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Adaptation to Climate Change through Crop Choice: A High Resolution Analysis*

Haoying Wang**

Ariel Ortiz-Bobea**

Shun Chonabayashi

Cornell University

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** All comments, suggestions, and other correspondences should be sent to: Haoying Wang (hw294@cornell.edu) and Ariel Ortiz-Bobea (ao332@cornell.edu).

Adaptation to Climate Change through Crop Choice: A High Resolution Analysis

Haoying Wang, Ariel Ortiz-Bobea, Shun Chonabayashi

Cornell University

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Abstract

Recent statistical studies suggest yields for major U.S. food crops will dramatically decrease under climate change due to the rise of extreme temperatures over the growing season. However, these results do not account for changes in the crop mix, therefore overestimating potential damages to the sector. In this study we seek to determine how the crop mix and growing regions would shift in response to climate change. The paper develops a dynamic multinomial discrete choice framework to model adaptation to climate change through crop choice. A major innovation of this study is the construction of a very large high-resolution data set for the econometric analysis and the computational procedure developed to obtain estimates. We combine data on crop cover (USDA Cropland Data Layer (CDL), 30*30 meter resolution) and climate variables (PRISM, 4*4 km resolution) for the study region, matched with crop prices and production costs at regional level. The data set provides billions of spatial units from which we sample for the spatial analysis. The main advantage of such an extensive and detailed data set is the careful consideration of the spatial heterogeneity within counties. The generality of our empirical framework allows prediction of crop choices at field level under various climate change scenarios. The preliminary empirical results show that both market state variables (yields, prices, and costs) and crop state variables (related to crop rotations) are important predictors of farmers' crop choice at field level.

***JEL classification*:** Q15, Q24, Q54, R14, C35, C61
***Keywords*:** Agricultural Land Use, Crop Choice, Discrete Choice, Dynamic Optimization, Climate Change

1. Introduction

A major focus of econometric climate impact assessments on agriculture has been the prediction of overall impacts by accounting for adaptation implicitly (e.g., Mendelsohn et al., 1994; Deschênes and Greenstone, 2007). While avoiding unpacking adaptation mechanisms may seem to simplify empirical investigation, it increases vulnerability to unknown confounding factors (Schlenker et al., 2005; Fisher et al., 2012). Modeling the structure of farmer adaptation explicitly could provide more transparent insights into the countervailing role of climatic factors and the role for alternative adaptation channels. Some progress has been made in this direction through the renewed interest in statistical crop yield models (e.g., Schlenker and Roberts, 2009). However, these models overstate projected damages when used in isolation because they restrict adaption to responses after planting. Obviously, a crucial margin of adaptation is crop choice. Farmers may change the crop mix as expected yields of alternative crops change under a different climate. In fact, the current spatial distribution of growing regions in the U.S. is a reflection of this field-level crop choice process.

In this study we develop a dynamic multinomial discrete choice framework to model adaptation to climate change through crop choice. A major innovation of this study is the construction of a very large high-resolution data set for the econometric analysis and the computational procedure developed to obtain estimates. We combine data on land and crop cover (CDL, 30*30 meter resolution) and climate variables (PRISM, 4*4 km resolution) for the study region. The data set provides billions of spatial units from which we sample for our statistical analysis. The main advantage of such an extensive and detailed data set is the careful consideration of spatial heterogeneity within counties. This approach differs from studies modeling crop choice based on aggregate county-level acreage allocation. The generality of our empirical framework allows prediction of crop choices at the field level under various climate change scenarios.

By aggregating predicted field level crop choices to larger spatial scales (e.g., county), our results may be used to project potential changes in crop growing regions across the country. This information can be used to inform researchers and policymakers in designing climate adaptation efforts such as revamped crop breeding programs and government policies. Though the current study is still at its preliminary stage, our upcoming results will help other researchers explore the potential environmental and socio-economic consequences of major climate-driven agricultural land use changes.

The paper is organized as follows. Section 2 introduces the dynamic discrete choice model and estimable framework. Section 3 reports data. Section 4 presents preliminary estimation results. Section 5 briefly concludes the paper.

2. Model

The aggregate land use change in agriculture can be modeled through a series of individual crop choices at field level. This paper models crop choice decisions of farmers in a finite-horizon framework. In each period (crop production year), farmers receive flow utility associated with their crop choice which may or may not be the same as last period. The choice set can be defined as a group of major crops grown in the study region.

In each period, farmers derive flow utility from crop sales return, benefits related to crop switch (e.g., rotational effects, fallow), other land premiums (e.g., due to good soils or better location), and an additively-separable crop choice-specific shock. This paper assumes that there are no switching costs associated with crop choice. Crop production related expenses are the only cost incurred each year. Lifetime utility is the sum of current flow utility and the discounted flow of expected utilities from all future periods. All farmers are forward looking

with respect to return (revenue net of costs) from crop production. Uncertainty can come into play from several aspects: crop yield (climatic conditions), market prices (of both inputs and outputs), and time-varying idiosyncratic shocks.

2.1. Net Return

In each year at each field, a farmer receives a location and time-specific net return from crop production. The return depends on crop yield, output price, and production costs, which are all modeled using expected measures. In this paper, the choice set is defined as: $j \in J = \{soybeans, corn, wheat, others\}$. For field i in year t, the crop-specific expected yield is given as:

$$Yield_{jit} = \alpha_i + \beta_0 trend_t + \beta_1 X_{it} + \varepsilon_{jit} \tag{1}$$

where $trend_t$ is a measure of time trend, X_{it} is the set of predictors which include measures on bio-physical conditions (mainly climatic conditions). α_i captures location fixed effects, β_0 and β_1 are parameters to be estimated. ε_{jit} represents random shocks to yield.

The crop-specific price information is usually observed at region level only, so is the production cost information. Due to lack of cross-sectional variations on both price and cost measures, an AR (1) time series model can be used to predict expected prices and costs. For a given region r and crop j,

$$Price^r_{j,t} = c^r_j + \varphi^r_j Price^r_{j,t-1} + \zeta^r_{j,t} \tag{2}$$

Similarly, production costs can be predicted as,

$$Cost^r_{j,t} = d^r_j + \phi^r_j Cost^r_{j,t-1} + \eta^r_{j,t} \tag{3}$$

where c^r_j and d^r_j are region-specific constant terms, $\zeta^r_{j,t}$ and $\eta^r_{j,t}$ are white noise. The cost prediction can be more sophisticated by including producer price index for farm products. However, the simple AR (1) specification in (3) is enough for the purpose of this study, considering that price and yield are the determinants that experience much more fluctuations.

Given yield, price, and cost, crop-specific expected net return per unit of land can be written as,

$$Return_{jit} = Yield_{jit} * Price^{i \in r}_{j,t} - Cost^{i \in r}_{j,t} \tag{4}$$

2.2. Dynamic Discrete Choice Model

In the world with exogenous uncertainty, a farmer (also the owner of the field) will consider the future stream of net return associated with growing a given crop in the choice set. By assuming additive separability of net returns over time, the farmer's lifetime (a considerable future) net return is then the discounted sum of net returns from each year. The farmer's decision making objective is to maximize the utility derived from the expected lifetime net return,

$$MAX_{d_t \in J} \quad \sum_{t=0}^{T} \delta^t \left[u_t(X_t, d_t) + \omega(d_t) \right] \tag{5}$$

where d_t is the farmer's crop choice in year t, and δ is the discount factor. $u_t(X_t, d_t)$ is the flow utility in year t if crop choice d_t is made. X_t denotes the vector of all state variables for the farmer in year t. The state variables include

net return, a time-invariant crop-specific component, and a set of indicators capturing crop and land use rotation, which is defined in detail later. Similar as in Bishop (2012), the transition of the states is assumed to be Markovian, so that X_{t+1} depends on X_t and d_t only. The transition probability of the state vector is denoted as $q(X_{t+1} \mid X_t, d_t)$. $\omega(d_t)$ is a time-varying idiosyncratic component of utility which follows an $i.i.d$ Type I extreme value distribution. The above setup of dynamic discrete choice has been commonly used in the literature (e.g., Rust, 1987; Bishop, 2012; Ji et al., 2014).

2.3. State Space and Utility Function

Following Scott (2013), the state space in this paper is divided into two categories: market state and physical state. The market state is represented through the aggregate measure $Return_{jit}$ which follows an Markov process by construction, given that both price and cost are predicted using an AR (1) process. $Return_{jit}$ also captures some physical states (e.g., climate, soil) through crop yield, but they do not enter the flow utility directly. The physical state consists of a set of three indicator variables regarding what was grown on the field in year $t-1$. Table 1 below summarizes the definitions:

State Variable	Definition	Category
$Return_{jit}$	crop-field-time specific net return	market state
$C1_{it}$	corns on field i in year $t-1$	physical state
$S1_{it}$	soybeans on field i in year $t-1$	physical state
$W1_{it}$	spring/winter wheat on field i in year $t-1$	physical state

Table 1: Summary of state variables

Similar to Ji et al. (2014), the flow utility at field i in year t, $U_{it}(X_{it}, d_{it})$ can be defined as,

$$U_{it}(X_{it}, d_{it}) = \begin{cases} \gamma_{c0} + \gamma_{cr} Return_{jit} + \gamma_{cc} C1_{it} + \gamma_{cs} S1_{it} + \gamma_{cw} W1_{it} + \omega_{jit} & if \quad j = corn \\ \gamma_{s0} + \gamma_{sr} Return_{jit} + \gamma_{sc} C1_{it} + \gamma_{ss} S1_{it} + \gamma_{sw} W1_{it} + \omega_{jit} & if \quad j = soybean \\ \gamma_{w0} + \gamma_{wr} Return_{jit} + \gamma_{wc} C1_{it} + \gamma_{ws} S1_{it} + \gamma_{ww} W1_{it} + \omega_{jit} & if \quad j = wheat \\ \gamma_{o0} + \gamma_{or} Rent_{it} + \omega_{jit} & if \quad j = others \end{cases} \tag{6}$$

where ω_{jit} is the time-varying idiosyncratic component of utility, $Rent_{it}$ is the average cash rent of farmland at location i in year t. Note that, if none of the three major crops is chosen, then the farmer will derive utilities from cash rent of the land and a fixed utility component γ_0. γ_{c0}, γ_{s0}, and γ_{w0} represent fixed utility component related to growing corn, soybean, and wheat, respectively. As pointed out in Ji et al. (2014), the physical state variables as defined in Table 1 are used to capture possible revenue differences associated with different types of crop rotations among major crops. They should not be treated as variables that capture any direct yield or cost-saving effects. Because these variables are constructed simply basing on crop rotation patterns.

2.4. Estimable Framework

The dynamic discrete choice model defined above has three basic assumptions: (1) X and ω are independent; (2) the evolution of market states and physical states follows is Markovian; (3) the additive separability of flow utility. These are common assumptions in the literature to make the problem computationally feasible (e.g., Rust 1987; Bishop, 2012). Given these assumptions, the Bellman equation for value functions can be written as,

$$V_t(X_t, \omega(d_t)) = MAX_{d_t \in J} \left[v_t(X_t, d_t) + \omega(d_t) \right] \tag{7}$$

where the value function $v_t(X_t, d_t)$ can be written as,

$$v_t(X_t, d_t) = u_t(X_t, d_t) + \delta \int \sum_{X_{t+1}} V_{t+1}(X_{t+1}, \omega(d_{t+1})) q(X_{t+1} \mid X_t, d_t) dF(\omega(d_{t+1})) \quad (8)$$

or equivalently,

$$v_t(X_t, d_t) = u_t(X_t, d_t) + \delta E(V_{t+1}(X_{t+1}, \omega(d_{t+1}))) \quad (9)$$

Since $\omega(d_t)$ follows an $i.i.d$ Type I extreme value distribution, replace the second term on the right hand side of (8) with Logit inclusive value, which gives:

$$v_t(X_t, d_t) = u_t(X_t, d_t) + \delta \sum_{X_{t+1}} ln \left[\sum_{j=1}^{J} exp\left(v_{t+1}(X_{t+1}, d_{t+1} = j)\right) \right] q(X_{t+1} \mid X_t, d_t) \quad (10)$$

This is a recursive equation which makes its estimation computationally difficult. Following Hotz and Miller (1993), Arcidiacono and Miller (2011), and Bishop (2012), it can be shown that,

$$
\begin{aligned}
v_t(X_t, d_t = j^{(t)}) = u_t(X_t, d_t = j^{(t)}) \\
&+ \delta \sum_{X_{t+1}} ln \left[P(d_{t+1} = j^{(t+1)} \mid X_{t+1})^{-1} \right] q(X_{t+1} \mid X_t, d_t = j^{(t)}) \\
&+ \delta \sum_{X_{t+1}} \left[u_{t+1}(X_{t+1}, d_{t+1} = j^{(t+1)}) \right] q(X_{t+1} \mid X_t, d_t = j^{(t)}) \\
&+ \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} ln \left[P(d_{t+2} = j^{(t+2)} \mid X_{t+2})^{-1} \right] \\
&* q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) q(X_{t+1} \mid X_t, d_t = j^{(t)}) \\
&+ \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} \left[u_{t+2}(X_{t+2}, d_{t+2} = j^{(t+2)}) \right] \\
&* q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) q(X_{t+1} \mid X_t, d_t = j^{(t)}) \\
&+ \delta^3 \sum_{X_{t+1}} \sum_{X_{t+2}} \sum_{X_{t+3}} ln \left[P(d_{t+3} = j^{(t+3)} \mid X_{t+3})^{-1} \right] \\
&* q(X_{t+3} \mid X_{t+2}, d_{t+2} = j^{(t+2)}) q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) q(X_{t+1} \mid X_t, d_t = j^{(t)}) \\
&+ \delta^3 \sum_{X_{t+1}} \sum_{X_{t+2}} \sum_{X_{t+3}} \left[u_{t+3}(X_{t+3}, d_{t+3} = j^{(t+3)}) \right] \\
&* q(X_{t+3} \mid X_{t+2}, d_{t+2} = j^{(t+2)}) q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) q(X_{t+1} \mid X_t, d_t = j^{(t)})
\end{aligned}
$$

where $P(\cdot)$ is the conditional choice probability, which is estimated in a preliminary step. $j^{(t)}$, $j^{(t+1)}$, $j^{(t+2)}$, and $j^{(t+3)}$ represent crop choices made in year t, $t+1$, $t+2$, and $t+3$, respectively. Given the Logit framework, the conditional choice probability is defined as,

$$
\begin{aligned}
P(d_t = j^{(t)} \mid X_t) &= \frac{exp\left(v_t(X_t, d_t = j^{(t)})\right)}{\sum_j exp\left(v_t(X_t, d_t = j)\right)} \\
&= \frac{1}{\sum_j exp\left(v_t(X_t, d_t = j) - v_t(X_t, d_t = j^{(t)})\right)}
\end{aligned}
$$

An estimate of $P(d_t = j^{(t)} \mid X_t)$, say $\hat{P}(d_t = j^{(t)} \mid X_t)$, can be used to replace

the conditional choice probability in value function $v_t(X_t, d_t = j^{(t)})$. Similarly, all transition probabilities $q(\cdot)$ can also be replaced with empirical estimates in a preliminary step. The above lengthy formula of value function $v_t(X_t, d_t = j^{(t)})$ can be further simplified using the fact that all state variables are Markovian. Given that the farmer only has one period memory, therefore the state dependence breaks after two periods. In the value function, regardless of the choice made in year t, the farmer will be indifferent on the current value of the choice he or she will make in year $t+3$. That is, given two different current period choices, say $j^{(t)} = a$ and $j^{(t)} = b$, we have,

$$
\begin{aligned}
v_t(X_t, d_t = a) - v_t(X_t, d_t = b) \\
&= u_t(X_t, d_t = a) - u_t(X_t, d_t = b) \\
&+ \delta \sum_{X_{t+1}} ln \left[P(d_{t+1} = j^{(t+1)} \mid X_{t+1})^{-1} \right] q(X_{t+1} \mid X_t, d_t = a) \\
&- \delta \sum_{X_{t+1}} ln \left[P(d_{t+1} = j^{(t+1)} \mid X_{t+1})^{-1} \right] q(X_{t+1} \mid X_t, d_t = b) \\
&+ \delta \sum_{X_{t+1}} \left[u_{t+1}(X_{t+1}, d_{t+1} = j^{(t+1)}) \right] q(X_{t+1} \mid X_t, d_t = a) \\
&- \delta \sum_{X_{t+1}} \left[u_{t+1}(X_{t+1}, d_{t+1} = j^{(t+1)}) \right] q(X_{t+1} \mid X_t, d_t = b) \\
&+ \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} ln \left[P(d_{t+2} = j^{(t+2)} \mid X_{t+2})^{-1} \right] \\
&* q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) q(X_{t+1} \mid X_t, d_t = a) \\
&+ \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} ln \left[P(d_{t+2} = j^{(t+2)} \mid X_{t+2})^{-1} \right] \\
&* q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) q(X_{t+1} \mid X_t, d_t = b) \\
&+ \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} \left[u_{t+2}(X_{t+2}, d_{t+2} = j^{(t+2)}) \right] \\
&* q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) q(X_{t+1} \mid X_t, d_t = a) \\
&+ \delta^2 \sum_{X_{t+1}} \sum_{X_{t+2}} \left[u_{t+2}(X_{t+2}, d_{t+2} = j^{(t+2)}) \right] \\
&* q(X_{t+2} \mid X_{t+1}, d_{t+1} = j^{(t+1)}) q(X_{t+1} \mid X_t, d_t = b)
\end{aligned}
$$

Note that, the above simplified value function difference term appears in the standard choice probability of Logit model. And in Logit model only the relative values that matter, hence the above simplified result can be used to construct log-likelihood function. Given the simplification, all of the structural parameters in the flow utility function $u(\cdot)$ become linear, which also makes the estimation of the Logit model more feasible. The log-likelihood is given by,

$$L(\gamma,\delta) = \sum_i \sum_t \sum_l ln\left(\frac{exp\left(v_t(X_t, d_t = l)\right)}{\sum_j exp\left(v_t(X_t, d_t = j)\right)}\right) \tag{11}$$

or equivalently,

$$L(\gamma,\delta) = \sum_i \sum_t \sum_l \left(v_t(X_t, d_t = l) - ln\sum_j exp\left(v_t(X_t, d_t = j)\right)\right) \tag{12}$$

3. Data

The empirical study in this paper uses crop production data of the state of Ohio. The crop choice data comes from 30*30 meter resolution cropland data layer developed by USDA. The study period is from 2008 to 2014. The CDL data basically consists of a large panel of micro-level crop choices, which is the dependent variable in this study. Crop yield, crop prices and production costs data come from the Commodity Costs and Returns database of Economic Research Service (ERS) at USDA. Climate data is derived from PRISM data. All yield, climate, prices and costs data are recorded at county level. To match with CDL crop choice data, all county level data are down-scaled to 30*30 meter resolution.

Ohio is one of the states where more than half of its land is classified as prime farmland. The major field crops in the state include soybeans, its largest crop, corn. Other field crops are wheat, hay, oats. This study includes soybeans, corn, and wheat (spring and winter). In the original CDL data, land uses are categorized into more than 200 codes. In this study they are recoded into four codes: 1 = corns; 2 = soybeans; 3 = spring and winter wheat; 4 = other uses. All double crops (may include corns, soybeans, and wheat in the rotation) are excluded from the study given that they may exhibit different behavior.

For three crops included, net return to production is computed as revenue net of all production costs except land rent. For other crops or other agriculture land use, the net return is set to the farmland rent which is available at county level. All the variables measured in dollar values are converted to a constant value, so that the net return is comparable over years. Two climate variables are used in the crop yield model: cumulative precipitation level for the growing season (April to October), and monthly average degree days over 29 Celsius degree for the growing season. The climate variables come into the corp yield prediction model in quadratic form.

4. Estimation Procedure and Results

The empirical estimation in this paper carries out in two stages. The First stage is a spatial block bootstrap which randomly selects a dynamic spatial panel from the raw data to reduce computational difficulty. Otherwise, the maximum likelihood estimation over billions of cells (30*30 meter cell) is computationally exhaustive. Other than reducing computation intensity, another advantage of the spatial block bootstrap method is that to some extent it keeps the spatial structure of the data. In the literature, spatial aggregation and random selection have been used to reduce the number of observations in estimation (e.g., Scott, 2013; Ji et al., 2014), which may not consider the spatial relationship between observations properly.

In this paper, 35 cell by 35 cell blocks are randomly selected over the entire land cover, which is close to an 300 acres size field. Several restrictions have been applied while selecting blocks to avoid nuisance blocks (e.g., blocks with all grassland or forestry land): (1) there has to be at least one third of the cells covered by major crops (corn, soybeans, and wheat); (2) all four choices (corn, soybeans, wheat, and others) have to appear in the block. In practice, (1) and (2)

are likely to be satisfied at the same time. After a block is selected, all the cells with null values are eliminated given that they are not informative regarding crop choice behaviors.

Maximum likelihood estimation is implemented on the cleaned data blocks with simulated anneal optimization algorithm (SANN, see Belisle (1992)), which belongs to the class of stochastic global optimization methods. The algorithm is usually found useful in getting to good estimates on a very rough surface, which is likely to be the case in this study. In such cases, derivative-based optimization methods (e.g., BFGS, L-BFGS) may not work well, given that they require a large number of function evaluations even with a small number of algorithm iterations.

As illustrated in section 2, the prediction of crop yields, prices, and production costs is completed in a preliminary step. In this study, the predictors of crop yields (equation (1)) include county fixed effects, year time trend, and two climate variables (cumulative precipitation level and monthly mean degree days above 29 Celsius degree) in quadratic form. The prediction of prices and costs follows AR (1) processes (equation (2) and (3)).

Table 2 summarizes the estimation results on all structural parameters to be estimated from equation (6). The estimates are obtained with 50 random draws. Note that the standard errors here are computed as the standard deviation of estimates from all draws. Therefore, the significance of the parameter estimates should not be over-interpreted, given that a smaller standard error can be potentially achieved by simply running more estimation draws. However, given that the model is designed for prediction purpose instead of identifying any specific causal effects, the interpretation of the results should focus on the sign of estimates.

As expected, higher net return from crop production leads to higher flow

utility and hence higher probability of choosing the given crop, which holds for all three major crops and the outside option (*others*). The state variables are used to capture potential effects related to crop rotations. In general, soybeans are the most rotation friendly crop. However, the rotation between corn and soybean is not a rotation pair that leads to mutual benefits. This can be seen from the estimates with opposite signs: $\gamma_{sc} = -1.6665$ and $\gamma_{cs} = 1.6708$, which are all significantly different from zero given the number of random draws at 50.

For corn and wheat, the results tell a different story. Both crops show a positive benefit of without rotating to other crops. This is potentially due to the unique growing periods of the crops. For example, corn production requires a relatively long growing season, which leaves small time window for other crops to proceed or succeed except in the case where corn is grown for foliage to support animal production.

	Crop Choice			
Parameters	Corn	Soybean	Wheat	Others
$\gamma_{\bullet 0}$	1.5505 (0.5133)	1.8496 (1.0910)	1.4105 (0.4783)	1.1208 (1.1507)
$\gamma_{\bullet r}$	0.4634 (0.2396)	0.4182 (0.1711)	0.6964 (0.3524)	0.8092 (0.3267)
$\gamma_{\bullet c}$	1.0417 (1.0743)	-1.6665 (0.7877)	-0.4098 (2.2057)	
$\gamma_{\bullet s}$	1.6708 (0.3315)	0.7401 (0.7071)	0.9484 (0.9446)	
$\gamma_{\bullet w}$	-0.7664 (0.9925)	0.3590 (0.5730)	1.3485 (0.6331)	
# of Draws	50	50	50	50

Note: standard errors are reported in parentheses, which is computed as the standard deviation of estimates from all 50 random draws through spatial block m-out-of-n bootstrap.

Table 2: Structural parameter estimates

The current study is only at its preliminary stage, the climate change impact analysis will be incorporated into future versions. The impact of climate change on agricultural land use pattern can be explored through both precipitation and temperature channels. Empirically, these changes influence farmers' crop

choice through yield prediction model in equation (1), that is, $\triangle X_{it} \rightarrow \triangle Yield_{jit} \rightarrow \triangle d_{jit}$.

5. Conclusion

In this study we develop a dynamic multinomial discrete choice framework to model adaptation to climate change through crop choice. A major innovation of this study is the construction of a very large high-resolution data set for the econometric analysis and the computational procedure developed to obtain estimates. We assemble a high resolution data set on agricultural land use and climate variables for the state of Ohio. The main advantage of such an extensive and detailed data set is the careful consideration of the spatial heterogeneity within counties. The generality of our empirical framework allows prediction of crop choices at field level under various climate change scenarios. The empirical results show that both market state variables (yields, prices, and costs) and crop state variables (related to crop rotations) are important predictors of farmers' crop choice. In general, soybeans are the most rotation friendly crops. Corn and wheat show a positive benefit of without rotating to other crops. This is potentially due to the unique growing periods of the crops. The current study is only at its preliminary stage, future versions will focus on climate change impact analysis on agricultural land use change.

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