Crop Choice and Rotational Effects: A Dynamic Model of Land Use in Iowa in Recent Years

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Abstract

A dynamic land use model, more specifically a dynamic discrete choice model, is developed in this paper to model Iowa farmers' crop choice decisions in recent years based on the newly released field-scale cropland data layers by National Agricultural Statistics Service. We explicitly consider the dynamic effects naturally arising in the corn/soybean crop system and estimate the model using the conditional choice probability method. Compared to static models, dynamic land use models perform relatively better. The dynamic models produce significantly different arc elasticities than the static model in a policy scenario when the corn price increases by 10 percent.

Keywords: Dynamic Discrete Choice Model, Land Use Change, Rotation Effects

1 Introduction

Land use changes play critical roles in feeding the increasing population and helping reduce green house emissions through alternative fuel substitution programs, such as US bio-fuel programs. As the major ethanol feedstock in US, corn increases in acreage recent years to meet the ethanol mandate cross US corn belt states either through conversion from other type of land, *i.e.* non-corn/soybean cropland to corn/soybean cropland, or expansion of continuous corn acreage in existing cropland (Wright and Wimberly [32], Associated Press [1]). With these kinds of land use change, some researches worry that the primary goal of reducing carbon dioxide emission may be compromised along with other ecosystem services, such as deterioration of water quality in major rivers (Timothy *et al.,* [29], Fargioner *et al.,* [9] and Donner and Kucharik [8]). Thus, to comprehensively evaluate policies which could result in indirect land use change via market signals like crop prices, farmers' decision on land use should be at the central stage.

One of the popular land use modeling techniques is to use discrete choice models, especially multinomial logit models, to model land use decisions at micro level (Wu *et al.,* [31], Lubowski *et al.,* [16] and [17]). The majority of these studies are based on static models and do not model the dynamic effects naturally embodied in the crop systems, such as the prevailing corn-soybean crop system in US corn belt states. In most recent years, there are several studies in which a fully dynamic discrete choice model is considered, such as De Pinto and Nelson [22] and Scott [25]. The lack of application of dynamic land use models is most likely due to two constraints: the availability of good quality data and econometric estimation techniques. With newly released US cropland data layers (CDL) from National Agricultural Statistic Service (NASS), we build a dynamic land use model to model crop choice by Iowa farmers in recent years using conditional choice probability (CCP) estimation methods based on Arcidiacono and Miller [3], along with static models and state dependent models in which decision makers lack forward looking behavior compared with the fully dynamic land use model.

Judged by the estimated log-likelihood values, the dynamic models have the similar performance as the state dependent model and perform much better than the static model. Dynamic models imply much larger marginal willingness to pay measure of soil attributes. These difference highlights the needs to consider the land use change from the dynamic perspective in which the consequence of the current choice have the cumulative effects on future choice.

To further consider the performance of different models, we conduct both within-sample prediction comparison and out-of-sample comparison with *winner-take-all* decision rule. In the prediction comparison, the static model performs the worst and the performance of dynamic models are in line with the state dependent model. The dynamic models perform weakly better in the within-sample comparison and the state dependent model performs slightly better in the out-of-sample comparison.

Finally, we also consider the price elasticities of corn price increase implied by the estimated preference parameters. For dynamic models, we consider two types of elasticities: elasticities without price regime change and elasticities with price regime change.[1] On average, the individual elasticities of corn and soybean choice are largest for the static model, followed by the state dependent model and dynamic models. When it comes to the price elasticities of combined corn and soybean choice, the state dependent model has the lowest elasticities. When it comes to the relationship between elasticities and soil quality, the static model has the most significant negative correlation between soil attributes and elasticities. When soil quality is poor, the elasticities is larger and vice versa. At the moderate soil quality, elasticities from the static model are comparable with the ones from dynamic models. The state dependent model has the smallest elasticities for combined corn and soybean choice even it has larger individual elasticities when only corn or soybean is considered. The two

[1] The definition of these two elasticities is given in section 2.

dynamic elasticities do differ from each other, however, their difference is quite small in our application.

The remaining of this paper is organized as follows: Section 2 describes the econometric method used to estimate the dynamic discrete choice land use model. The construction of variables is discussed in Section 3. The estimation results and discussions are presented in Section 4. We conclude in Section 5.

2 Methodology

2.1 Empirical Dynamic Discrete Choice Model and N-periods-ahead dependence

As in Lubowski *et al.,* [16] and Scott [25], the decision makers, *i.e.,* farmers in this paper, make crop decision d_t among a choice set of $J = \{corn, soybean, other\}$ to maximize a flow of utilities defined on the expected revenue on the cropland plot given the state variable X_t at time t.

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

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.[2]

[2]There are three categories of state variables: market level state variables, deterministically evolved

- d_t, an option chosen by the decision maker at time t among J possible options.

- β, the discounting factor

- ηs, independent and identical extreme value Type I random variables.

The formalization of a dynamic discrete choice like above first appeared in the seminal paper of Rust [23] about bus engine replacement decisions. Under some regularity conditions, the above choice problem defines the following functions:

- Alternative specific value function $\nu(X_t, j)$.

$$\nu(X_t, j) = \mu(X_t, j|\theta_1) + \beta E(V(X_{t+1}|\theta_1, \theta_2)) \tag{2}$$
$$\text{where the expectation is taken} w.r.t \quad f(X_{t+1}|X_t, d_t, \theta_2)$$

- Unconditional value function, $V(X_t)$

$$V(X_t|\theta_1, \theta_2) = \max_{j \in J}[\nu(X_t, j) + \eta_{tj}] \tag{3}$$

- If ηs are $i.i.d.$ extreme value Type I random variables, the above unconditional value function could be rewritten as

$$V(X_t|\theta_1, \theta_2) = ln[\sum_{j=1}^{J} exp(\nu(X_t, j))] + \gamma \tag{4}$$

  where γ is Euler coefficient. Since only the utility differences matter, the choice probability of $p(j|X_t)$ could be written without γ as following

$$p(j|X_t) = \frac{exp(\nu(X_t, j))}{\sum_{r=1}^{J} exp(\nu(X_t, r))} \tag{5}$$

individual crop histories and fixed state variables like soil attributes. The detailed discussion is provided below.

where $J = 3$ in this paper.

Then under conditional independence assumption (See, in Rust [23]), the observation of $\{x_{nt}, d_{nt}\}$ about individual n defines the log-likelihood function for n as

$$llik_n = \sum_{t=1}^{T} (ln[p_t(d_{nt}|x_{nt}, \theta_1)] + ln[f(x_{nt+1}|x_{nt}, d_{nt}, \theta_2)])$$

With N individuals for T periods, the estimates of θs will be the solution to

$$\hat{\theta} = argmax \sum_{n=1}^{N} \sum_{t=1}^{T} (ln[p_t(d_{nt}|x_{nt}, \theta_1)] + ln[f(x_{nt+1}|x_{nt}, d_{nt}, \theta_2)]) \tag{6}$$

Generally there is no closed solution for the value function resulting from solving Bellman equation for the dynamic discrete choice problems, thus there is no closed form expression of $p_t(\bullet)$. Rust [23] proposed the nested two stages estimation method. In the first stage, the transition processes of state variables,*i.e.,* θ_2s, are estimated based on the rational expectation assumption in the sense that the observed distribution of state variables is the expected distribtion. In the second stage, the value of θ_1 is searched to maximize the sum of the log-likelihood function over the first terms in the equation (6). The searching process will include an inner nested process to solve the Bellman function $w.r.t$ the value of θ_1 at each step, which will be used to update $p_t(\bullet)$ by equation (5) via equation (4) and (2). The repeated solving of the Bellman equation imposes the great burden on computation. When the state space is large, the computation cost may be prohibitive to carry out the original estimation algorithm although some methods have been proposed in the literature to mitigate the computation cost by Rust [24] and Keane and Wolpin [15], among others.

Different from the nested estimation method mentioned, we utilize the two stage estimation method based on conditional choice probability (CCP) along the literature line of Hotz and Miller [12], Aguirregabiral and Mira [2] and Arcidiacono and Miller [3] in this paper. Hotz and Miller [12] prove that under certain conditions the difference in conditional value functions can be written in choice probabilities alone.

Given the formula of the unconditional value function $V(\bullet)$ in equation (3), we could rewritten $V(\bullet)$ with respect to an arbitrary choice, d_t^*, as follows:[3]

$$\begin{aligned} V(X_t) &= ln[exp(\nu(X_t, d_t^*))\{\frac{\sum_{d_t \in J} exp(\nu(X_t, d_t))}{exp(\nu(X_t, d_t^*))}\}] + \gamma \\ &= \nu(X_t, d_t^*) + ln\{\frac{\sum_{d_t \in J} exp(\nu(X_t, d_t))}{exp(\nu(X_t, d_t^*))}\} + \gamma \\ &= \nu(X_t, d_t^*) - ln[p(d_t^*|X_t)] + \gamma \end{aligned} \tag{7}$$

The intuition behind the equation (7) is not difficult to understand. If you use the alternative specific value function, $\nu(X_t, d_t^*)$ in this case, to represent the unconditional value function, the nonnegative term of $-ln[p(d_t^*|X_t)]$ measures the possible penalty when d_t^* is not the optimal choice given X_t.[4]

With this new representation of $V(\bullet)$, we could rewrite the alternative specific value function $\nu(X_t, d_t)$ in equation (2)with respect to the arbitrary reference choice,d_{t+1}^*.

$$\begin{aligned} \nu(X_t, j) &= \mu(X_t, j) + \beta E(V(X_{t+1})) \\ &= \mu(X_t, j) + \beta \int (\nu(X_{t+1}, d_{t+1}^*) - ln[p(d_{t+1}^*|X_{t+1})])dF(X_{t+1}|X_t, d_t) + \beta\gamma \end{aligned} \tag{8}$$

In Arcidiacono and Ellickson [4], they summarize two types of scenarios in which the extension of conditional value function into one period ahead is sufficient to take the computational advantages of CCP. One type of scenarios is that there is a terminal option which will terminate the choice process and the value associating with this option is a flow of fixed utility or utility functions with parametric forms. A recent application of this approach to the housing market could be found in Murphy [19] in which the decision to build houses on a plot of

[3] To keep mathematics equations concise, we drop the unknown parameters in the representation.

[4] When d_t^* is more likely to be optimal choice, the choice probability goes to 1 which results in a zero penalty. Due to the errors usually assumed in the dynamic discrete choice models, the penalty, however, can never be zero.

cropland terminates the land use decision. Another type of scenarios is that when there is a renewal option which once chosen will reset the decision process and wash away the effects of previous decisions.

Arcidiacono and Miller [3] generalize this one-period-ahead dependence idea into multiple periods-ahead dependence case. In this paper, the decision process we specified has the property of two-periods-ahead dependence. The following is a simplified representation of multiple periods-ahead dependence, the interested readers should refer to Arcidiacono and Miller [3] for more details in the more general settings.

To see what it is and how the two-periods-ahead dependence could help us simplify the estimation difficulty, we could extend equation (8) into two more periods ahead. Let d^*_{t+2} be the reference option in period $t+2$, we could have

$$
\begin{aligned}
\nu(X_t, j) &= \mu(X_t, j) + \beta E(V(X_{t+1})) \\
&= \mu(X_t, j) + \beta \int (\nu(X_{t+1}, d^*_{t+1}) - ln[p(d^*_{t+1}|X_{t+1})])dF(X_{t+1}|X_t, d_t) + \beta\gamma \\
\text{one period ahead} &= \nu(X_t, j) + \beta \int (\mu(X_{t+1}, d^*_{t+1}) - ln[p(d^*_{t+1}|X_{t+1})])dF(X_{t+1}|X_t, d_t) \\
&+ \beta^2 \int\int [\underbrace{\nu(X_{t+2}, d^*_{t+2}) - ln[p(d^*_{t+2}|X_{t+2})]}_{V(X_{t+2})}]dF(X_{t+2}|X_{t+1}, d^*_{t+1})dF(X_{t+1}|X_t, j) \\
&+ \beta\gamma + \beta^2\gamma \\
\text{two periods ahead} &= \nu(X_t, j) + \beta \int (\mu(X_{t+1}, d^*_{t+1}) - ln[p(d^*_{t+1}|X_{t+1})])dF(X_{t+1}|X_t, d_t) \\
&+ \beta^2 \int\int [\mu(X_{t+2}, d^*_{t+2}) - ln[p(d^*_{t+2}|X_{t+2})]]dF(X_{t+2}|X_{t+1}, d^*_{t+1})dF(X_{t+1}|X_t, j) \\
&+ \beta^3 \underbrace{\int\int\int [V(X_{t+3})]dF(X_{t+3}|X_{t+2}, d^*_{t+2})dF(X_{t+2}|X_{t+1}, d^*_{t+1})dF(X_{t+1}|X_t, j)}_{V^{t+3}((d_t=j, d^*_{t+1}, d^*_{t+2})|X_t)} \qquad (9) \\
&+ \beta\gamma + \beta^2\gamma + \beta^3\gamma
\end{aligned}
$$

Let $V^{t+3}((d_t = j, d^*_{t+1}, d^*_{t+2})|X_t)$ represent the expected value function at the period of $t+3$ if the current period choice is d_t and the choice pair in next two periods is (d^*_{t+1}, d^*_{t+2}), the two-periods-ahead dependence requires that no matter what you choose at current period (j), this expected value will be the same if you follow this choice pair in the future. If this is the case, the $V^{t+3}(\bullet)$ term in the above equation (9) will be the same for all the choice you made at the current period. In random utility maximization framework, only utility difference matters. Thus in the estimation stage, researchers could drop this term in the estimation along with Euler coefficients terms. The computation advantage to invoking two-periods-ahead dependence is that it is no longer required to solve the Bellman equation in the estimation. The choice probabilities and the transition processes could be estimated in the first stage and substitute the estimated terms into equation (9) and equation (6) to estimate a standard multinomial logistic model.[5]

In this paper, the flow utility $\mu(X_t, d_t)$ for plot i at period t is specified as following:

$$\mu(X_t, d_t) = \begin{cases} \alpha_c + \theta_r R_{ict} + \theta_{c1} S1_{it} + \theta_{c2} S2_{it} + \theta_{c3} G1_{it} + \eta_{ijt} & \text{if j=1(Corn)} \\ \alpha_s + \theta_r R_{ist} + \theta_{s1} S1_{it} + \theta_{s2} S2_{it} + \theta_{s3} G1_{it} + \eta_{ijt} & \text{if j=2(Soybean)} \\ \lambda Soil_i + \eta_{ijt} & \text{if j=3(Other crops)} \end{cases} \tag{10}$$

where $R_{ijt} = P_{ijt} * Yield_{ijt} - C_{ijt}, j = 1, 2$ is the net revenue of growing corn or soybean in plot i at period t.[6] $S1$ is a dummy variable whose value equals one if the crop grown in period $t-1$ at plot i is soybean. $S2$ is a dummy variable whose value equals one if the crop grown in period $t-2$ is soybean. $G1$ is also a dummy variable if other crops were chosen in the period $t-1$. Since grassland and idle cropland constitutes the majority of the acreage in addition to corn and soybean, there may be some clearing and preparation cost if the farmer wants to switch from them to corn/soybean so we introduce this dummy variable to control for that. $Soil_i$ is a vector of soil attributes of plot i which serves as land quality

[5]The final estimated logistic model is not exactly a standard model. The discount factor, β, is usually set into a known value.

[6]The revenue of growing other crops is normalized to zero.

controls. The specific soil attributes used in this analysis are the slope of the plot (Slope), land capability class(LCC) and corn suitability rating(CSR).[7] If a plot has a larger slope, it is difficult to keep soil moisture and nutrients thus leads to a low productivity. LCC is a general measure of the soil productivity. There are eight categories in LCC (I-VIII) and low classes mean higher productivity (USDA [33]). CSR is an index that rates soil types based on their productivity for row-crop production (Miller [20]). CSR values can range from a high of 100 to a low of 5 points.

These two state variables about whether soybean were grown in previous years are used to represent the possible revenue shifters associated with the rotational effects in the corn-soybean crop system. Hennessy [11] finds out that there could be up to two years of rotation effects within the corn-soybean crop system by analyzing a panel data set of Iowa experimental field data. Subsequently, Cai *et al.* [6] and Livingston *et al.* [18] incorporate these two-year rotation effects in their models to analyze the possible rotational pattern changes under different uncertainties, such as uncertainties of the price of corn, soybean or inputs. Scott [25] also allows the dynamic effects of state variables to exist up to two years, however he does not specifically relate the effects to the corn-soybean rotation. Different from Cai *et al.* [6] and Livingston *et al.* [18], we do not solve the Bellman equation with specific assumptions about the magnitude of rotational effects. Instead, we estimate the observed crop choice econometrically. These crop state dummies serve as the revenue shifters and should not be thought as truly capturing the physical yield effects or cost-saving effects since we do not have the field-level information about yields, prices and costs and we only have county-level information. So these crop history variables will not only capture the rotational effects but also capture some of the difference between revenues calculated with county level information and the real revenues due to the lack of farm level information. Scott [25] proposed a reduced form method to recover all the relevant preference parameters under a dynamic discrete choice setting with one assumption that the individual state variables, the

[7]Only utility differences matter in the random utility maximization framework, thus we intersect the soil attributes with the outside option.

crop history in our case, are independent of the market state variables, prices and costs in our case. Different from that paper, we allow the growing cost of continuous corn to be different from the growing cost of corn after soybean.[8]

The two-periods-ahead dependence could be seen from the specification of flow utility functions and the assumption that market level state variables like prices and costs is independent from individual farmers' crop decision on a small plot.[9] Using growing corn in the future two periods as an example of renewal action, no matter what the farmer decides to grow in this period, the individual state variables, $S1, S2, G1$ will be set to the same values after two years of corn in the future (See, Table 5). Combining with the independence assumption of individual and market state variables, the term $V^{t+3}(\bullet|X_t)$ in equation (9) will be the same for whatever choice of d_t made at period t. Thus, we could use the two stages CCP method to estimate this dynamic discrete choice model.

Once we specify the flow utility forms, we can use the two stages CCP method to recover the preference parameters θ. We consider three types of models:

- A static model

  We define the static model is the one in which farmers neglect the any rotation effects within in corn/soybean crop system, *i.e.,* $S1, S2$ and $G1$ are not included in the flow utility function and the farmers only maximize the current utility, *i.e.,* $\beta = 0$.

- A state dependent model

  A state dependent model is defined as the one in which farmers do consider the possible rotation effects, *i.e.,* $S1, S2$ and $G1$ are included in the flow utility function, but there is no forward-looking behavior,*i.e.,* $\beta = 0$.

- Two dynamic models with $\beta = 0.95$ and $\beta = 0.99$.

[8] We are not absolutely sure about the inapplicability of the method proposed in Scott [25]. The difference in the cost assumption is of importance in determining to choose the current modeling method.

[9] This independence assumption between market state variables and individual state variables is one of the key assumptions used in Scott [25] to derive the reduced form regression equations.

A dynamic model is defined as the one in which farmers consider both rotation effects and are forward-looking decision makers. Magnac and Thesmar [21] points out that the discounting factor β is usually not identified. Like many other applications, we estimate the model with some pre-specified values of β, 0.95 and 0.99.[10]

2.2 Elasticities

The elasticity of own price change or cross price change is well defined with the static model and state-dependent model (See, Train [28]). The arc elasticity for a given price change from P_1 to P_2 could be calculated by the difference in choice probabilities before and after the price change. With the dynamic model, a price change of P_1 to P_2 from period t to period $t+1$ could have different interpretations which are crucial to construct corresponding elasticities. In the dynamic model, the primitives in the preference are $\mu(X_t, d_t|\theta_1), \beta$ and $F(X_{t+1}|X_t, d_t, \theta_2)$. Knowing the change of X_t to X_{t+1} only tells one about the change in the flow utility, $\mu(\bullet)$. However, the choice probability of equation (5) is defined on the alternative specific value function of $\nu(\bullet)$ which depends on the movement of state variable X_t. A price change could happen for a state variable with or without underlying changes in the movement process and there are two types of elasticities associated with this price change.

The first type of elasticity we consider is the one without changes in the movement process of (a) state variable(s), *Elasticity without a regime change.* In this case, the movement process of X_t is the same as estimated in the first stage. For example, if we use an AR(1) process to mimic the movement process, $F(X_{t+1}|X_t, d_t)$, then we could use the estimated conditional choice probabilities $\hat{p}(d_t|X_t)$ to construct the alternative specific value function in equation (9) and then the choice probability in equation (5).

We call the second type of elasticity as *Elasticity with a regime change* in which the movement

[10] These two values of discounting factor amount to 0.05 and 0.01 annual interest rate, respectively.

process itself changes. In the AR(1) process of $X_{t+1} = \mu(1-\rho)+\rho X_t+\epsilon_t$, the possible changes are numerous by changing the value of μ and ρ. In this paper, for a change of 10% for one state variable, we will limit our focus to scenarios in which other state variables are in their long-run means and we translate the 10% to a 10% change in μ.[11] Since the conditional choice probabilities are associating with a particular movement process of state variables, we could no longer use the estimated choice probabilities in the first stage to help construct the alternative specific value function. To calculate choice probabilities, we could use the estimated parameters, θs, to solve the Bellman value function and then construct relative probabilities. When we fix other state variables at the long run means, it is quick to solve the Bellman equation with only one state variable in the value function.[12]

3 Data Summary

The data used in this paper comes from several public data bases. The crop history information is derived from the Cropland Data Layers (CDL), provided by National Agricultural Statistics Service(NASS). The future prices of corn and soybean are obtained via R package "Quandl" provided by Quandl.[13] The crop cost information comes from the annual report of *Estimated Costs of Crop Production* prepared by Professor Duffy in Department of Economics,Iowa State University.[14] The county yield information on corn and soybean is obtained from NASS web site. Monthly average temperature and precipitation data is downloaded from National Climatic Data Center.[15] The soil attributes information is de-

[11]When we limit the elasticity in this way, it is similar as the elasticity defined in Scott [25]. However, Scott [25] do not consider whether the movement process has been changed.

[12]Focusing on this narrowly constrained elasticity do give us computational advantages, however, we should keep in mind that this is only one of infinity possible elasticities. When we conduct any policy analysis in which the elasticity is important, we should know under which set of assumptions the elasticity is discussed.

[13]To know how to get assess more than 10 million data sets, interested readers could visit the company's web site via the link.

[14]One special feature of these state wide crop budget reports is that it provides two types of crop costs for corn: continuous corn and rotational corn (soybean as the precedent crop). The cost information used in Scott [25] is at regional level or state level, it does not consider the rotational effects.

[15]The original data downloaded from the NOAA has not been aggregate into one weather variable per county. It simply includes the weather variable from all the associating weather station for that county, the

rived from county level Soil Survey Geographic database (SSURGO) maps downloaded via USDA's Geospatial Data Gateway. The following subsections will discuss briefly how we construct variables used in this paper. A more detailed description is included in the appendix

3.1 Crop History Data

The cropland data layers (CDL) are geo-spatial raster files which have the land use information derived from satellite images produced by National Agricultural Statistics Service. Starting from 2008, nation-wide CDLs have been provided at resolution levels of 30 meters or 56 meters. State level CDLs are also available for previous years for a subset of states. For Iowa, state level CDLs start from year 2000. In this paper, we will use Iowa CDLs from 2001 to 2011.[16]

We constructed a panel of crop history at thousands plus randomly selected points (fields) in Iowa. Due to the way land use information is categorized in CDLs, there are some accuracy issues with crop specification. For example, one plot of corn may be misclassified to other crops, such as soybean. Stern *et al.* [30] reports the overall accuracy of Iowa CDLs between 2001 and 2010 has improved from around 80% to 95% and the reporting accuracy of corn and soybean is relatively higher and stable at more than 95%. Hendricks *et al.* [13] mitigate the possible misclassification by limiting the points to be the centroid of Common Land Unit (CLU) boundaries. In this paper, we randomly select points whose neighbouring eight cells in a three by three cell area have the same land use value as the chosen point in the starting year of 2001.[17] Figure 1 shows the spatial distribution of points. The sample points are concentrated in the upper-northwestern part of Iowa because of the constraints we imposed

averages are obtained by taken the mean of the all the available values for that county in a particular month.

[16] The Iowa 2000 CDL does not cover the whole state and is excluded in the analysis. 2012 and 2013 CDLs are only used in the out-of-sample prediction part and not used in the estimation.

[17] We acknowledge that neither methods can guarantee absolute correctness, by imposing this constraint, we believe it mitigates the severity of possible misclassification.

in the data generating process.

[Figure Here]

There are more than a dozen land use types with the category of crop defined in the NASS CropScape. Figure 2 shows the percentage shares of all the land use types summarized by Iowa CDL 2001 in the category of crop. The combined percentage of four leading land use types, *ie.,* corn, soybean, grassland, idle cropland, account for more than 95% of area. The other types account for around the left 5%. In this study, corn and soybean will be singled out as two types of crop, the other types of crops are grouped into as the outside option.

[Figure Here]

Table 1 and 2 summarize the acreage changes of corn, soybean and other crops in the research period.[18] The summary for the whole state of Iowa from CDLs is in Table 1 and the summary for samples points is in Table 2. For the whole state, the total acreage of corn and soybean in 2011 increases almost 16% from 2001. The once sizeable share of idle cropland disappeared entirely.[19] Within the corn-soybean group, the annual share of corn acreage also varies significantly between range of 109% to 162%. These percentage changes are indication of possible changing rotation patterns, such as more continuous corns as the response to the changes of relative payoff between corn and soybean. Table 2 shows a slightly different picture from Table 1 because of the constraint we imposed when we select random points. The share of corn within corn-soybean group generally follows the same pattern as the one shown in Table 1.[20]

[18]In the tables, the acreage of corn and soybean is separately reported, all the other land use types in the category of crop in CDLs are combined into the *other* category.

[19]The are more land use types identified in most recent years. For example, there are only 8 identified land use types in 2001 within the category of crop. The number becomes 33 in 2011. It is possible that some part of the idle cropland have been reassigned to new land use types, which also could lead to disappearance of idle land. However, we think it is the changing economic incentives that caused the transition instead of the technique redefinition.

[20]The share of corn acreage is a coarse measure of choice probability at the given year which is crucial in CCP methods. The recovery of unconditional value function depends on these choice probabilities. To estimate the econometrical models, the difference between the whole state summary and sample summary will not affect the implementation of the method. When we need to postulate the results from the model to

[Tables Here]

3.2 Expected Revenues

3.2.1 Expected Prices

Similar to Hendricsk [13], the expected price of corn faced by farmers in planting season is assumed to be the sum of the mean futures price in March of December corn at Chicago Mercantile Exchange and the expected county base which was calculated as the difference between the mean of spot prices of corn and futures price of May corn in March. The expected price of soybean is calculated similarly except that the futures prices of November soybean is used in the place of December corn.

The location spot prices of corn and soybean is download from Agricultural Marketing Service (AMS), USDA. The prices are report for several regions in Iowa starting from 1992. To figure out the base for all the counties in Iowa, we first locate the most likely county for each region in AMS reports and calculate bases at these counties. For other counties, we use the inverse distance weighting scheme to interpolate bases for these counties.

Assume we have observed values of bases, $(b_1, b_2, \ldots, b_R)$, at locations, $(l_1, l_2, \ldots, l_R)$, the bases at other location like location l_k will be calculated as

$$b_k = \sum_{r=1}^{R} w_{rk} b_r \tag{11}$$

$$\text{where } w_{rk} = \frac{1}{distance^2_{rk}} / [\sum_{i=1}^{R} \frac{1}{distance_{ik}}]$$

. The distances between county centroid are calculated in ArcGis 10.1.

the whole state, we need to notice the difference and take the right adjusting weights.

3.2.2 Expected Costs

The annual report of *Estimated Costs of Crop Production* includes the cost information of corn and soybean by expected yield levels and previous crops. There are three levels of cost to grow corn in each year corresponding to three levels of expected yields for two types of corn: the continuous corn and the rotational corn (the previous crop is soybean).[21] There is only one type of soybean cost with three levels.[22] To figure out the county level growing costs, we first rank counties by historical average yields of corn and soybean for the last three decades from 1980, then group them into three groups based on their position in the yield distribution: *high, middle, low.* For example, if county A's average yield of corn is in the lowest 33.3% percentile, county A will be in the *low* group and assigned the cost with lowest expected yields in a given year.

3.3 Expected Yield

We use a modified version of yield weather function as in USDA [34] to calculate the expected yield in each county.

$$Yield_{ijt} = \alpha_i + \theta_t t + \theta_w W_{it} + \epsilon_{ijt} \tag{12}$$

where $Yield_{ijt}$ is the yield of crop $j, j = (Corn, Soybean)$ in county i in year t. The vector of weather variables,W, includes mean temperature and square term at July, mean precipitation and square term at July and the June precipitation shortfall in the corn yield function.[23] In the soybean yield function, the mean temperature and precipitation in July and August are used. ϵs are the error terms.

[21] The main difference in cost between continuous corn and rotational corn is the cost of nitrogen fertilizer.

[22] The soybean cost in the report is associated with the rotational soybean, *i.e.,* the previous crop is corn. We assume the cost for continuous corn is the same.

[23] In USDA [34], the variable of June precipitation shortfall is defined as the difference of average precipitation in June and the actual precipitation if the actual precipitation is bellow the lowest 10 percentile of historical statistic distribution.

Table 3 shows the yield function regression results. It generally shows the nonlinear yield response to monthly average temperature and precipitation in growing seasons and in line with findings in the literature (Such as Schlenker and Roberts [26]). On average, corn yield are expected to increase by 1.9 bushels per acre per year and soybean yield is expected to increase by 0.46 bushels per acre per year in Iowa. To calculate the expected yield at a given year t at a given county, we will evaluate the yield function with historical average weather variables at that county.

[Table Here]

3.4 Soil Attributes

County SSURGO map is a polygon shape file with spatial information. To find out soil attributes at random selected points, we first build a point shape file of selected points. Then we use built-in functions in Arcgis 10.1 to match each point to a specific soil polygon in the corresponding county SSURGO map to get the map unit key, $MUKEY$, which uniquely identifies a soil type in the database. From them, we can find out those soil attributes we are interested in. Table 4 shows the summary of the three soil attributes. Figure 3 and 4 and 5 show the spatial distribution of these soil attributes. Clearly, the middle and north part of the state has relatively good productivity lands.

[Table Here]

[Figures Here]

4 Results and Discussion

4.1 Estimation Results

The CCP method is carried out in two stages. In the first stage, we shall estimate the movement process of state variables and conditional choice probabilities. In the second stage, we will estimate a multinomial logit model with estimated conditional choice probabilities and movement process of state variables substituted in equation (5) via equation (9).

4.1.1 First Stage Estimation

The individual state variables will evolve deterministically. For example, if you choose to grow soybean this period, the $S1$ in next period will be one and $S2$ will be one if you grew soybean in last period and the $G1$ will be zero. Table 5 shows the individual state variables transition after two years of corn. It is clear that after two years of continuous corn, the individual state variables are reset to be the same no matter the choice made currently. Another set of deterministic state variables are expected yields. The next year's yield will increase by a fixed amount found out in Table 3.

For market state variables like prices and costs, we use AR(1) process to mimic their movement. Using AR(1) process in dynamic discrete choice models in the first stage estimation could be found in Bishop [5] and Cullen and Shcherbakov [7]. Table 6 show the estimation results of market state variables. For expected county prices, we pool all the price data together and regress the current price of corn or soybean on the lagged price with county fixed effects.

[Table Here]

In the first stage, we also need estimate the conditional choice probabilities. In an ideal world, we could use the bin counting method to estimate these probabilities nonparametrically.

In a state space with moderate dimensions like our model, it is not efficient to use bin estimators because the sample observations is so sparse compared with the potential number of bins.[24] Instead, we use a flexible logit model with interaction of state variables to smoothly approximate these choice probabilities.[25]

4.1.2 Second Stage Estimation

With the first stage estimates, the transition of state variables and conditional choice probabilities, we can use equation (5) to form a simple multinomial logit model.[26] We consider several model specifications differing in the set of soil attributes and individual state variables entering in the flow utility functions. For each specification, we estimate four models: a static model, a state dependent model and two fully dynamic models with $\beta = 0.9$ and $\beta = 0.99$. Table 7 lists all the model specifications.

[Table Here]

The second stage results with model specification VIII is reported in Table 8. The first observation is that the static model have the poorest model fitting performance. Considering crop histories and forward looking behavior greatly improves the model fit. From the state dependent model to fully dynamic models, the log-likelihood value slightly decreased. This could be caused by the accumulated numerical approximation errors built in the estimation methods of CCP. The possible contributors could be the smoothing approach we take in approximate the conditional choice probabilities, the number of random draws used to calculate the conditional choice probabilities and the transition process we used to mimic the movement of random state variables.

[24] The number of bins increases exponentially in dimensions of state variables.

[25] This smoothing technique is also used by Bishop [5] and Cullen and Shcherbakov [7]. In this application, we use the linear terms of all the state variables, such as market prices and growing costs, soil attributes, expected yields and individual crop history , and the cross interact terms of these variables.

[26] The model is not a standard multinomial logit model since the value of discount factor β is actually constricted to be a certain value like 0.95 or 0.99 here.

The second observation is that the direction of coefficients in these models is quite stable. For example, all the models suggest the farmer is more likely to choose to grow other crops on a plot if the soil quality is not good. Higher CSR values lead to a lower chance to grow other crops. However, the magnitude of coefficients differ greatly. Due to the scaling issue, it is better to look at the ratio of the coefficients of soil attributes, like CSR, over the price coefficient, *Revenue*,to evaluate the difference. This ratio could serve as a coarse measure of marginal willingness to pay for option attributes. Table 9 shows these ratios for three soil attributes considered in the model. The magnitudes of these ratios increase from the static model to dynamic models. Taking CSR as example, the value of -2.38 dollars per unit means that to keep the choice at other crops, a farmer would like to accept the marginal compensation at 2.38 dollars per unit. A plot with the moderate value of CSR at 60, the compensation needed for farmers to choose other crops is around 138 dollars. The compensation requirement for the same plot increases to 187 dollars in the state dependent model, to 252 dollars in the dynamic model I and to 266 dollars in the dynamic model II.[27] The possible reason behind this is that when you want to limit the choice to a specific option, the decision makers lose the real option value. In the static world, you only compare the tradeoff between current options. In the dynamic world, the tradeoff you need to consider increases because every choice made today also have cumulative effects on discounted future values through changing state variables. In that sense, more limits are associated with the losing option in the current periods. In a recent paper, Song *et al.,* [27] find out the reversibility cost of between switch grass and the corn-soybean system affects the cutoff value for the conversion under the real option framework. Specifically, if the reversibility cost is larger, the revenue cutoff for conversion from the corn-soybean system to switch grass is also larger. Though the methods used in that paper is different from ours, the common finding that when there are more constraints put on the option in a dynamic world, the compensation needed for farmers to foregone that option becomes larger. The difference

[27] The value of discount factor, β, is 0.95 and 0.99 in the dynamic model I and II, respectively.

in these ratios also suggests that when you design an incentive compatible compensation program to promote certain practices, it is better to consider the compensation scheme from a dynamic perspective. The compensation level from a static perspective may be much lower than the optimal levels to achieve the targeted participation rate.

[Table Here]

4.2 Model Prediction Comparison

To decide the crop choice at each sample point, we take the decision rule of *Winner-take-all.*[28] Under this rule, we will first calculate the predicted choice probabilities for each crop and choose the crop with the highest predicted probability as the final choice. We have eight different model specifications differing in ways the crop history was introduced into the flow utility function and which set of soil attribute is controlled in the model (See, Table 7). For illustration purpose, we only discuss the results with model specification VIII here. Similar results from other model specifications are included in the appendix.

4.2.1 Within Sample Prediction Comparison

Table 10 shows the within sample predictions cross four models: *static model*, *state dependent model* and two *dynamic models with* $\beta = 0.95$ *and* $\beta = 0.99$. We not only report the overall prediction about how many corn or soybean are chosen in a given year, also breakdown the prediction according to the actual crop chosen in that year. For example, the state dependent model predicts, in total, corn will be chosen to grown in 3,731 plots. That includes 2,975 plots with corn as the actual choice, 640 plots of which the actual crop is soybean and 116 plots of which the actual crop is other crop.

[Table Here]

[28] Pinto and Nelson [22] also takes this rule in their analysis.

The first observation is that if the *winner-take-all* decision rule is correct, the overall prediction performance of the static model is the worst. It pays too much weight on growing corn and too few weight on growing soybean. In some years, the model predicts no soybean will be grown which is obviously not consistent with observations at all. Since there is no adjustment terms in the flow utility function of growing corn in the static model, *i.e.,* the crop history variables, there is no any cost saving or yield enhancing effect with growing soybean. Thus it is highly possible that corn is the dominant choice under certain situations like high corn price.

When crop history is considered, the prediction performance is greatly improved either in the state dependent model or in the dynamic model. There is no obvious evidence that suggest which type of model is better in overall performance. In general, the state dependent model has more correct predictions in corn, *i.e.*, the predicted choice of corn is also the actual choice in that year. The dynamic models have a relatively better performance in prediction of soybean. However, we could not translate this relativity into the total prediction. For example, in 2005, the state dependent model have more correct prediction of corn than dynamic models do. While dynamic models have a closer total prediction of corn than the state dependent model. In 2004, the situation is opposite for soybean prediction.

With year by year predictions, we also could compare the prediction of crop history from 2003 to 2009 which is reported in the last row of Table 10. No doubt, the static model has the least correct prediction. Dynamic models have predicted slightly more correct crop histories, 2101(2099) vs 2055.

4.2.2 Out of Sample Prediction Comparison

Since we have a panel data set from 2001 to 2013 and only use the data from 2001-2011 in the estimation, we could use the data from 2012 to 2013 for the purpose of out-of-sample prediction.[29] Table 11 shows the out-of-sample prediction results for the model specification VIII.[30]

[Table Here]

Similar as the within sample prediction, the static model performs the worst with zero prediction of soybean in 2012 and 2013. Among state dependent and dynamic models, they generally produce very similar prediction for all the three crop options. Though the state dependent model still slightly has more correct corn prediction and dynamic models have more correct soybean prediction, the difference is not so significant as the case in within sample prediction. The overall prediction for the crop choice sequence in 2012 and 2013 also reveal the similarity with a slightly higher number of correct prediction (5294 vs 5291(5289)) in the state dependent model. The static model falls far behind with only 1,444 correct predictions.

4.3 Elasticity Comparison

As argued in Arcidiacono and Ellickson [4], to evaluate a possible policy change which could affect the transition processes of state variables is not easy. The difficulty comes from the fact conditional choice probabilities only capture the information available at that time for decision makers. If a policy has the potential to change the course of state variables, researchers should have observations covering that period and invoke the assumption that decision makers have already incorporated the information into their decisions and reveal that to researchers through conditional choice probabilities. However, if we would like to give up the convenience of representing value function with conditional choice probabilities. We still could use numerical methods to solve Bellman value function with estimated preference

[29] Since we include two years of crop history as state variables and the two periods ahead dependence will consume another two years observation. A panel data from 2003 to 2009 can be used in the final stage of estimation.

[30] Results with other model specification are included in the appendix.

and transition parameters to conduct certain type of scenario analysis, a hybrid method.

In this part, we use the method discussed in section 2 to evaluate farmers' crop choice change in a scenario where prices and costs are fixed at the long-run mean except that corn price is assumed to increase by 10% from the long-run mean. We also distinguish two cases in this scenario differing in whether the underlying transition process of corn price has changed. Though our assumptions simplified the numerical algorithm solving of value function, it is still impractical to consider all the sample points and instead, we will limit our focus to evaluate crop choice changes with model specification VIII at one pseudo-point per county with average soil attributes in that county in six different crop history scenarios (See, Table 5).[31] The time needed to solving Bellman value function increases dramatically when the discounting factor (β) is 0.99. It takes significantly more time to solve the value function with $\beta = 0.99$ compared with $\beta = 0.95$. Thus we only solve the value function in the case of $\beta = 0.95$.[32]

Table 12 summarizes average soil attributes in each county in Iowa. On average, Iowa soil is highly productive with the average land capability class index between 2 and 3.[33] A spatial map could be found in Figure 4.

[Table Here]

Table 13 shows price elasticities of the corn, soybean acreage with respect to 10% corn price change when the crop history is growing corn in the last two years. The static model has the biggest acreage response among all models either for corn or for soybean. Since, by assumption, the farmers represented by the static model will not take into account the rotation effects and the future effects of the current decision, they will interpret the temporal price change as a permanent change and thus respond to price changes more dramatically.

[31] This arrangement greatly reduces the total number of solving Bellman value function from more than 7000 to less than 600 (99×6).

[32] For a typical point, it takes less than 8 minutes in the case of $\beta = 0.95$. The counterpart time in the case of $\beta = 0.99$ is more than 1 hour.

[33] The summary statistics is the raw summary over soil attributes in the random sample points.

The state dependent model generates second largest response. Since when the crop history considered here is growing two years of corn in the past, the different response from the static model should only reflect the difference in parameters estimation. The rotational effects will be found with other crop histories. The dynamic model produces the smallest response. The two dynamic elasticities are quite similar with or without price regime changes.

The combined response of corn and soybean tells a slightly different story. In this case, the average response of the state dependent model is the smallest and the other three models produce very similar results. The combined response from the static model have a relatively larger variation. Between two dynamic elasticities, once farmers believe the higher price implies a possible price regime change in which the long-run corn price is higher, their responses are relatively stronger as expected since the price regime change implies the overall revenue from growing corn and soybean will be bigger thus growing them becomes more appealing. While given the set of values we consider here, the difference is quite small.

[Table Here]

Figure 6, 7 and 8 shows the relationship between soil quality, represented by corn suitability ratings (CSR), and the price elasticities: corn, soybean and combined. The own price elasticities of corn choice from all the models show a positive relation on CSR. Since CSR measures the productivity of soil to growing corn, it is natural to see more productive the land is, more choice of corn there will be given an increase in corn price. The relation goes opposite when we considered the cross price elasticity of soybean choice (See, Figure 7). When it comes to the elasticity of combined corn and soybean choice, elasticities seem to be negatively correlated with soil quality. The negative relation is revealed more dramatically in the static model. When the land plot has a poor quality, *i.e.,* CSR is around 40, the elasticity is more than 0.1 and while it becomes less than 0.05 if the land quality is good ($CSR > 80$). The logic is straightforward. When the land quality is good, the chance to growing corn or soybean is already high at original price levels, thus it can not respond as big as in a case when you start with a poor quality land.

[Figures Here]

The elasticities with other crop histories are showed in the appendix tables. The patterns of elasticities from different models is similar as the one found in Table 13. However, the magnitude of elasticities vary cross different crop histories. If other crops were chosen last year, the elasticity is the smallest. Instead, if soybean was chosen last year, the elasticity is the biggest. These variations imply that the historical land use matters when we try to predict future land use change induced by price changes or policy changes.

With some assumptions, we could find out the overall elasticity of combined corn and soybean choice.[34] Figure 9 shows the relation between elasticities and soil quality. The elasticities are generally negatively correlated with soil quality with smaller elasticities for good quality lands. The state dependent model suggest the smallest overall elasticity. The elasticity generated by the static model is biggest when soil quality is poor, then starts to decline. When the soil quality is moderate, dynamic models imply similar elasticities as does the static model. When the soil quality is good, dynamic models suggest a higher elasticity.

5 Conclusion

Based on the literature on the CCP estimation of the dynamic discrete choice models, we estimate dynamic land use models along with previous prevailing static and status dependence models with recent land use data in Iowa through NASS cropland data layers. The estimation results show that dynamic models perform better than the static model and achieve the similar performance as state dependent model judged by the within-sample and out-of-sample prediction under the *Winner-take-all* decision rule. The dynamic models also

[34] We could assign weights to each crop history, thus we could find the overall elasticity. In this practice, weights are assumed to be $(0.225, 0.225, 0.05, 0.225, 0.225, 0.05)$ corresponding to crop histories $[(0,0,0),(1,0,0),(0,0,1),(0,1,0),(1,1,0),(0,1,0)]$.

produce different estimates on the marginal willingness to pay of soil attributes. We differentiate two types of elasticities associated with dynamic model in a pseudo scenario differing in whether the underlying transition processes of state variable changes. The results show that the major difference happen between static and dynamic models. Within the dynamic modeling framework, the two types of elasticities differ in a relatively smaller scale compared with the cross model difference in the application.

One of the caveats of this paper is that we do not consider farmers' heterogeneous preference. There are several methods proposed in the literature to incorporate heterogenous preference in the dynamic discrete choice models, such as Hartman [10],Imai *et al.,* [14] and Arcidiacono and Miller [3]. Another caveat is that the data used in this paper is highly aggregate in the sense except for the crop history data and soil attributes, other price and cost information is at county-level or even regional level. If more micro level data sets are obtained, we believe, the performance of dynamic models will be improved substantially.

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Appendix

Data Preparation

Extract Land Use Values to Points

Once the spatial locations are decided for the set of random points, we use built-in function in the spatial analyst tool of ArcGis 10.1 to extract land use values to these points in a series of national or Iowa CDLs. The specific function we used is *Extract Multi Values to Points* or *Extract Values to Points* depending on how many raster files we feed into the function. If we want to extract land use information from a set of raster files like several CDL maps at once, the first function can do the work. Otherwise, the second function is used. The syntax to use these powerful functions, please check online help or ArcGis manuals.

Match Soil Attributes to Points

This work is carried out in two stages. The first stage is to use ArcGis built-in function to match each point to a specific map unit in county-level SSURGO map. With the points' spatial location data, such as longitudes and latitudes, it is convenient to generate a point shape file in ArcGis. Once this step is done, we can use built-in functions like *intersect* in the analysis tools to locate the specific map unit in the county-level soil map. With the matched map unit identifier, it is straightforward to find out interested soil attributes like slope, LCC.

Appendix Tables and Figures

These tables and figures can be found at the online appendix.

Tables and Figures

Tables

Table 1: Summary of Land Use in Iowa (2001-2011) from CDLs (in 10^6 acre)

Year	Corn	Soybean	C/S(\%)	Corn+Soybean	Other	Other: Idle
2001	11.8	10.8	109.3	22.6	9.2	2.2
2002	11.7	9.4	124.5	21.1	10	1.8
2003	12.2	10.5	116.2	22.7	10.3	1.5
2004	11.9	10.3	115.5	22.2	7.9	1.3
2005	11.4	10.1	112.9	21.5	6.9	1.4
2006	11.9	10.3	115.5	22.2	6.5	1
2007	12.7	7.8	162.8	20.5	8.4	0
2008	12.3	9.2	133.7	21.5	7.7	0
2009	12.5	9.3	134.4	21.8	7.4	0
2010	13.2	9.6	137.5	22.8	7.1	0
2011	13.7	9.2	148.9	22.9	6.3	0
Mean	12.3	9.7	126.8	22	8	0.8

Note: 1. Acreage information is extracted and compiled from CropScape service by NASS.

Table 2: Summary of Land Use in Iowa at sample points (2001-2011)

Year	Corn	Soybean	C/S(\%)	Corn+Soybean	Other
2001	4258	4314	98.7	8572	1076
2002	4395	3665	119.9	8060	1283
2003	4337	4052	107	8389	1220
2004	4569	3724	122.7	8293	837
2005	4299	3928	109.4	8227	828
2006	4125	3397	121.4	7522	1281
2007	4205	3013	139.6	7218	1417
2008	4298	3118	137.8	7416	1249
2009	4075	3367	121	7442	1231
2010	4398	3610	121.8	8008	1138
2011	4996	3569	140	8565	526
Mean	4360	3614	120.6	7974	1099

Note: 1.The land use type at sample points is extracted from Iowa CDLs.
2.These points are not the final points used in the modeling, the points which have land use type outside the category of crop defined in CDLs in any given year are excluded.

Table 3: Estimation Results of Yield Functions

	Corn	Soybean
Time	1.905^{***}	0.465^{***}
	(0.016)	(0.005)
Temp.Jul	26.493^{***}	
	(3.103)	
Temp.Jul sq	-0.652^{***}	
	(0.067)	
Prec.Jul	0.257^{***}	
	(0.010)	
Prec.Jul sq	-0.001^{***}	
	(0.000)	
DPrec.Jun	-0.076^{***}	-0.012^{***}
	(0.011)	(0.003)
Temp.Jul-Aug		6.599^{***}
		(0.958)
Temp.Jul-Aug sq		-0.160^{***}
		(0.021)
Prec.Jul-Aug		0.122^{***}
		(0.005)
Prec.Jul-Aug sq		0.000^{***}
		(0.000)
R^2	0.982	0.987
Adj. R^2	0.981	0.986
Num. obs.	4983	4987

Note: 1. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.
2. Standard deviations are shown in parenthesises.
3. County fixed effects are controled.

Table 4: Summary of Soil Attributes

Variable	Mean	Std. Dev.	Min	Max
Slope	3.87	3.55	0.5	29
LCC	2.17	0.77	1	8
CSR	72.15	16.62	5	100

Table 5: Transition of Individual State Variables, (S_1, S_2, G_1)

Current State	Crop Choice at t	Corn at $t+1$	Corn at $t+2$	State at $t+3$
	Corn	(0,0,0)	(0,0,0)	
(0,0,0)	Soybean	(1,0,0)	(0,1,0)	(0,0,0)
	Other	(0,0,1)	(0,0,0)	
	Corn	(0,1,0)	(0,0,0)	
(1,0,0)	Soybean	(1,1,0)	(0,1,0)	(0,0,0)
	Other	(0,1,1)	(0,0,0)	
	Corn	(0,0,0)	(0,0,0)	
(0,0,1)	Soybean	(1,0,0)	(0,1,0)	(0,0,0)
	Other	(0,0,1)	(0,0,0)	
	Corn	(0,0,0)	(0,0,0)	
(0,1,0)	Soybean	(1,0,0)	(0,1,0)	(0,0,0)
	Other	(0,0,1)	(0,0,0)	
	Corn	(0,1,0)	(0,0,0)	
(1,1,0)	Soybean	(1,1,0)	(0,1,0)	(0,0,0)
	Other	(0,1,1)	(0,0,0)	
	Corn	(0,0,0)	(0,0,0)	
(0,1,1)	Soybean	(1,0,0)	(0,1,0)	(0,0,0)
	Other	(0,0,1)	(0,0,0)	

Table 6: Estimation Results of AR(1): $Y_t = \mu(1-\rho) + \rho Y_{t-1} + \epsilon_t$

	CC1[a]	CC2[a]	CC3[a]	SC1[a]	SC2[a]	SC3[a]	CS1[a]	CS2[a]	CS3[a]	Price C[b]	Price S[b]
μ	295.3	316.1	338.5	265.7	286.6	308.2	165.0	170.0	175.3	0.83	3.29
	[55.4]	[59.3]	[59.8]	[50.2]	[53.9]	[55.9]	[15.8]	[16.1]	[16.8]	[0.19]	[0.60]
ρ	0.88	0.88	0.86	0.88	0.88	0.87	0.71	0.68	0.67	0.76	0.58
	[0.12]	[0.12]	[0.12]	[0.11]	[0.12]	[0.12]	[0.18]	[0.19]	[0.19]	[0.02]	[0.02]
σ_ϵ	36.1	38.9	42.7	31.7	34.7	38.4	20	21.7	23.4	0.69	2.09
Llik	-70.81	-71.85	-73.1	-69.1	-70.3	-71.7	-62.2	-63.3	-64.33	-1301.5	-2726.2

Note: a. These state variables are estimated by ARIMA in Stata.
b. These state variables are estimated with regression in State, thus $\mu(1-\rho)$ is reported in stead of μ.

Table 7: Model Specifications

ID	(S_1, S_2, G_1)	Soil Attributes
I	w/ corn	Slope
II		LCC
III		CSR
IV		Slope,LCC,CSR
V	w/ corn + soybean	Slope
VI		LCC
VII		CSR
VIII		Slope,LCC,CSR

Table 8: Estimation Result of Model Specification VIII

	Static		State Dependent		Dynamic I		Dynamic II	
Variable	Est	Std.Dev	Est	Std.Dev	Est	Std.Dev	Est	Std.Dev
Corn	1.8727	0.1245	2.2169	0.1653	-0.3100	0.1656	-0.4145	0.1661
Soybean	1.6317	0.1247	2.0192	0.1657	-0.6580	0.1875	-0.7604	0.1897
SLOPE	0.0326	0.0054	0.0195	0.0073	0.0161	0.0074	0.0159	0.0074
LCC	0.3969	0.0297	0.1748	0.0387	0.0603	0.0388	0.0552	0.0388
CSR	-0.0074	0.0011	-0.0047	0.0015	-0.0034	0.0015	-0.0033	0.0015
Revenue	0.0031	0.0001	0.0015	0.0001	0.0008	0.0001	0.0007	0.0001
S1:Corn			0.8060	0.0549	0.2631	0.0551	0.2399	0.0552
S2:Corn			-0.3000	0.0491	-0.3223	0.0493	-0.3233	0.0493
G1:Corn			-3.3945	0.0568	-3.4079	0.0572	-3.4103	0.0572
S1:Soybean			-1.2699	0.0575	-1.5527	0.0578	-1.5712	0.0578
S2:Soybean			1.3447	0.0484	1.3257	0.0488	1.3261	0.0489
G1:Soybean			-0.4723	0.0556	-0.4217	0.0563	-0.4242	0.0563
Log-llike	-47091		-31650		-32049		-32099	

Note: a. Dynamic model I with $\beta = 0.95$, Dynamic model II with $\beta = 0.99$.
b.All the coefficients are significant at 1% except the coefficient of LCC in two dynamics models.

Table 9: Marginal Willingness to Pay of Soil Attributes ($ per unit)

Variable	Static Model	State Dependent Model	Dynamic Model I	Dynamic Model II
SLOPE	10.57	12.96	20.21	21.32
LCC	128.52	116.10	75.46	73.86
CSR	-2.38	-3.12	-4.21	-4.44

Note: a.The ratios are calculated at the means of estimated coefficients.

Table 10: Within Sample Prediction Comparison

Year	Crop	Actual	Static Model				State Dependant Model				Dynamic Model with $\beta = 0.95$				Dynamic Model with $\beta = 0.99$			
			Corn	Soybean	Other	Total	Corn	Soybean	Other	Total	Corn	Soybean	Other	Total	Corn	Soybean	Other	Total
2003	Corn	3633	3626	3338	414	7378	2975	640	116	3731	2732	448	97	3277	2717	441	94	3252
	Soybean	3354	0	0	0	0	446	2528	62	3036	705	2760	88	3553	720	2768	92	3580
	Other	438	7	16	24	47	212	186	260	658	196	146	253	595	196	145	252	593
2004	Corn	3839	315	85	10	410	3217	661	142	4020	2934	416	118	3468	2928	415	118	3461
	Soybean	3155	3507	3066	395	6968	513	2400	63	2976	804	2673	90	3567	810	2677	90	3577
	Other	431	17	4	26	47	109	94	226	429	101	66	223	390	101	63	223	387
2005	Corn	3681	3033	1601	272	4906	3195	785	138	4118	3007	602	121	3730	3006	597	121	3724
	Soybean	3282	640	1645	155	2440	407	2382	87	2876	597	2576	108	3281	598	2582	108	3288
	Other	462	8	36	35	79	79	115	237	431	77	104	233	414	77	103	233	413
2006	Corn	3646	3621	2966	753	7340	2628	1173	369	4170	2364	995	338	3697	2354	983	336	3673
	Soybean	2987	0	0	0	0	862	1711	220	2793	1128	1894	253	3275	1139	1906	255	3300
	Other	792	25	21	39	85	156	103	203	462	154	98	201	453	153	98	201	452
2007	Corn	3788	3779	2684	915	7378	3209	1068	207	4484	3072	937	196	4205	3053	924	194	4171
	Soybean	2697	0	0	0	0	510	1584	55	2149	652	1720	111	2483	671	1733	114	2518
	Other	940	9	13	25	47	69	45	678	792	64	40	633	737	64	40	632	736
2008	Corn	3838	3833	2788	790	7411	3195	694	75	3964	3187	691	75	3953	3186	689	75	3950
	Soybean	2791	0	0	0	0	518	1993	37	2548	533	1997	38	2568	533	1999	38	2570
	Other	796	5	3	6	14	125	104	684	913	118	103	683	904	119	103	683	905
2009	Corn	3672	3661	2973	744	7378	3309	724	88	4121	3309	723	88	4120	3309	723	88	4120
	Soybean	2985	0	0	0	0	267	2210	31	2508	267	2210	31	2508	267	2210	31	2508
	Other	768	11	12	24	47	96	51	649	796	96	52	649	797	96	52	649	797
Crop History			89				2055				2101				2099			

Table 11: Out-of-Sample Prediction Comparison

Year	Crop	Actual	Static Model				State Dependant Model				Dynamic Model with $\beta = 0.95$				Dynamic Model with $\beta = 0.99$			
			Corn	Soybean	Other	Total	Corn	Soybean	Other	Total	Corn	Soybean	Other	Total	Corn	Soybean	Other	Total
2012	Corn	4337	4,327	2,758	312	7397	3,731	387	72	4190	3,697	377	72	4146	3,676	368	72	4116
	Soybean	2763	0	0	0	0	606	2,376	253	3235	640	2,386	240	3266	661	2,395	240	3296
	Other	325	10	5	13	28	0	0	0	0	0	0	13	13	0	0	13	13
2013	Corn	4070	4,065	3,000	339	7404	3,585	615	78	4278	3,585	615	78	4278	3,582	613	77	4272
	Soybean	3006	0	0	0	0	485	2,391	271	3147	485	2,391	260	3136	488	2,393	261	3142
	Other	349	5	6	10	21	0	0	0	0	0	0	11	11	0	0	11	11
Crop History			1444				5294				5289				5281			

Table 12: Summary Statistics of Average County Soil Attributes in Iowa

Variable	Obs	Mean	Std.Dev	Min	Max
SLOPE	99	5.13	2.76	1.63	15.72
LCC	99	2.51	0.61	1.66	4.32
CSR	99	66.73	10.63	37.03	85.72

Table 13: Price Elasticity of Crop Acreage I

Crop	Model	Mean	Std.Dev	Min	Max
Corn	Static	0.44	0.03	0.37	0.48
	State Dependent	0.22	0.01	0.19	0.23
	Dynamic w/o Regime Chg	0.11	0.01	0.09	0.12
	Dynamic w/ Regime Chg	0.11	0.01	0.1	0.12
Soybean	Static	-0.38	0.05	-0.44	-0.23
	State Dependent	-0.20	0.02	-0.22	-0.16
	Dynamic w/o Regime Chg	-0.05	0.01	-0.06	-0.03
	Dynamic w/ Regime Chg	-0.04	0.01	-0.05	-0.02
C+S	Static	0.06	0.02	0.04	0.14
	State Dependent	0.02	0.01	0.01	0.04
	Dynamic w/o Regime Chg	0.06	0.01	0.06	0.08
	Dynamic w/ Regime Chg	0.07	0.01	0.06	0.09

Figures

Figure 1: Selected Points in Iowa

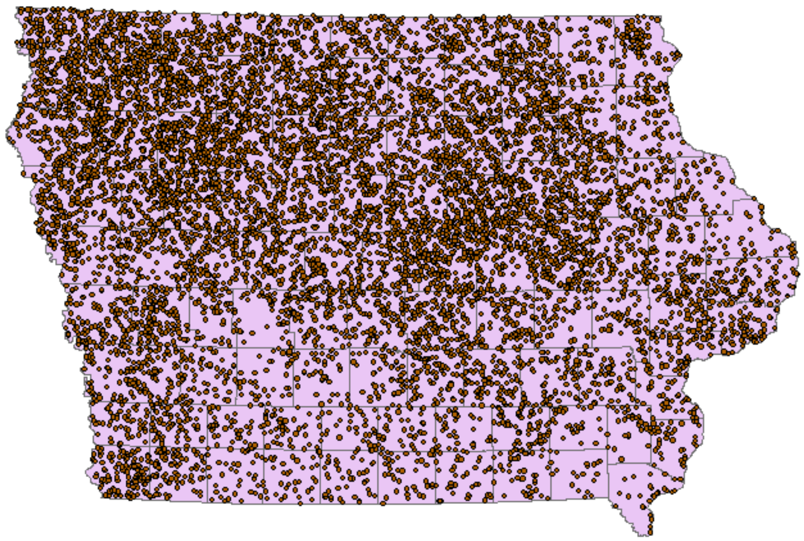


Figure 2: Land Use Status in Iowa (2001)

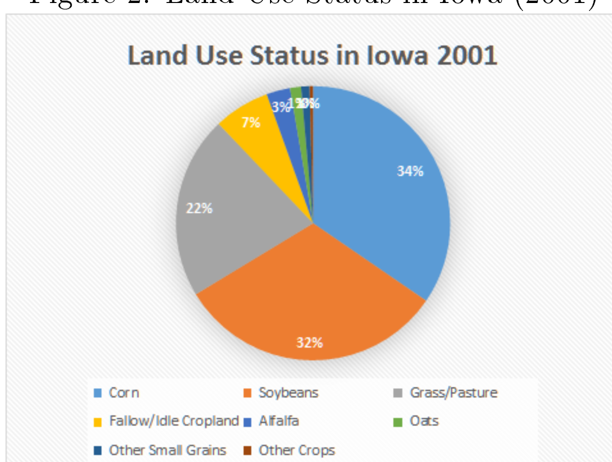
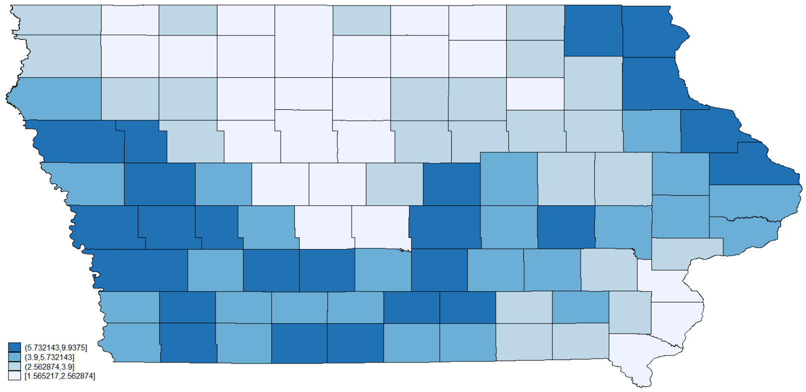
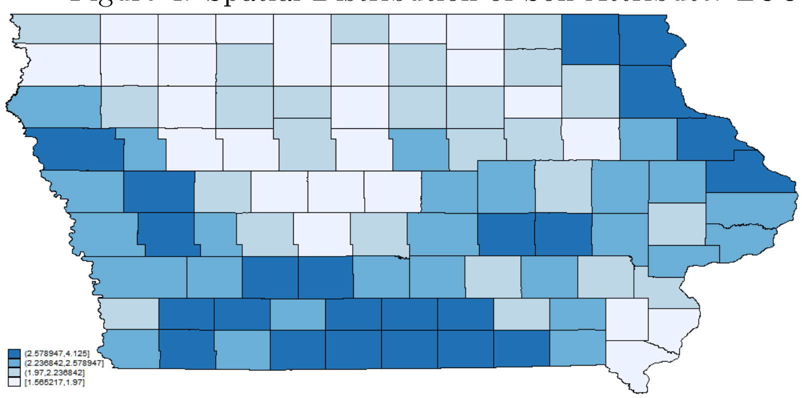


Figure 3: Spatial Distribution of Soil Attribute: Slope



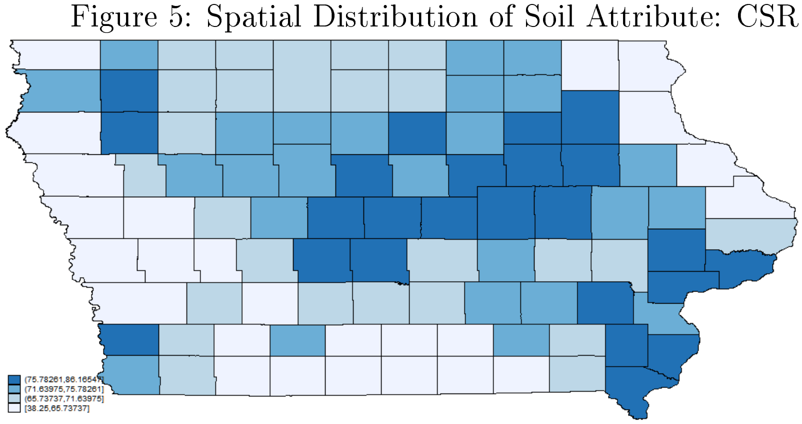
Note: 1.Light blue means low slope values, dark blue means high slope values.

Figure 4: Spatial Distribution of Soil Attribute: LCC



Note: 1.Light blue means low LCC values, dark blue means high LCC values.

Figure 5: Spatial Distribution of Soil Attribute: CSR



Note: 1.Light blue means low CSR values, dark blue means high CSR values.

Figure 6: Price Elasticity of Corn with Crop History (0,0,0)

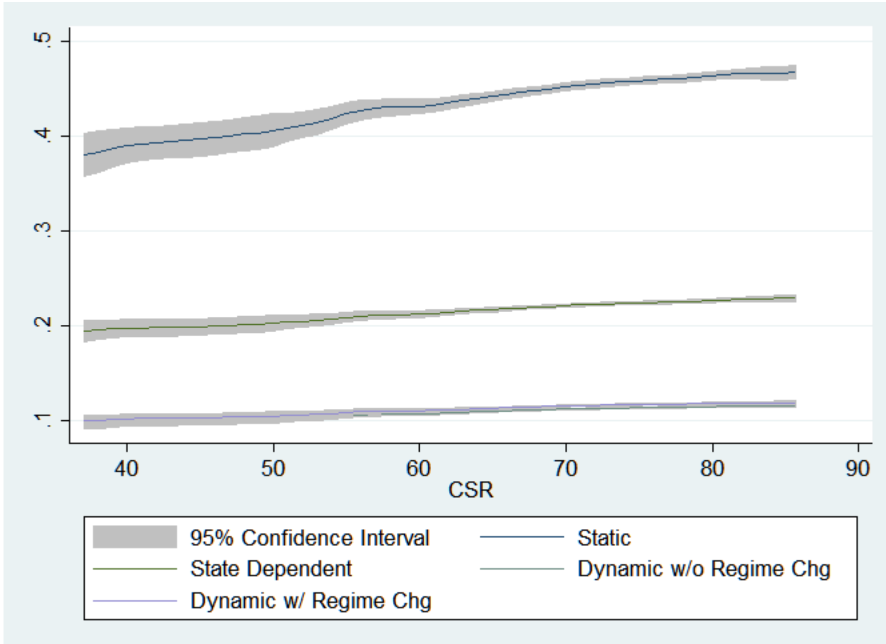


Figure 7: Price Elasticity of Soybean with Crop History (0,0,0)

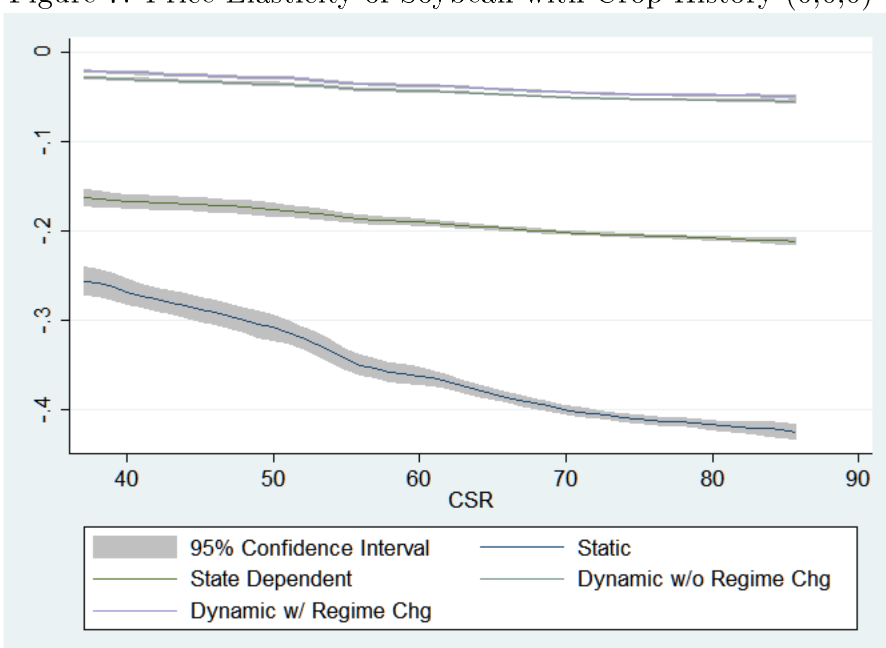


Figure 8: Price Elasticity of Combined Corn and Soybean with Crop History (0,0,0)

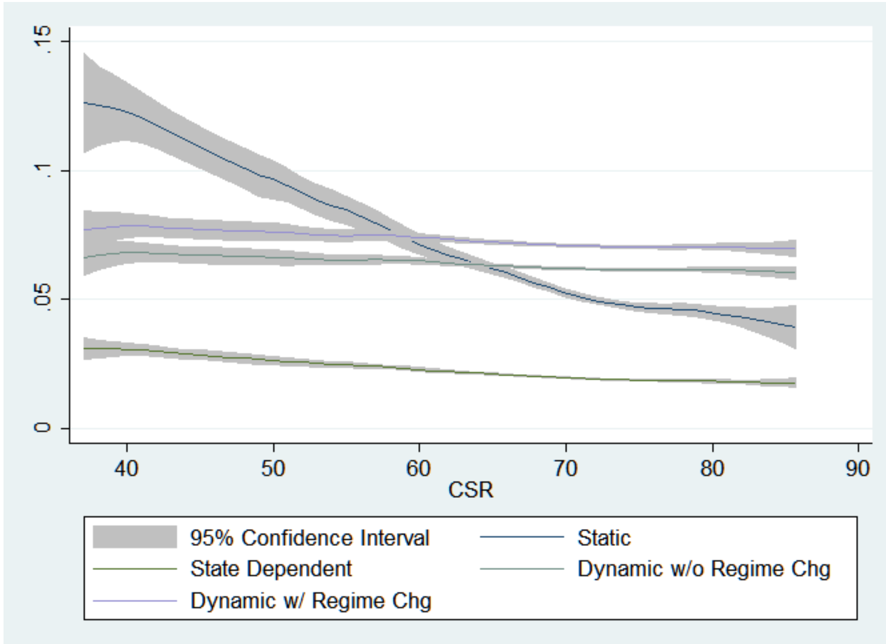


Figure 9: Price Elasticity of Combined Corn and Soybean