Estimating Adoption of Cover Crops Using Preferences Revealed by a Dynamic Crop Choice Model

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Selected Paper prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA, July 26-28

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This Version:May 27, 2015

Preliminary Draft - Please do not Quote without Permission

Abstract In this paper, we propose a framework based on micro-level dynamic land use models to predict the adoption of cover crops in the Upper-Mississippi River Basin. We use preferences recovered using a dynamic discrete model of crop choice to build a dynamic optimization framework to evaluate a range of scenarios based on the cover crops' effect on cash crop yields, costs of cover crop operations, and government support. We use a conditional choice probability method to estimate the dynamic crop choice model based on field-scale panel data and value function iteration method to assess counterfactual cover crop scenarios. The framework is expected to be applicable to modeling decisions to adopt conservation technologies in the absence of individual-level adoption data or for cases when conservation technology is new. The dynamic crop choice model yields expected results and reveals preferences for net revenues in line with previous literature. Simulation results predict baseline cover crop adoption rates which, although in line with some recent farmer surveys, are quite a bit higher than rates reported in 2012 Census of Agriculture. We attribute these results to substitution patterns implied by a dynamic logit model estimated, and suggest using aggregated Census of Agriculture data on state-wide adoption of cover crops to calibrate the constants in the the estimated dynamic logit model as a possible remedy under paucity of data related to individual decisions on cover crops adoption.

Introduction

The first National Rivers and Streams Assessment (NRSA) conducted by USEPA puts phosphorus and nitrogen pollution as the leading factors contributing to water quality impairments (USEPA, 2013[28]). The expansion of row crops (such as corn) and tile drainage in cropland in recent years are likely to increase the pressure on actions to improve the ecological health of rivers, streams, and coastal zones nationwide. More cropland conservation practices capable of reducing nutrient loadings from cropland are definitely required at a large scale to meet the stated national or regional water quality goals such as the desired reduction in the Gulf of Mexico hypoxic zone (e.g., Rabotyagov *et al.*, 2014[25]).

Among many conservation practices considered in the literature and policy discussion, cover crops have several desirable properties. In a recent meta-analysis (Basche *et al.*, 2014[5]), cover crops have been found to produce several water quality related benefits such as reducing soil erosion and nitrate losses (Kaspar *et al.*, 2012 [17] and Dabney *et al.*, 2001 [10]). Though cover crops have these beneficial effects, they are not widely adopted in the US Corn Belt states. Cold weather, short growing season after row crops (corn and soybean) mature and the distribution of benefits the most benefits associated with cover crops are public benefits such as reducing nitrogen leaching from the plots, and even some negative effects on row crop yields found in these areas in some studies (Kaspar et al., 2007 [18] and 2012 [17]) - are likely the reasons behind the small scale of cover crops adoption.

Although cover crops have not been widely adopted to date, they are thought to play a more important role in the future. In a survey in Corn Belt states, farmers show willingness to increase the tile drainage in their fields when presented with possible future threats from climate change (Arbuckle et al., 2013 [1]). As a consequence, increased nutrients released to rivers and streams will make the effort to improve water quality in these systems even more challenging given other water quality beneficiary practices, such as cover crops or reinstallment of wetlands, are not extensively adopted.

In this study, using a structural dynamic crop choice model, we build a framework to predict the adoption of cover crops and evaluate the subsequent water quality benefits in a number of future scenarios. Our proposed framework combines (1) a dynamic crop choice model, and (2) the use of relative change in revenues to reflect uncertainties associated with adoption of cover crops. The results can serve as ready inputs to the environmental assessment models to evaluate water quality benefits of cover crops.

With the spatially detailed land use data and other economic data from various sources, we have estimated a dynamic discrete choice crop choice model. The estimated coefficients are generally well expected and relative preferences for crop net revenues are in line with previous research. Based on the estimated parameters, we also extend the model framework to predict the choice probabilities of cover crops under a variety of scenarios. The primary results show relatively high predictions of probabilities to adopt cover crops under all scenarios. There are two reasons for this high baseline prediction. First, this is likely the manifestation of the independence of irrelevant alternatives (IIA) property of the logistic framework. Strictly speaking, this property does not hold generally in the dynamic discrete choice models because of the continuation value associated with each option. However, a closer look at the simulated value function in this study shows that this part does not exhibit sufficient variation to significantly depart from predicted probability behavior associated with the IIA property. Together with a small coefficient on revenue variables, the utility payoff of cover crops looks very similar to the option without cover crops. Second, since we do not have similar spatial data about cover crops as the land use data, we are not able to build the option to use cover crops specifically into the model. The effect of cover crops on choice is simulated relying on the imposed behavioral assumption that it will affect farmer decisions via changes in revenues. However, the coefficient associated with the revenue in the expected utility function is fairly small, which makes it difficult to change decision given moderate changes in revenue. Although our results match quite closely the cover crop adoption rates presented in a recent survey (CTIC-SARE, 2014 [8]), they appear rather inflated when compared to USDA's official Census of Agriculture state-wide estimates. Given that we place more confidence in the USDA Census estimates, we propose a calibration remedy based on re-adjusting the alternative specific constants associated with cover crop options to calibrate the model so that the base scenario probabilities match the observed share of cropland with cover crops in the NASS Census of Agriculture 2012 data. Using such aggregated data for field-level model calibration appears necessary prior to using results for policy analysis.

Methodology and Related Literature

The prevailing row cropping system in the study area is corn/soybean rotational crop system. One of the features of this crop system is the natural dynamic links between soybeans and corn in rotation. Some recent modeling frameworks have been proposed in the literature to capture these dynamics, such as Cai et al. (2012) [7] and Livingston et al. (2014) [22]. The common feature of these studies is that the researchers allow their models to incorporate up to several years of rotational benefits in the corn-soybean system using a known form (i.e., the yield effect in each year is known), which is based on the findings in Hennessy (2006) [13]. DePinto and Nelson (2006) [11], Scott (2013) [26] and Ji and Rabotyagov [16] also propose a dynamic framework built on the observational data using a flexible functional form to capture rotational effects.

The crop choice model used in this study is based on the framework in Ji and Rabotyagov [16], a dynamic discrete model of cropping choices. The econometric estimation method used in this model (i.e., the conditional choice probability method as in Arcidiacono and Miller [3]) is fairly straightforward to apply and greatly reduces the computation cost compared with other estimation methods such as the two-stage nested estimation method of Rust (1987) [24].

The process to estimate farmers crop-practice decisions is proposed as follows: (1) a dynamic crop choice model is estimated using field-scale data from remote-sensing-based cropland data layers (CDL) provided by USDA-NASS, and data on the local soil conditions and economic information (i.e., prices and growing costs of corn and soybean); (2) given the estimated crop choice model, farmers adoption of cover crop will be predicted by changing the expected net revenues under different combinations of cost reimbursement rates and yield effects.

For example, we could assume a scenario where there is a cost of $40/acre associated with cover crop (i.e., seed cost, planting and harvest costs) and government agencies set up a full cost sharing program with farmers to promote adoption of cover crops. By incorporating this cost into the expected net revenue calculation, we can use the crop choice model to estimate the probability of a farmer at a specific location participating in such a program. By assuming that there is only a short term yield effect of cover crop (i.e., the current cover crop will only affect the yield of the crop immediately following), we also can use the model to infer a general spatial pattern of expected program participation. Using field-scale predictions of crop rotation and cover crop adoption, we propose to use environmental assessment models such as the Environmental Policy Integrated Climate (EPIC) model to evaluate the nutrients leaving the field or the Soil and Water Assessment Tool (SWAT) to evaluate effects on nutrients at the watershed scale. We plan to apply this modeling framework to the whole Upper-Mississippi River Basin since this area is critical in achieving the goals set by the Gulf of Mexico Hypoxic Zone Task Force (e.g., Rabotyagov *et al.*, 2014[25]).

By predicting the spatial distribution of modeled adoption of cover crops for a range of subsidy scenarios and the implied effects on the supply of water quality benefits, our framework can be used to inform the policy makers interested in targeting cover crops as instruments for improving water quality.

Land Use Decision

The general framework in this study is in line with Wu *et al.* [27] and Lubowski *et al.* [20]. Differing from these studies, we add a dynamic component into the farmers' decision. In the research area, Iowa, Illinois, Minnesota and Wisconsin, the prevailing row crop system is the corn-soybean rotation system which naturally lends itself to dynamic modeling to capture farmers' understanding and anticipation of rotational effects.

As in Ji and Rabotyagov [16], farmers maximize a flow of conditional utility defined on the expected revenue on the plot given the vector of state variables X_t at time t.

$$\max_{d_t} E\{\sum_{t=0}^{T} \beta^t[\mu(X_t, d_t|\theta_1]\} \tag{1}$$

where

- $\mu(X_t, d_t|\theta_1)$, the flow utility function at time t if option d_t is chosen, where θ_1 is a vector of unknown parameters.
- X_t, a vector of state variables at time t, the transition of X_t is governed by $f(X_{t+1}|X_t, d_t, \theta_2)$, where θ_2 is a vector of unknown parameters which govern the movement of state variables.
- d_t, an option chosen by the decision maker at time t among J possible options.
- β, the discount factor

Since we focus on land use decisions in midwestern US states and the prevailing crop system is dominated by row crops such as corn and soybean, we group farmers' crop choice into three categories: corn, soybean and other crops. Thus, the flow utility $\mu(X_t, d_t)$ for plot i at time t could be specified as following:

$$\mu(X_t, d_t) = \begin{cases} \alpha_c + \theta_r R_{ict} + \theta_{soilc} Soil_i + \theta_{soilrc} R_{ict} \times Soil_i + \theta_{c1} S1_{it} + \theta_{c2} S2_{it} + \theta_{c3} G1_{it} + \eta_{ijt} & \text{if j=1(Corn)} \\ \alpha_s + \theta_r R_{ist} + \theta_{soils} Soil_i + \theta_{soilrs} R_{ict} \times Soil_i + \theta_{s1} S1_{it} + \theta_{s2} S2_{it} + \theta_{s3} G1_{it} + \eta_{ijt} & \text{if j=2(Soybean)} \\ \eta_{ijt} & \text{if j=3(Other crops)} \end{cases} \tag{2}$$

where ηs are independent and identical extreme value Type I random variables (logistic error terms), representing state variables unobservable to the researchers, $R = Price * yield - Cost$ is the expected net revenue defined as expected harvest price multiplying the expected yield and subtracting the growing cost. $S1$ and $S2$ represent the soybean history at a given plot in last two years, respectively. It takes value of 1 if soybean was the chosen crop in that year. $G1$ is a dummy variable with value 1 if other than corn or soybean crops are grown at that plot in the previous year. These state variables are used to represent the utility shifters in the conditional utility function and capture the dynamic effects in the crop system. The non-irrigation land capability class (LCC), is also used here as a utility shifter in this model, providing spatial differentiation in utilities.

A similar specification of the crop choice model, specifically the assumption of up to 2 periods dependence on crop history, has been used in several empirical studies focusing on dynamic links within a corn-soybean crop system (Hennessy, 2006 [13]). The application of 2 periods dynamic links within corn-soybean system can also be found in Livingston *et al,* [22] and Cai *et al,* [7]. With this assumption, the complicated dynamic discrete choice model can be estimated in two stages with the conditional choice probability (CCP) method as in Ji *et al.*, (2014) [16] and Bishop (2008) [6].

Prediction of Cover Crop Choice

Since we do not have micro-level field data on the adoption of cover crop, the aforementioned crop choice model will serve as a benchmark to predict the choice of cover crop under counterfactual scenarios with the assumption that the decision on whether to adopt the cover crop practice will be influenced by the change in net revenues via cost and revenue changes (*i.e.,* yield effects). We acknowledge that the adoption decision is far more complicated than the simple approximation here. The study is intended to introduce a framework which features the dynamic land use decision and adoption of cover crop and provide a new tool for the policy analysis purpose.

In our framework, a combination of two parameters, the operating cost of cover crop (C_{cc}) and the yield effect of cover crop on next season's crop (δ_c for corn and δ_s for soybean). We do not allow cover crop be an option for growing other crops and we acknowledge that cover crops are sometimes used by farmers for other crops (CTIC-SARE, 2014 [8]).[1] There are relatively good estimates about the operation cost of cover crops, including planting cost and harvest cost, but not so much consensus about the yield impacts on next season's crop. Some studies found that the possible yield effect may be negative for corn and almost no yield effects on soybean(Kaspar *et al.* [17] and [18]). The recent national survey about cover crops indicates that there are significantly positive effects both on corn and soybean yields, although the magnitude of these yield-enhancing effects vary substantially across regions (CTIC-SARE, 2014 [8]), and reported results may be suffering from a selectivity bias. In this study, we will choose a range of values to reflect the uncertainties of these yield effects by changing the values of δs. The details about the scenario specifications are described in the next section.

By adoption of cover crops, the expected utility function $\mu(\bullet)$ will be changed in two parts.

[1] We think these assumption are accepted because corn and soybean are the dominant row crops in the research areas.Also, the cover crop adoption in this corn-soybean crop system has most important implications for water quality issues.

First, the annual cost directly change the current year revenue of growing either corn or soybean. Second, it will also change the expected revenue for next year's harvest because of the yield effects δ_c and δ_s. Farmers will balance between current costs and future benefits when they consider whether to adopt cover crops or not. Mathematically, the introduction of cover crops into the land use model will add another state variable $CC1$ into the system, which takes value of 1 when cover crops were adopted in last year. [2] The new decision problem becomes

$$\mu(X_t, d_t) = \begin{cases} \alpha_c + \theta_r R_{ict} + \theta_{soilc} Soil_i + \theta_{soilrc} R_{ict} \times Soil_i + \theta_{c1} S1_{it} + \theta_{c2} S2_{it} + \theta_{c3} G1_{it} + \eta_{ijt} & \text{if j=1} \\ \alpha_c + \theta_r (R_{ict} - Cost_{cc}) + \theta_{soilc} Soil_i + \theta_{soilrc} (R_{ict} - Cost_{cc}) \times Soil_i + \theta_{c1} S1_{it} + \theta_{c2} S2_{it} + \theta_{c3} G1_{it} + \eta_{ijt} & \text{if j=2} \\ \alpha_s + \theta_r R_{ist} + \theta_{soils} Soil_i + \theta_{soilrs} R_{ict} \times Soil_i + \theta_{s1} S1_{it} + \theta_{s2} S2_{it} + \theta_{s3} G1_{it} + \eta_{ijt} & \text{if j=3} \\ \alpha_s + \theta_r (R_{ist} - Cost_{cc}) + \theta_{soils} Soil_i + \theta_{soilrs} (R_{ict} - Cost_{cc}) \times Soil_i + \theta_{s1} S1_{it} + \theta_{s2} S2_{it} + \theta_{s3} G1_{it} + \eta_{ijt} & \text{if j=4} \\ \eta_{ijt} & \text{if j=5} \end{cases} \tag{3}$$

where the five options are *corn without cover crop, corn with cover crop, soybean without cover crop, soybean with cover crop and other crops.* The revenue (R) is defined as $Price * (1 - \delta * CC1) * yield - Cost$ and $CC1$ equals 1 if cover crop is adopted in last year. From here, we can see why we can make prediction without need to re-estimate the models. The decision to adopt cover crops or not will only change the calculation of state variables in the model instead of having direct impacts on the parameters. We must admit that we do not have evidence to exclude other type of assumptions and the way introducing impacts of cover crops used here make it feasible to do the prediction work relying on the data currently available.[3]

Different from the static discrete choice models, we still need find out the value function for the dynamic decision problem in (1) even we do not need re-estimate the model. To do

[2] The assumption that cover crops will only affect expected utility functions via revenue change allow us to use the estimated parameters from the land use model to construct the new decision problem without re-estimating a new dynamic model with cover crop history as a new state variable.

[3] If equipped with detailed plot-level cover crop adoption data, it is possible to completely abandon these assumptions like in Wu *et al.*,[27] to predict the adoption pattern in different policy scenarios.

this, we will use the value function iteration method suggested in Rust (1987)[24] to recover the value function. With the numerically approximated value function, we can construct the choice probability of each of the 5 options above based on the logistic structure of error terms.

Data Summary and Scenario Specification

Land Use Data Sets

The land use data comes from the panel Cropland Data Layer dataset, provided by NASS, USDA.[4] In these spatial data layers, different land use categories are assigned to spatial units (usually in 30 by 30 meters spatial resolution, 56 by 56 meters specifications are also used in some years) based on satellite remote sensing data. The base land use unit used in this analysis are randomly selected from these spatial units within the Upper-Mississippi River Basin area. The selection work is done in Arcgis 10.1 with the built-in function of "Creating Random Points". More than 10,000 points were originally generated and more than 8000 points in four states of Illinois, Iowa, Minnesota and Wisconsin are used in the final analysis.[5] Figure 1 shows the spatial distribution of the final points.

[Figure 1 Here]

The cost data comes from the cost and revenue reports for corn and soybean compiled by the Economic Research Service (ERS), USDA. The most recent reports group cost and revenue statistics into several regions.[6] The yield data is obtained with queries from the QuickStats

[4] The national data layer starts from 2008. State level data layers can go back as early as 1997 for North Dakota

[5] Points are excluded due to two reasons. First, one set of points will be dropped because there is no matched soil conditions. Second, CDL has some land use categories such as developed land and forest land. We exclude any points with these land use types. In addition, we also exclude those points with land use type of Alfalfa. The reason for exclusion of alfalfa is that it also have the nitrogen fixation function as soybean and if it is included in the model, the model will become much more complicated.

[6] ERS, USDA also provides a matched list between counties and regions. The list allows us to match

service provided by National Agricultural Statistic Service, USDA.[7]

The expected prices are constructed in the same way as in Hendricks *et al.* [14] and consist of two parts. The first part is the mean March future price of December corn at Chicago Mercantile Exchange. The second part is the expected county basis defined as the difference between the spot price of corn and the March future price of May corn. The sum of these two parts are the expected corn price faced by farmers when they are making the crop choice decision. The expected price of soybean is constructed similarly except the mean March future price of November soybean is used in the first part. Our historical spot price data comes from the compiled price data by Iowa State University Extension and Outreach, Ag Decision Maker Program.[8]

Although we have pseudo "parcel" level land use data from CDLs, the cost, price and yield data collected above only allow us to construct county-level revenue for each crop. As in Lubowski *et al.* [20] and [21], we will use land productivity proxies, the non-irrigation land capacity class, to introduce the plot-level variation into the model.[9]

Cover Crops Data and Scenario Specification

The cost of cover crops depends on various factors, such as which type of cover crops used, the seeding methods and the termination methods and so on. Iowa nutrient reduction strategy

regional cost data to each county in our sample data set. The report groups cost information into different categories and we exclude the cash rental rate when we construct the cost sequence since only difference matters in the logistic framework.

[7] The web link to the web-base query services is http://quickstats.nass.usda.gov/

[8] The spot price is associated with spatially and sparsely distributed facilities, such as corn elevators. We first calculate basis at these locations and use the inverse distance weight method to extrapolate to county centers. The basis data is generously provided by Prof. Chad E. Hart at the department of economics, Iowa State University.

[9] The pseudo "parcel" here is represented by points generated in Arcgis. Using the geo-location information of these points, we can match them with county-level SSURGO maps to find out soil attributes at these points. For a typical soil category, defined by the field "MUKEY" in the SSURGO maps, there are usually more than one sub-categories. Thus, we use the sub-category labelled as the major component as the corresponding soil type at that point. At the same time, we will again, as in these papers, divide LCC into four groups: I-II, III-IV, V-VI and VII- VIII.

puts the cost estimate around $29 to $32 per acre before any consideration of yield effects (IDALS-IDNR-ISU, 2014 [15]). In the SARE-CTIC 2014 ([8]) annual report, the median cost of cover crops is estimated around $49 per acre in the Midwest.[10] In this analysis, we will use $40 per acre as the baseline cost of cover crops absent of any yield effects. In counterfactual scenarios, this cost can be reimbursed by some government supported programs to promote the adoption of cover crops.

Concern about possible negative yield effects are reported as one of important factors influencing cover crops adoption (CTIC-SARE,2014 [8]). However, the yield effect of cover crops is quite uncertain. Iowa nutrient reduction strategy used an average of -6% yield impact for corn when rye is used as cover crops and zero yield impact on soybean yield based on several empirical studies. While CTIC-SARE (2014) reports more favorable yield enhancing effects of cover crops based on farmers' reported yield increase. In 9 Midwestern states, the increase in corn yield after cover crops ranges from 2.2% to 7.9% and soybean yield effect ranges from 3.1% to 8.1%. Given these mixed yield effect accounts, different yield impacts are assumed in the counterfactual scenarios to reflect these uncertainties.

A counterfactual scenario in this analysis is defined by a combination of cost reimbursement rate and yield effects. We assume three cost reimbursement rates, 0%, 50% and 100%. Three yield effect levels are assumed for both corn and soybean. For corn, the level of impacts are -6%, 0% and 6% (de)increase in next season's yield. For soybean, the impact levels are -3%,0% and 3% (de)increase in next season's yield. [11]

[Table 1 Here]

[10] The report gives separate accounts on seeding cost, establishment cost and seed cost. The corresponding median cost estimates are $12 per acre (commercial seeding), $12 per acre (establishment cost) and $25 per acre (seed cost) in the Midwest. The median cost in other regions are higher according to the report.

[11] The framework proposed is not limited by these scenario specifications. We choose these specifications to balance the scope of the uncertainty covered and the computation cost associated.

Results and Discussion

Land Use Estimation Results

Estimation Strategies

We adopts the two-stage conditional choice probability methods to estimate this dynamic crop choice model. In the first stage, the transition process of state variables and the 2-periods ahead choice probabilities will be estimated. Some of the state variables, like LCCs, are fixed which means farmers' crop choice will not affect the status of these variables. Some state variables, like the crop history variables, are deterministic variables. For example, if you grow soybean this year, the crop history variable (S_1) will be one next year. The expected yield variables of corn and soybean are also assumed to be deterministic here. The yield function takes forms as in Ji and Rabotyagov [16]. State variables also can be random processes, such as the expected price and cost. We also need to approximate the 2-period ahead conditional choice probability function in the first stage. As in Bishop [6], we use a flexible logit model which connects the choice of growing corn with the current state variables. In the second stage, a simple constraint logistic model is estimated.[12]Details about the estimation strategy can be found in Ji and Rabotyagov [16].

Estimation Results

Since the majority of corn-soybean acreage in Upper-Mississippi river basin is located in four states: Illionis, Iowa, Minnesota and Wisconsin, we separate sample points into four state groups and estimate them separately. Table 2 lists the second stage estimation results.

[Table 2 Here]

There are several interesting observations in the results. First, the sign of coefficients of key

[12]The constraint here is to set the value of discounting rate β to 0.95, which implicitly assume the equivalent interest rate is 5%. Restricting the discounting factor in dynamic discrete choice model literature is a common practice due to the poor identification problem (See Rust [24] and Magnac and Thesmar [23]).

variables are expected in general. For example, the negative coefficients of LCC dummy variables imply the low quality land plots are less valuable when compared with high quality plots. Usually, when a piece of land was converted to grow row crops, there should be some associated conversion cost. This thinking is confirmed by the negative coefficients of dummy variables about whether other crops was grown in last year. Second, the highly significant coefficients of crop history state variables give support on our assumptions about the dynamic linkage in the corn-soybean rotation system. Third, there are some discrepancies in both signs and magnitudes of estimated coefficients cross state samples. Given differences in the natural conditions, such as the weather pattern and soil conditions, the difference seems natural. For example, the corn yield and soybean yield in Iowa and Illinois are higher than those in Minnesota and Wisconsin.

Prediction of Cover Crop Adoption

With the prediction strategy described in the section before, we first approximate the value function under each scenario and then construct the choice probability for each five crop-practice combination.[13] These probabilities define a multinomial distribution and we will draw a random realization from this distribution to decide farmers' choice among five options. A solution to the dynamic decision problem also depends on the movement process of state variables. For simplicity, we fix the state variables such as yield, prices and costs at levels of 2011 when we solve for the value function using value function iteration.[14]

Since we introduce the "pseudo" spatial variation into the problem by inclusion of LCC dummies and their interaction terms with revenue, the prediction, thus, will also vary by LCC categories along with crop history. Table 3 shows summary statistics about predicted

[13] Specifically, the five choice sets are the option of corn with cover crops, the option of corn without cover crops, the option of soybean with cover crops, the option of soybean without cover crops and other crop option.)

[14] A full consideration of all the possible states will bring up the problem of "Curse of Dimensionality" in solving the Bellman function. The estimation method, conditional choice probability method, alleviates this problem in estimation. However, it can not be used in the new problem.

choice probabilities of cover crop for the first two LCC groups given the the crop history is "(corn,corn)" in last two years in two scenarios, the most favorable scenario (27) and the least favorable scenario (1).

[Table 3 Here]

Our model predicts somehow unrealistic probabilities of adoption of cover crops in all scenarios. Even in the least favorable scenario (1), our model predict there will be around 40% plots with cover crops after either corn or soybean. The CTIC-SARE report shows that in the Midwest, 36% of their respondents reported they used cover crops before both corn and soybean ([8],page17). However, the most recent Census of Agriculture (2012) conducted by USDA regarding use of conservation practices reports that the average share of land treated with cover crops in this area is well below 5%.[15] Given that in Scenario 1, cash crop yields suffer, and cover crop planting and harvesting costs are positive, such probability predictions are probably not plausible based on theoretical reasons and also do not conform to the most reliable (Census of agriculture) aggregate observations. The way we introduce cover crop option into the model and the value of estimated net revenue coefficient can explain this gap. First, the observed results are likely tied to the well-known propery of multinomial logit models to draw proportionally from probabilities of other alternatives when a new alternative is introduced (a consequence of the independence of irrelevant alternatives (IIA) property). Although strictly speaking, IIA property does not hold generally in the dynamic discrete choice models because the continuation value appearing in the choice probability expression includes the value of each available option. However, a closer look at the simulated value function in this study shows that this part does not exhibit sufficient variation to significantly depart from predicted probability behavior associated with the IIA property. Together with a small coefficient on revenue variables, the utility payoff of cover crops looks very similar to the option without cover crops. Second, since we do not have similar spatial

[15] The state level cover crops usage data could be queried via the NASS QuickStats service, using the 2012 Census of Agriculture and selecting conservation practice option.

data about cover crops as the land use data, we are not able to build the option to use cover crops specifically into the model. The effect of cover crops on choice is simulated relying on the imposed behavioral assumption that it will affect farmer decisions via changes in revenues. However, the coefficient associated with the revenue in the expected utility function is fairly small, which makes it difficult to change decision given moderate changes in revenue. Although our results match quite closely the cover crop adoption rates presented in a recent survey (CTIC-SARE, 2014 [8]), they appear rather inflated when compared to USDA's official Census of Agriculture state-wide estimates. Given that we place more confidence in the USDA Census estimates, we propose a calibration remedy based on re-adjusting the alternative specific constants associated with cover crop options to calibrate the model so that the base scenario probabilities match the observed share of cropland with cover crops in the NASS Census of Agriculture 2012 data. Using such aggregated data for field-level model calibration appears necessary prior to using results for policy analysis.

Given that we do not have revealed preference data on micro-level cover crop adoption decisions, it is not possible to employ other choice modeling specifications which may better represent substitution patterns. However, one remedy may lie in using available aggregate data on cover crop adoption at the state level to calibrate the alternative- specific constants in the utility functions to match observed cover crop adoption shares.

Furthermore, our way to introduce cover crops options critically depends on the assumption that cover crop will affect farmers' decision by altering the net revenue calculation. Thus, the scale of the coefficients of revenue related variables in the model will determine the choice probabilities of cover crops. The estimated coefficients reported in Table 2 is comparable with the similar coefficients found in other papers using similar discrete choice frameworks.[16] However, given these coefficients, the utility change caused by using cover crops will be limited.[17]

[16] Lubowski *et al.* [20] estimated the similar coefficient at value of 0.578. Scott [26] estimated the coefficients of revenue in the range of (0.0211, 0.2703) depending on model specifications.

[17] The coefficient of revenue variable in Iowa is 0.268. With this value and the logistic structure, a loss of

Except the high base choice probabilities for cover crop alternatives, the results show some well expected patterns (See, Figure 2). Given the yield impacts, the probability to choose cover crop for either crop will be higher if the most cost gets reimbursed. Due to the same reason discussed above, the increase in probability is moderate. At the same time, depending on the crop history, the relative probability to choose to grow cover crops after corn and soybean varies because of the rotational effects captured by the state variables, $S1, S2$ and $G1$. It is very natural to see relatively high chance to see cover crop after corn when the last year's crop is soybean.

Connection to Water Quality Benefit

With these predicted probabilities, each "pseudo" point will be matched to a probability portfolio based on the crop history and LCC class. Then, one option among the five options will be chosen according the probability portfolio. The prediction process then enters into the next period with updated crop history (See, Table 4). This prediction process will be repeated three times to get a choice sequence for three years. Then these choice sequences, along with soil information at each point will be used in the Environmental Policy Integrated Climate (EPIC) model to figure out the average total N and total P changes at the edge of the field. In the EPIC model, the types of cover crops used will be Ryegrass, a typical winter cover crop in the Midwest (CTIC-SARE, 2014 [8]) and Bromegrass grass will be used to represent the other crop.

Given the current high base predicted probabilities, we feel that the baseline model results are not directly suitable for policy analysis and integration with environmental assessment models. As discussed above, calibration work using auxiliary aggregate cover crop adoption data is needed to first match the prediction in one scenario to the state-level cover crops usage status reported in 2012 NASS, USDA conservation practice survey. The specific scenario we

40 dollars due to operational cost of cover crops implies the relative choice probability, such as probability of choosing corn with cover crops over probability of choosing just corn, will be around 0.76.

will use in the calibration process is the first scenario. Then, we will conduct prediction work and assess the impacts of the adoption of cover crops on water quality with EPIC model.

Conclusion

In this paper, we propose an analysis framework to simulate farmers' cover crops adoption and to further estimate associated water quality benefits with the help of environmental assessment models based on preferences recovered from a dynamic discrete choice crop choice model. In this framework, we consider the dynamic linkage in the dominant corn-soybean crop system. We also characterize the uncertainties of cover crops into two main components: the operation cost (with or without reimbursement from programs) and the yield effect on corn/soybean. Using finite dependence properties associated with a typical corn/soybean rotation, we use a conditional probability approach to estimate structural parameters associated with preferences for net revenue. We use estimated parameters to formulate a dynamic optimization problem of adoption of a conservation technology for which data on adoption is not available at the micro-scale level. Although dynamic discrete choice models, in principle, do not possess the IIA property, simulated probabilities of adopting a conservation technology (cover crops) with no private farmer benefits have been found to be unrealistically large. We propose a remedy based on using available auxiliary aggregate data on technology adoption to calibrate the baseline model before simulation results can be used for policy analysis. Results highlight the fact that caution is needed in using econometric approaches in characterizing farmer behavior in the absense of (a) readily available micro-scale economic data and (b) revealed preference data on adoption of new conservation technologies.

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Tables and Figures

Figures

Figure 1: The Spatial Distribution of Sample Points

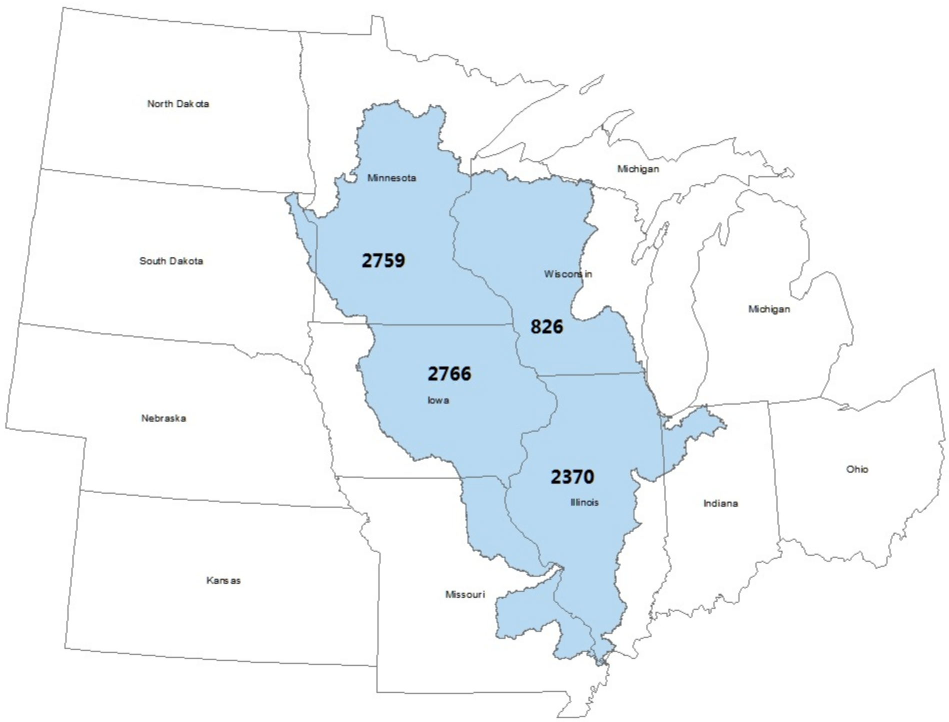
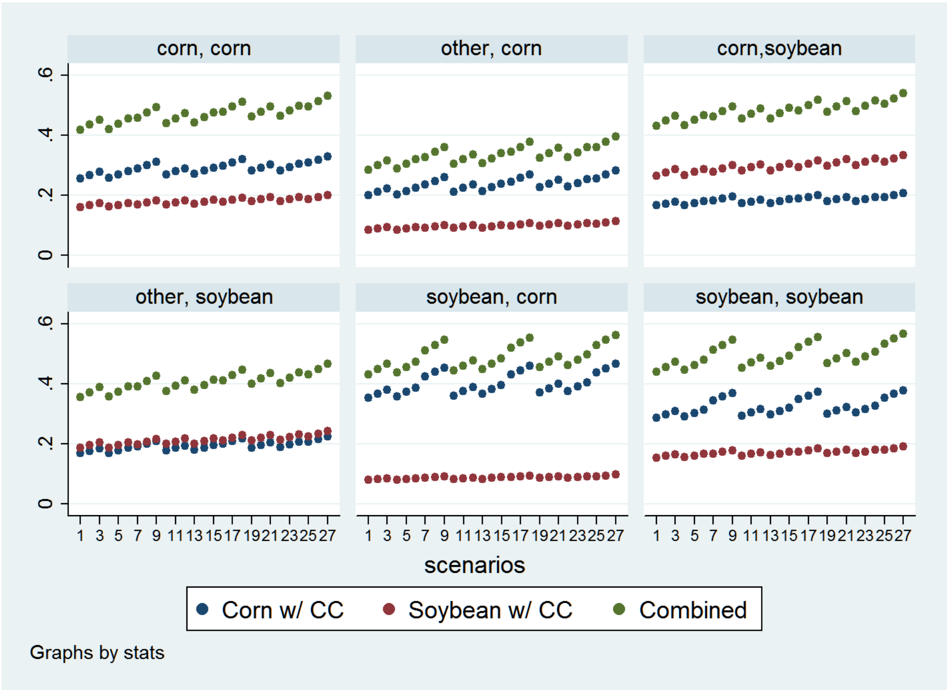


Figure 2: Predicted Probability of Cover Crops by Crop History (LCC:I,II)



Tables

Table 1: Scenario Specifications

Specification	Yield Effect on Corn($)	Yield Effect on Soybean (%)	Cost Reimbursement Rate (%)
1	-6	-3	0
2	-6	-3	50
3	-6	-3	100
4	-6	0	0
5	-6	0	50
6	-6	0	100
7	-6	3	0
8	-6	3	50
9	-6	3	100
10	0	-3	0
11	0	-3	50
12	0	-3	100
13	0	0	0
14	0	0	50
15	0	0	100
16	0	3	0
17	0	3	50
18	0	3	100
19	6	-3	0
20	6	-3	50
21	6	-3	100
22	6	0	0
23	6	0	50
24	6	0	100
25	6	3	0
26	6	3	50
27	6	3	100

Total:27

Table 2: Second Stage Estimation Results ($\beta = 0.95$)

Variable	IL		IA		MN		WI	
	Est	$z-value$	Est	$z-value$	Est	$z-value$	Est	$z-value$
DCORN	-0.356^{***}	-4.56	-0.553^{***}	-7.14	-0.966^{***}	-10.51	-1.044^{***}	-12.74
DSOY	-1.439^{***}	-10.53	-1.335^{***}	-10.17	-2.232^{***}	-15.91	-2.794^{***}	-15.82
REV	0.559^{***}	17.94	0.268^{***}	8.73	0.231^{***}	6.56	0.244^{***}	4.26
LCC2C	-0.645^{***}	-5.63	-1.082^{***}	-9.85	-0.882^{***}	-6.24	-0.495^{***}	-4.25
LCC3C	-1.196^{***}	-3.16	-2.132^{***}	-6.20	-0.442	-1.08	-0.537^{**}	-2.05
LCC4C	-0.399	0.00	-2.246^{***}	-4.61	-4.579^{**}	-2.40	-0.511^{**}	-2.51
LCC2CREV	-0.113^{*}	-1.73	0.187^{***}	3.29	0.186^{***}	2.86	-0.075	-0.84
LCC3CREV	-0.145	-0.67	0.298^{*}	1.69	-0.459^{**}	-2.17	-0.034	-0.16
LCC4CREV	-36.394^{***}	-1167.79	0.298	1.18	1.226^{*}	1.65	-0.123	-0.89
LCC2S	0.197	1.42	-0.604^{***}	-4.42	-1.444^{***}	-7.44	-0.630^{***}	-3.29
LCC3S	-0.368	-0.75	-1.064^{**}	-2.23	-2.706^{***}	-3.40	-1.198^{**}	-2.39
LCC4S	0.011	0.00	-1.040	-1.47	-1.717	-0.71	-0.515	-1.43
LCC2SREV	-0.581^{***}	-6.52	-0.094	-1.17	0.371^{***}	3.24	0.055	0.46
LCC3SREV	-0.311	-1.01	-0.433	-1.53	0.697	1.49	0.554^{*}	1.74
LCC4SREV	-9.461	-0.04	-0.666	-1.47	-0.738	-0.53	-0.219	-1.05
S1	0.021	0.30	0.636^{***}	8.65	-0.001	-0.02	0.282^{***}	2.76
S2	0.106	1.60	-0.095	-1.41	1.000^{***}	12.08	0.785^{***}	7.48
G1	-2.250^{***}	-28.65	-3.060^{***}	-41.97	-2.486^{***}	-32.10	-2.186^{***}	-27.69
S1S	-1.319^{***}	-18.06	-0.643^{***}	-8.57	-0.140	-1.59	-0.245^{**}	-1.98
S2S	1.522^{***}	22.48	1.410^{***}	21.09	1.247^{***}	14.59	1.497^{***}	13.13
G1S	-3.020^{***}	-34.14	-3.163^{***}	-41.27	-3.027^{***}	-33.54	-2.483^{***}	-24.16

Note: 1. *,**,*** represent the significant level at 10%, 5% and 1%.
2. z-value is the ratio of coefficients over the estimated standard deviation.
3. The unit of REV(revenue) is in hundreds of dollars.

Table 3: Summary of Predicted Choice Probabilities

Crop History		LCC(I,II)		LCC(III,IV)	
t-1	t-2	*Scenario*1	*Scenario*27	*Scenario*1	*Scenario*27
Option 2 Corn w/ Cover Crop					
corn	corn	0.26	0.33	0.25	0.33
other crop	corn	0.20	0.28	0.14	0.21
corn	soybean	0.17	0.21	0.18	0.23
other crop	soybean	0.17	0.22	0.13	0.19
soybean	corn	0.35	0.47	0.34	0.43
soybean	soybean	0.29	0.38	0.3	0.37
Option 4:Soybean w/ Cover Crop					
corn	corn	0.16	0.20	0.12	0.15
other crop	corn	0.09	0.11	0.05	0.07
corn	soybean	0.27	0.33	0.23	0.29
other crop	soybean	0.19	0.24	0.13	0.17
soybean	corn	0.08	0.10	0.05	0.08
soybean	soybean	0.15	0.19	0.12	0.16
Combined Choice: Option 2 + Option 4					
corn	corn	0.42	0.53	0.37	0.48
other crop	corn	0.29	0.47	0.18	0.27
corn	soybean	0.43	0.54	0.41	0.52
other crop	soybean	0.35	0.47	0.26	0.36
soybean	corn	0.43	0.56	0.4	0.51
soybean	soybean	0.44	0.57	0.42	0.53

Note: 1. Summary Statistics for all scenarios are shown in the Appendix.

Table 4: State Transition in the Prediction Process

State (Crop History)	S1	S2	G1	CC	Option				
					1	2	3	4	5
1	0	0	0	0	1	7	5	9	2
2	0	0	1	0	1	7	5	9	2
3	0	1	0	0	1	7	5	9	2
4	0	1	1	0	3	8	6	10	4
5	1	0	0	0	3	8	6	10	4
6	1	1	1	0	1	7	5	9	2
7	0	0	0	1	1	7	5	9	2
8	0	1	1	1	1	7	5	9	2
9	1	0	0	1	3	8	6	10	4
10	1	1	1	1	3	8	6	10	4

Note: 1.Option 1 corn w/o cover crops; 2: corn w/ cover crops; 3: soybean w/o cover crops; 4: soybean w/ cover crop; 5: other crops
2.Numbers in the columns from 6 to 10 represent the deterministic transition between states. For example, 7 in the cell (1,7) means that if the crop history state is 1, then choosing option 2 (corn w/cover crops) in this period will update the crop history state at the beginning of the next period to the state 7 (where the value of CC (cover crops chosen in the previous period) is set to 1).