing farmers' net private benefits. Comparing the baseline and restriction groups, there is no economically or statistically significant difference in the percentages of farmers using cover crops, no-till or strip-till, and split N application. Figure 2 shows a raw data analysis that summarizes farmers' responses to the choice questions. We observe that the take-up rate for the hypothetical program 1 and 2 are 5 and 7 percentage points higher, respectively, than that of the baseline program. Overall, the participation rate of the restricted program has seen an increase of 11 percentage points relative to the baseline program.

Logit Model Regression Results

Table 3 shows the estimation results from our conditional logit (CL) and random parameters logit (RPL) model. In the random parameters logit model, as we expect, program payment has a positive and statistically significant effect on utility, indicating that farmers are more willing to accept a contract with a higher payment rate. Mean coefficient estimates for contract length are negative and statistically significant at the 1% level, suggesting that generally, farmers prefer not to be locked into long-term conservation contracts. There are several things worth noting regarding the estimated coefficients for our conservation practice attributes. First, the estimated mean coefficients for cover crops and no-till/strip-till have statistically significant and negative signs under both contract types, which suggests that on average, Iowa farmers dislike growing cover crops or using no-till/strip-till practices on their field. The estimated mean coefficients for split N application are also negative under both contract types but only statistically significant for restriction contracts. Second, comparing the results under baseline versus restricted programs, the magnitudes of the estimated coefficients on cover crops and split N increase but decrease for no-till/strip-till, though none of these differences are statistically significant.[4] Third, the results also reveal that farmers have a more dispersed taste for cover crops under the restricted contract, which can be seen from the larger standard deviation on cover crops. In general, preference estimates for conservation practice attributes do not appear to differ in a systematic way between restricted and unrestricted respondents.

The largest difference in preferences we find between restricted and baseline contracts is captured by the status quo ASC, which captures the mean utility level of the status quo alternative relative to the conservation contract options. We expect the ASC in the restricted program to be smaller than that of the baseline program, which indicates that farmers are more willing to join a program when they perceive their efforts are indispensable for environmental improvement. From Table 3, the coefficient on ASC is positive for baseline contracts while negative and statistically significant for restricted contracts,[5] which implies that farmers are more likely to agree to a contract when they know enrollment restrictions apply to the program. However, both distributions have large standard deviations, which illustrates farmers' dispersed taste for these programs.

To test whether our findings are robust to other model specifications, we additionally present results from a conditional logit (CL) model with the same set of attributes. The results of the CL model are largely similar and consistent with the RPL model results. However, the CL model assumes that the respondents share the same utility functions, thereby

[4] T-tests with a null hypothesis in which the mean parameter estimate for the conservation practice in restricted programs is equal to the mean parameter estimate in baseline programs yield p values of 0.764, 0.124, and 0.277 for cover crops, no-till/split-till, and split N application, respectively.

[5] The difference between the two means is statistically significant (the p-value for the two-sided hypothesis t-test is 0.009). This evidence helps illustrate that enrollment restrictions play a significant signaling role in farmers' contract choice behavior.

the taste parameters are homogeneous across all farmers in the sample. Previous studies (Broch and Vedel, 2012) show that farmers' preference heterogeneity for agri-environmental contracts is a key aspect to take into account for policy improvements, and this heterogeneity could have a profound influence on the efficacy of program and public policy design (Hudson and Lusk, 2004; Sun et al., 2021).

Additionally, we test for farmer preference heterogeneity based on individual demographics in our survey (presented in Appendix Table A1). In particular, we explore whether preferences for contract payments diverge among farmers with varying farm income levels (high-gross farmers exceeding \$250,000 in annual gross farm sales compared to low-gross farmers) and whether preferences for contract length vary based on the age of the farmer (those over 60 years old vs. those 60 years old or younger). In the RPL model, our results indicate no statistically significant differences in contract length preferences across age groups. However, we identify variations based on farm income. Interestingly, our findings suggest that farmers with higher gross sales exhibit a larger marginal utility of payments compared to their counterparts with lower gross sales, somewhat counterintuitive to our expectations.

Lastly, we examine whether our different findings for restricted and baseline respondents could be driven by sample selection issues, as most early adopters are excluded from the sample in our restriction group but are included in the baseline group. If these early-adopting farmers have different preferences for these programs, their exclusion might be driving some of the differences in groups we attribute to the treatment. To test whether such sample selection is driving our results, we conduct two robustness checks. First, we divide the sample into early and future adopter subsamples (future adopters would be eligible for all contracts in both restricted and baseline groups), and then run both CL and RPL model regressions (see Appendix A—Tables A2 for regression results). Comparing the results from the full sample vs. the future-adopting sample, we find the regression results are quite similar and consistent with each other. As with the full sample, t-tests shows the mean coefficient of *Status-Quo ASC* for the restriction group is economically and statistically different from zero for future adopters (the coefficient is -2.848), while not statistically significant for current adopters (the coefficient is 0.267). This finding also underscores the external validity of our study given that the additionality-based program can be highly effective in incentivizing the targeted population, future adopters, to participate. In the second robustness check, we screen samples to ensure balanced choice alternatives by excluding farmers with any ineligible option, which accounts for 15% (62 farmers) of the full sample, and then conduct the model regressions. In Tables A3, the t-test result shows that the difference between the mean coefficient of *Status-Quo ASC* for the restricted group is again economically and statistically significant (the coefficient is -2.278). These are strong evidence that our findings are not driven by early/future adopter sample selection issues.

Policy Simulation Results

In this section, we examine the results of our policy simulations. All simulated conservation contracts are four years in length, and we consider six different combinations of practices (CC, NT, SN, CC + NT, CC + SN, and NT + SN).[6] In Table 4, we estimate farmers' WTA for each program with and without enrollment restrictions using Equation 7 and the model from Table 3. The reduction percentage of WTA for each program under restriction compared with WTA under no restriction is also shown in the last column of Table 4. In the RPL model, we consider two approaches to generate our WTA estimate. The first approach, in the top panel of Table 4, uses the estimated mean preference parameter values on each random attribute to calculate WTA. The second approach, shown in the bottom panel, uses individual-specific preference parameter estimates generated from our model to estimate farmer-specific WTA values for each contract and then calculates the median WTA in our sample for each contract. The introduction of enrollment restrictions reduces WTA for no-till/strip-till, split N application, and cover crops contracts by a remarkable 55%, 69%, and 52%, respectively. In addition, we can see that the two approaches generate similar WTA

[6]CC denotes cover crops, NT denotes no-till or strip-till, and SN denotes split N application.

values and percentage differences for all contracts, which means that our results are quite robust. We use the estimates from the CL model to conduct a robustness check, as shown in the left part of Table 4. We consistently observe a reduction of approximately 40% to 50% in WTA values for the single practices. We show in Figure 4 the boxplots of WTAs for the simulated contracts. For each contract, either single practice or bundle practices, the restriction group demonstrates a lower WTA than the baseline group. Specifically, we observe a reduction in the median value of WTA of 51%, 65%, and 45% for the CC, NT, and SN contracts, respectively.

Furthermore, we find that the aggregation of WTAs for any two single contracts outweighs that of a bundled contract. For example, the WTA for two separate contracts, CC and NT, about is \$150, while it is \$118 for a bundled contract combining the same practices. This pattern suggests that bundling contracts together can be an effective approach for cost savings. Apart from that, we compare WTA estimates between early and future adopters, as illustrated in Table A4. We observe that future adopters exhibit particularly higher WTAs than early adopters, especially for cover crops. This pattern illustrates the rationale behind their hesitance to embrace conservation practices. In the last column of Table A4, we notice that the additionality requirement significantly reduces the WTAs of cover crops and no-till for future adopters, while having no significant effect for early adopters. This observation underscores the external validity of our findings as an appropriate enrollment requirement has the potential to effectively reduce the WTAs of practice adoption of the targeted audience of prospective enrollees.

Finally, we plot participation supply curves for the same three specified four-year contracts in Figure 5. There are three curves in each plot: the blue curve denotes supply for baseline programs; the red curve is a naive supply curve for programs with enrollment restrictions, which we describe as naive because it focuses on estimated WTA without examining whether the farmer in question is eligible for the contract; and, the green curve (the amended restriction supply curve) uses WTA estimates for enrollment restriction contracts but accounts for the restriction by excluding ineligible early adopters. As an example, if a conservation practice was currently used by 25% of our sample, this amended supply curve could never exceed 75% enrollment at any payment level.

For each curve, given a payment rate, we predict the participation rate in our sample. For example, given an annual cost-share payment of $50/acre for cover crops, we predict that 21% of farmers would enroll in the baseline contract and 40% would enroll in the naive restricted contract. After mediating by the percentage of the sample that is ineligible, which is about 13% for cover crops, our amended restriction supply curve indicates enrollment of about 33%, lower than our naive supply curve but still higher than the supply curve for our baseline contract. For the three practices, when payments are relatively low, the take-up rate for contracts with enrollment restrictions far exceeds the take-up rate for comparable contracts without restrictions. As payments rise, the gap between the two curves narrows, though the rate of this narrowing is principally a function of the proportion of farmers for whom the enrollment restriction is binding. Specifically, in our sample, a much larger share of farmers use split N application, and as one might expect, this translates to enrollment restrictions being less advantageous when it comes to spurring greater levels of enrollment.

Discussions and Conclusion

Using a mixed-mode mail and online survey of 424 farmer respondents in the Boone and North Raccoon River watersheds, we build a discrete choice model and estimate preferences for voluntary conservation programs to examine farmer behavior responses to a new policy design—enrollment restrictions in cost-share programs. Our empirical results demonstrates that farmers are more likely to favor conservation contracts that have specific enrollment requirements aimed at encouraging new or additional practices. This has far-reaching implications for policy design, as it suggests a strategy for increasing the efficacy of conservation programs through well-crafted enrollment restrictions.

Our simulations revealed a notable decrease in the mean willingness-to-accept (WTA) rates for various conservation contracts—cover crops, no-till, and split nitrogen applications—by 55%, 69%, and 52%, respectively, when enrollment restrictions were applied. This outcome suggests a substantial potential for cost savings in implementing conservation practices, making the programs more financially sustainable in the long run. Moreover, we observed that such restrictions led to increased overall program enrollment, although this effect was more pronounced at lower compensation levels and diminished as the pool of eligible farmers decreased.

Overall, our study offers valuable insights for policy-makers, program designers, and stakeholders interested in optimizing the performance of large-scale conservation initiatives. Achieving environmental improvements with limited funding is a key challenge for agri-environmental programs. This is especially true in cases where conservation budgets are tight and the incentivized practices have relatively low adoption rates. Our study fills a research gap by examining the efficacy of enrollment restrictions as a behavioral nudge to guide farmers towards sustainable agriculture, thereby enhancing the performance of agri-environmental programs. However, there is a caveat—the overall effectiveness of enrollment restrictions is influenced by the size of the excluded population as well as the target enrollment goal of the program. It is critical to know the current practice adoption rates at the county and/or watershed level and correspondingly adjust enrollment restrictions in contract design to achieve policy goals. Further, this study does not attempt to measure any dynamic and potentially negative behavioral consequences of enrollment restrictions. If, for example, enrollment restrictions lead to reductions in the voluntary (and uncompensated) adoption of incentivized management practices, the relative merits of enrollment restrictions would be overstated in this analysis. This is an important area of future study, and particularly a future examination of how an enrollment restriction policy can be crafted to minimize these negative behavioral spillovers would be a valuable extension of this current work.

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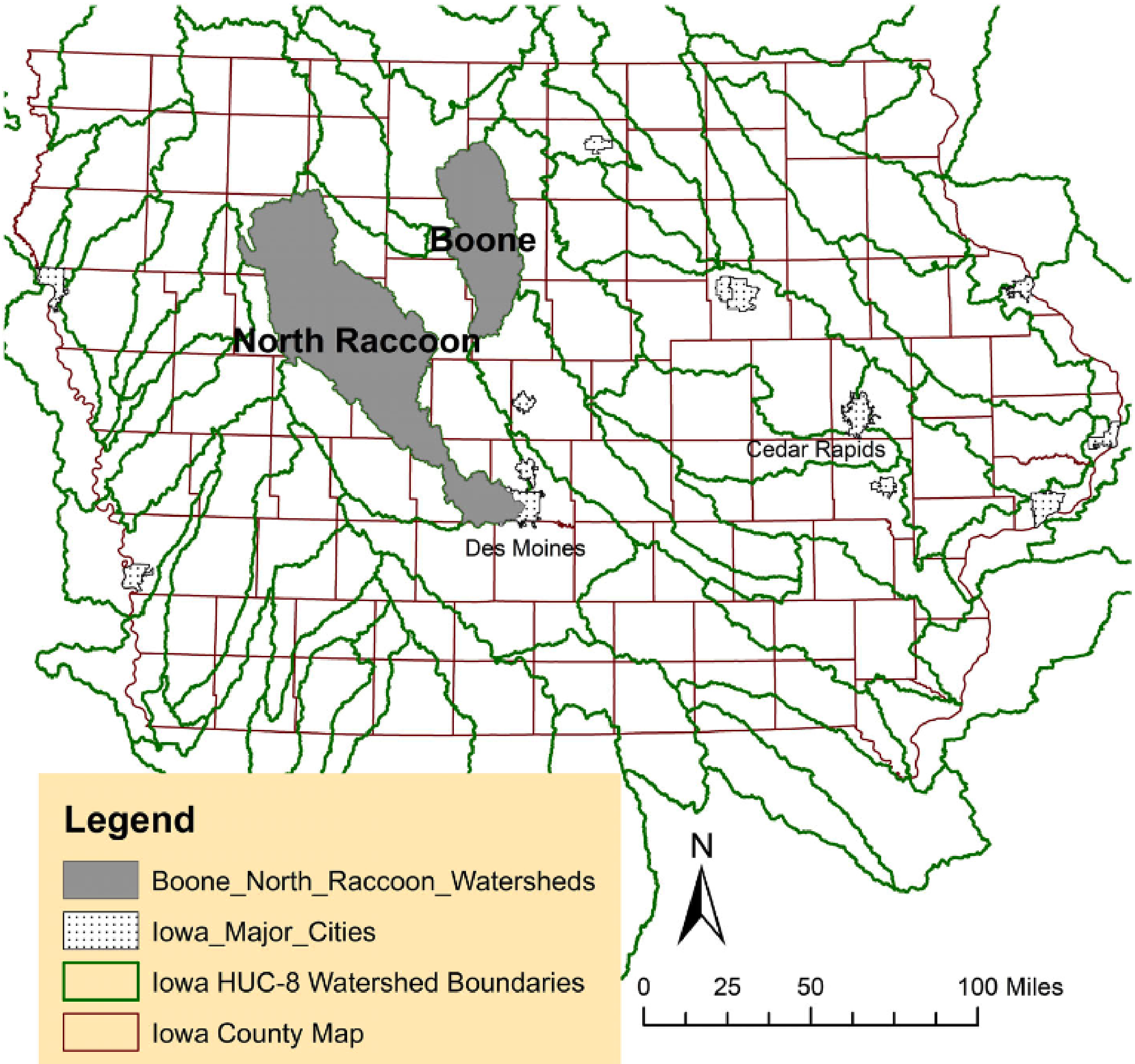

Figure 1: The Boone and North Raccoon River watersheds in Iowa

Table 1: Descriptive Statistics

Characteristics	Full Sample		Baseline		Restriction		*p*-value
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	
Age	58.97	12.67	59.39	12.43	58.28	13.06	0.39
Gender	0.96	0.19	0.96	0.19	0.96	0.19	0.90
Income [1]	0.54	0.50	0.55	0.50	0.53	0.50	0.71
Farm years	34.09	14.53	34.39	14.53	33.61	14.55	0.60
College [2]	0.40	0.49	0.40	0.49	0.41	0.49	0.89
Owned farm size	309.84	410.44	320.19	449.59	293.58	340.74	0.53
Rented farmland ratio	0.64	0.33	0.65	0.32	0.63	0.33	0.68
# Farmers	424		259		165		

[1] Income is an indicator variable for reported gross annual farm income exceeding $250,000.

Table 2: Farmers' Actual Conservation Practice Adoption Rates in the Previous Year

	Full Sample		**Baseline**		**Restriction**	
	%Farmer	#Farmers	%Farmer	#Farmers	%Farmer	#Farmers
Future adopters	52.99%	301	50.17%	149	56.09%	152
Early adopters	47.01%	267	49.83%	148	43.91%	119
Cover crops	13.91%	79	13.80%	41	14.02%	38
No-till/Strip-till	21.48%	122	22.22%	66	20.66%	56
Split N Application	32.22%	183	34.01%	101	30.26%	82

Notes: the t-test compares the conservation adoption rates between baseline and additionality restriction groups. All t-statistics are quite small and the corresponding two-tailed p-values are greater than 0.05. We conclude that the difference in adoption rates between restricted and unrestricted groups is not different from 0.

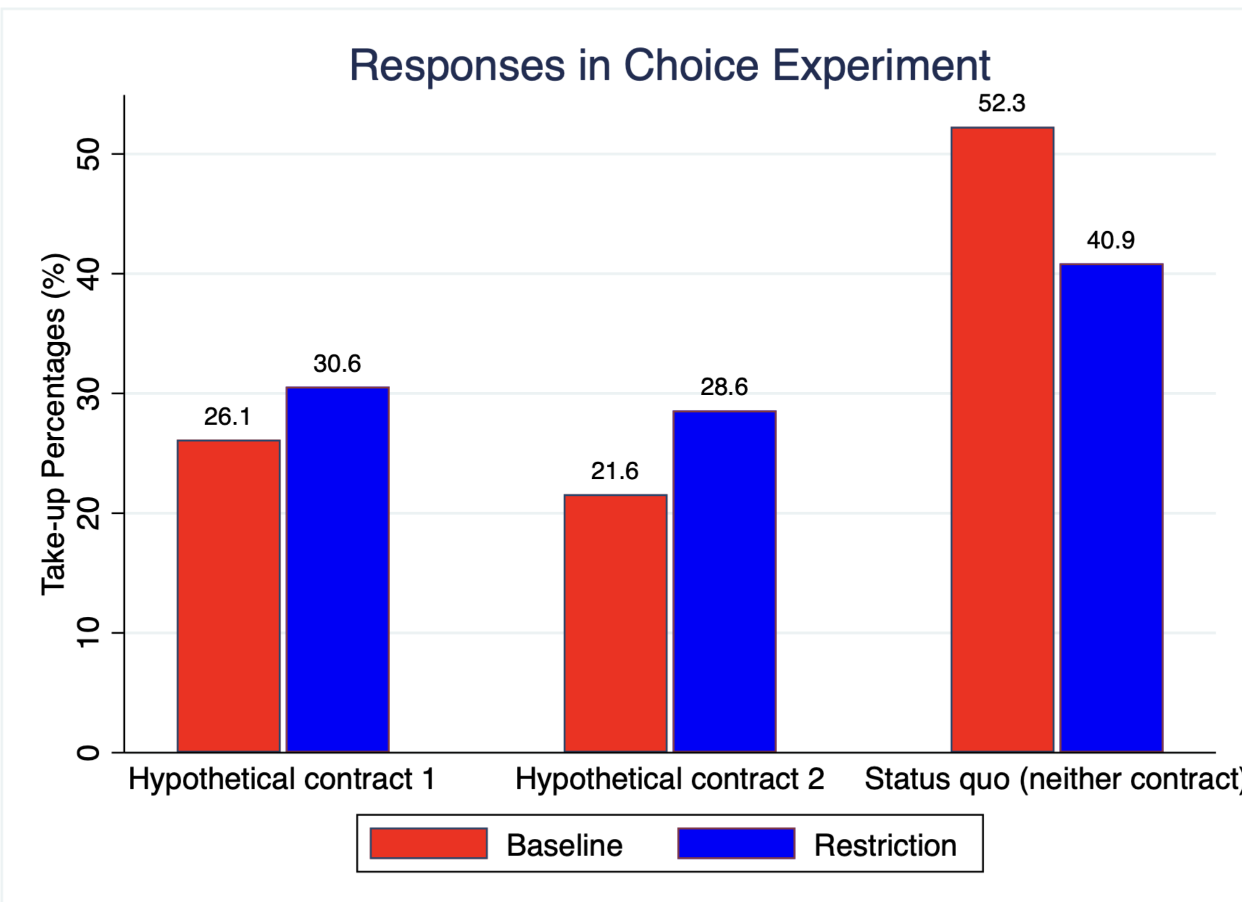

Figure 2: Respondents' Take-up Percentages for the Three Choice Alternatives

Table 3: Conditional and Random Parameter Logit Results

Attributes	Restriction	CL Model	RPL Model	
		Mean	**Mean**	**Std. Dev.**
Payment		0.012***	0.029***	
		(0.054)	(0.006)	
Length		-0.227***	-0.702***	0.611**
		(0.001)	(0.206)	(0.298)
CoverCrops	No	-0.555***	-1.195***	0.619
		(0.162)	(0.374)	(0.988)
	Yes	-0.508**	-1.362**	2.758***
		(0.213)	(0.612)	(1.032)
NoTill	No	-0.734***	-2.384***	3.077***
		(0.169)	(0.652)	(0.880)
	Yes	-0.556***	-1.133**	0.167
		(0.206)	(0.534)	(1.612)
SplitN	No	-0.035	-0.253	1.592**
		(0.171)	(0.347)	(0.734)
	Yes	-0.251	-1.026*	1.376
		(0.214)	(0.553)	(1.013)
Status-Quo ASC	No	0.379	0.206	3.981***
		(0.268)	(0.620)	(0.794)
	Yes	-0.371	-2.272**	5.169***
		(0.316)	(0.982)	(1.372)
Observations		2,266	2,266	
(Respondents)		(424)	(424)	

Notes: Standard deviations in parentheses.
***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.
We model all attributes with normal preference distributions except for *Payment*, which is fixed. The model uses the expectation-maximization algorithm with 500 Halton draws for simulation. Our t-test results show the differences on the coefficient of *Status-Quo ASC* are economically and statistically significant in both CL and RPL model. In RPL model, the coefficient is -2.707 with p-value 0.009; in CL model, the the coefficient is -0.75 with p-value 0.021.

Table 4: WTA Values for Baseline vs. Restriction Contracts

		CL Model			**RPL Model**		
	Practices	Baseline ($)	Restriction ($)	Reduction (%)	Baseline ($)	Restriction ($)	Reduction (%)
Mean Preference Values	CC	156.35***	88.67***	43.29***	144.71***	65.19**	54.95***
		(18.50)	(19.32)	(0.13)	(18.79)	(28.10)	(0.20)
	NT	171.60***	92.80***	45.92***	185.61***	57.32**	69.11***
		(19.40)	(21.07)	(0.13)	(24.56)	(27.81)	(0.15)
	SN	112.23***	66.85***	40.44**	112.30***	53.65*	52.22**
		(16.48)	(21.31)	(0.20)	(16.66)	(28.26)	(0.25)
	CC+NT	218.72***	135.93***	37.85***	226.71***	104.16***	54.05***
		(23.92)	(23.37)	(0.11)	(28.92)	(30.40)	(0.14)
	CC+SN	159.34***	109.98***	30.98**	153.41***	100.49***	34.50*
		(19.45)	(21.80)	(0.14)	(18.89)	(30.34)	(0.20)
	NT+SN	174.59***	114.11***	34.64***	194.30***	92.62***	52.33***
		(18.22)	(20.86)	(0.13)	(24.19)	(26.99)	(0.14)
Median Value from Individually-generated Preference Values	CC				160.47	78.89	50.83
	NT				201.17	70.65	64.88
	SN				120.14	66.47	44.67
	CC+NT				242.37	117.71	51.43
	CC+SN				161.99	114.94	29.04
	NT+SN				210.91	105.39	50.03

Notes: ***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively.
CC denotes cover crops, NT denotes no-till or strip-till, SN denotes split N application.
Standard errors are generated using the delta method are shown in parentheses. All programs assume four-year contracts.

Section 3: Hypothetical Voluntary Conservation Program for Your Field

Conservation Program Overview.

Consider a hypothetical situation where a government agency or conservation group is offering multiple ***voluntary conservation contracts*** *with different lengths* ***starting the 2020 growing season*** (from after harvest in the fall of 2019 until harvest in the fall of 2020). All contracts include the adoption of one or more management practices to reduce nutrient loss that **are not already in use or planned for use in the 2019 growing season**, as well as an annual per-acre cost-share payment to the farmer. The practices, as well as the per-acre cost share, apply to the acreage of the entire field.

These conservation programs are designed to encourage **additional, new** acres of three conservation practices: no-till or strip-till, cover crops, and split N application. As a result, not all acres are eligible for this program. For example, a field which currently uses cover crops is not eligible for conservation programs adding cover crops.

24. Still considering your field from the previous section, please indicate whether this field would be eligible for a voluntary conservation program based on the practices you will use in the 2019 season. Note that in this new conservation funding concept, **funding is only available to add additional, new conservation practices.**

    (Circle all that apply.)

    1 = I will not use no-till/strip-till, cover crops, or split-N-application on this field in 2019, so it is eligible for any conservation contracts presented in the next two scenarios.

    2 = No-till/strip-till will be used on this field for the 2019 crop, so it is not eligible for contracts in 2020 ***adding*** no-till/strip-till.

    3 = Cover crops will be planted on this field for the 2019 year (post-harvest 2018 until harvest 2019), so it is not eligible for contracts in 2020 ***adding*** cover crops.

    4 = Split nitrogen application will be used on the field for the 2019 crop, so it is not eligible for contracts in 2020 ***adding*** the practice of split nitrogen application.

Scenario 1

Please consider the terms of Programs A & B below for your field and answer the questions that follow as if a real conservation contract was being offered to you.

	Program A	**Program B**
Length of Contract	2 years (2020, 2021)	4 years (2020 - 2023)
No-Till or Strip-Till (Leaving more than 90% residue)	Not Required	Must be used in 2020-23, ***not*** used in 2019
Cover Crops (Planting a crop after harvesting the main cash crop)	Not Required	Must be used in 2020-23, ***not*** used in 2019
Split Nitrogen application (Apply some N preplant/at-plant and the remainder sidedress)	Must be used in 2020-21, ***not*** used in 2019	Must be used in 2020-23, ***not*** used in 2019
Annual Cost Share Payment to You	$70/acre	$100/acre

25. As mentioned earlier, the program is available for fields currently not using these practices. Based on the information above, is your field eligible for either Program A or Program B for the 2021 growing season?

    1 = Yes, eligible for A and B
    2 = Yes, but eligible for A only
    3 = Yes, but eligible for B only
    4 = Not eligible for either (If not eligible for either, go to Page 7)

26. If your field is eligible, which program do you prefer?

    1 = Program A 2 = Program B 3 = Neither Program (If Neither, go to Page 7)

Figure 3: An Example of Conservation Program Choice Scenarios with (this page) and without (next page) Enrollment Restrictions

Section 3: Hypothetical Voluntary Conservation Program for Your Field

Conservation Program Overview.

Consider a hypothetical situation where a government agency or conservation group is offering multiple ***voluntary conservation contracts*** *with different lengths* ***starting the 2020 growing season*** (from after harvest in the fall of 2019 until harvest in the fall of 2020). All contracts include the adoption of one or more management practices to reduce nutrient loss that **are not already in use or planned for use in the 2019 growing season**, as well as an annual per-acre cost-share payment to the farmer. The practices, as well as the per-acre cost share, apply to the acreage of the entire field.

Scenario 1

Please consider the terms of Programs A & B below for your field and answer the questions that follow as if a real conservation contract was being offered to you.

	Program A	**Program B**
Length of Contract	2 years (2020, 2021)	4 years (2020 - 2023)
No-Till or Strip-Till (Leaving more than 90% residue)	Not Required	Must be used in 2020-23,
Cover Crops (Planting a crop after harvesting the main cash crop)	Not Required	Must be used in 2020-23,
Split Nitrogen application (Apply some N preplant/at-plant and the remainder sidedress**)**	Must be used in 2020-21,	Must be used in 2020-23,
Annual Cost Share Payment to You	$70/acre	$100/acre

24. Which program do you prefer?

1 = Program A 2 = Program B 3 = Neither Program (If Neither, go to Page 7)

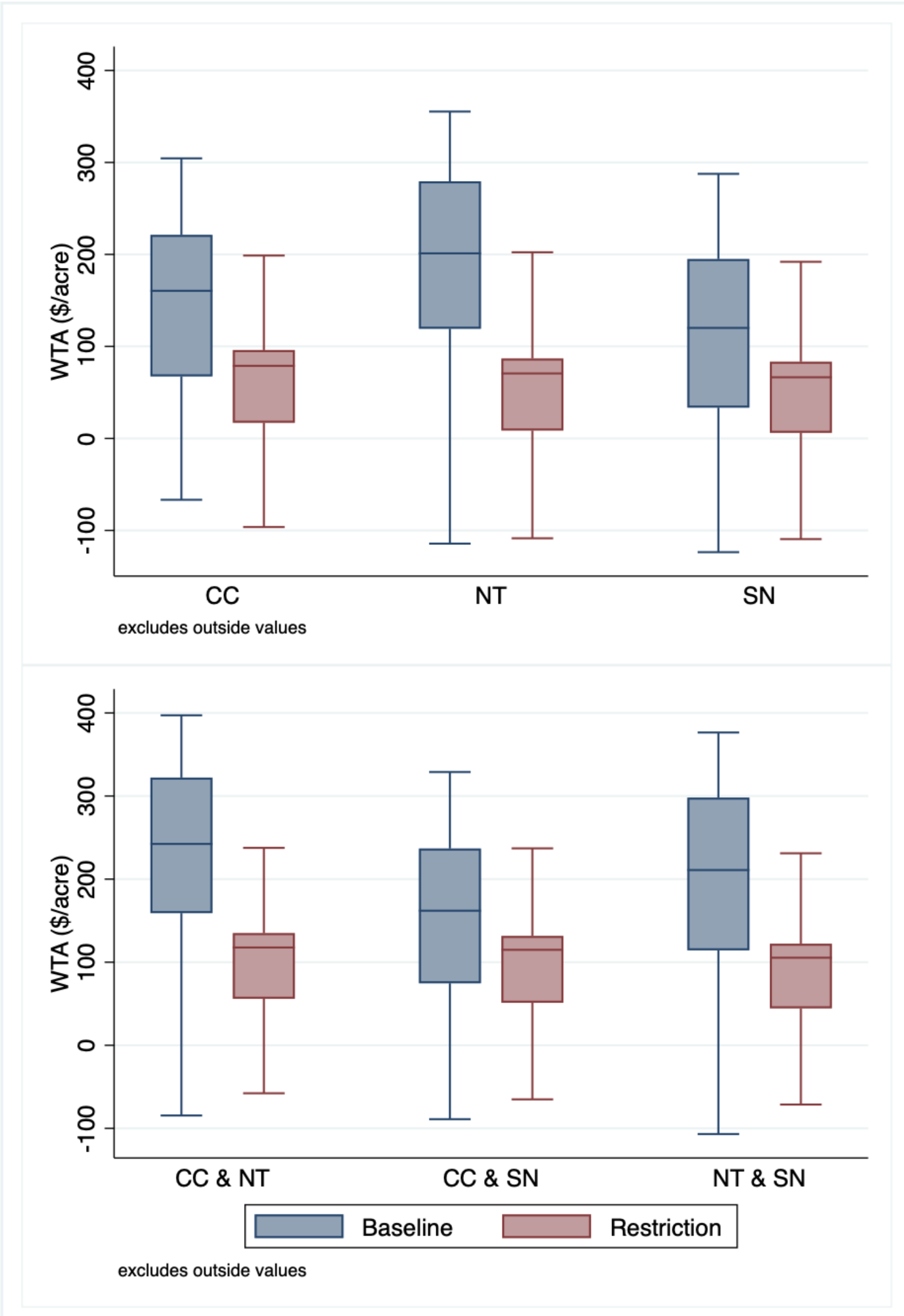

Figure 4: Willingness-to-Accept Boxplot for Conservation Contracts

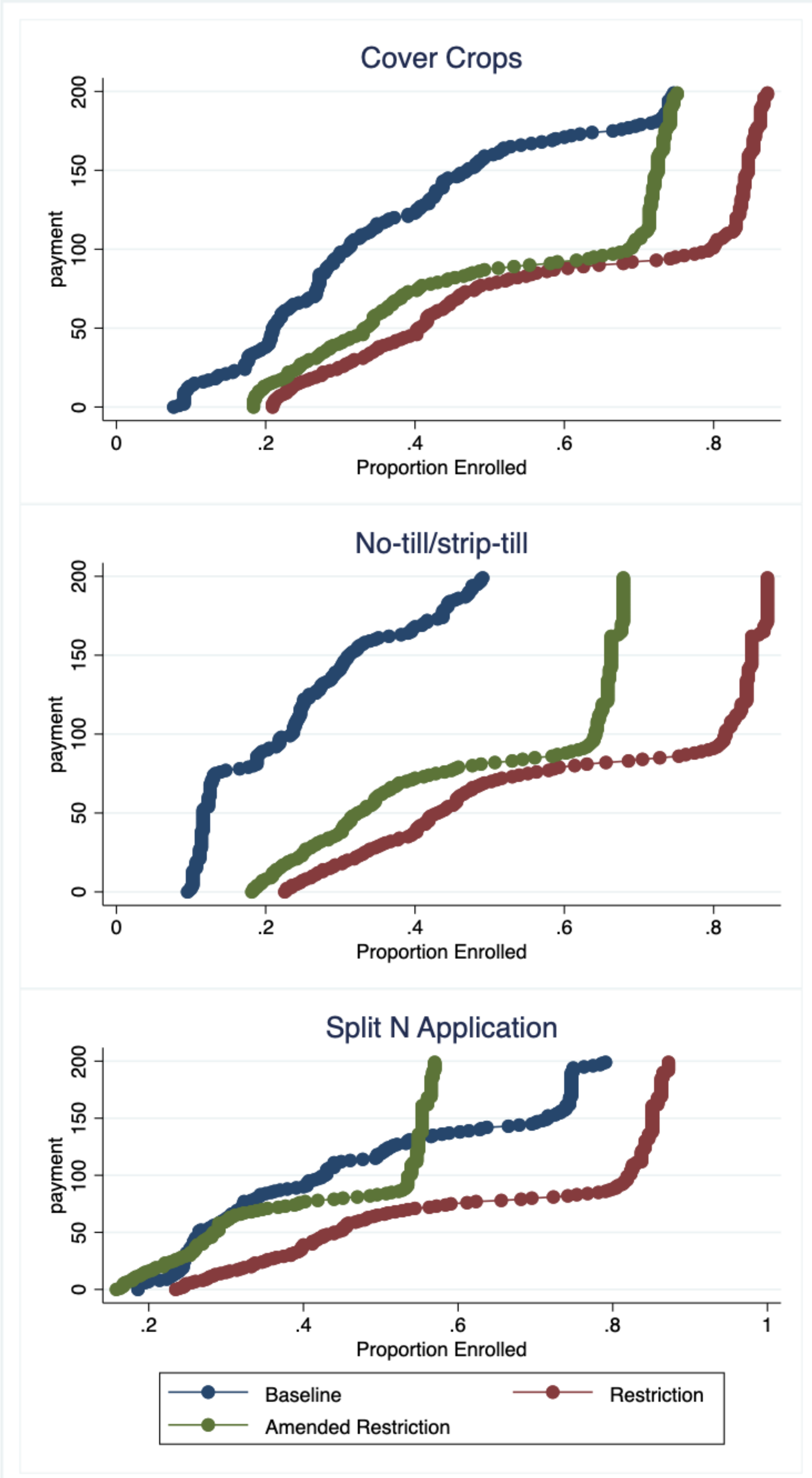

Figure 5: Participation Supply Curves for Conservation Contracts

Appendix A

Table A1. Conditional and Random Parameters Logit Results: Modeling Heterogeneous Preferences by Farmer Characteristics

Table A2. Random Parameters Logit Results: Early and Future Adopters

Table A3. Conditional and Random Parameters Logit Results: No Missing Alternatives

Table A4. WTA Values for Baseline vs. Additionality-based Contracts: Early and Future Adopters

Table A1: Conditional and Random Parameters Logit Results: Modeling Heterogeneous Preferences by Farmer Characteristics

Attributes	**Restriction**	**CL Model**	**RPL Model**	
		Mean	**Mean**	**Std. Dev.**
Payment		0.010***	0.022***	0.676**
		(0.002)	(0.006)	(0.263)
Payment $\times$ ***High Income***		0.003*	0.015**	0.280
		(0.002)	(0.006)	(0.607)
Length		-0.173***	-0.654***	0.777
		(0.059)	(0.211)	(1.043)
Length $\times$***I (Age*** $>$ ***60)***		-0.124**	-0.281	3.122**
		(0.058)	(0.177)	(1.277)
CoverCrops	No	-0.559***	-1.287***	3.221***
		(0.161)	(0.424)	(1.043)
	Yes	-0.494**	-1.502**	-0.184
		(0.216)	(0.718)	(1.753)
NoTill	No	-0.746***	-2.440***	1.683**
		(0.169)	(0.730)	(0.817)
	Yes	-0.556***	-1.327**	1.671
		(0.206)	(0.613)	(1.156)
SplitN	No	-0.030	-0.319	3.599***
		(0.171)	(0.369)	(0.768)
	Yes	-0.231	-1.082*	5.768***
		(0.217)	(0.646)	(1.524)
Status-Quo ASC	No	0.346	0.018	0.676**
		(0.268)	(0.626)	(0.263)
	Yes	-0.386	-2.680**	0.280
		(0.320)	(1.109)	(0.607)
Observations		2266	2266	
(Respondents)		(424)	(424)	

Notes: Standard deviations in parentheses.
***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively. The t-test results show the difference between the mean coefficient of *Status-Quo ASC* is economically significant in both CL and RPL model. In RPL model, the coefficient is -2.260 with p-value 0.018; in CL model, the coefficient is -0.732 with p-value 0.026.

Table A2: Random Parameters Logit Results: Early and Future Adopters

Attributes	Restriction	Early Adopters		Future Adopters	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Payment		0.0324***	0.261	0.027***	
		(0.009)	(0.563)	(0.007)	
Length		-0.523**	-0.232	-0.663***	0.531*
		(0.231)	(1.161)	(0.254)	(0.308)
CoverCrops	No	-0.329	2.847	-1.834***	0.148
		(0.434)	(1.935)	(0.555)	(1.098)
	Yes	-0.0007	3.892**	-1.926**	3.146**
		(0.889)	(1.713)	(0.889)	(1.604)
NoTill	No	-2.366**	0.285	-1.792***	-0.943
		(0.984)	(2.221)	(0.666)	(1.413)
	Yes	0.340	-1.671	-1.330*	-0.159
		(0.871)	(1.072)	(0.739)	(1.773)
SplitN	No	-0.580	0.402	0.228	0.869
		(0.474)	(2.292)	(0.495)	(1.445)
	Yes	1.096	4.401***	-1.734**	1.559
		(0.946)	(1.129)	(0.805)	(1.101)
Status-Quo ASC	No	0.425	3.381***	0.381	3.183***
		(0.828)	(1.293)	(0.808)	(0.955)
	Yes	0.267	0.261	-2.848*	7.663***
		(1.115)	(0.563)	(1.648)	(2.776)
Observations		1081		1095	
(Respondents)		(212)		(195)	

Notes: Standard deviations in parentheses.
***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively. In RPL model, t-test shows the difference between the mean coefficient of *Status-Quo ASC* is economically and statistically significant for future adopters (the coefficient is -3.052 with p-value 0.034), while not statistically significant for current adopters (the coefficient is -0.346 with p-value 0.776).

Table A3: Conditional and Random Parameters Logit Results: No Missing Alternatives

Attributes	**Restriction**	**CL Model**	**RPL Model**	
		Mean	**Mean**	**Std. Dev.**
Payment		0.013***	0.034***	
		(0.002)	(0.007)	
Length		-0.251***	-0.852***	0.722**
		(0.058)	(0.267)	(0.322)
CoverCrops	No	-0.546***	-1.314***	-0.666
		(0.163)	(0.432)	(0.894)
	Yes	-0.435*	-1.575*	3.223**
		(0.261)	(0.820)	(1.261)
NoTill	No	-0.734***	-2.753***	3.616***
		(0.171)	(0.815)	(1.110)
	Yes	-0.707***	-1.400*	0.809
		(0.248)	(0.753)	(1.371)
SplitN	No	-0.0386	-0.367	1.901**
		(0.174)	(0.399)	(0.824)
	Yes	-0.311	-1.665*	-2.409*
		(0.259)	(0.901)	(1.346)
Status-Quo ASC	No	0.400	0.187	4.274***
		(0.280)	(0.706)	(0.937)
	Yes	-0.127	-2.278	7.365***
		(0.389)	(1.415)	(2.472)
Observations		2046	2046	
(Respondents)		(360)	(360)	

Notes: Standard deviations in parentheses.
***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively. In RPL model, t-test shows the difference between the mean coefficient of *Status-Quo ASC* is economically and statistically significant (the coefficient is -2.531 with p-value 0.055), while in CL model, the difference is not statistically significant (the coefficient is -0.527 with p-value 0.174).

Table A4: WTA Values for Baseline vs. Additionality-based Contracts: Early and Future Adopters

	Practices	Early Adopters			Future Adopters		
		Baseline ($)	Restriction ($)	Reduction (%)	Baseline ($)	Restriction ($)	Reduction (%)
Mean Preference Values	CC	87.70***	72.69**	17.11	182.06***	64.72	64.45**
		(19.96)	(29.55)	(0.38)	(29.05)	(50.68)	(0.28)
	NT	150.48***	62.20**	58.66	180.48***	42.44	76.48***
		(29.04)	(25.69)	(0.19)	(28.53)	(51.38)	(0.29)
	SN	95.43***	38.88	59.25	104.94***	57.53	45.18
		(20.12)	(32.50)	(0.35)	(23.46)	(50.09)	(0.49)
	CC+NT	160.63***	62.23**	61.26	249.09***	114.48**	54.04***
		(30.80)	(31.18)	(0.21)	(37.86)	(54.06)	(0.22)
	CC+SN	105.57***	38.90	63.15	173.55***	129.57***	25.34
		(20.68)	(35.17)	(0.34)	(28.43)	(52.93)	(0.31)
	NT+SN	168.36***	28.42	83.12	171.97***	107.28**	37.61
		(28.83)	(31.62)	(0.19)	(28.06)	(48.96)	(0.29)
Median Value from Individually-generated Preference Values	CC	92.95	75.91	18.33	186.60	75.07	59.77
	NT	155.86	64.72	58.48	185.47	51.82	72.06
	SN	100.03	41.32	58.69	107.52	68.14	36.63
	CC+NT	166.10	65.30	60.69	253.94	124.80	50.85
	CC+SN	110.20	42.11	61.79	176.19	140.95	20.00
	NT+SN	173.93	30.95	82.21	175.51	117.77	32.90

Notes: Standard deviations in parentheses.
***,**, and * indicate significance at the 1%, 5%, and 10% level, respectively. CC denotes cover crops, NT denotes no-till or strip-till, and SN denotes split N application. Standard errors are generated using the Delta Method in parentheses. All programs assume 4-year contracts.

Appendix B: Sample Survey Questionnaire

Survey of Iowa Farmers:
Boone and Raccoon River Watersheds

This survey should be completed by the principal decision maker of your farm business. Answer each question with the response you believe is most representative of you and your farm.
Thank you in advance for your time and attention!

Section 1: About You and Your Farm

1. Did you operate a farm in 2019?

1 = No
2 = Yes

2. Do you plan to operate a farm in 2020?

1 = No
2 = Yes

If you answered No to Q2, please return the blank survey in the postage paid envelope provided. Thank you!

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3. How many of the acres that you farm are:

a. **owned by you**? ____________ # Acres owned

b. **rented from others?** ____________ # Acres rented
(including cash rent, flexible lease, crop share)

4. How many of the **FIELDS** that you farm are:

a. **owned by you**? ____________ # *Fields* owned

b. **rented from others**? ____________ # *Fields* rented
(including cash rent, flexible lease, crop share)

5. How many acres of corn and soybeans did you harvest in 2019?

a. ____________________Corn Acres b. _____________________Soybean Acres

6a. Since 2010, have you converted woodland, pasture, wasteland, fallow, or CRP land into cropland?

1 = No
2 = Yes ➡ 6b. If Yes, how many acres? _______________acres

7. Do you use any of the following tillage practices? If yes, how many acres are tilled in each way?

	No	Yes	# Acres
a. Conventional Tillage (30% residue or less)	1	2	
b. Conservation Tillage (30 – 90% residue)	1	2	
c. Strip-till (90% residue or more)	1	2	
d. No-till (90% residue or more)	1	2	

8. Do you have land enrolled in any of the following programs?

	No	Yes	# Acres Enrolled
a. Conservation Reserve Program (CRP)	1	2	
b. Environmental Quality Incentive Program (EQIP)	1	2	
c. Iowa Department of Agriculture and Land Stewardship (IDALS) Cost Share Programs	1	2	
d. Conservation Stewardship Program (CSP)	1	2	
e. Iowa Mississippi River Basin Initiative (MRBI)	1	2	

9. Did you raise the following types of livestock in 2019? Please circle all that apply.

1 = Beef cattle
2 = Dairy cattle
3 = Hogs
4 = Poultry
5 = Other (Please specify:__________________________)

Section 2: Nutrient Management on a Specific Field

Please answer the following questions in reference to **ONE** of your fields that plan to operate for 2020 and 2021, and where soil erosion and nutrient runoff may be a potential problem. If there are several possible fields to choose from, choose **the field where *erosion or runoff is of greatest concern***.

10. What is the size of this field in acres? _______________ # acres

11. In which County and Township is this field located?

__________________________ County __________________________ Township

12a. Does this field have drainage tile installed?

1 = No
2 = Yes → 12b. If Yes, what is the depth of the tile? ______________feet
3 = Unsure

13. What is the general slope of this field?

1 = 0-2%
2 = 2-5%
3 = 5-10%
4 = More than 10%
5 = Not sure

14. Are there buffer strips on this field?

1 = No
2 = Yes

15. How close is the nearest stream, ditch or other surface water to this field?

1 = Less than 25 feet
2 = 25 – 200 feet
3 = Greater than 200 feet

16. What is the **dominan**t soil type in this field? (Please circle all that apply.)

a. Clarion soil
b. Nicollet soil
c. Webster soil
d. Marna soil
e. Kossuth soil
f. Bode soil
g. Other
h. Not sure

17. When do you ***typically*** plant crops in this field?

1 = April 15 or before
2 = April 16-30
3 = May 1-15
4 = May 15-31
5 = June 1-10
6 = after June 10

18a. Do you rent this field from someone else?

1 = No [If No, go to Q19]
2 = Yes → 18b. If Yes, who makes the nutrient management decisions for this field?

1 = I do, with **no** landlord input
2 = I do, with landlord input
3 = My landlord and I equally
4 = My landlord, with my input
5 = My landlord alone
6 = Someone else

19. In the 2020 crop year, what would typical cash rent be for this field? $___________/acre
(Please provide an estimated cash rent even if you operate this field or rent it on a crop-share basis.)

20a. What crop was planted on this field in 2019?

1 = Corn 2 = Soybeans 3 = Some other crop

20b. What crop will be planted on this field in 2020?

1 = Corn 2 = Soybeans 3 = Some other crop

21. How much nitrogen and phosphorous, from both commercial and manure sources, do you plan to apply on this field**, in total**, for the 2019 and 2020 crop years?

a. Nitrogen (**in total** for the 2019 and 2020 crop years:________________lbs/acre

b. Phosphate (P_2O_5) before corn ____________lbs/acre

c. Phosphate (P_2O_5) before soybeans: ____________lbs/acre

22. The following table lists potential nutrient management practices. Are you ***planning to use*** any of these practices on **this** field in during the ***2020*** growing season (spanning from after harvest in the fall of 2019 until harvest in the fall of 2020)?

Practices	**Will not use in 2020**	**Will use in 2020 as part of a conservation cost share agreement**	**Will use in 2020 but not part of a conservation cost share agreement**
a. Plant winter cover crops	1	2	3
b. Use conservation tillage (30-90% of residue)	1	2	3
c. Use no-till or strip-till (> 90% residue)	1	2	3
d. Apply manure, if needed, based on P index	1	2	3
e. Place P & K more than 2 inches below the soil surface	1	2	3
f. Use split N application (apply some N preplant/at-plant and the remainder sidedress)	1	2	3

23. Do you expect to use any of these practices on **this** field ***during the 2021 growing season*** (from after harvest in the fall of 2020 until harvest in the fall of 2021)***?***

Practices	**Will not use in 2021**	**Will use in 2021 as part of a conservation cost share agreement**	**Will use in 2021 but not part of a conservation cost share agreement**
a. Plant winter cover crops	1	2	3
b. Use conservation tillage (30-90% of residue)	1	2	3
c. Use no-till or strip-till (> 90% residue)	1	2	3
d. Apply manure, if needed, based on P index	1	2	3
e. Place P & K more than 2 inches below the soil surface	1	2	3
f. Will use split N application (apply some N preplant/at-plant and the remainder sidedress)	1	2	3

Section 3: Hypothetical Voluntary Conservation Program for Your Field

Conservation Program Overview.

Consider a hypothetical situation where a government agency or conservation group is offering multiple ***voluntary conservation contracts*** *with different lengths* ***starting the 2021 growing season*** (from after harvest in the fall of 2020 until harvest in the fall of 2021). All contracts include the adoption of one or more management practices to reduce nutrient loss that **are not already in use or planned for use in the 2020 growing season**, as well as an annual per-acre cost-share payment to the farmer. The practices, as well as the per-acre cost share, apply to the acreage of the entire field.

These conservation programs are designed to encourage **additional, new** acres of three conservation practices: no-till or strip-till, cover crops, and split N application. As a result, not all acres are eligible for this program. For example, a field which currently uses cover crops is not eligible for conservation programs adding cover crops.

24. Still considering your field from the previous section, please indicate whether this field would be eligible for a voluntary conservation program based on the practices you will use in the 2020 season. Note that in this new conservation funding concept, **funding is only available to add additional, new conservation practices**.

    (Circle all that apply.)

    1 = I will not use no-till/strip-till, cover crops, or split-N-application on this field in 2020, so it is eligible for any conservation contracts presented in the next two scenarios.

    2 = No-till/strip-till will be used on this field for the 2020 crop, so it is not eligible for contracts in 2021 ***adding*** no-till/strip-till.

    3 = Cover crops will be planted on this field for the 2020 crop year (post-harvest 2019 until harvest 2020), so it is not eligible for contracts in 2021 ***adding*** cover crops.

    4 = Split nitrogen application will be used on the field for the 2020 crop, so it is not eligible for contracts in 2021 ***adding*** the practice of split nitrogen application.

Scenario 1

Please consider the terms of Programs A & B below for your field and answer the questions that follow as if a real conservation contract was being offered to you.

	Program A	Program B
Length of Contract	2 years (2021, 2022)	4 years (2021 - 2024)
No-Till or Strip-Till (Leaving more than 90% residue)	Not Required	Must be used in 2021-24, ***not*** used in 2020
Cover Crops (Planting a crop after harvesting the main cash crop)	Not Required	Must be used in 2021-24, ***not*** used in 2020
Split Nitrogen application (Apply some N preplant/at-plant and the remainder sidedress)	Must be used in 2021-22, ***not*** used in 2020	Must be used in 2021-24, ***not*** used in 2020
Annual Cost Share Payment to You	$70/acre	$100/acre

25. As mentioned earlier, the program is available for fields currently not using these practices. Based on the information above, is your field eligible for either Program A or Program B for the 2021 growing season?

    1 = Yes, eligible for A and B
    2 = Yes, but eligible for A only
    3 = Yes, but eligible for B only
    4 = Not eligible for either (If not eligible for either, go to Page 7)

26. If your field is eligible, which program do you prefer?

    1 = Program A 2 = Program B 3 = Neither Program (If Neither, go to Page 7)

27. Consider that your decision to the above scenario is binding, and you receive compensation according to your choice. **In addition to** the conservation practices specified in the program of your choice, would you use any of the following practices in this field **in the 2021 growing season?**

Practices	**Would not use in 2021**	**Would use in 2021 with a cost share**	**Would use in 2021 without cost share**
a. Use conservation tillage (30-90% of residue	1	2	3
b. Apply manure based on P index	1	2	3
c. Place P & K more than 2 inches below the soil surface	1	2	3
d. Use buffer strips	1	2	3

Scenario 2

The table below describes **different** conservation programs. Please consider the terms of Programs C & D and answer the questions that follow as if a real contract was being offered to you.

	Program C	Program D
Length of Contract	2 years (2021, 2022)	4 years (2021 - 2024)
No-Till or Strip-Till (Leaving more than 90% residue)	Must be used in 2021-22, ***not*** used in 2020	Not Required
Cover Crops (Planting a crop after harvesting the main cash crop)	Must be used in 2021-22, ***not*** used in 2020	Not Required
Split Nitrogen application (Apply some N preplant/at-plant and the remainder sidedress)	Not Required	Must be used in 2021-24, ***not*** used in 2020
Annual Cost Share Payment to You	$10/acre	$130/acre

28. As mentioned earlier, the program is available for fields currently not using these practices. Based on the information above, is your field eligible for either Program C or Program D for the 2021 growing season?

    1 = Yes, eligible for C and D
    2 = Yes, but eligible for C only
    3 = Yes, but eligible for D only
    4 = Not eligible for either (If not eligible for either, go to Q31)

29. If your field is eligible, which program do you prefer?

    1 = Program C   2 = Program D   3 = Neither Program (If Neither, go to Q31)

30. Consider that your decision to the above scenario is binding, and you receive compensation according to your choice. **In addition to** the conservation practices specified in the program of your choice, would you use any of the following practices in this field **in the 2021 growing season?**

Practices	**Would not use in 2021**	**Would use in 2021 with a cost share**	**Would use in 2021 without cost share**
a. Use conservation tillage (30-90% of residue	1	2	3
b. Apply manure based on P index	1	2	3
c. Place P & K more than 2 inches below the soil surface	1	2	3
d. Use buffer strips	1	2	3

Section 4: More about You

31. Are you male or female? 1 = Male 2 = Female

32. What is your age? _________ Years old

33. How many years have you been farming? _________ Years

34. What is the highest level of education you have completed?

1 = Some high school	4 = Bachelor's degree
2 = High School diploma or GED	5 = Graduate or Professional degree
3 = Some college, or Associate's degree	

35. What was your **total farm operation's** annual gross income in 2018?

1 = Less than $50,000	4 = $250,000 - $499,999
2 = $50,000 - $99,999	5 = $500,000 or greater
3 = $100,000 - $249,999	

36a. Does anyone in your household receive income from off farm sources such as an off-farm job, social security, retirement income, or something else?

1 = No [If No, go to Q37]
2 = Yes ➡ 38b. If Yes, what percent of your household's annual gross income comes from off-farm sources? _______________%

37. ***In general*** are you someone who is willing to take risks or do you try to avoid taking risks?

Avoid taking risks					**Willing to take risks**	
1	**2**	**3**	**4**	**5**	**6**	**7**

38. ***In your occupation as a farmer***, are you someone who is willing to take risks or do you try to avoid taking risks?

Avoid taking risks					**Willing to take risks**	
1	**2**	**3**	**4**	**5**	**6**	**7**

39. Please record any other thoughts or comments about water quality issues in Iowa.

Thank you!! Please mail your completed survey in the postage-paid envelope provided.