The Spillover Effects of Biofuel Policy on Participation in the Conservation Reserve Program

Feng Wu
Gulf Coast Research and Education Center, University of Florida
Zhengfei Guan*
Gulf Coast Research and Education Center, University of Florida
Fan Yu
Claremont McKenna College and Shanghai Advanced Institute of Finance
Robert J. Myers
Dept. of Agricultural, Food, and Resource Economics, Michigan State University

Abstract

This paper studies the spillover effects of rising biofuel production on participation in the Conservation Reserve Program. Landowner participation decisions are modeled using a real options framework. We develop a land use decision model that captures biofuel-driven structural changes in market demand and derive threshold conditions that trigger participation in the program. We then quantify the impacts of biofuel production on participation at both the national and state levels using Monte Carlo simulations. The model is also used to analyze how changes in the persistence of the biofuel production boom and in the volatility of farming returns affect conservation participation decisions. Policy implications of the results are discussed.

Keywords: Spillover, Biofuel production, Conservation reserve, Risk and uncertainty, Real options

JEL classification: C61, D81, Q24

* Corresponding author, contact information:
University of Florida
Gulf Coast Research and Education Center
14625 CR 672, Wimauma, FL 33598
Phone: +1-813- 633-4138
Fax: +1-813- 634-0001
E-mail: guanz@ufl.edu

The Spillover Effects of Biofuel Policy on Participation in the Conservation Reserve Program

1. Introduction

Over the past few decades, increased public awareness of environmental issues has prompted the U.S. government to make environmental protection a priority policy area. The Conservation Reserve Program (CRP), enacted in 1985, is a major environmental protection initiative in the U.S. The program aims to retire 10 percent of the U.S. cropland from production and is by far the most important U.S. land conservation program in terms of scale and budget. It aims to provide environmental benefits (e.g., reduce erosion and sequester carbon) through retiring environmentally sensitive cropland. In exchange, participants are given a dependable source of income in the form of CRP land rental payments. The program's economic and environmental benefits have been well documented (see, e.g., Young and Osborn, 1990; Wu, 2000; Wu et al., 2001; Wu and Lin, 2010). In its first twenty years of implementation, the program has prevented an estimated 450 million tons of soil from erosion and sequestered 50 million tons of carbon dioxide per year (USDA-FSA, 2007).

Another policy initiative that has had profound environmental and economic impacts is the 2005 and 2007 Energy Acts (2005 Energy Policy Act and 2007 Energy Independence and Security Act (EISA)), which set a roadmap for bioenergy production and mandates in the U.S. This policy was designed to mitigate greenhouse gas emissions and reduce U.S. dependency on energy imports. It has caused significant increases in domestic biofuel production, and possible structural changes in agricultural commodity markets and farming returns (USDA-ERS, 2007; Collins, 2008; Lipsky, 2008; Frank and Garcia, 2010). Supported by ethanol tax credits and mandates on biofuel consumption, annual ethanol production has increased dramatically along with acreage of corn, a major feedstock for ethanol production in the U.S. While the desire to reduce greenhouse gas emissions was an important driver of the increased biofuel production, the ethanol-driven structural changes in U.S. agriculture have been pressuring lands out of conservation into crop production. As of 2009, CRP enrollment stood at 31.2 million acres, approximately 5 million acres lower than in 2007 (USDA-FSA, 2010). Land use changes due to exits from CRP result in increased greenhouse gas emissions and have compromised the very goal of emission reduction of the biofuel policy. This research studies the spillover effects of biofuel policy on CRP participation and analyzes the implications of potential policy options. We illustrate the nature of competition and extent of spillover between these two major government policies.

The analysis requires understanding landowners' conservation participation decision process. When making participation decisions, landowners trade off the costs and benefits of participation. Factors such as annual CRP land rental payments and farming returns are likely to be key determinants (e.g., Parks and Kramer, 1995; Lubowski et al., 2008; Suter et al., 2008; Change and Boisvert, 2009). Since the Energy Policy Act was passed in 2005, farming returns have experienced a sharp increase, suggesting returns to agricultural production have entered a high growth state, departing from the former low growth state. The prospect and persistence of the biofuel driven agricultural boom will have direct impacts on landowners' participation decisions. Another important factor that impacts participation is risk and uncertainty (Capozza and Li, 1994; Dixit and Pindyck, 1994; Schatzki, 2003; Isik and Yang, 2004). This is particularly relevant in the current context because of the structural changes and uncertainties surrounding the magnitude and persistence of the changes. Faced with these uncertainties, landowners may choose to wait for more information about future returns and thus delay participation. Though participation in the CRP offers landowners a stable stream of cash flow from government payments over the contract period, once enrolled, the land will be locked up for 10 or 15 years, so the participation decision is essentially irreversible during the fixed contract period. In particular, landowners who participate in the CRP may be losing out economically due to higher, forgone farming returns in the future in the context of increasing biofuel production.

In this study we propose a two-state continuous time Markov chain process to model structural change in farming returns and investigate the impacts of biofuel production on conservation participation using a real options framework. Traditionally, real options models assume uncertain returns follow a geometric Brownian motion (GBM), in which the location (mean) of the distribution is assumed to be fixed (see, e.g., Dixit and Pindyck, 1994). Under biofuel-driven structural changes, however, the assumption of a *constant* growth rate for farming returns would be inappropriate. In this study we allow the growth rate of farming returns to follow a two-state process, in which the current high growth state may revert to a low growth state as the ethanol industry matures, or as a result of policy changes (e.g., repealing the ethanol tax credit or removing the ethanol import tariff). The process is general enough to allow for multiple state shifts in the future as farming may move through booms (high return growth rate) and busts (low return growth rate) as the industry and biofuel policy evolve. We further assume that the durations of high and low growth states are random due to exogenous economic and policy uncertainties. The model we propose in this study assumes a geometric Brownian motion with a *stochastic* growth rate (Gennotte, 1986; Brennan, 1998; Xia, 2001; Abasov, 2005), in which landowners continuously update their expectations, conditional on new information arriving at the time of the decision. The expectation formation with information updating is consistent with the actual decision process facing landowners as they observe only historical information and make decisions based on their expectations of the future, which is particularly true at a time of structural change when past realizations only contain partial information about the future growth rate. The parameter uncertainty of stochastic growth rate causes an extra layer of uncertainty compared to the traditional GBM assumption. This has not been addressed in the literature modeling land use decisions.

Based on the proposed model, we derive thresholds of farming returns (profit per acre) that would make land conversion attractive, which is then used to investigate the impacts of biofuel production on program participation at both the national and state levels using Monte Carlo simulations. We further analyze the sensitivity of the land-use conversion thresholds to changes in market conditions, including the expected duration of the biofuel boom and the uncertainty surrounding future agricultural returns. The results provide a number of important insights with significant policy implications.

2. Landowner Decision Making under Uncertainty

The CRP provides an annual per-acre rental payment to landowners to take highly erodible or environmentally sensitive cropland out of production. The payment is fixed over the contracted period once the land is enrolled. The program also provides cost-share assistance to participants who establish approved resource-conserving vegetative covers on eligible cropland. The cost-share assistance can be no more than 50 percent of the participants' costs in establishing covers. Landowners who decide to enroll in the program must enter into a $\bar{T}$ year contract (10 or 15 years).

Consider a landowner facing a decision to convert a unit of land from crop production to conservation.[1] We assume that the participation decision is made in a continuous-time framework. Defining the farming return as R_t, the expected discounted farming return forgone over the $\overline{T}$ year horizon is:

$$V(R_t) = E_t \int_t^{t+\overline{T}} R_t e^{-\rho t} dt \,, \tag{1}$$

where ρ is the continuous discount rate.

After participation, the annual rental payment Q is fixed. The land rental payment received over the $\overline{T}$ years of the CRP contract is:

$$V(Q) = \int_t^{t+\overline{T}} Q e^{-\rho t} dt - (1-k)C = \frac{Q(1-e^{-\rho \overline{T}})}{\rho} - (1-k)C \,, \tag{2}$$

where C is the total land cover establishment cost when participating in the CRP and k is the portion paid by the government as an incentive for participation.

Denote $M(R_t, Q) = V(Q) - V(R_t)$ as the benefit from land conversion at time *t*. The minimum requirement for conversion is that $M(R_t, Q)$ be positive. The conversion decision can be characterized as an optimal stopping problem given uncertain market conditions, in which landowners choose when to stop waiting and participate in the CRP. The optimal stopping problem can be represented as:

$$J(R_t) = \max_T \; E_t[e^{-\rho(T-t)} M(R_T, Q)] \,, \tag{3}$$

which reflects the landowner's choice of the optimal conversion time, $T \geq t$, to maximize the discounted expected conversion benefit at *t*.

3. Structural Change and Parameter Uncertainty

The participation problem is similar to an American put option: landowners have an option to put the land into conservation, with discounted total rental payments over the contract period as the exercise price. Valuation of American put options usually assumes the underlying asset return follows a geometric Brownian motion (GBM) (Carey and Zilberman, 2002; Isik and Yang, 2004):

$$dR_t = \theta R_t dt + \sigma R_t dW_t \, , \tag{4}$$

where θ is a constant drift term, σ is a constant volatility parameter, and W_t is a standard Brownian motion, defined on a complete probability space.

This model incorporates the strong assumption that the parameters of the process are known. That is, all possible sources of uncertainty that affect the farming return are summarized in the form of a log-normal distribution with a *known, constant* growth rate θ and a volatility parameter σ, which in practice must be estimated from historical farming return data. This assumption is often plausible. Given the current structural changes in farming returns, however, the assumption would be too restrictive and likely does not hold; and assuming a constant, known farming return growth rate may result in substantial error (Gennotte, 1986).

It is more realistic to assume that the growth rate of agricultural returns in the biofuel era may be different than at other times, and that landowners' expectations about growth vary at different points in time. To capture the impact of structural change on expectations about future agricultural returns, we assume the growth rate (θ) is stochastic and unobservable. We use a two-state continuous time Markov chain to model θ_t, allowing for a high growth state (α) and a low growth state (β). Transitions between α and β are generated by changes in the underlying economic and policy environment (e.g., addition or removal of biofuel mandates, technological breakthroughs in cellulosic ethanol production, oil price shocks, etc.). The possibility of transitions back and forth between high and low growth states allows for the possibility of rebalancing to a new equilibrium, or to agricultural boom and bust cycles (Boehlje et al., 2012). In the generalized farming return model, θ_t is specified as:

$$\theta_t \in \{\alpha, \beta\}, \quad \alpha > \beta , \tag{5}$$

where α and β are the growth rates of the two states. The duration of state i $(i = \alpha, \beta)$, denoted by T_i, is assumed to follow an exponential distribution with parameter λ_i (Liggett, 2010):

$$prob(T_i \geq t) = \exp(-\lambda_i t) . \tag{6}$$

To estimate θ_t, we use the Kalman filter information updating algorithm, which is a recursive algorithm that continuously updates model estimates using new information. The Kalman filter minimizes the estimated error variance and generates more efficient parameter estimates compared to other estimation procedures (Kalman, 1960). We allow landowners to update their information and thus learn about the true parameter distribution with each new farming return realization. At time t, there is a prior distribution of the random growth rate. As new farming returns are observed over time, this prior distribution is updated. Liptser and Shiryaev (1977) derived the basic equation for optimal nonlinear filtering under a partially observable random process.

Specifically, the conditional probability of the growth rate being in the low growth state β is defined as:

$$p_t = prob(\theta_t = \beta | \Omega_t^R) . \tag{7}$$

Based on the information set Ω_t^R available to landowners at time t,[2] landowners form expectations about the value of θ_t,

$$m_t = E(\theta_t \big| \Omega_t^R) = (1 - p_t)\alpha + p_t \beta . \tag{8}$$

Given parameter uncertainty, the Brownian motion W_t is also unobserved. However, we can define a process based on the observed farming return R_t and its expected growth rate m_t as:

$$d\overline{W}_t = \frac{1}{\sigma}(\frac{1}{R_t} dR_t - m_t dt) . \tag{9}$$

Liptser and Shiryaev (1977) showed that $\overline{W}_t$ is a standard Brownian motion with respect to the information set Ω_t^R. Rearranging (9), we obtain:

$$dR_t = R_t m_t dt + R_t \sigma d\overline{W}_t . \tag{10}$$

Substituting (4) into (9) yields

$$d\overline{W}_t = dW_t + \frac{1}{\sigma}(\theta_t - m_t)dt . \tag{11}$$

Landowners seek to extract information on the expected growth rate from observed past returns, and keep updating the expectation when new return realizations come along. The conditional mean m_t evolves according to (see Appendix A for the derivation):

$$dm_t = \left[\lambda_\alpha(\beta - m_t) - \lambda_\beta(m_t - \alpha)\right]dt + \frac{1}{\sigma}(\alpha - m_t)(m_t - \beta)d\overline{W}_t . \tag{12}$$

Combining (3), (10), and (12), we arrive at the following decision model:

$$\begin{cases} J(R_t, m_t) = \max_T E_t[e^{-\rho(T-t)} M(R_T, Q)] \\ dR_t = R_t m_t dt + R_t \sigma d\overline{W}_t \\ dm_t = \left[\lambda_\alpha(\beta - m_t) - \lambda_\beta(m_t - \alpha)\right]dt + \frac{1}{\sigma}(\alpha - m_t)(m_t - \beta)d\overline{W}_t \end{cases} . \tag{13}$$

In this framework, landowners maximize option value J by choosing the optimal time T to enter into the CRP contract. Landowners continuously update their estimate of the growth rate of farming returns based on new return realizations. With the uncertain growth rate, there is no analytical solution to the decision problem. The problem is therefore formulated as a linear complementarity problem (LCP), and solved numerically using an implicit finite difference approach (Wilmott et al., 1993).

4. Linear Complementarity Problem

Under known regularity conditions, there will be a critical return level R^* for a given initial expected growth rate, such that participating in the CRP is optimal if $R_t < R^*$, while continuing in farming is optimal if $R_t \geq R^*$. The solution to the participation problem involves finding this threshold R^*. Using Ito's lemma, we derive a partial differential equation in a continuous region of the farming return (see Appendix B for the derivation):

$$\begin{aligned}&\rho J - R_t m_t J_R - \left[\lambda_\alpha(\beta - m_t) - \lambda_\beta(m_t - \alpha)\right] J_m - \frac{1}{2} R_t^2 \sigma^2 J_{RR} \\ &- \frac{1}{2\sigma^2}(\alpha - m_t)^2 (m_t - \beta)^2 J_{mm} - R_t(\alpha - m_t)(m_t - \beta) J_{Rm} = 0\end{aligned}, \tag{14}$$

where J denotes the put option value, J_R and J_{RR} denote, respectively, the first and second derivatives of J with respect to R_t, and J_{Rm} denotes the cross derivative of J with respect to R_t and m_t.

We solve the optimal stopping problem (13) numerically using an LCP algorithm. This technique is often used to solve American options due to the existence and uniqueness of solutions (Wilmott et al., 1993), but to our knowledge this technique has not been used previously to solve a land conversion problem, except for some applications to optimal forest harvesting (Insley and Rollins, 2005; Creamer, 2010). Define the left-hand side of (14) as HJ :

$$HJ = \rho J - \begin{bmatrix} R_t m_t J_R + \left[\lambda_\alpha (\beta - m_t) - \lambda_\beta (m_t - \alpha)\right] J_m + \frac{1}{2} R_t^2 \sigma^2 J_{RR} + \\ \frac{1}{2\sigma^2} (\alpha - m_t)^2 (m_t - \beta)^2 J_{mm} + R_t (\alpha - m_t)(m_t - \beta) J_{Rm} \end{bmatrix}, \tag{15}$$

where ρJ is the opportunity cost of holding the option (i.e., the required return for holding it). The expression within the outer square brackets represents the expected return from waiting due to the change in the option value. Then, the LCP can be specified as:

$$\min\left\{HJ; \left[J - M(R_t, Q)\right]\right\} = 0 . \tag{16}$$

This LCP describes the strategy with regard to holding versus exercising the option. If HJ >0, the required return for holding the option exceeds the expected return, and it is optimal to exercise the option immediately. If HJ =0, the required return equals the expected return, and the landowners can either hold the option or exercise it. When $J > M(R_t, Q)$, the option value is larger than the intrinsic value of participating immediately in the CRP, and holding the option is optimal. If HJ =0 and $J = M(R_t, Q)$, then landowners are indifferent between participation and non-participation.

Because of the uncertainty surrounding the growth rate of the farming return, the optimal participation problem does not have a closed-form solution. However, it is possible to solve the problem numerically. The numerical algorithm for determining the value of the option involves the discretization of the LCP in (16) using an implicit finite difference method (see Appendix C). For a numerical solution of the LCP, we must specify the boundary conditions. [3]

Boundary condition 1. It can be seen from (10) that once R_t reaches zero, it will stay there because $dR_t = 0$. Therefore, it is optimal to exercise the option immediately when R_t goes to zero, in which case:

$$J(0, m_t, t) = M(0, Q)\,. \tag{17}$$

Boundary condition 2. At a very high farming return $R_{\max}$, the put option is deeply out of the money and we can set the option value to zero:[4]

$$J(R_{\max,} m_t, t) = 0\,. \tag{18}$$

Boundary condition 3. Since we are searching for a solution on a rectangular domain in the space of (R_t, m_t), we apply two other boundary conditions, $m_{\min} = \beta$ and $m_{\max} = \alpha$. In particular, we use boundary condition BC2 on $m_{\min}$ and $m_{\max}$ (Tavella and Randall, 2000).[5]

Terminal condition. The terminal condition follows from the observation that at $t = \infty$ there is no uncertainty about the true value of the growth rate. As a result, m_t becomes a constant. Hence, $J(R_t, m, \infty)$ is the solution to the one-dimensional problem:

$$\begin{cases} J(R_t, m, \infty) = \max_T \; E_t[e^{-\rho(T-t)} M(R_T, Q)] \\ dR_t = R_t m dt + R_t \sigma d\overline{W}_t \end{cases}, \tag{19}$$

which can be solved in closed form. In this case, the put option value will be (see Appendix D for the derivation):

$$J(R_t, m, \infty) = \begin{cases} M(R^*, Q)\left(\dfrac{R_t}{R^*}\right)^{\gamma} & R_t \ge R^* \\ M(R_t, Q) & R_t \le R^* \end{cases}, \tag{20}$$

where $R^{*}=\frac{\gamma}{\gamma-1}\cdot\frac{(\rho-m)V(Q)}{(1-e^{-(\rho-m)\bar{T}})}$ and $\gamma=\frac{-(m-\frac{1}{2}\sigma^{2})-\sqrt{(m-\frac{1}{2}\sigma^{2})^{2}+2\rho\sigma^{2}}}{\sigma^{2}}$.

5. Data and Parameter Estimation

To analyze the landowners' decision, we need to first estimate parameters in the proposed land-use model, which include the growth rates and volatility of farming returns, namely, α, β, and σ. In addition, we also need to derive parameters λ_{α} and λ_{β} associated with the durations of growth states. We begin with a nationally representative landowner in the U.S. and later move on to allow for regional heterogeneity.

5.1. Data on Farming Returns

Assume that a representative landowner in the U.S. is making a decision to convert croplands to conservation.[6] Annual per-acre cropland returns are calculated as the weighted average of the net returns of three major crops — corn, soybean, and wheat.[7] The weight is the percentage of planted acreage for each crop relative to total planted acreage. Data on marketing-year-average prices and national level yields used to calculate the value of production are from the National Agricultural Statistics Services (NASS), USDA. Per-acre crop production costs are from the Economic Research Service (ERS), USDA, which include operating costs and allocated overhead, excluding the opportunity cost of land.[8] The net cropland return is the gross value of production less crop production costs. Per-acre government payments received for crop production are also included in cropland returns and are calculated by dividing direct government payments (excluding conservation payments) by total cropland acreage reported in the *Major land Uses* series of the ERS, USDA. National direct government payments by program are available from the ERS, USDA.[9] The calculated annual cropland returns from 1975 to 2009 form a sample of 35 observations.

5.2. Parameter Estimation

In July 2005, the 2005 Energy Policy Act was passed. This Act established the Renewable Fuel Standard mandating the mix of biofuels in transportation fuels sold in the United States. As a result, biofuel production increased considerably from 2006, which led to an increased demand for and higher prices of agricultural commodities. Recent studies also recognize biofuel production as the major driver of a structural change of commodity prices and farming returns. Frank and Garcia (2010) identified a structural change in 2006 for agricultural commodity prices using data from 1998 to 2009 and found that the agricultural markets, especially the corn market, have been more energy-driven since 2006. A report from USDA evaluated the effects of biofuel production on farm income and predicted that biofuel production would substantially improve net farm income during 2007-2016 (USDA-ERS, 2007). Given these evidences, we assume that a shift of farming returns to high growth occurred in 2006 and use annual returns before 2006 to estimate the low growth rate β.

When farming return follows a GBM, the logarithm of the return can be described as:

$$d\ln(R_t) = (\beta - 0.5\sigma^2)dt + \sigma dW_t \, . \tag{21}$$

To verify whether $\ln(R_t)$ follows the process described above, (21) must be approximated in discrete time. The discretized version of (21) can be written as:

$$\ln(R_t) - \ln(R_{t-1}) = (\beta - 0.5\sigma^2)\Delta t + \sigma\varepsilon_t\sqrt{\Delta t} \, , \tag{22}$$

where ε_t is a normally distributed random variable with mean 0 and variance 1.

We perform an augmented Dickey–Fuller test with a trend on the logarithm of the return series to investigate whether the data-generating process is nonstationary. The null hypothesis of unit root cannot be rejected at standard significant levels. Based on the test result, we assume that the farming return follows a GBM in the low growth state. The maximum-likelihood estimates of the drift β and the volatility σ for farming returns are β =4% and $\sigma = 0.26$.

Based on (6), the expected time of staying in the high growth state is $1/\lambda_\alpha$, after which the ethanol industry attains equilibrium and agricultural returns re-enter the low (normal) growth period. Tokgoz et al. (2008) predicted that the long-run equilibrium of the ethanol industry may be achieved in 2016. Therefore, we assume that $\lambda_\alpha = 1/7$, which is equivalent to assuming that the high growth (α) state will continue for an *average* of 7 years (2010-2016). The high growth rate α is computed based on annual farming returns from 2006 to 2009 and the report of USDA Agricultural Projections to 2016 conducted in 2010. This report shows that although increases in corn-based ethanol production in the United States are projected to slow, the demand for ethanol remains high. This affects the production, use, and pricing of farm commodities throughout the sector. Consequently, although net farm income initially declines from the highs of 2007 and 2008, it remains historically strong and will rebound according to the projections. With the projected data for corn, soybean, and wheat, we estimate the high growth rate α to be 8.5%.[10] We further assume that $\lambda_\beta = 1/32$, which means that, on average, agriculture's boom cycle emerges every 32 years. This assumption is consistent with the past cycles.[11] For other parameters, a risk-adjusted discount rate ρ of 6% is used,[12] and the government's cost share proportion (k) for establishing land cover is 50%. The cost C depends on the land cover but was set at the typical cost of \$60/acre. The annual rental payment is set at \$65 according to recent CRP reports and statistics.

6. Results

The option value, $J(R_t, m_t)$, is determined using the numerical methods described in Appendix C. Figure 1 plots the value of the option to participate in the CRP under any two different expected growth rates ($m_t = 0.049$ or $m_t = 0.085$) for the baseline case where $\alpha = 8.5\%$, $\beta = 4\%$, $\lambda_\alpha = 1/7$, λ_β=1/32, k=0.5, C=60, $\sigma = 0.26$, $\rho = 0.06$, $\overline{T} = 15$, and $Q = 65$. This figure shows that the option value increases (decreases) as the farming return or its expected growth rate decreases (increases).

<Figure 1>

Table 1 shows the option value on a grid. The highlighted cells represent combinations of the farming return and its expected growth rate for which the landowner is indifferent between waiting and participating immediately in the CRP. The numbers below these highlighted cells give the value of continuing to hold the option to convert the land, while the numbers in the upper part of the table give the value of participating immediately in the program. These combinations specify the critical farming return as a function of the expected growth rate. Farming returns lower than the threshold will make the CRP attractive enough for landowners to stop waiting and participate in the CRP; farming returns higher than the threshold make the CRP less attractive, and landowners will choose to wait.

<Table 1>

Our main findings can be summarized as follows: 1) The option value decreases when farming return R_t and the expected growth rate m_t increase, as illustrated in Figure 1; the threshold return R^* declines when the expected growth rate increases, making conversion less likely. 2) The option value increases with λ_α (recall that $1/\lambda_\alpha$ represents the average time of staying in the high growth state), which means that the longer the high growth state is expected to persist, the lower is the value of the option. This suggests that the threshold at which the landowner is likely to enroll in the CRP is lower, making participation less likely. 3) The option value decreases with λ_β, implying that the option is less valuable when the low growth state is less persistent. These results are intuitive: higher farming returns, higher expected growth rates, and a longer (shorter) time of remaining in the high (low) growth state all reduce the incentive for conservation. This is consistent with the observation of reduced participation in the last few years when farming returns grew rapidly.

The land-use model developed in this study can be used to simulate CRP participation probabilities. We conducted Monte Carlo simulations to investigate the enrollment probability for a piece of land with baseline characteristics discussed above. We use the Euler method to simulate the dynamics of farming return (eq. 10) and growth rate (eq. 12). The farming return and growth rate dynamics are simulated over a 5-year horizon from 2010. The initial farming return in 2009 is assumed to be $104 per acre;[13] and the initial growth rate expectation is set at 6.89%, which is the mean growth rate for 2009 according to the dynamics of eq. 12, implying that the landowner believes that the growth rate has a 36% chance of immediately reverting to the low level according to eq. 8. The conversion thresholds (i.e., the highlighted boundaries in Table 1) are used as the decision criteria: at a certain growth rate expectation, if the simulated farming return is lower than the threshold anytime in the 5-year horizon, the land would be enrolled into the conservation program but otherwise would stay in farming. The results of 20,000 Monte Carlo replications show that in 5 years the land with the baseline characteristics discussed would have a 3.27% probability of being enrolled in the CRP. To get a feel for how sensitive the participation decision is to initial farming returns, we conducted an additional simulation setting the initial farming return at a low value of $90 per acre, which resulted in a participation rate of 5.00%. These results yield an elasticity of -3.93 of the participation probability with respect to farming returns, which indicates that participation is very sensitive to changes in initial farming returns.

To evaluate the impact of structural change, we perform another simulation assuming $\alpha = \beta = 4.0\%$, which is equivalent to assuming the traditional geometric Brownian motion without parameter uncertainty. Accordingly, the initial farming return in 2009 is set at $66, which is calculated using the realized farming return in 2005 and an annual growth of 4%, adjusted for the lower productivity of CRP lands. New conversion thresholds are derived and used in the Monte Carlo simulation. The simulation result shows that the participation rate rises to 19.46%, six times higher than the baseline case of 3.27%. That is, the structural change has reduced the probability of CRP participation by 83%. This shows that ignoring uncertainty surrounding growth rates can have a huge impact on estimated participation.

Though biofuel production is a major source of structural change, other factors may also be important. Based on evidence from the literature, we assume that biofuel production accounted for 60 percent of the increase in corn prices, 40 percent of the increase in soybean prices, and 26 percent of the increase in wheat prices (Collins, 2008; Lipsky, 2008).[14] Assuming the same effect on net returns for each crop and using the historical average planted ratio of each crop as weights, biofuel production contributes roughly 40% of the jump in growth rates from 4% to 8.5%. To separate the impact of biofuel production on CRP participation, we re-simulate the participation probability excluding biofuel production's effect on the growth rate. For this purpose, we reset $\alpha = 6.7\%$ (keeping $\beta = 4\%$) and re-calculate the land conversion threshold returns under different growth expectations. With an adjusted initial growth rate of 5.73% (similarly, assuming the landowner holds the same 36% belief on the probability of the growth rate immediately reverting to the low level) and an adjusted initial farming return of $74 for 2009, the simulation results show that the participation rate would be 10.24% in the next 5 years, which is more than three times higher than the baseline case of 3.27%.[15] That is, of the entire structural change impact (an 83% drop from 19.46% to 3.27%), biofuel production accounts for 43% of the reduction. Further simulation shows that, to offset the participation loss due to the biofuel impact, the government would need to raise the per-acre rental payment by $26. This represents an increase of 40%.

The negative effect of the biofuel boom on participation is intuitive. Policies designed to support biofuel production would create incentives to move resources into biofuels. For example, the 2005 Energy Policy Act mandates 7.5 billion gallons of renewable fuel to be added to gasoline by 2012. Subsequent tax incentives and subsidies (e.g. federal tax credits of 51 cents a gallon for ethanol blenders) have paved the way for the increase in biofuel production. The growing demand for biofuels has decreased participation in the CRP, as shown by our simulations. This unintended consequence on conservation programs will counteract the emission reduction benefits of biofuel and thus need to be taken into consideration in the evaluation of biofuel policy. It raises the question of whether corn ethanol production could lead to effective net greenhouse gas emission reductions compared to the reductions achieved by the CRP itself (Searchinger et al., 2008; Piñeiro et al., 2009).

6.1. Parameter Sensitivity Analysis

A sensitivity analysis is undertaken to determine landowner's response to changes in various parameters. In particular, we analyze landowner's response to changes in market conditions.

6.1.1. Expected Duration of the High Growth State, $1/\lambda_{\alpha}$

In this section we investigate the impact of high growth duration on conservation participation. Figure 2 shows the return boundaries under different expectations of the high growth duration, namely, 4, 7, 12 and 20 years. For example, if the landowner expects the growth rate to be at 7.15% and persist for 12 years (corresponding to the 2022 target set in the 2007 energy act), he would be willing to participate in the CRP at a lower, $29.75/acre farming return. The Monte Carlo simulation result indicates that the participation probability in a 5-year horizon reduces from 3.27% to 2.68% when the high growth duration extends from 7 years to 12 years. Persistence of the biofuel boom has a clear impact on the length of the high growth state and therefore would lead to decreased conservation participation. Figure 2 also shows that the lower the initial growth rate expectation, the less sensitive is the boundary to the duration of the high growth state.

The duration of the biofuel boom and the high growth rate in farming returns are, to a large extent, dependent on a long list of incentives that the state and Federal governments have implemented to support ethanol production since the 1970s. The most prominent are the Federal ethanol tax credit and ethanol import tariff. While the tax credit goes to ethanol refiners, farmers have benefited because with sufficiently high competition among blenders, the corn price increases by almost the full amount of the credit (Elobeid et al., 2007). Also, imposing an ethanol import tariff raises domestic ethanol and corn prices. However, rising food prices, the desire to reduce federal budget deficits, and criticisms of corn-based ethanol from environmental organizations have not led to elimination of ethanol tax credits and import tariffs to date. Elobeid and Tokgoz (2008) simulated the effect of removing the tax credit and trade distortions and found that corn demand and prices would decline substantially. Importantly, the ethanol industry may end its boom sooner, which would cause farming returns to revert to a lower growth rate within a shorter duration. In that case, we have a larger λ_α value and would expect an increase in program participation.

<Figure 2>

6.1.2. The Effect of Volatility, σ

We further study the effect of uncertainty on the participation threshold. We vary the standard deviation of the logarithm of farming returns while keeping other parameters in the baseline unchanged. The impact of changes in volatility is illustrated in Figure 3.

<Figure 3>

Figure 3 shows that volatility in the farming return contributes to a decrease in the participation threshold. As expected, when the volatility of the farming return increases, the option value increases and the threshold decreases, indicating the landowner would wait for a lower farming return realization before committing to land conversion. For example, when volatility changes from 0.2 to 0.26, the participation threshold decreases from $32.25/acre to $30.75/acre at the 7.15% growth rate expectation. The decrease in the threshold value will have a negative effect on participation. However, besides lowering the critical trigger value, higher volatility could also make the farming return more likely to reach the critical value, which would have a positive effect on participation. To determine the overall effect of volatility, we examine the probability of participation using Monte Carlo simulation. The result shows that when volatility increases from 0.20 to 0.26, the probability of participation actually moves up, from 0.52% to 3.27%, suggesting that risk in agriculture would induce conservation. The implication is that reducing risk and uncertainty in agricultural returns using programs on farm income stabilization, for example, will have a negative impact on CRP participation and environmental conservation.

6.2. Regional Analysis

We further investigate CRP participation effects by state. Understanding how the effects vary across states will present a more informative picture of the spatial distribution of projected land use changes in regions that are heterogeneous both geographically and in production. We conduct simulations for 20 states for which data are available, which cover six agricultural regions, namely, Appalachian, Corn Belt, Lake States, Northeast, Northern Plains, and Southeast[16] (Figure 4). This vast area accounts for most agricultural activity in the U.S. These regions have different climates and exhibit significant degrees of heterogeneity in both agricultural activity and productivity, providing a rich setting for analyzing the varying effects of biofuel policy on CRP participation across states.

Table 2 reports estimates of current farming returns and parameters describing the movement of the returns before and after structural changes across states.[17] The numbers in Table 2 exhibit several interesting features. First, initial farming returns (R) vary significantly from state to state. Returns were generally higher in states across the Corn Belt, overall three times higher than those in the Southeast. Iowa is the leading corn and ethanol-producing state and has by far the highest farming return as of 2009. The farming return in South Carolina was the lowest because of the low proportion of corn area. As discussed above, a high farming return will reduce the probability of participation in the CRP. The variation in the extent of structural change across regions and states will also impact participation. The Corn Belt and Lake States experienced more prominent structural changes, evidenced by substantial differences in growth rates (α and β) while the Southeast had the smallest changes. Even in the same region, the intensity of structural changes differs by state. For instance, in the Corn Belt region, Missouri deviates significantly from the rest because of its shorter and hotter growing season limiting corn production. Differing farming returns also cause differences in CRP rental payments (Q), which is determined by soil productivity, farming returns, and CRP contract demand. Payments range from $33 to $99 per acre across the states.

To undertake the state-level analysis, we derive the threshold returns for different states and conduct simulations to investigate participation probabilities for each state. The Monte Carlo results (last column, Table 2) show a wide range of variation in participation probabilities across the states, ranging from 0.17% in Minnesota to 15.14% in Alabama. It is not surprising that the Northern Plains, Lake States, and Corn Belt have the lowest participation possibilities because they are the traditional corn growing areas where the effects of the biofuel boom are largest. This result is supported by USDA projections that these regions would likely see the largest corn acreage expansion by 2015 (USDA-ERS, 2009). Among these three regions, two states, North Dakota and Missouri, provide interesting cases that are worth noting. North Dakota is located at the edge of corn-producing areas, where corn production is limited traditionally due to its cooler and shorter growing season. But global warming is making North Dakota more appropriate for corn production, which would cause lower CRP participation. As a major contributor to the CRP program accounting for 9% of total CRP area as of 2009, North Dakota will face a big challenge in maintaining its CRP participation level. In contrast, corn production in Missouri has been adversely influenced by climate change (e.g., changing rain pattern and more heat stress). The corn planting area of Missouri in 2009 decreased by 100,000 acres compared to the 2005 level. Our results project a higher participation probability for Missouri comparing to other Corn Belt states. While the effect of biofuel policy on CRP participation is magnified by climate change in North Dakota, it is dampened in Missouri.

The Appalachian, Northeast, and Southeast regions have the highest probabilities of participation as these regions are less suited for corn production and therefore not among major corn producers. However, although these three regions have comparable probabilities of CRP participation, the factors motivating the high participation are not the same. The high probability in the Appalachian region is a result of high variation in returns (high σ). Appalachian agriculture is characterized by smaller sizes of farm operations, less consolidated farm lands, and thinner, rocky soils. These conditions preclude large scale, mechanized agricultural production systems and make crops more susceptible to weather risk. In addition, a higher percentage of cash crop production makes farming more susceptible to market risk. The high CRP participation probabilities in this region are mainly due to higher volatilities in returns. In contrast, the high probabilities in the Northeast and Southeast regions are more related to the small differences between CRP rental payments and farming returns, which would cause returns to reach participation thresholds more easily. However, note that the relatively high growth rate (α) in Pennsylvania makes its participation probability significantly lower than the other states in the region. Pennsylvania, a major wheat producer, has a high growth rate, which is likely due to the corn-to-wheat market spillover effect.

7. Conclusions

Biofuel policies have spurred biofuel production and discouraged participation in conservation programs, offsetting the emission reduction goal of biofuel policy and increasing the potential for environmental degradation. This study proposes a general land-use decision model to analyze the spillover effects of biofuels policy on CRP participation. The proposed model captures the biofuel-driven structural changes in the agricultural sector and is used to simulate landowners' conservation participation decision under different layers of uncertainty. The model also allows investigation of the factors that affect this decision. The model provides a useful tool for quantifying the spillover effects, determining optimal land use, and for policy makers to develop informed, cost-effective incentives to participate in conservation programs. Methodologically, we derive numerical solutions to the land-use decision problem under parameter uncertainty using a technique that can handle a fairly general class of specifications for the source of uncertainty. More specifically, we use a nonlinear Kalman filter approach to addressing parameter uncertainty, which continuously updates information observed by landowners and estimates the random growth rate of farming returns with minimum error. The real options problem is formulated as a linear complementarity problem and solved with a fully implicit finite difference approach.

We find a strong negative effect of biofuel production on CRP enrollment. At the national level, structural changes have reduced the probability of CRP participation by 83%, and 43% of this reduction stems solely from biofuel production. Our simulation results further suggest that, to offset the participation loss caused by biofuel production, the government would have to increase the per-acre rental payment by 40%. Our regional analysis shows that states in different regions exhibit significant heterogeneity in participation probability. States in the

Northern Plains, Lake States, and the Corn Belt have the lowest probability of participation in the 5-year horizon, while states in the Appalachian, Northeast, and Southeast have the highest participation probability. The results show that higher farming returns, higher expected growth rates, and longer (shorter) duration in the high (low) growth state all reduce the incentive for conservation due to the decreasing value of the conservation option for landowners. We also find that, though higher volatility of agricultural return reduces the threshold of farming returns that would trigger participation, its overall effect on participation is positive, which implies that government programs aiming to reduce farm income risk would have a negative effect on conservation participation.

Acknowledgements

Comments by Jinhua Zhao, Richard Baillie, and two anonymous reviewers are gratefully acknowledged.

[1] We limit our discussion to a single switching decision from cropland to the CRP. After the contract expires, the landowner is faced with an opposite land conversion decision – stay in the CRP or convert back to production. Our model could also be extended to address this problem, but such an extension is outside the scope of the current study.

[2] In the landowners' information set, the agricultural return R_t is observable, while its growth rate θ_t is not.

[3] In our model, the LCP is time-independent, or of the elliptic type. However, in practice, it appears that there is no satisfactory method dealing with elliptic LCPs. Following Abasov (2005), we introduce an artificial time variable into the partial differential inequalities of the elliptic LCP and solve the resulting parabolic LCP. Therefore, a terminal condition (with respect to the time variable) is required to implement this method.

[4] In the numerical implementation, $R_{\max}$ is set to be three times the average farming return.

[5] The boundary conditions proposed by Tavella and Randall (2002) are to apply the pricing equation itself as a boundary condition, rather than to appeal to other financial arguments. BC1 postulates a linear dependence of the option value on the underlying variable, while BC2 discretizes the drift and volatility with second order one-sided differential operators. BC2 yields smaller errors when we compute the option value using a finite difference method.

[6] USDA defines CRP eligible land as "cropland (including field margins) … physically and legally capable of being planted in a normal manner to an agricultural commodity".

[7] In 1975-2009, combined corn, soybean, and wheat acreage on average accounted for 62% of the U.S. total cropland.

[8] The cost and return accounts were categorized into cash and economic costs for all commodities from 1975 to 1994. Beginning in 1995, the accounts were revised to conform to methods recommended by the American Agricultural Economics Association Task Force on Commodity Costs and Returns, which recommended that the cost and return accounts be divided into operating costs and allocated overhead costs. To be consistent throughout, we adjust the account item "taxes and insurance" from 1975 to 1994 according to the new method. The comparison of USDA's former and new cost of production estimation methodology can be found at: http://www.ers.usda.gov/data/costsandreturns/compare.htm.

[9] Payments include receipts from deficiency payments, marketing loan gains, indemnity programs, disaster payments, and production flexibility contract payments, etc.

[10] Since the number of observations are small, we use the simple average of annual growth rates to proxy for α.

[11] Historically, U.S. agriculture experienced four booms in the 1910s, the 1940s, and the 1970s (Boehlje, et al., 2012).

[12] Instead of assuming risk-neutral valuation (and discounting at the risk-free rate) and relying on the risk-neutral dynamics of *R*, we use a risk-adjusted discount rate along with the dynamics of *R* estimated under the physical measure. This allows us to solve the optimal stopping problem using dynamic programming techniques. Although we use a risk-adjusted discount rate (at 6%) similar to those used in the literature (Ince and Moiseyev, 2002; Insley, 2002; De La Torre Ugarte et al., 2003; Insley and Rollins, 2005), we have verified that our findings are not sensitive to the choice of the discount rate being used..

[13] Since the land eligible for CRP participation generally has lower productivity, the initial farming return for CRP land is the general cropland return multiplied by a coefficient of 0.68, which is the average ratio of the rental payment of CRP land to the cash rent of the general cropland, assuming proportional downward adjustment.

[14] The impacts of biofuel policy on commodity prices are summarized in Zilberman et al. (2012).

[15] The initial farming return of $74 is calculated using the realized farming return in 2005 and an annual growth of 6%, adjusted for the lower productivity of CRP lands.

[16] The Delta States, Mountain, Pacific, and Southern Plains regions are excluded because of data availability problems.

[17] State-level farming return data are not directly available. We examine the dominant, cash rent component (85-90%) of the national farming return and find it is approximately the same as the average of state level cash rents. In addition, its parameters (β, σ, α) are also close to the average of those of state level cash rents. Therefore, we assume the state level farming returns follow the same pattern as national returns in average values of returns and parameters β, σ, α, and thus normalized the state level cash rents and parameters (β, σ, α) to reflect this pattern and, in so doing, calculate state level farming returns and the parameters of these returns (Table 2).

Appendix A. Derivation of equation 12

Let $d\xi_t = A_t(\theta_t, \xi)dt + B_t(\xi)dW_t$, where the unobservable component θ_t is described by a continuous-time Markov chain with transition matrix $\lambda_{\alpha\beta}(t)$ and state space E with states α and β. Let $\pi_\beta(t) = prob(\theta_t = \beta \big| \Omega_t^\xi)$. According to Liptser and Shiryaev (1977) Theorem 9.1, $\pi_\beta(t)$ satisfies the following equation:

$$d\pi_\beta(t) = \sum_{\gamma \in E} \lambda_{\gamma\beta}(t)\pi_\gamma(t)dt + \pi_\beta(t)\frac{A_t(\beta,\xi) - \overline{A}_t(\xi)}{B_t(\xi)}d\overline{W}_t, \qquad \text{(A.1)}$$

where $\overline{A}_t(\xi) = \sum_{\gamma \in E} A_t(\gamma, \xi)\pi_\gamma(t)$ and $d\overline{W}_t = \frac{1}{B_t(\xi)}d\xi_t - \frac{\overline{A}_t(\xi)}{B_t(\xi)}dt$.

In our setup, $dR_t = \theta_t R_t dt + \sigma R_t dW_t$, and $p_t = prob(\theta_t = \beta \big| \Omega_t^R)$, which means that $A_t(\theta_t, \xi) = \theta_t R_t$, $B_t(\xi) = \sigma R_t$, and $\overline{A}_t(\xi) = p_t \beta R_t + (1 - p_t)\alpha R_t$. From our Markov system, we can derive that $\lambda_{\alpha\beta} = \lambda_\alpha$ and $\lambda_{\beta\beta} = -\lambda_\beta$ under state space $E = \{\alpha, \beta\}$. An application of Theorem 9.1 yields:

$$dp_t = [\lambda_\alpha(1 - p_t) - \lambda_\beta p_t]dt + \frac{p_t(1-p_t)(\beta - \alpha)}{\sigma}d\overline{W}_t, \qquad \text{(A.2)}$$

where $d\overline{W}_t = dW_t + \frac{1}{\sigma}(\theta_t - m_t)dt$.

Plugging $p_t = \frac{m_t - \alpha}{\beta - \alpha}$ into the above equation yields:

$$dm_t = [\lambda_\alpha(\beta - m_t) - \lambda_\beta(m_t - \alpha)]dt + \frac{1}{\sigma}(\alpha - m_t)(m_t - \beta)d\overline{W}_t. \qquad \text{(A.3)}$$

Appendix B. Derivation of Equation 14

The derivation is through Ito's Lemma. We know that $dR_t = m_t R_t dt + \sigma R_t d\overline{W}_t$ and $dm_t = \left[\lambda_\alpha(\beta - m_t) - \lambda_\beta(m_t - \alpha)\right]dt + \frac{1}{\sigma}(\alpha - m_t)(m_t - \beta)d\overline{W}_t$. Taking the square of the first equation obtains:

$$(dR_t)^2 = (R_t m_t dt)^2 + 2R_t^2 m_t \sigma dt d\overline{W}_t + R_t^2 \sigma^2 (d\overline{W}_t)^2 . \tag{B.1}$$

We already know that $(dt)^2$ and cross product $dtd\overline{W}_t$ are equal to zero in the mean square sense, and $(d\overline{W}_t)^2 = dt$, therefore:

$$E(dR_t)^2 = R_t^2 \sigma^2 dt . \tag{B.2}$$

Similarly, we obtain:

$$E(dm_t)^2 = \frac{1}{\sigma^2}(\alpha - m_t)^2 (m_t - \beta)^2 dt , \tag{B.3}$$

$$E(dR_t dm_t) = R_t(\alpha - m_t)(m_t - \beta)dt . \tag{B.4}$$

Applying Ito's Lemma to $J(R_t, m_t)$, we can derive a partial differential equation:

$$dJ(R_t, m_t) = J_R dR_t + J_m dm_t + \frac{1}{2}\left[J_{RR}(dR_t)^2 + J_{mm}(dm_t)^2 + 2J_{Rm} dR_t dm_t)\right]. \tag{B.5}$$

Substituting B.2, B.3, and B.4 into B.5, we obtain:

$$E[dJ(R_t, m_t)] = \begin{bmatrix} R_t m_t J_R + \left[\lambda_\alpha(\beta - m_t) - \lambda_\beta(m_t - \alpha)\right]J_m + \frac{1}{2}R_t^2\sigma^2 J_{RR} \\ + \frac{1}{2\sigma^2}(\alpha - m_t)^2(m_t - \beta)^2 J_{mm} + R_t(\alpha - m_t)(m_t - \beta)J_{Rm} \end{bmatrix} dt . \tag{B.6}$$

The Bellman equation for eq. 13 is expressed as:

$$\rho J(R_t, m_t)dt = E\left[dJ(R_t, m_t)\right]. \tag{B.7}$$

Therefore,

$$\rho J - \begin{bmatrix} R_t m_t J_R + \left[\lambda_\alpha(\beta - m_t) - \lambda_\beta(m_t - \alpha)\right] J_m + \dfrac{1}{2} R_t^2 \sigma^2 J_{RR} \\ + \dfrac{1}{2\sigma^2}(\alpha - m_t)^2 (m_t - \beta)^2 J_{mm} + R_t(\alpha - m_t)(m_t - \beta) J_{Rm} \end{bmatrix} = 0\,. \tag{B.8}$$

Appendix C. Discretization of the LCP

This Appendix describes the numerical approach used to solve the LCP for valuing the option to participate in the CRP. For a general discussion of numerical methods of option valuation, refer to Wilmott et al. (1993). A finite difference scheme is used in this paper, which involves reducing a continuous partial differential equation to a discrete set of difference equations. Two basic finite difference methods are the implicit method and the explicit method. When applied to the partial differential equation, backward and forward difference approximations for the derivative of option value with respect to time lead to implicit and explicit finite-difference schemes, respectively (Wilmott et al., 1993). The implicit finite-difference method is robust because it can overcome the stability and convergence problems that plague the explicit finite-difference method. In this paper, we use an implicit difference scheme—the Crank-Nicolson scheme.

To explain the three-dimensional (R,m,t) discretization for eq. 15, consider a three-dimensional space formed by the farming return R, the growth rate m, and time t. We divide the R-axis into equally-spaced nodes a distance ΔR apart, the m-axis into equally-spaced nodes a distance Δm apart, and the t-axis into equally spaced nodes a distance Δt apart. This divides the (R,m,t) space into a grid, where grid points have the form $(s\Delta R, n\Delta m, i\Delta t)$. We then compute the option value J at these points:

$$R = \{R_0, R_1, R_2, \cdots, R_S\},\ m = \{m_0, m_1, m_2, \cdots, m_N\}, t = \{t_0, t_1, t_2, \cdots, t_I\}. \qquad \text{(C.1)}$$

The finite difference method involves replacing partial derivatives by approximations based on Taylor expansions near the point of interest. At any point on the grid $(R,m,t) = (R_s, m_n, t_i)$, the value of the option is denoted as $J_{s,n,i}$. A formula for approximating the partial derivatives using the implicit difference method can be found in Wilmott et al. (1993). Replacing these derivatives in eq. 15 yields a series of difference equations:

$$HJ_i = \begin{bmatrix} a_{s-1,n-1}J_{s-1,n-1} + a_{s-1,n}J_{s-1,n} + a_{s-1,n+1}J_{s-1,n+1} + a_{s,n-1}J_{s,n-1} + a_{s,n}J_{s,n} \\ + a_{s,n+1}J_{s,n+1} + a_{s+1,n-1}J_{s+1,n-1} + a_{s+1,n}J_{s+1,n} + a_{s+1,n+1}J_{s+1,n+1} \end{bmatrix}^i, \text{(C.2)}$$

Where $a_{s-1,n-1} = -\frac{R_{s-1}(\alpha - m_{n-1})(m_{n-1} - \beta)}{4\Delta R \Delta m}$, $a_{s-1,n} = \frac{R_{s-1}m_n}{2\Delta R} - \frac{R_{s-1}^2\sigma^2}{2\Delta R^2}$,

$$a_{s-1,n+1} = \frac{R_{s-1}(\alpha - m_{n+1})(m_{n+1} - \beta)}{4\Delta R \Delta m},$$

$$a_{s,n-1} = -\frac{(\alpha - m_{n-1})^2(m_{n-1} - \beta)^2}{2\sigma^2 \Delta m^2} - \frac{\lambda_\alpha(m_{n-1} - \beta) + \lambda_\beta(m_{n-1} - \alpha)}{2\Delta m},$$

$$a_{s,n} = \frac{(\alpha - m_n)^2(m_n - \beta)^2}{2\sigma^2 \Delta m^2} + \rho + \frac{R_s^2\sigma^2}{2\Delta R^2},$$

$$a_{s,n+1} = -\frac{(\alpha - m_{n+1})^2(m_{n+1} - \beta)^2}{2\sigma^2 \Delta m^2} + \frac{\lambda_\alpha(m_{n+1} - \beta) + \lambda_\beta(m_{n+1} - \alpha)}{2\Delta m},$$

$$a_{s+1,n-1} = \frac{R_{s+1}(\alpha - m_{n-1})(m_{n-1} - \beta)}{4\Delta R \Delta m},$$

$$a_{s+1,n} = -\frac{R_{s+1}m_n}{2\Delta R} - \frac{R_{s+1}^2\sigma^2}{2\Delta R^2}, \text{ and } a_{s+1,n+1} = -\frac{R_{s+1}(\alpha - m_{n+1})(m_{n+1} - \beta)}{4\Delta R \Delta m}.$$

The superscript i on the right-hand side means that all variables within the square brackets are evaluated at t_i.

The difference equation must also be specified when the growth rate is at its maximum and minimum values. We use BC2 boundary condition on $m_{\min} = \beta$ and $m_{\max} = \alpha$ (Tavella and Randall, 2000). The one-sided difference for J_{mm} (the second derivative of J with respect to m) and the forward-backward difference for J_{Rm} (the cross derivative of J with respect to R and m) are used at $m_{\max} = \alpha$:

$$J_{mm} = \left[\frac{J_{s,n} - 2J_{s,n-1} + J_{s,n-2}}{\Delta m^2}\right]^i, \; J_{Rm} = \left[\frac{J_{s,n} - J_{s-1,n} - J_{s,n-1} + J_{s-1,n-1}}{\Delta m \Delta R}\right]^i. \tag{C.3}$$

Then, in eq. 15,

$$HJ_i = \begin{bmatrix} a_{s-1,n-1}J_{s-1,n-1} + a_{s-1,n}J_{s-1,n} + a_{s,n-2}J_{s,n-2} \\ + a_{s,n-1}J_{s,n-1} + a_{s,n}J_{s,n} + a_{s+1,n}J_{s+1,n} \end{bmatrix}^i, \tag{C.4}$$

where $a_{s-1,n-1} = -\dfrac{R_{s-1}(\alpha - m_{n-1})(m_{n-1} - \beta)}{\Delta R \Delta m}$,

$$a_{s-1,n} = \frac{R_{s-1}(\alpha - m_n)(m_n - \beta)}{\Delta R \Delta m} + \frac{R_{s-1}m_n}{2\Delta R} - \frac{R_{s-1}^2\sigma^2}{2\Delta R^2},$$

$$a_{s,n-2} = -\frac{(\alpha - m_{n-2})^2(m_{n-2} - \beta)^2}{2\sigma^2\Delta m^2} - \frac{\lambda_\alpha(m_{n-2} - \beta) + \lambda_\beta(m_{n-2} - \alpha)}{2\Delta m},$$

$$a_{s,n-1} = \frac{(\alpha - m_{n-1})^2(m_{n-1} - \beta)^2}{\sigma^2\Delta m^2} + \frac{R_s(\alpha - m_{n-1})(m_{n-1} - \beta)}{\Delta R \Delta m},$$

$$a_{s,n} = -\frac{(\alpha - m_n)^2(m_n - \beta)^2}{2\sigma^2\Delta m^2} + \rho + \frac{R_s^2\sigma^2}{\Delta R^2} + \frac{\lambda_\alpha(m_n - \beta) + \lambda_\beta(m_n - \alpha)}{2\Delta m} - \frac{R_s(\alpha - m_n)(m_n - \beta)}{\Delta R \Delta m},$$

and $a_{s+1,n} = -\dfrac{R_{s+1}m_n}{2\Delta R} - \dfrac{R_{s+1}^2\sigma^2}{2\Delta R^2}$.

Similarly, the one-sided difference for J_{mm} and the forward-backward difference for J_{Rm} are used at $m_{\min} = \beta$:

$$J_{mm} = \left[\frac{J_{s,n+2} - 2J_{s,n+1} + J_{s,n}}{\Delta m^2}\right]^i, \; J_{Rm} = \left[\frac{J_{s,n+1} - J_{s,n} - J_{s-1,n+1} + J_{s-1,n}}{\Delta m \Delta R}\right]^i. \tag{C.5}$$

Then, in eq. 15,

$$HJ_i = \begin{bmatrix} a_{s-1,n} J_{s-1,n} + a_{s-1,n+1} J_{s-1,n+1} + a_{s,n} J_{s,n} \\ + a_{s,n+1} J_{s,n+1} + a_{s,n+2} J_{s,n+2} + a_{s+1,n} J_{s+1,n} \end{bmatrix}^i, \tag{C.6}$$

where $a_{s-1,n} = -\dfrac{R_{s-1}(\alpha - m_n)(m_n - \beta)}{\Delta R \Delta m} + \dfrac{R_{s-1} m_n}{2\Delta R} - \dfrac{R_{s-1}^2 \sigma^2}{2\Delta R^2}$,

$$a_{s-1,n+1} = \frac{R_{s-1}(\alpha - m_{n+1})(m_{n+1} - \beta)}{\Delta R \Delta m},$$

$$a_{s,n} = -\frac{(\alpha - m_n)^2 (m_n - \beta)^2}{2\sigma^2 \Delta m^2} + \rho + \frac{R_s^2 \sigma^2}{\Delta R^2} + \frac{\lambda_\alpha (m_n - \beta) + \lambda_\beta (m_n - \alpha)}{2\Delta m} + \frac{R_s(\alpha - m_n)(m_n - \beta)}{\Delta R \Delta m},$$

$$a_{s,n+1} = \frac{(\alpha - m_{n+1})^2 (m_{n+1} - \beta)^2}{\sigma^2 \Delta m^2} - \frac{R_s(\alpha - m_{n+1})(m_{n+1} - \beta)}{\Delta R \Delta m},$$

$a_{s,n+2} = -\dfrac{(\alpha - m_{n+2})^2 (m_{n+2} - \beta)^2}{2\sigma^2 \Delta m^2}$, and $a_{s+1,n} = -\dfrac{R_{s+1} m_n}{2\Delta R} - \dfrac{R_{s+1}^2 \sigma^2}{2\Delta R^2}$.

Equations C.2, C.4 and C.6 form a system of equations, which can be written in matrix form and solved by iteration (Insley, 2002).

The accuracy of a numerical scheme depends critically on the grid size for each dimension. To check whether the solution has an acceptable degree of accuracy, we refine the grid further to see how much the solution changes. We examined the change of the option value when we double the total number of nodes. The results show that the solution at R =33 and m =0.067 changes only by 0.15%.

Appendix D. Derivation of equation 20

The simple optimal stopping problem without parameter uncertainty is:

$$\begin{cases} J(R_t, m, \infty) = \max_T E_t[e^{-\rho(T-t)} M(R_T, Q)] \\ dR_t = R_t m dt + R_t \sigma d\overline{W}_t \end{cases} . \tag{D.1}$$

Using Ito's lemma, the fundamental differential equation of this optimal stopping problem is an ordinary differential equation:

$$\frac{1}{2} R_t^2 \sigma^2 J_{RR} + R_t m J_R - \rho J = 0 , \tag{D.2}$$

where J_R and J_{RR} are the first and second derivatives of J with respect to R_t .

Let R^* represent the threshold value, which triggers participation in the CRP. This ordinary differential equation is solved subject to the following boundary conditions. First, the continuity condition is:

$$J(R^*) = M(R^*, Q) = V(Q) - \frac{R^*(1 - e^{-(\rho - m)\overline{T}})}{\rho - m} . \tag{D.3}$$

Second, the smooth pasting condition is:

$$J_R(R^*) = M_R(R^*, Q) = -\frac{(1 - e^{-(\rho - m)\overline{T}})}{\rho - m} . \tag{D.4}$$

In addition, we have:

$$J(\infty, m, \infty) = 0 , \tag{D.5}$$

which says that when the farming return approaches infinity, the land conversion option is worthless. The general form of the solution to equations is

$$J(R_t, m, \infty) = \begin{cases} M(R^*, Q)\left(\dfrac{R_t}{R^*}\right)^{\gamma} & R_t \geq R^* \\ M(R_t, Q) & R_t \leq R^* \end{cases}, \tag{D.6}$$

where $\gamma = \dfrac{-(m - \frac{1}{2}\sigma^2) - \sqrt{(m - \frac{1}{2}\sigma^2)^2 + 2\rho\sigma^2}}{\sigma^2}$, which is the negative root of the fundamental quadratic equation $\frac{1}{2}\sigma^2\gamma(\gamma - 1) + m\gamma - \rho = 0$, and the threshold $R^* = \dfrac{\gamma}{\gamma - 1} \cdot \dfrac{(\rho - m) \cdot V(Q)}{(1 - e^{-(\rho - m)\bar{T}})}$.

References

Abasov, T.M., 2005. Dynamic learning effect in corporate finance and risk management. PhD dissertation, University of California, Irvine.

Boehlje, M.D., Gloy, B.A., Henderson, J.R., 2012. U.S. farm prosperity: the new normal or reversion to the mean. American Journal of Agricultural Economics, 1-8; doi: 10.1093/ajae/aas051.

Brennan, M.J., 1998. The role of learning in dynamic portfolio decisions. European Finance Review 1, 295–306.

Capozza, D., Li, Y., 1994. The intensity and timing of investment: the case of land. American Economic Review 84, 889-904.

Carey, M.J., Zilberman, D., 2002. A model of investment under uncertainty, modern irrigation technologies and emerging markets in water. American Journal of Agricultural Economics 84, 171-183.

Change, H., Boisvert, R.N., 2009. Distinguishing between whole-farm vs. partial-farm participation in the Conservation Reserve Program. Land Economics 85, 144–161.

Collins, K., 2008. The role of biofuels and other factors in increasing farm and food prices, a review of recent developments with a focus on feed grain markets and market prospects. http://www.staff.ncl.ac.uk/david.harvey/ACE2006/Principles/CollinsFoodPriceJune2008.pdf.

Creamer, S.F., 2010. Econometric analysis of family forest owners' forest certification program participation behavior and optimal harvesting decision under uncertainty. PhD dissertation, Washington State University.

De La Torre Ugarte, D.G., Walsh, M.E., Shapouri, H., Slinsky, S.P., 2003. The economic impacts of bioenergy crop production on U.S. agriculture. Washington DC, U. S. Department of Agriculture, Agricultural Economic Report No. 816, February.

Dixit, A.R., Pindyck, R. S., 1994. Investment under Uncertainty. Princeton University Press, Princeton.

Elobeid, A., Tokgoz, S., 2008. Removing distortions in the US ethanol market, what does it imply for the United States and Brazil? American Journal of Agricultural Economics 90, 918-932.

Elobeid, A., Tokgoz, S., Hayes, D.J., Babcock, B.A., Hart, C.E., 2007. The long-run impact of corn-based ethanol on the grain, oilseed, and livestock sectors with implications for biotech crops. AgBioForum 10, 11-18.

Frank, J., Garcia, P., 2010. How strong are the linkages among agricultural, oil, and exchange rate markets? Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO.

Gennotte, G., 1986. Optimal portfolio choice under incomplete information. The Journal of Finance 3, 733-746.

Ince, P.J., Moiseyev, A.N., 2002. Forestry implications of agricultural short-rotation woody crops in the USA, in: Teeter, L., Cashore, B., Zhang, D. (Eds.), Forest Policy for Private Forestry, Global and Regional Challenges, CABI Publishing, New York, pp. 177-188.

Insley, M., 2002. A real options approach to the valuation of a forestry investment. Journal of Environmental Economics and Management 44, 471-492.

Insley, M., Rollins, K., 2005. On solving the multirotational timber harvesting problem with stochastic prices, a linear complementarity formulation. American Journal of Agricultural Economics 87, 735-755.

Isik, M., Yang, W., 2004. An analysis of the effects of uncertainty and irreversibility on farmer participation in the Conservation Reserve Program. Journal of Agricultural and Resource Economics 29, 242-259.

Liggett, T.M., 2010. Continuous Time Markov Processes: An Introduction. American Mathematical Society, Rhode Island.

Lipsky, J., 2008. Commodity prices and global inflation. http://www.imf.org/external/np/speeches/2008/050808.htm.

Liptser R.S., Shiryaev, A.N., 1977. Statistics of Random Processes: General Theory. Springer-Verlag, New York.

Lubowski, R.N., Plantinga, A.J., Stavins, R.N., 2008. What drives land-use changes in the United States? a national analysis of landowner decisions. Land Economics 84, 529-550.

Kalman, R.E., 1960. A new approach to linear filtering and prediction problems. Journal of Basic Engineering 82, 35–45.

Parks, P.J., Kramer, R.A., 1995. A policy simulation of the Wetlands Reserve Program. Journal of Environmental Economics and Management 28, 223–240.

Piñeiro, G., Jobbágy, E.G., Baker, J., Murray, B.C., Jackson, R.B., 2009. Set-asides can be better climate investment than corn ethanol. Ecological Applications 19, 277-282.

Schatzki, T., 2003. Options, uncertainty and sunk costs, an empirical analysis of land use change. Journal of Environmental Economics and Management 46, 86–105.

Searchinger, T., Heimlich, R., Houghton, R.A., Dong, F., Elobeid, A., Fabiosa, J., Tokgoz, S., Hayes, D., Yu, T., 2008. Use of U.S. croplands for biofuels increases greenhouse gases through emissions from land-use change. Science 319, 1238 – 1240.

Suter, J.F., Poe, G.L., Bills, N.L., 2008. Do landowners respond to land retirement incentives? evidence from the Conservation Reserve Enhancement Program. Land Economics 84, 17–30.

Tavella, D.A., Randall, C., 2000. Pricing Financial Instruments, The Finite Difference Method. Wiley, New York.

Tokgoz, S., Elobeid, A., Fabiosa, J., Hayes, D.J., Babcock, B.A., Yu, T., Dong, F., Hart, C.E., 2008. Bottlenecks, drought, and oil price spikes, impact on U.S. ethanol and agricultural sectors. Review of Agricultural Economics 30, 1-19.

U.S. Department of Agriculture, 2007. Agricultural baseline projections, baseline presentation, 2007-2016. Economic Research Service (ERS), Washington DC, February.

U.S. Department of Agriculture, 2007. Conservation Reserve Program, summary and enrollment statistics FY 2006. Farm Service Agency (FSA), Washington DC, May.

U.S. Department of Agriculture, 2009. Ethanol and a changing Agricultural landscape. Economic Research Service (ERS), Washington DC, November.

U.S. Department of Agriculture, 2010. Conservation Reserve Program, monthly summary – August 2010. Farm Service Agency (FSA), Washington DC, September.

Wilmott, P., Howison, S., Dewynne, J., 1993. Option Pricing, Mathematical Models and Computation. Oxford Financial Press, Oxford.

Wu, J., 2000. Slippage effects of the Conservation Reserve Program. American Journal of Agricultural Economics 82, 979-992.

Wu, J., Zilberman, D., Babcock, B.A., 2001. Environmental and distributional impacts of conservation targeting strategies. Journal of Environmental Economics and Management 41, 333-350.

Wu, J., Lin, H., 2010. The effect of the Conservation Reserve Program on land values. Land Economics 86, 1–21.

Xia, Y., 2001. Learning about predictability, the effects of parameter uncertainty on dynamic asset allocation. Journal of Finance 56, 205-246.

Young, C.E., Osborn, C.T., 1990. The Conservation Reserve Program, an economic assessment. Washington DC, U.S. Department of Agriculture, Agricultural Economic Report No. 626, February.

Zilberman, D., Hochman, G., Rajagopal, D., Sexton, S., Timilsina, G., 2012. The impact of biofuels on commodity food prices: assessment of findings. American Journal of Agricultural Economics 95, 275-281.

Figure 1
Option Value of Land Conversion Opportunity under Two Different Expected Growth Rates (the Baseline Case)

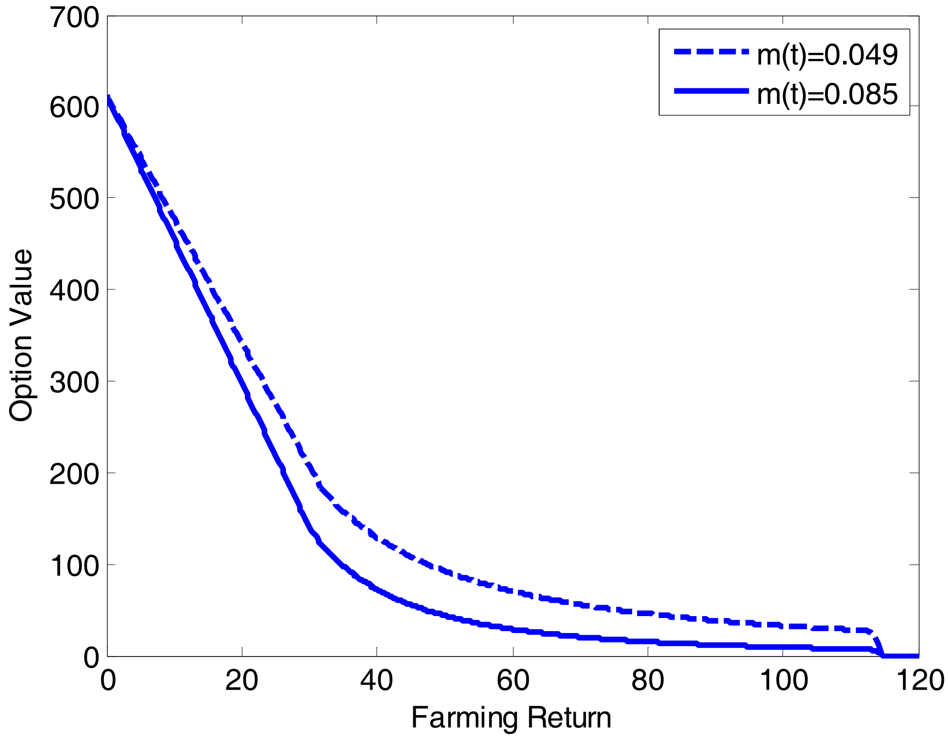


Figure 2

Farming Threshold Returns (R^*) versus Growth Rate Expectations (m_t) under Different Durations of the High Growth State

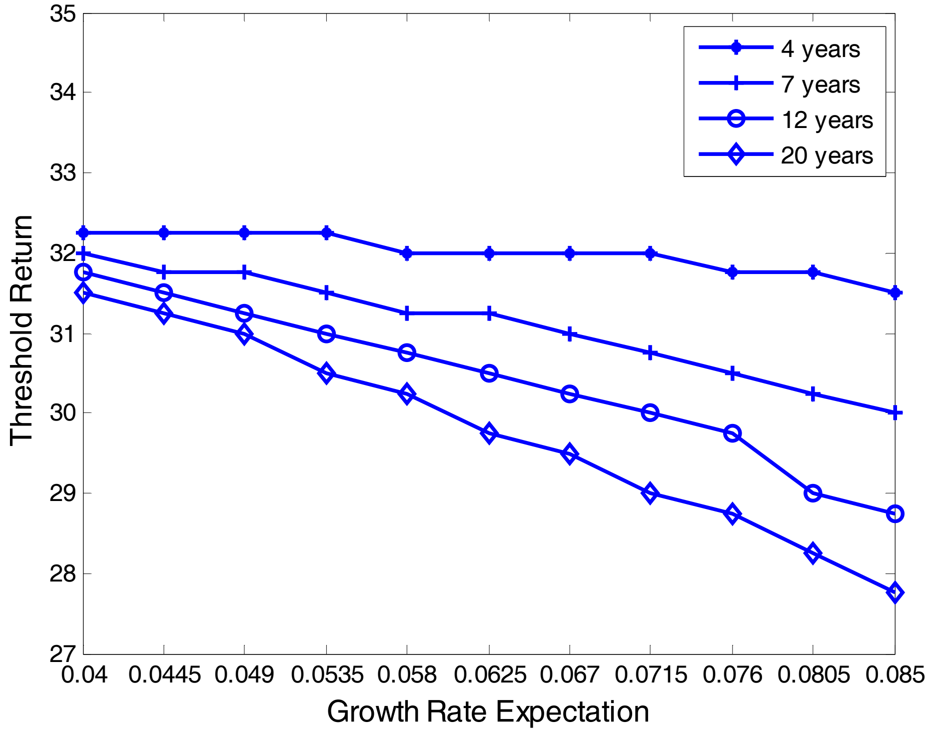


Figure 3

Farming Threshold Returns (R^*) versus Growth Rate Expectations (m_t) under Different Volatility Parameters

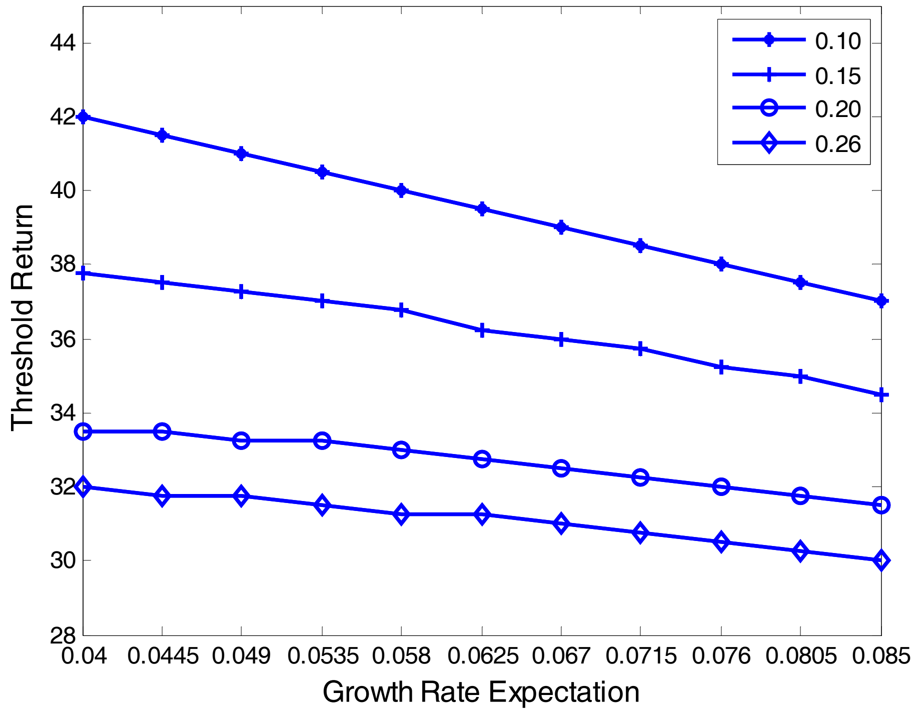
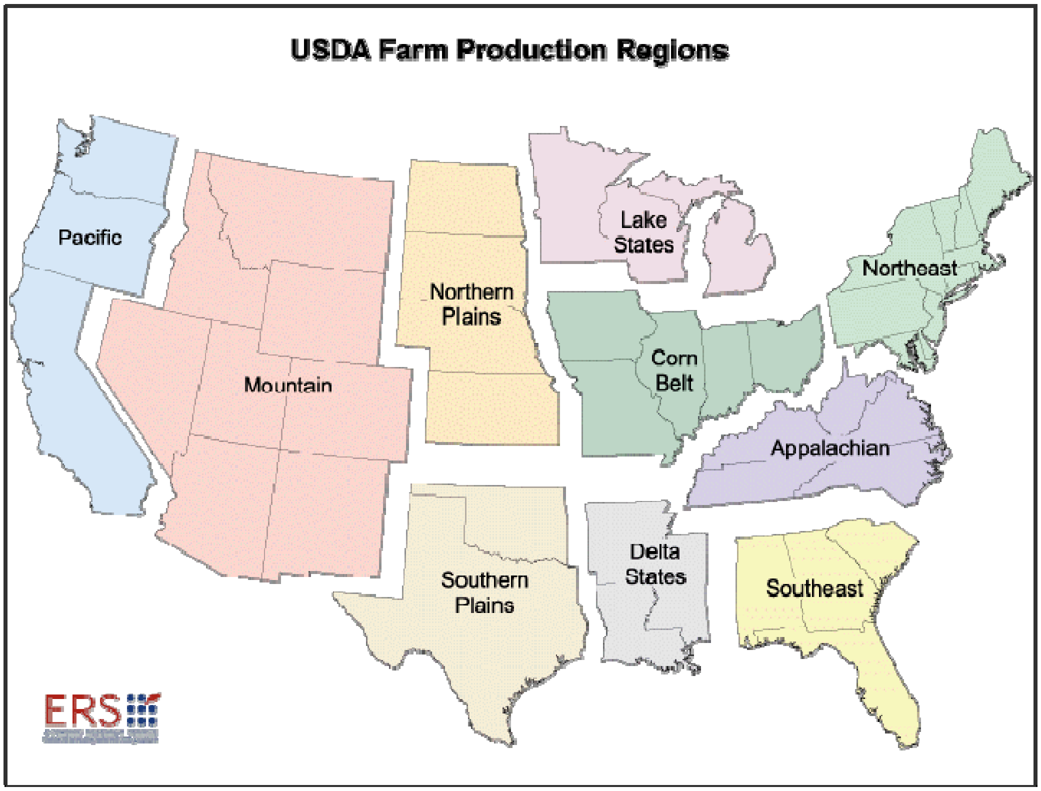


Figure 4
Farm Production Regions in the United States



Source: USDA-ERS

Table 1
Option Value of Participation in the CRP for the Baseline

R_t / m_t	*0.04*	*0.0445*	*0.049*	*0.0535*	*0.058*	*0.0625*	*0.067*	*0.0715*	*0.076*	*0.0805*	*0.085*
0.00	612.9	612.9	612.9	612.9	612.9	612.9	612.9	612.9	612.9	612.9	612.9
0.25	609.6	609.5	609.4	609.4	609.3	609.3	609.2	609.1	609.1	609.0	608.9
0.50	606.2	606.1	606.0	605.9	605.8	605.6	605.5	605.4	605.3	605.1	605.0
0.75	602.9	602.7	602.6	602.4	602.2	602.0	601.8	601.6	601.4	601.3	601.1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
29.50	220.4	213.6	206.8	199.8	192.7	185.5	178.2	170.7	163.2	155.5	147.7
29.75	217.1	210.2	203.3	196.3	189.1	181.9	174.5	167.0	159.4	151.6	143.8
30.00	213.7	206.9	199.9	192.8	185.6	178.3	170.8	163.3	155.6	147.8	**139.8**
30.25	210.4	203.5	196.4	189.3	182.0	174.6	167.1	159.5	151.8	**143.9**	136.6
30.50	207.1	200.1	193.0	185.8	178.5	171.0	163.4	155.8	**147.9**	140.7	134.1
30.75	203.8	196.7	189.6	182.3	174.9	167.4	159.8	**152.0**	144.9	138.3	131.6
31.00	200.4	193.3	186.1	178.8	171.3	163.8	**156.1**	149.1	142.5	135.8	129.2
31.25	197.1	189.9	182.7	175.3	**167.8**	**160.2**	153.4	146.8	140.1	133.5	126.9
31.50	193.8	186.6	179.2	**171.8**	164.5	157.8	151.1	144.5	137.8	131.2	124.6
31.75	190.4	**183.2**	**175.8**	169.0	162.3	155.6	148.9	142.2	135.6	128.9	122.4
32.00	**187.1**	180.2	173.5	166.8	160.1	153.4	146.7	140.0	133.4	126.8	120.2
32.25	185.1	178.1	171.4	164.7	157.9	151.2	144.5	137.8	131.2	124.6	118.1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Note: threshold returns under different growth rate expectations can be easily detected from highlighted cells.

Table 2
Participation Probabilities across States

Regions	R	β	σ	α	Q	Prob.
Appalachian						
Kentucky	99	0.0421	0.3314	0.1257	71	7.66%
North Carolina	65	0.0401	0.3324	0.0589	45	11.18%
Tennessee	77	0.0382	0.2731	0.0642	59	9.57%
Corn Belt						
Illinois	173	0.0418	0.2231	0.1053	82	0.27%
Indiana	147	0.0327	0.2200	0.0998	80	0.68%
Iowa	186	0.0375	0.2286	0.1251	99	0.56%
Missouri	95	0.0450	0.2819	0.0554	67	5.92%
Ohio	107	0.0386	0.2346	0.0830	76	2.90%
Lake States						
Michigan	86	0.0452	0.2459	0.1183	62	2.11%
Minnesota	120	0.0457	0.2284	0.1176	54	0.17%
Wisconsin	92	0.0431	0.2142	0.1058	69	1.20%
Northeast						
Delaware	74	0.0466	0.2622	0.0740	70	10.95%
Pennsylvania	58	0.0429	0.2425	0.1038	46	2.92%
Northern Plains						
Kansas	46	0.0250	0.1724	0.0660	39	2.18%
Nebraska	103	0.0584	0.2771	0.1284	52	0.94%
North Dakota	48	0.0384	0.2130	0.0830	33	1.00%
South Dakota	76	0.0608	0.2788	0.1304	39	0.88%
Southeast						
Alabama	51	0.0383	0.3180	0.0553	45	15.14%
Georgia	52	0.0222	0.2648	0.0682	41	10.17%
South Carolina	36	0.0289	0.2400	0.0541	32	7.73%