Producer Preference for Land-Based Biological Carbon Sequestration in Agriculture: An Economic Inquiry

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Abstract

This study was intended to develop an understanding of producer preference for land-based carbon sequestration in agriculture. We conducted a mail survey to elicit producer choice to provide marketable carbon offsets by participating in different carbon credit programs characterized by varying practices. Based on a quantitative analysis, we found that: 1) the market price for carbon offsets could increase producer participation in carbon sequestration; 2) producers perceived differentially different but correlated private costs for adopting carbon sequestering practices, depending on production attributes; and 3) relatively high carbon prices would be needed to stimulate producer provision of carbon offsets by land-based carbon sequestration activities. A simulation of producer choice with agricultural census data estimated potential carbon offsets supply in the Northern Great Plains region. This study contributes to the economic understanding of agricultural potential for greenhouse gas mitigation.

Keywords: greenhouse gas, carbon sequestration, producer stated preferences, agriculture, economics, carbon offsets, carbon markets

JEL code: Q54, Q52, Q58

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I. Introduction

As agricultural land-based carbon sequestration represents an important option in the portfolio of climate change mitigation strategies (McCarl and Sands 2007, NRC 2010), understanding producer preference for on-farm carbon sequestration activities are critically important. Carbon sequestration is a new concept for producers. Land-based activities to provide marketable carbon offsets represent a new farm opportunity with which most producers have no experience. On the other hand, agricultural producers are risk-averse and this risk attitude has historically negatively affected commodity supply in the agricultural market (e.g., Chavas and Holt 1996). With an emerging market for greenhouse gas (GHG) emission offsets, a realistic question is how producers would respond to the carbon sequestration potential on their farmland. Producer preference for available carbon-sequestering practices apparently would affect carbon offsets supply and economic assessment of agricultural potential in climate change mitigation.

Economic studies have arisen attempting to estimate agricultural carbon sequestration potential using different approaches. For example, a group of studies mostly focused on forestation explicitly considered producer revealed preferences in land use and management decision to estimate the potential carbon sequestration supply under different policies (Stavins 1999, Newell and Stavins 2000, Lubowski et al. 2006). Based on a farm production survey, Antle et al. (2001) estimated and used the producer decision model combined with biophysical simulation to assess economic potential for agricultural carbon sequestration. Another group of studies examined carbon sequestration along with a set of other GHG mitigation strategies in the U.S. agricultural sector in a competitive equilibrium framework (e.g., Lewandrowki et al. 2004, Schneider et al. 2007). While these studies found that agricultural carbon sequestration could be competitive with other GHG mitigation options, little is known about the preference of producers who manage farmland with their own production decision.

This study was motivated to develop an understanding of producer preference for carbon sequestration opportunities on agricultural lands. It was intended to reveal producer preferences by focusing on producer behavior in a hypothetical market for carbon offsets. This study attempted to explore: 1) what effect the market price for carbon offsets would have on producer adoption of practices that could sequester carbon in soils and biomass; 2) to what extent producer decision to adopt different carbon-sequestering practices could be linked to their costs as perceived by producers that could be stratified by producer production attributes; and 3) how producer preference interacts between carbon sequestration activities and varies by producer. An examination of the three questions is potentially useful for developing economic appraisal for land-based carbon sequestration in agriculture.

In this study, we conducted a mail survey to elicit producer willingness to provide marketable carbon offsets at a given price by participating in different carbon credit programs characterized by varying practices. We used producer stated preference to calibrate a behavior model that quantitatively linked producer carbon program choice to potential carbon revenues and perceived costs for program participation stratified by the production attributes of the producer. Based on the Bayesian method, we identified the producer behavior model and preference variations by producer and by carbon program. We applied the producer behavior model combined with agricultural census data to simulating potential agricultural supply of carbon emission offsets by land-based carbon sequestration in the Northern Great Plains (NGP) region.

This study is of policy interest. As the science community has identified GHG emissions reduction as a core element to shape policy-making in America's climate choices (NRC 2010), a comprehensive, strategic action plan with a portfolio of GHG mitigation activities is needed to effectively combat climate change. Previous studies have established that agricultural land-based carbon sequestration could serve as a low-cost strategy bridging to future climate change mitigation. Yet, adoption of carbon-sequestering activities depends critically on the decisions of producers who manage agricultural land. Producers may perceive differently than non-producers on the potential benefit and cost of sequestering carbon by various land-based practices. Producer perception on and preference for carbon sequestration might depend on production attributes while being heterogeneous by person and by activity. Understanding producer preferences and potential response would inform policy design in developing a cost-effective, implementable action plan to mitigate climate change.

In addition, possible energy and climate change legislation by the U.S. Congress has raised concern on the potential cost impact of GHG emissions regulation on agriculture (AFBF 2010). If regulating and reducing GHG emissions represent an inevitable political choice for the U.S., agriculture ultimately needs to adjust to government climate policy by identifying opportunities to mitigate the cost impacts of GHG regulation. While providing marketable GHG emissions offsets might represent such an opportunity to which the agricultural sector should pay close attention, understanding producer preferences has important implication for government policy to facilitate and promote agricultural participation in climate change mitigation.

This paper is organized as follows. Section 2 summarizes producer preference survey including survey design and producer response. Section 3 describes our modeling method to analyze producer stated preferences. Section 4 estimates and compares alternative specifications for the producer behavior model. Section 5 applies the estimated producer behavior model to simulating acreage enrollment in different carbon sequestration activities and potential supply of carbon emission offsets in the NGP region. Section 6 concludes the paper with some discussion.

II. Producer Preference Survey

Our survey questionnaire was composed of three sections designed to explore potential linkage between producer preference for carbon sequestration and production attributes. Section 1 was intended to elicit producer choice to adopt different practices to provide carbon emission offsets in a hypothetical market. This section first described available carbon credit programs characterized by different practices that producers could choose to adopt to participate in these programs. In the survey, we presented four carbon programs, which were adopted from the voluntary carbon programs administrated by the National Farmers Union (NFU) that collects and sells carbon credits in the Chicago Climate Exchange (CCX) (NFU 2009). These programs included conservation tillage, cropland conversion to grass, rangeland management, and tree planting. For each program, we listed available carbon credits that could be claimed for payment on a per acre basis by enrolled producers with required practices. Given the market price for carbon offsets, we calculated in the survey the expected payment per acre for participating in each program (see Table 1 for an example).

In section 1, we asked two types of questions. These questions served to separate a small group of producers currently in the voluntary carbon programs from the majority who were not. For each group, a different set of close-ended questions was raised to elicit producer choice of carbon credit programs for participation. Section 2 contained questions to collect information on producer socio-economic background and their attitude to climate change and polity. In section 3, questions were raised on producer current production practices, such as land use, acreages, and tillage practice. Data collected by sections 2 and 3 altogether defined the production attributes of each producer.

The survey was administered by the USDA National Agricultural Statistics Service (NASS) field office in North Dakota (ND). We designed six different versions of survey questionnaires to incorporate different levels of the market price for carbon offsets ranging from $5 to $70 per metric ton of carbon (and thus varying profitability for carbon program participation). For each version of the questionnaire, a sample of 500 producers across ND was randomly selected from the USDA NASS database to receive the survey. Survey questionnaires were mailed out on January 15, 2010, followed by a postcard reminder after two weeks. A total of 316 questionnaires were returned, among which 35 were not filled out and the remaining 281 had at least one question answered.

Table 2 summarizes the survey response. As shown by Table 2, the carbon price in the returned questionnaire ranged from $5 to $70 per metric ton of carbon and seemed to be correlated somehow with survey return rates. For example, the carbon price at $70 per metric ton was associated with the highest return rate of 20%, which was in contrast to the lowest return rate of 14% when the price dropped to $5 per metric ton. While the difference in the survey return rate between the highest and lowest carbon prices might motivate the hypothesis that a higher carbon price caused more attention and thus increased survey response, no similar trends were found for the price range of $15-50 per metric ton of carbon.

Producers currently in the voluntary carbon credit program were rare. Table 2 indicates that only about 7% of the producers who returned their questionnaires were in the voluntary carbon programs. Excluding those producers, less than half were willing to participate in the carbon programs for their given carbon prices, with the majority (or 26%) considering conservation tillage followed by 20% in cropland conversion to grass and 19% in rangeland management. Tree planting had the smallest portion of the producers at 12%.

Producers typically were in their middle ages. Nearly half of them were between 46 and 59 years old, around one third over 60. Most (or 72%) producers had more than 20 years of production experience. Sixty percent of the producers indicated agricultural production being the major source of household income. Around 40% had 4 years of college or some college education with the rest being evenly distributed among high school or less, technical training beyond high school, and graduate degree or coursework. Producer attitude was divided between climate change and climate mitigation legislation. While 44% were concerned about climate change, only 18% would support government climate legislation.

Producer land tenure varied by farmland type. Eighty fiver percent owned cropland and 58% owned rangeland. The percentages for renting cropland and rangeland were 50% and 31%, respectively. It is worth noting that the categories of land ownership by farmland type may not be mutually exclusive. A producer who owns cropland and/or rangeland may also rent cropland and/or rangeland at the same time. The survey response confirmed this possibility.

We grouped producers into four categories by how they used their land, including crop farming, land in CRP, rangeland management, and rental. These land use categories can overlap as producers may have land allocated in one or more uses. As demonstrated by Table 2, land use was unevenly distributed among the four categories. Crop farming accounted for the highest percentage of 67% as a single land use type, which was followed by rangeland management at 59% and land in the Conservation Reserve Program (CRP) at 43%. Accounting for 26% of the producers, farmland rental was the category with the lowest percentage.

III. Modeling Method

In the survey, each producer was presented with 4 carbon credit programs from which they could choose any or all 4 programs at most to participate in or not participating at all. The choice situation was characterized by multiple rather than single, mutually exclusive choice for each producer. Table 3 characterizes the distribution of producer stated choice by carbon programs and the number of programs selected. While different approaches could be used to model the potentially multiple choices of each producer, we consider each producer making participation decision on one carbon program at a time. By this approach, each producer faced 4 choice situations and in each situation he decided participating or not participating in a specific carbon program. The choices that each producer made for the 4 carbon programs were likely to be correlated with each other.

Consider a producer j's carbon program choice. Denote $U_{ij} = V_{ij} + \varepsilon_{ij}$ as producer j's utility from participating in a carbon program i, where V_{ij} is the average utility that producer j may expect to derive from the carbon program i, and ε_{ij} is the difference between the expected average utility V_{ij} and the producer j's individual utility. This difference is unobservable and may be regarded as a random variable reflecting the variation of producer j individual taste. Without losing generality, we standardize producer j's utility for not participating in carbon program i to be zero to represent the status quo. Based on the random utility theory, the probability of producer j to participate in carbon program i can be formulated as

$$\Pr_{ij}(y_{ij} = 1 | y_{\bar{i}j}) = \Pr_{ij}(U_{ij} > 0 | U_{\bar{i}j}) = \Pr_{ij}(\varepsilon_{ij} > V_{ij} | \varepsilon_{\bar{i}j}, V_{\bar{i}j}), \quad \bar{i} = \{h : h \in \mathbf{I}, h \neq i\} \tag{1}$$

where y_{ij} is a choice variable with 1 indicating producer j's participation in carbon program i and 0 otherwise, **I** represents the set of available carbon programs, and h indicate a specific carbon program in **I**. Note that the probability of producer j to select program i for carbon sequestration is expressed as a conditional probability to account for possible correlation among producer j's choices with respect to all 4 carbon programs.

The probability of producer j's choice for carbon program i, either participating or not participating, can be expressed as

$$\Pr_{ij}(y_{ij} | y_{\bar{i}j}) = [\Pr_{ij}(\varepsilon_{ij} > V_{ij} | \varepsilon_{\bar{i}j})]^{y_{ij}} [1 - \Pr_{ij}(\varepsilon_{ij} > V_{ij} | \varepsilon_{\bar{i}j})]^{(1-y_{ij})} \tag{2}$$

Denote $\mathbf{Y}_j = [y_{1j}, y_{2j}, y_{3j}, y_{4j}]'$ as producer j's choice set regarding all 4 carbon programs. The probability of producer j's choice $\mathbf{Y}_j$ would be

$$\Pr_j(\mathbf{Y}_j) = \prod_{i=1}^{4} \Pr_{ij}(y_{ij} \big| \mathbf{y}_{\bar{i}j}) \tag{3}$$

Correspondingly, the log-likelihood function of all producer stated choices would be

$$LL = \sum_j \sum_i \ln[\Pr_{ij}(y_{ij} \big| y_{\bar{i}j})] = \sum_{j=1} \sum_{i=1} \{y_{ij} \ln[\Pr_{ij}(\varepsilon_{ij} > V_{ij} \big| \varepsilon_{\bar{i}j})] + (1 - y_{ij}) \ln[1 - \Pr_{ij}(\varepsilon_{ij} > V_{ij} \big| \varepsilon_{\bar{i}j})]\} \tag{4}$$

Once a proper distribution is specified for ε with V parameterized as a function of observable variables **X** and preference parameters **β** to be estimated, the probability $\Pr_{(\cdot)}$ ($\varepsilon_{(\cdot)}$>$V_{(\cdot)}$) of a producer participation choice on each carbon program can be numerically or analytically calculated. The preference parameters **β** can then be estimated by maximizing the log-likelihood function (4).

In the conditional logit model, ε is assumed following the extreme value distribution. If this assumption holds true, then the probability of producer j to participate in carbon program i can be measured by a logistic function

$$\Pr_{ij}(y_{ij} = 1) = \frac{e^{V_{ij}(X_{ij}, \beta_{ij})}}{1 + e^{V_{ij}(X_{ij}, \beta_{ij})}} \tag{5}$$

However, to account for possibly correlated producer choices among carbon programs requires either correlated ε or a structure in the expected average utility V that allows correlated utility U among carbon programs for individual producers. Consequently, to maintain the logistic function representing producer choice probability with independently distributed ε then dictates correlated expected average utility V.

To parameterize the producer utility function with the required property while linking producer choice to production attributes in an economically meaningful way, we consider producer decision on carbon program participation in a profit-maximizing framework. Denote $\Delta\pi_{ij}$ as the marginal profit that would result to producer j's income from participation in carbon program i. We introduce a utility function to link producer j's participation choice for carbon program i to the marginal profits $\Delta\pi_{ij}$ such that

$$U_{ij} = V_{ij}(\Delta\pi_{ij}) + \varepsilon_{ij} \quad (6)$$

With an active carbon offsets market, producer j's total profit from producing both agricultural commodities and carbon offsets by participating in carbon program i may be expressed as

$$\pi_{ij} = \mathbf{P}\mathbf{Q}_{ij}(q_{ij}) + p_c q_{ij} - C_{ij}(\mathbf{Q}_{ij}, q_{ij}) \quad (7)$$

where **P** represents a vector of market prices for agricultural commodities, $\mathbf{Q}_{ij}$ denotes a vector of production outputs for these commodities, q_{ij} denotes the amount of carbon offsets produced by adopting the practice required by carbon program i, and $C_{ij}(\mathbf{Q}_{ij}, q_{ij})$ is the production cost for commodity output $\mathbf{Q}_{ij}$ with carbon offsets yield q_{ij}, and p_c is the market price for carbon offsets. Because producing carbon offsets by participating in carbon program i requires changing practices or land use, the production outputs of commodities $\mathbf{Q}_{ij}$ and their production cost C_{ij} may be indirectly affected by carbon offsets yield q_{ij}.

For profit-maximizing producers to provide carbon offsets (i.e., $q_{ij} > 0$), the Kuhn-Tucker condition requires $\left.\frac{\partial\pi_{ij}}{\partial q_{ij}}\right|_{q_{ij}=0} > 0$, i.e.,

$$\left.\frac{\partial\pi_{ij}}{\partial q_{ij}}\right|_{q_{ij}=0} = \mathbf{P}\frac{\partial\mathbf{Q}_{ij}(q_{ij})}{\partial q_{ij}} + p_c - \frac{\partial C_{ij}(\mathbf{Q}_{ij}, q_{ij})}{\partial\mathbf{Q}_{ij}}\frac{\partial\mathbf{Q}_{ij}}{\partial q_{ij}} - \left.\frac{\partial C_{ij}(\mathbf{Q}_{ij}, q_{ij})}{\partial q_{ij}}\right|_{q_{ij}=0} > 0 \quad (8)$$

Denote $\Delta C_{ij}^{\mathbf{Q}}$ as the production cost increment attributed to the commodity output effect of changing production practice required by carbon program i and ΔC_{ij}^{q} as the cost increment directly linked to the program participation. For a positive carbon yield $\Delta q_{ij} > 0$, the Kuhn-Tucker condition (8) in discrete case can be written as

$$\Delta\pi_{ij} = p_c\Delta q_{ij} - [-(\mathbf{P}\Delta\mathbf{Q}_{ij} - \Delta C_{ij}^{\mathbf{Q}}) + \Delta C_{ij}^{q}] > 0 \quad (9)$$

The expression (9) indicates that profit-maximizing producers will participate in carbon program i if the marginal revenue from adopting the required practice is greater than its marginal cost including both the opportunity cost of commodity production and the direct cost of the practice. This condition establishes our modeling framework for specifying and estimating an econometric producer behavior model on carbon program participation once producer preference is known.

Denote $\Delta E_{ij} = [-(\mathbf{P}\Delta\mathbf{Q}_{ij} - \Delta C_{ij}^{\mathbf{Q}}) + \Delta C_{ij}^{q}]$ and $R_{ij} = p_c\Delta q_{ij}$. Consequently, $\Delta\pi_{ij} = R_{ij} - \Delta E_{ij}$. While producer j decides whether or not to participate in carbon program i based on his evaluation of the marginal profit $\Delta\pi_{ij}$, the producer j perceived $\Delta\pi_{ij}$, particularly the marginal cost ΔE_{ij}, in general is not observed or unavailable. In the discrete choice modeling framework, however, only the differences of these marginal costs (or profits) among carbon programs matter to modeling producer choice, and thus it is not necessary to measure the absolute value of $\Delta E_{(\cdot)}$ or $\Delta\pi_{ij}$ if R_{ij} is known. As the producer private costs $\Delta E_{(\cdot)}$ depends on the opportunity costs in addition to the program-specific costs, both of which are affected by producer current production practices, we introduce an index function to stratify and parameterize $\Delta E_{(\cdot)}$ for adopting required carbon sequestering practices by production attributes such that:

$$\Delta E_{ij} = \overline{\Delta E_{ij}}(\mathbf{J}_j) + \eta_{ij} \tag{10}$$

where $\mathbf{J}_j$ is a vector of producer j observable production attributes, $\overline{\Delta E_{ij}}(\mathbf{J}_j)$ represents the private cost for participating in carbon program i expected by producer j with production attributes $\mathbf{J}_j$, and η_{ij} is a random error in measuring the private cost. We assume that producer attributes **J** can characterize and stratify producer costs for adopting different carbon-sequestering practices so as to lead to different choices by producers among carbon programs. The production attribute **J** may include land use, production practices, land ownership, demographics, and attitude to climate change and policy.

Substituting $\Delta E_{(\cdot)}$ and $\Delta\pi_{ij}$ into the utility function yields

$$U_{ij} = V(R_{ij}, \overline{\Delta E_{ij}}(\mathbf{J}_j), \eta_{ij}) + \varepsilon_{ij} \tag{11}$$

While there is no reason to expect those private cost deviations $\eta_{(\cdot)}$ to be independently distributed across carbon programs, it is likely that $\eta_{(\cdot)}$ is correlated with each other across carbon programs for each producer. In other words, a producer who perceives a high cost for, say, converting cropland to grass to provide carbon offsets, might also assign a high cost for planting tree for the same purpose although it might not always be the case. The introduction of the index function of producer costs ΔE_{ij} with correlated $\eta_{(\cdot)}$ provides a structure allowing correlated utilities and thus choices among carbon programs while offering desirable interpretation on producer choice consistent with economic production theory.

To parameterize the utility function, we consider a specification with the following characteristics: 1) different producers perceive different costs and benefits for participating in a same carbon program; 2) a producer perceives different costs and benefits for participating in different carbon programs; and 3) these different producer perceptions are due to production attributes and may be correlated across carbon programs. A desirable specification of the utility function may be formulated as

$$U_{ij} = \sum_k \sum_l \beta_{ij}^{kl} \mathbf{J}_j^l \mathbf{I}_i^k{}' , \quad \boldsymbol{\beta}_j = [\boldsymbol{\beta}_{1j}', \boldsymbol{\beta}_{2j}', ..., \boldsymbol{\beta}_{nj}']' \sim \Psi(\boldsymbol{\beta}_j^0, \boldsymbol{\Omega}) \tag{12}$$

Where $\mathbf{I}_i^k$ indicates the k element of the vector of observed attributes $\mathbf{I}_i$ that describes carbon program i, $\mathbf{J}_j^l$ indicates the l element of the vector of observed attributes $\mathbf{J}_j$ that describes producer j, β_{ij}^{kl} is the corresponding coefficient parameter, $\boldsymbol{\beta}_j$ is the vector of coefficient parameters for all available carbon programs for producer j, $\boldsymbol{\beta}_{(\cdot)j}$ is the vector of coefficient parameters for a specific carbon program for producer j, and $\Psi(\boldsymbol{\beta}^0, \boldsymbol{\Omega})$ represents the distribution of $\boldsymbol{\beta}_j$ with population mean $\boldsymbol{\beta}^0$ and covariance matrix $\boldsymbol{\Omega}$. Here, we use the random coefficient parameters $\boldsymbol{\beta}_j$ to allow different producer perceptions for the costs and benefits depending on production attribute $\mathbf{J}_j$. These parameters are jointly distributed with a general variance-covariance matrix $\boldsymbol{\Omega}$ that may accommodate correlated expected utilities (and thus choices) across the choice situations faced by individual producers. This specification leads to the mixed logit model of producer carbon program choice instead of the conditional logit model that is no longer appropriate by assuming independent producer choices across carbon programs.

Given preference parameters vector $\boldsymbol{\beta}_j$ and observed variables matrix $\mathbf{X}_j = [\mathbf{X}_{1j}, \mathbf{X}_{2j}, X_{3j}, \mathbf{X}_{4j}]' = [\mathbf{I}_{1j}\mathbf{J}_j', \mathbf{I}_{2j}\mathbf{J}_j', \mathbf{I}_{3j}\mathbf{J}_j', \mathbf{I}_{4j}\mathbf{J}_j']'$ representing producer j's attributes interacted with carbon programs, the probability of producer j's choice $\mathbf{Y}_j$ would be

$$\Pr_j(\mathbf{Y}_j | \mathbf{X}_j, \boldsymbol{\beta}_j) = \prod_{i=1}^{4} [\Pr_{ij}(y_{ij} | \mathbf{X}_j, \boldsymbol{\beta}_j)]^{y_{ij}} [1 - \Pr_{ij}(y_{ij} | \mathbf{X}_j, \boldsymbol{\beta}_j)]^{(1-y_{ij})} \tag{13}$$

The population mean or unconditional probability of producer j's choice would be

$$\Pr_j(\mathbf{Y}_j \big| \mathbf{X}_j, \boldsymbol{\beta}^0, \boldsymbol{\Omega}) = \int \Pr_j(\mathbf{Y}_j \big| \boldsymbol{\beta}_j, \mathbf{X}_j)\, f(\boldsymbol{\beta}_j \big| \boldsymbol{\beta}^0, \boldsymbol{\Omega}) d\boldsymbol{\beta}_j \tag{14}$$

where $f(\boldsymbol{\beta}_j | \boldsymbol{\beta}^0, \boldsymbol{\Omega})$ represents the probability distribution of preference parameters $\boldsymbol{\beta}_j$. Consequently, the log-likelihood function of all producer choices with respect to carbon credit programs would be

$$LL = \sum_{j=1} \ln \Pr_j(\mathbf{Y}_j \big| \mathbf{X}_j, \boldsymbol{\beta}^0, \boldsymbol{\Omega}) \tag{15}$$

With the joint distribution of random parameters specified, the distributional parameters of producer preferences theoretically can be estimated by maximizing the log-likelihood function (15). The integration over the joint distribution of preference parameters (i.e., equation (15)) usually cannot be completed analytically with a closed form result. Numeric method has to be used to approximate the unconditional choice probability of individual producers.

In this study, we use the Bayesian approach with a Markov Chain Monte Carlo (MCMC) simulation to identify the distributional parameters of producer preferences. The foundation of the Bayesian approach is the Bayes rule $P(B)P(A|B) = P(A)P(B|A)$, which summarizes the probabilistic relationship between two random variables A and B which may be used for statistic inferences. In the classic Bayesian statistics, a probability distribution, say, P(B) is specified to characterize prior information on the unknown parameter B of a sampling process $P(A|B)$. With a sample A generated by the sampling process $P(A|B)$, the prior distribution P(B) is modified and updated with a posterior distribution $P(B|A) = P(B)\, P(A|B)/P(A)$ to reflect new information on the parameters B implied by the sample A. The MCMC simulation as a sampling approach has gained popularity in Bayesian statistics for summarizing the posterior probability distribution (Gelfand and Smith 1990, Gelman 1995, Gilks 1996). For the posterior distribution $P(B|A)$, a sample of the unknown parameters B can be generated by the MCMC simulation such that sample means and deviations can be calculated as the Bayesian estimation of B and standard errors in the classic statistics.

In our mixed logit model, because producer preference parameters $\boldsymbol{\beta}_{(\cdot)} \sim \Psi(\boldsymbol{\beta}^0, \boldsymbol{\Omega})$ is unknown, the unconditional choice probability $\Pr_j(\mathbf{Y}_j | \mathbf{X}_j, \boldsymbol{\beta}^0, \boldsymbol{\Omega})$ of producer j is used in the likelihood function

$$L(\mathbf{Y}|\boldsymbol{\beta}^0, \boldsymbol{\Omega}) = \prod_{j=1} \int \Pr_j(\mathbf{Y}_j | \boldsymbol{\beta}_j, \mathbf{X}_j) f(\boldsymbol{\beta}_j | \boldsymbol{\beta}^0, \boldsymbol{\Omega}) d\boldsymbol{\beta}_j \tag{16}$$

Denote $P^0(\boldsymbol{\beta}^0, \boldsymbol{\Omega})$ as the prior distribution and $P^1(\boldsymbol{\beta}^0, \boldsymbol{\Omega})$ as the posterior distribution of the preference parameter $(\boldsymbol{\beta}^0, \boldsymbol{\Omega})$. According to the Bayes rule, the posterior distribution of the preference parameter would be

$$P^1(\boldsymbol{\beta}^0, \boldsymbol{\Omega}|\mathbf{Y}) = \frac{L(\mathbf{Y}|\boldsymbol{\beta}^0, \boldsymbol{\Omega}) P^0(\boldsymbol{\beta}^0, \boldsymbol{\Omega})}{g(\mathbf{Y})} \propto L(\mathbf{Y}|\boldsymbol{\beta}^0, \boldsymbol{\Omega}) P^0(\boldsymbol{\beta}^0, \boldsymbol{\Omega}) \tag{17}$$

where $g(\mathbf{Y})$ is the unconditional probability of $\mathbf{Y}$, which is a constant not depending on $\boldsymbol{\beta}^0$ and $\boldsymbol{\Omega}$. Although the MCMC simulation could be used to draw a sample of the population parameter based on the posterior distribution (17), the integration involved in the likelihood function to estimate the unconditional probabilities of individual producer choices would be burdensome. Following Train (2009), producer-specific preference parameter $\boldsymbol{\beta}_{(\cdot)}$ is introduced along with its distribution parameters such that the conditional choice probability of individual producers rather than their unconditional choice probability is calculated with the integration no longer needed. Consequently, the new posterior distribution with producer-specific preference parameter $\boldsymbol{\beta}_{(\cdot)}$ would be

$$P^1(\boldsymbol{\beta}^0, \boldsymbol{\Omega}, \boldsymbol{\beta}|\mathbf{Y}) \propto L(\mathbf{Y}|\boldsymbol{\beta}) f(\boldsymbol{\beta}|\boldsymbol{\beta}^0, \boldsymbol{\Omega}) P^0(\boldsymbol{\beta}^0, \boldsymbol{\Omega}) \tag{18}$$

where $\boldsymbol{\beta} = \{\boldsymbol{\beta}_{(\cdot)}\}$. This manipulation improves the feasibility and computational efficiency of the Bayesian approach with the MCMC simulation to estimating the mixed logit model, particularly when a large number of random parameters could be involved with varying distributions for individual parameters.

The Bayesian estimation of the mixed logit model with the MCMC simulation can be conducted with Gibbs sampling (Train 2009). Essentially, Gibbs sampling for the mixed logit model constructs a Markov chain by iteratively taking a draw from the posterior for each parameter conditional on the other parameters with their draws taken previously. Once the conditional posterior of each parameter is derived, taking draws from them is straightforward. It can be shown that the conditional posteriors of individual parameters for the joint posterior (18) are as follow: 1) $P^1(\boldsymbol{\beta}_{(\cdot)}|\boldsymbol{\beta}^0, \boldsymbol{\Omega}, \mathbf{Y}) \propto L(\mathbf{Y}|\boldsymbol{\beta}_{(\cdot)}) f(\boldsymbol{\beta}_{(\cdot)}|\boldsymbol{\beta}^0, \boldsymbol{\Omega})$, 2) $P^1(\boldsymbol{\beta}^0|\boldsymbol{\beta}_{(\cdot)}, \boldsymbol{\Omega}) \sim N(\sum \boldsymbol{\beta}_{(\cdot)}/T, \boldsymbol{\Omega}/T)$, and 3) $P^1(\boldsymbol{\Omega}|\boldsymbol{\beta}_{(\cdot)}, \boldsymbol{\beta}^0) \sim IW(K+N, (K\mathbf{E}+N\mathbf{S})/(K+N))$, where N represents the normal distribution, IW represents the inverted Wishart distribution, K denotes the dimension of preference parameter vector $\boldsymbol{\beta}_{(\cdot)}$, T indicates the sample size, **E** is an indentify matrix, and $\mathbf{S} = \sum(\boldsymbol{\beta}_j - \mathbf{b})(\boldsymbol{\beta}_j - \mathbf{b})'/T$ is a matrix of standard deviations (Train 2009). Note that the above conditional posteriors are based on the assumption of normally distributed preference parameters $\boldsymbol{\beta}_{(\cdot)}$ with population mean $\boldsymbol{\beta}^0$, covariance matrix $\boldsymbol{\Omega}$, and a prior with extremely large variances for the parameters. They may vary depending on the specific distributions assumed for the preference parameters $\boldsymbol{\beta}_{(\cdot)}$. Train (2009) provided a detailed guidance on the Bayesian estimation of mixed logit models using Gibbs sampling, including procedures for taking draws from the conditional posteriors based on different priors.

IV. Modeling Results

We estimated and compared different choice models with varying specifications to identify the preference that best describes producer choice among carbon programs. Models considered included conditional logit and mixed logit with different specifications on the producer utility function. Table 4 compares these models by their structural characteristics, simulated log-likelihood of producer choices, and in-sample choice prediction. As the choice prediction could be different depending on its focus on either each choice or all the 4 choices of each producer, we calculated these two types of prediction for comparison. The ideal producer choice model should have a large log-likelihood for producer choice, high sample prediction rates by producer and by choice, and theoretically sound, reasonable representation of producer preferences.

In Table 4, Models 1-3 represent conditional logit models. These models range from a simple specification of producer utility depending only on the attributes of carbon programs to a more sophisticated specification with interacted attributes between producers and carbon programs. As demonstrated by Table 4, Model 2, which assumed similar producer perceptions on carbon revenue but different perceptions on the private costs of individual carbon programs depending on production attributes, performed better than Models 1 and 3 in terms of simulated log-likelihood and sample prediction by individual choice. Although Model 1 performed the best in sample prediction, it had a poor fit with the sample data, which implied less effective representation of producer preferences and thus the out-of-sample prediction in future policy application would be less reliable. The poor performance of Model 3 rejected the hypothesis that producers perceived carbon revenue differentially depending on their production attributes.

Models 4-8 are mixed logit models. The theoretical foundation for these models was heterogeneous producer preferences as represented by random rather than fixed coefficient parameters in the utility function. By the Bayesian method with the MCMC sampling technique, both individual-level and population-level parameters of producer preferences can be estimated, a characteristics desirable particularly when there is no reason to expect a same preference structure for all producers. For the mixed logit models, we calculated the two types of in-sample prediction using two different approaches: one by sampling preference parameters for individual producers; and the other by using population-level preference parameters. Based on the population-level parameters (with corresponding predictions in parentheses in Table 3), all mixed logit models performed better than or at least comparable to the conditional logit models. The sampling-based choice prediction by mixed logit models was also comparable with that from the conditional logit, particularly by individual choice prediction.

Overall, Model 6 performed reasonably well as compared to other models. Models 8 and 6 had the largest simulated log-likelihood, but Model 8 had the lowest prediction rate either by the sampling approach or on average by population parameters. Models 4 and 6 were ranked the highest in sample prediction by the sampling approach. Yet Model 4 had a simple preference structure with a poor data fitting, which raised serious concern on its ability to represent producer preferences and to conduct out-of-sample prediction. Although Model 5 performed better in sample prediction by using population parameter, Models 6 had a better data fit with a larger log-likelihood estimate and more accurate sample choice prediction by the sampling approach.

It is worth noting that the only difference between Models 5 and 6 was the covariance matrix of the random parameters that were independent in Model 5 but correlated in Model 6. As the choices of each producer might be correlated among carbon programs, Model 6 seemed to better account for potentially correlated choices as demonstrated by its larger log-likelihood estimate. This was consistent with Model 6 better performance in sample prediction by the sampling approach that allowed generation of correlated coefficient parameters. This advantage, however, could not show up in sample prediction based on population level parameters as only one set of parameters was used such that the correlation among parameters became irrelevant. Based on the above comparison, we selected Model 6 as the best model that better fited the producer choice data with a desirable specification on the structure of producer preferences and their variation within population.

Table 5 presents the estimated coefficient parameters for Model 6. As expected, the potential revenue from carbon offsets provision could significantly increase the probability of producer participation in carbon programs. The production attributes of producers did affect their perceived private costs for participating in carbon programs to provide carbon offsets, and the effects of the attributes varied across carbon programs. In our model estimation, the producer attributes were measured by their deviations from the sample means. Consequently, the coefficients for *Constant* interacted with the carbon program dummies would be interpreted as the perceived private costs for carbon programs of a representative producer with the sample "average" production attributes. The insignificance of these coefficients suggests that: 1) the production attributes of producers accounted for the difference in their perceived costs for carbon program participation, and 2) the difference in the average perceived costs for carbon programs by the representative producer could not be rejected, a result consistent with the model specification that the population mean of producer perceived private costs for each carbon program depends on production attributes.

The current land use practice of producers differentially affected their perceptions of the costs for participating in different carbon programs. Crop farming was found to be associated with lower perceived costs for conservation tillage, cropland conversion to grass, and tree planting but a higher cost for rangeland management. This may reflect the fact that crop farming makes more profits such that producers with more land in crop farming would be subject to some opportunity costs if they also devoted time to rangeland management to provide carbon offsets. CRP seemed to only affect the cost perception for tree planting, suggesting that a producer with CRP land would assign a lower cost than the sample average for planting tree. This is consistent with the expectation that producers with marginal land might have lower opportunity costs for allocating land to trees to provide carbon offsets. Rangeland reduced producer costs for participating in carbon programs, particularly for the program of rangeland management. It is interesting to note the differential effects of the current land use on producer cost perception for a same carbon program. For example, compared to crop farmers with the sample average production portfolio, producers managing more rangeland were associated with higher costs for conservation tillage, and vice versa for the program of rangeland management.

As demonstrated by Table 4, land tenure had differential effects on producer cost perceptions for different carbon programs — significantly lower perceived costs for those programs that would require major changes on current land use, which would be less feasible if the potential participant had a weak control of the land. This may be attributed to lower transaction costs or more flexibility for landowners to enroll their land in carbon programs with contracts. Specifically, compared to the sample average, landowners assigned the lowest cost for tree planting followed by cropland conversion to grass, both of which would be more feasible with stronger land tenure. In comparison, the estimated coefficients for *Rent land*, although not strongly significant, were negative for cropland to grass and tree planting, indicating higher perceived costs as compared to for conservation tillage that may be consistent with current land use without requiring major land use change and that seems not to be as critical in ownership requirement for program participation. In addition, *Own land* had stronger effect in reducing the perceived cost for conservation tillage than did *Rent land*. While *Own land* had similar effects on producer cost perceptions for conservation tillage and rangeland management, *Rent land* increased the cost for rangeland management but decreased the cost for conservation tillage.

Producer age tended to increase the perceived cost for conservation tillage and decrease the cost for cropland to grass. In other words, the older the producer, the higher his cost for conservation tillage and the lower for cropland to grass. A possible explanation is that conservation tillage requires changing machinery that may dictate a capital investment not worth its return, particularly for older producer s. Indeed, quite a few survey respondents indicated that they were too old to consider expensive capital investment necessary for adopting conservation tillage. In contrast, this was less of an issue for cropland to grass that could be more suitable for aged producers to participate in carbon sequestration without requiring as much investment in both capital and land management.

Years of production experience seemed to affect the cost perception for rangeland management, with more experienced producers seeing less costs to earn carbon credits in this program. College education and above marginally reduced producer perceived costs for tree planting but had no effect for other programs. For producers concerned about climate change, a lower cost was perceived for cropland to grass, followed in turn by rangeland management and conservation tillage but perhaps a higher cost for tree planting. For producers supporting a cap-and-trade climate policy, lower costs were more likely to be assigned to conservation tillage, rangeland management, and tree planting but a higher cost to cropland to grass. This may be attributed to the opportunity cost of converting cropland to grass that all other programs do not necessarily incur. This result seems to suggest that climate policy supporters do not necessarily value all carbon programs and, in our sample, were more likely to participate in conservation tillage, rangeland management, and tree planting but less likely in cropland to grass.

One of the advantages of the mixed logit model is its ability to reveal the distribution of random coefficient parameters. Figure 1 shows the distribution of the costs perceived by producers with the sample average attributes for adopting different carbon sequestering practices. The perceived costs for carbon program participation were negative for the majority of the producers. On average, the perceived costs for different carbon programs followed the order conservation tillage < rangeland management < cropland to grass ≈ tree planting. This may reflect lower opportunity costs for both conservation tillage and rangeland management, both of which require no major land use change as compared to cropland to grass and tree planting. Figure 1 also shows that producer cost perceptions tended to be more concentrated for conservation tillage and rangeland management, a result probably attributed to their familiarity with both production practices. In contrast, there was high variation in the perceived costs for cropland to grass and tree planting, which might be attributed to less familiarity or diverse impacting factors and thus a wide range of perceived costs, particularly for tree planting.

Table 5 reveals the correlation between the perceived costs for carbon programs by producers with the sample average attributes. It shows that producer perceived costs were positively correlated with each other between different carbon programs. Specifically, the cost for tree planting was more strongly correlated with that for conservation tillage and rangeland management than with that for cropland to grass. This means that if a producer perceived a high cost for conservation tillage or rangeland management, he was more likely to also assign a high cost for tree planting than for cropland to grass. Producer perceived costs for cropland to grass were more closely correlated with those for conservation tillage than with those for rangeland management and tree planting. The existence of the correlation between producer perceived costs justifies our expectation of correlated producer stated choices between carbon programs and thus our model specification.

V. An Empirical Application

The Bayesian method with the mixed logit model allows a sampling approach to simulating individual producer choices in adopting carbon sequestering practices. To develop an application, we assume that U.S. climate policy has established national carbon credit programs similar to the programs modeled in this study, which provides payments at fixed rates for qualified carbon sequestration activities adopted by producers. We apply the sampling-based choice simulating capacity combined with agricultural census data to estimating acreage enrollment in carbon credit programs by practice and carbon offsets supply in the NGP region. We assume that producer preference for adopting carbon sequestering practices is consistent between the NGP region and the ND State, an assumption justifiable by the delineation of the NGP region (USDA ERS 2010). Our explicit consideration of the heterogeneity in both producer preferences and farm production characterized by county-level agricultural census data supports a more reliable simulation exercise.

We first classify producers into different types by their production attributes vector $\mathbf{J}$. We assume that agricultural production is homogeneous among producers of a same type with the same production attributes and heterogeneous across different producer types with varying production attributes. Denote $\mathbf{a}(\mathbf{J})$ as the vector of farmland acreages in different land use operated by producers of type $\mathbf{J}$. With $\mathbf{Pr}(\mathbf{J}, \mathbf{R})$ representing the vector of probabilities of participating in different carbon credit programs with potential carbon revenues $\mathbf{R}$, the amounts of land in different use that producers of type $\mathbf{J}$ would enroll in carbon programs can be calculated as $\mathbf{Pr}(\mathbf{J}, \mathbf{R})\mathbf{a}(\mathbf{J})'$.

In each county, there are many types of producers with varying production attributes vector **J**; and the distribution of producers by type differs across counties. Suppose the probability distribution of producer type **J** in county w is $F_w(\mathbf{J})$. If the county w has a total number of N_w producers, the county-level acreages used to produce carbon offsets for carbon revenues **R** can be estimated as:

$$\sum_{\mathbf{J}} \mathbf{Pr}(\mathbf{J}, \mathbf{R}) \mathbf{a}_w(\mathbf{J}) F_w(\mathbf{J}) N_w \tag{19}$$

The regional total acreages of farmland enrolled in carbon credit programs would be

$$\sum_{w} \sum_{\mathbf{J}} \mathbf{Pr}(\mathbf{J}, \mathbf{R}) \mathbf{a}_w(\mathbf{J}) F_w(\mathbf{J}) N_w \tag{20}$$

If each acre of farmland in different carbon programs can sequester $\boldsymbol{\alpha}$ metric ton of carbon, the regional total carbon offsets supply can be calculated as

$$\boldsymbol{\alpha} \sum_{w} \sum_{\mathbf{J}} \mathbf{Pr}(\mathbf{J}, \mathbf{R}) \mathbf{a}_w(\mathbf{J}) F_w(\mathbf{J}) N_w \tag{21}$$

In this study, we consider five types of land use and management that cover the majority of farmland with carbon sequestration potential and that are incorporated in producer production attributes with available agricultural census data. Not all land in their current use are equally qualified for the carbon credit programs. While different assumptions can be made for the potentially available amount of land for each carbon program, we assume that producers enroll their land in a way by which they could reduce potential uncertainties and risks associated with programs and would not incur high opportunity costs. As different carbon credit programs are targeted at different land use types and management practices, we assume that the considered carbon prices would not be sufficient to cause shifts among land use except for changes in management practices entailed by the target suitable carbon program. Table 7 summarizes the 2007 agricultural census data used in our simulation exercise for the NGP.

Table 8 presents our simulation results on potential producer acreage enrollment in carbon programs and carbon offsets supply. The total acreage in carbon programs would expand from around 28.9 million to 46 million when the carbon price rises from $5 to $70 per metric ton of carbon. Rangeland management accounted for at least over 70% of the total enrolled land, which was in contrast with the second largest contribution of around 25% at best by conservation tillage. This result may be attributed to the significance of rangeland in the region and its relatively low producer perceived costs for providing carbon offsets through better management. The other two carbon programs, cropland to grass and tree planting, contributed small portions of land in carbon offset provision, which were 3.3% and 1.2% at highest, respectively, for a carbon price of $70 per metric ton.

The share of rangeland management in the total acreage enrollment decreased from approximately 87% to 70% with the rising carbon price. The reduced percentage was balanced by the increased shares of the other three carbon programs, with the acreage contribution rising from approximately 13% to 26% for conservation tillage, from 0.3% to 3.3% for cropland to grass, and from 0.03% to 1.17% for tree planting. The changing acreage distribution among carbon programs seems to suggest that producer program participation with rising carbon prices would be least responsive for rangeland management and most responsive for conservation tillage although all the carbon programs would see a growing enrollment.

The total supply of carbon offsets increased from 4.6 million metric ton to 10.7 million metric ton per year as the carbon price rose from $5 to $70 per metric ton of carbon. Corresponding to a relatively slow growth in land enrollment, the share of rangeland management also dropped from around 65% to 36%. Both cropland to grass and tree planting played an increasing role in the supply of carbon offsets with their shares rising from 2% to 14% and from 0.3% to 6.2%, respectively. Conservation tillage still was one major contributor to the carbon offsets supply. Indeed, with its share increasing from 33% to 44%, conservation tillage surpassed rangeland management for a carbon price over $60, becoming the largest offset contributor.

In all, both conservation tillage and rangeland management seemed to be the major source of potential carbon offset supply in the region, particularly when carbon prices were relatively low. Although both program sequesters less carbon than tree planting does on a per acre basis, their significance in carbon offsets supply may be attributed to the fact that they could be applied to the majority of farmland in the region in their current use without incurring significant opportunity costs. The acreage available for planting tree and conversion to grass might be limited due to opportunity costs, conversion costs, uncertainties in carbon markets, or the loss of option value. Yet a rising carbon price seemed to have stronger effect on land enrollment for both programs as compared to for rangeland management. The relatively large amount of carbon that could potentially be sequestered in tree and biomass made tree planting and cropland conversion to grass also significant options for carbon offsets provision, particularly when the carbon price reached a high level.

VI. Conclusion

In this study, we explored producer preference for land-based carbon sequestration potential on agricultural lands. Based on producer stated choice among carbon programs in a hypothetical carbon market, our analysis found that producers would respond to the revenue from carbon sequestration, a result consistent with previous studies assuming responsive producer behavior to the carbon sequestration opportunity. Higher market prices for carbon offsets increased the probability of producer participation in carbon sequestration. However, within our modeling framework, we also found that producers perceived high private costs relative to the perceived benefits of carbon revenue for participating in carbon credit programs with a 5-year contract. High carbon revenue (or carbon prices) would be needed to offset these costs to stimulate producer participation in carbon programs. Without considering producer private costs would likely lead to overestimated agricultural potential for GHG mitigation by land-based carbon sequestration. Cost-sharing programs by government are needed to promote biological carbon sequestration on agricultural lands.

Our analysis also found that producer perceived costs were correlated while differing between carbon-sequestering practices, varied across producers, and could be stratified by production attributes. Accounting for the effects of production attributes, the distribution of producer perceived costs suggested that producer had better, consistent understanding on the private costs for adopting conservation tillage followed by rangeland management. The wide range in producer cost perceptions for converting land to grass and tree planting might reflect large uncertainty in estimating the opportunity and operation costs associated with both practices. In all, the distributions of these private costs demonstrated heterogeneous producer preferences and agricultural production, suggesting that failure to consider the heterogeneity may lead to unreliable estimation of the economic potential for agricultural carbon sequestration and its marginal costs.

Findings from previous studies implied that the NGP region might be the forerunner in the carbon offsets market if land-based biological carbon sequestration came into play (Plantinga et al. 2001, Antle et al. 2002). Our simulation of producer preferences revealed potential supply of carbon offsets by agricultural land-based carbon sequestration in the NGP. In this region, conservation tillage and rangeland management could play a major role, due to their significance in terms of acreage in the region. Cropland conversion to grass and tree planting seemed more responsive to the carbon price, and could also contribute significantly to carbon offsets supply if the carbon price could reach a high level. The NGP may provide a desirable context to explore agricultural carbon sequestration in a market setting.

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Table 1. Example of carbon credit programs by practice included in survey questionnaire[a]

Carbon credit program[b]	Available carbon credits	Market return rate (carbon credits earned × carbon price[f])
Conservation tillage[c]	0.4 metric ton/acre/year	\$10/acre/year
Cropland conversion to grass	1.0 metric ton/acre/year	\$25/acre/year
Rangeland management	0.12 metric ton/acre/year	\$3/acre/year
Tree planting[d]	0.7-1.8 metric ton/acre/year[e]	\$17.5-45/acre/year

a. Carbon credit programs were adopted from the voluntary programs managed by the National Farmer Union (2010). In the survey, we also included methane management. This study is focused on land-based carbon sequestration practices.
b. All programs required at least 5 year commitment.
c. Including planting methods commonly referred to as: no till, strip till, direct seed, zero till, slot till, and zone till.
d. A contract longer than 5 years might be required.
e. Credits depend on tree age and species; at least a 20 acres enrollment was required.
f. \$25 per metric ton of carbon was assumed in this example.

Table 2. Summary of producer survey response

Attribute	Level	Percentage
Assigned carbon price	\$5/metric ton	14%
	\$15/metric ton	18%
	\$25/metric ton	17%
	\$35/metric ton	15%
	\$50/metric ton	16%
	\$70/metric ton	20%
Carbon program participation	Currently enrolled	7%
	Not enrolled but willing to participate	46%
	Conservation tillage	26%
	Cropland to grass	20%
	Rangeland management	19%
	Tree planting	12%
Age	≤45 years old	18%
	46-59 years old	46%
	≥60 years old	33%
Farming experience	≤10 years	11%
	11-19 years	13%
	≥20 years	72%
Major source of household Income	Farming	60%
Education	High school or less	20%
	Technical training beyond high school	20%
	4 year college or some college	39%
	Graduate degree or coursework	19%
Attitude to climate change and policy	Concerned about climate change	44%
	Support climate policy	18%
Land tenure by land use type	Own cropland	85%
	Rent cropland	50%
	Own rangeland	58%
	Rent rangeland	31%
Land use/management	Crop farming	67%
	CRP	43%
	Rangeland management	59%
	Rental	26%

Table 3. Stated choice distribution among carbon sequestration practices by producers willing to participate in carbon programs

Carbon credit program	Total number of carbon credit programs to enroll			
	1	2	3	4
Conservation tillage	21%	16%	11%	8%
Cropland to grass	10%	18%	7%	8%
Rangeland management	7%	15%	10%	8%
Tree planting	2%	10%	7%	8%

Table 4. Comparison of logit models of producer stated choice for participating in carbon credit programs

Model	Characteristics	Simulated log-likelihood	Sample prediction by farmer	Sample prediction by choice
Model 1	Conditional logit, fixed coefficient for carbon revenue, fixed coefficients for program dummies	-452.31	51.15%	77.30%
Model 2	Conditional logit, fixed coefficient for carbon revenue, fixed coefficients for program dummies varying by farmer attributes with fixed effects	-377.12	51.61%	79.84%
Model 3	Conditional logit, fixed coefficient for carbon revenue varying by farmer attributes with fixed effects, fixed coefficients for program dummies varying by farmer attributes with fixed effects	-1006.50	23.04%	64.52%
Model 4	Mixed logit, fixed coefficient for carbon revenue, random coefficients for program dummies correlated and jointly normally distributed	-412.24	76.96% (51.15%)	94.24% (77.30%)
Model 5	Mixed logit, fixed coefficient for carbon revenue, random coefficients for program dummies independently and jointly normally distributed with population mean depending on farmer attributes with fixed effects	-394.53	92.17% (53.92%)	97.58% (80.30%)
Model 6	Mixed logit, fixed coefficient for carbon revenue, random coefficients for program dummies correlated and joint normally distributed with population mean depending on farmer attributes with fixed effects	-348.63	94.01% (53.92%)	98.27% (80.30%)
Model 7	Mixed logit, fixed coefficient for carbon revenue varying by farmer attributes with fixed effects, random coefficients for program dummies correlated and jointly normally distributed with population mean depending on farmer attributes with fixed effects	-396.81	100% (51.15%)	100% (77.53%)
Model 8	Mixed logit, random coefficient for carbon revenue truncated normally distributed, random coefficients for program dummies correlated and jointly normally distributed with population mean depending on farmer attributes with fixed effects	-347.34	100% (39.17%)	100% (74.88%)

Table 5. Estimated coefficient parameters for the mixed logit model of producer stated choice of carbon credit programs [a]

Attributes[b]	Carbon revenue[c]		Conservation tillage		Cropland to grass		Rangeland manage.		Tree planting	
Constant	0.0779**	(0.0391)	-3.5955	(3.1738)	-11.8706	(13.1002)	-4.3771	(3.4375)	-16.0868	(11.6830)
Farming	-		2.2895***	(0.6397)	1.0748	(0.9056)	-0.2029	(0.8256)	3.8181***	(1.1382)
CRP	-		1.2942*	(0.7824)	1.7414**	(0.8248)	0.3811	(0.6882)	1.1925	(0.9241)
Rangeland	-		1.2838*	(0.8072)	2.5727	(2.2687)	4.8513***	(0.7565)	2.6922***	(0.6462)
Own land	-		1.9946*	(1.2548)	3.4058***	(0.9173)	1.4896	(1.4484)	2.2612**	(1.0028)
Rent land	-		3.5533**	(1.5567)	-1.7252**	(0.8582)	-0.7581***	(0.7882)	-0.2394	(0.7482)
Age	-		-0.1784*	(0.0992)	0.1431	(0.2433)	-0.1197	(0.0933)	-0.1974	(0.2570)
Years of experience	-		-0.0714	(0.1061)	0.1832	(0.4287)	0.2965**	(0.1491)	0.1170	(0.3361)
≥ College education	-		0.3085	(0.8667)	0.4606	(1.2240)	-1.0486*	(0.6735)	2.0460	(1.5895)
Concerned about climate	-		1.6070**	(0.7854)	1.8640***	(0.7504)	1.3436*	(0.8752)	-1.0195	(1.0427)
Support climate policy	-		1.9609***	(0.6855)	3.2180***	(1.1982)	1.8519**	(0.9662)	2.1277**	(0.9119)

a. Dummy variables were created for individual carbon programs to allow for preference variation regarding program participation depending on farmer attributes. The dummy variable for conservation tillage is omitted with the coefficient estimates for the other three carbon programs representing the differences in utility relative to conservation tillage. The standard errors of the estimated coefficients are in parenthesis. *** denotes significance at the 0.01 level, ** denotes significance at the 0.05 level, and * denotes significance at the 0.1 level.

b. Producer production attributes were measured by deviations from their sample averages, which were interacted with carbon program dummies to create independent variables incorporated in the mixed logit model. The coefficients for the *Constant* variable represent the sample average utility across carbon programs. The coefficients for other independent variables represent the marginal utility for one unit deviation in these variables from their sample averages.

c. Carbon revenue varies depending on the carbon program. Based on the model comparison in Table 4, a fixed effect independent of producer production attributes was specified for carbon revenue across programs.

Table 6. Correlation between random parameters in producer choice model

Random parameter	ConstXDtillage	ConstXDgrass	ConstXDrnglnd	ConstXDtree
		Estimated correlation for posterior distribution		
ConstXDtillage	1.0000	0.5665	0.5727	0.5771
ConstXDgrass	0.5665	1.0000	0.5398	0.3292
ConstXDrnglnd	0.5727	0.5398	1.0000	0.6760
ConstXDtree	0.5771	0.3292	0.6760	1.0000
		Simulated correlation based on posterior distribution		
ConstXDtillage	1.0000	0.5563	0.5910	0.5970
ConstXDgrass	0.5563	1.0000	0.5520	0.3309
ConstXDrnglnd	0.5910	0.5520	1.0000	0.6760
ConstXDtree	0.5970	0.3309	0.6760	1.0000

Table 7. Summary of 2007 agricultural census data by states for the Northern Great Plains region

Agricultural attributes	Number of farms	Acreage
Land use and management		
Harvested cropland	20,408	22,035,709
Cropland only used for pasture or grazing	4,025	778,654
Other cropland	17,326	4,688,627
Permanent pasture and rangeland	14,964	10,418,874
Land in conservation	15,253	3,434,047
Land tenure		
Own land	29,099	19,977,605
Rent land	15,667	19,696,981
Principle operator age group		
Less than or equal to 45 years	6,376	NA
46 to 59 years	12,707	NA
60 years and over	12,887	NA

Data source: USDA (2010)

Table 8. Simulated farmland enrollment in carbon credit programs by practices and carbon offsets supply in the Northern Great Plain region

Carbon price $/metric ton	Conservation tillage	Cropland to grass	Rangeland management	Tree planting	Total
Acreage of farmland enrolled, acres (%)					
	3,775,504	89,841	25,017,764	9,624	28,892,733
5	(13.07)	(0.31)	(86.59)	(0.03)	(100)
	4,199,690	127,990	25,762,035	13,420	30,103,134
10	(13.95)	(0.43)	(85.58)	(0.04)	(100)
	4,661,953	180,756	25,999,684	17,691	30,860,085
15	(15.11)	(0.59)	(84.25)	(0.06)	(100)
	5,082,689	192,338	26,952,422	26,155	32,253,604
20	(15.76)	(0.60)	(83.56)	(0.08)	(100)
	6,124,369	331,192	27,818,065	47,671	34,321,297
30	(17.84)	(0.96)	(81.05)	(0.14)	(100)
	7,323,529	547,978	28,942,664	100,110	36,914,281
40	(19.84)	(1.48)	(78.41)	(0.27)	(100)
	8,651,203	770,023	29,728,067	186,454	39,335,748
50	(21.99)	(1.96)	(75.58)	(0.47)	(100)
	10,123,927	1,169,747	30,861,480	359,788	42,514,942
60	(23.81)	(2.75)	(72.59)	(0.85)	(100)
	11,758,080	1,526,409	32,146,361	537,355	45,968,204
70	(25.58)	(3.32)	(69.93)	(1.17)	(100)
Carbon offsets, metric ton/year (%)					
	1,510,202	89,841	3,002,132	12,031	4,614,204
5	(32.73)	(1.95)	(65.06)	(0.26)	(100)
	1,679,876	127,990	3,091,444	16,774	4,916,085
10	(34.17)	(2.60)	(62.88)	(0.34)	(100)
	1,864,781	180,756	3,119,962	22,114	5,187,613
15	(35.95)	(3.48)	(60.14)	(0.43)	(100)
	2,033,075	192,338	3,234,291	32,694	5,492,398
20	(37.02)	(3.50)	(58.89)	(0.60)	(100)
	2,449,748	331,192	3,338,168	59,589	6,178,696
30	(39.65)	(5.36)	(54.03)	(0.96)	(100)
	2,929,412	547,978	3,473,120	125,138	7,075,647
40	(41.40)	(7.74)	(49.09)	(1.77)	(100)
	3,460,481	770,023	3,567,368	233,068	8,030,940
50	(43.09)	(9.59)	(44.42)	(2.90)	(100)
	4,049,571	1,169,747	3,703,378	449,736	9,372,431
60	(43.21)	(12.48)	(39.51)	(4.80)	(100)
	4,703,232	1,526,409	3,857,563	671,693	10,758,898
70	(43.71)	(14.19)	(35.85)	(6.24)	(100)

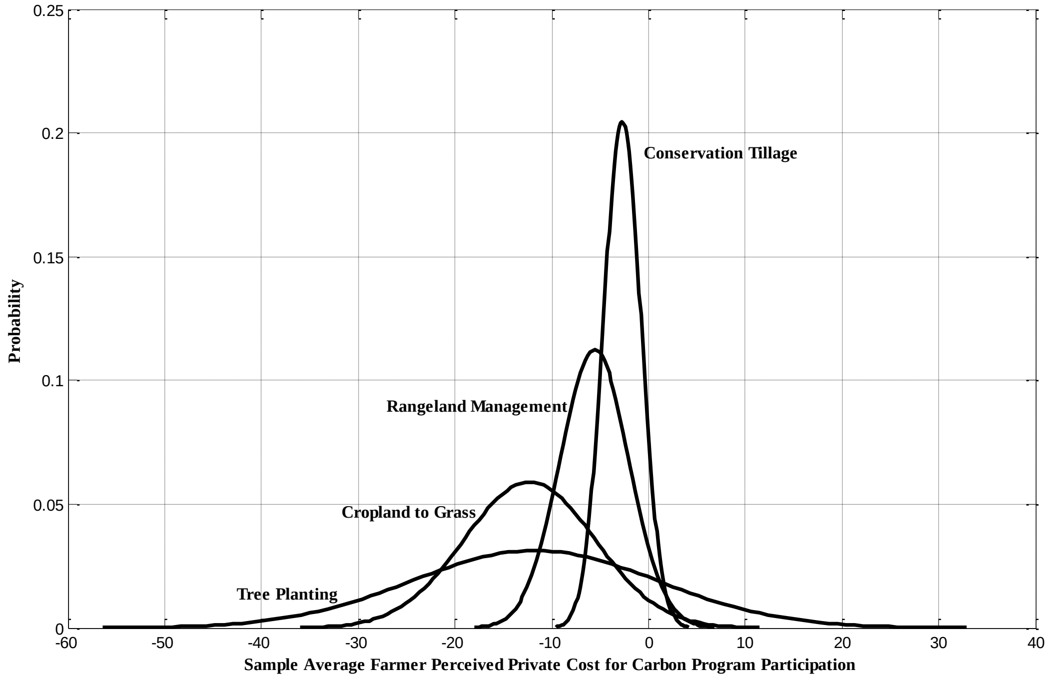

Figure 1. Probability distribution of sample average producer perceived private costs for participating in carbon credit programs by different practices