Optimal Sequential Plantings of Corn and Soybeans Under Price Uncertainty

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Optimal crop choice and fertilizer applications depend on the stochastic dynamics of commodity prices, fertilizer prices, and the agronomic effects of rotation versus monoculture. The efficient decision rule accounts for real option values associated with maintaining land disposition in an environment with highly uncertain future prices and irreversible past planting decisions. We parameterize a baseline model for a representative acre in Iowa and compare the model's predictions and profits to relatively naive, shorter horizon decision rules, and a field managed with optimal fertilizer applications conditional on corn and soybeans always being rotated. We also examine the effects of a permanently larger premium on corn prices relative to soybean prices, which has been observed in locations near recently established ethanol plants. We then compare the various decision rules to actual crop choices in a panel of over 6,500 Iowa plots during 1979–2007. As compared to less forward-looking objectives, we find the agronomic benefits of rotations coupled with real option values can lead to a more inelastic response of planting decisions to both transitory and permanent price changes. Always rotating, regardless of prices, is close to optimal, but so are shorter-horizon objectives. One implication is that reduced corn monoculture and fertilizer application rates might be implemented with modest incentive payments of $4 per acre or less.

Key words: Crop rotations, dynamic programming, option value, supply response, uncertainty.

JEL codes: Q11, Q12.

Corn and soybeans, the two largest crops in the United States and among the most important food staples in the world, are typically grown in rotation. That is, on any given parcel, a farmer will typically grow soybeans in one year and corn the next. For example, based on the US Department of Agriculture's Agricultural Resource Management Survey Phase II survey data, an estimated 63 percent of acres planted to corn in Iowa in 2005 were planted with soybeans the year before. This rotation practice is predominant in the highly productive Corn Belt region and some, but not all, other regions of the United States. The main incentive to rotate crops comes from higher yields and lower input costs enjoyed by farmers who rotate in comparison to farmers with similar land that grow the same crop every year. Yields of rotated crops are higher because rotations reduce pest problems and enrich soils. Soybeans, for example, fix nitrogen that is used by the subsequent corn crop, thereby reducing fertilizer costs for corn (Mallarino, Ortiz-Torres, and Pecinovsky 2004; Hennessy 2006). Farm-level rotational decisions are thus fundamental to crop supply and input use, and factor greatly into the amount of nutrient runoff and water quality problems that affect the nation and the world. It is therefore critical for policy considerations to understand the economic tradeoffs that underlie these decisions.

Due to the productivity gains of rotation, it may only be optimal to plant the same crop two years in a row if a crop's relative price is high enough to offset lost productivity. If a farmer believes a crop's relatively high price

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could possibly increase further in subsequent years, it may still be optimal to rotate even if the price premium exceeds the immediate costs of monoculture. This additional benefit of rotation (or cost of not rotating) comprises an option value (Dixit and Pindyck 1994) that to our knowledge has not been previously considered. The option value accounts for the ongoing value of maintaining maximal productive efficiency, a value that pays off when unusual high-price opportunities arise. A myopic rule that does not account for the value of exercising the option of planting corn after corn instead of planting soybeans after corn, for example, would call for planting corn after corn too often. Generalizing this idea, the optimal decision rule ultimately depends on the relative prices of corn and soybeans in the current year, and the whole distribution of anticipated prices for corn and soybeans in futures years, in addition to the agronomic tradeoffs embodied in past planting decisions.

While the basic agronomic benefits of rotations are well known and fairly well understood, the phenomenon presents a challenging stochastic dynamic economic problem surrounding optimal planting decisions in an environment when commodity and fertilizer prices are uncertain and highly autocorrelated over time. In this article, we solve this problem and demonstrate some implications for the supply of these prevalent commodities. As intuited above, in comparison to the solution to the static problem, the forward looking, dynamic optimum is much less likely to deviate from rotating corn after soybeans and vice versa, in response to price movements. Somewhat counterintuitively, a farmer applying a simple rule of always rotating, regardless of price, often performs better over the longer run than a farmer optimizing over a shorter time horizon. Stochastic-dynamic considerations may therefore help to explain an inelastic supply response of agricultural commodities or, more generally, farm management practices that nearly mimic agronomic maximization, at least with respect to crop choice.

Burt and Allison (1963) were first to consider crop rotations in a stochastic and dynamic programming (SDP) framework. Their article, among the first applications of SDP, considered the decision to leave a field fallow or to plant wheat in an environment where soil moisture evolved according to a Markov process. In subsequent work, Burt and other scholars have considered specialized crop management decisions in contexts with random state variables pertaining to pest problems, irrigation water, and other agronomic factors (Burt and Stauber 1971; Dudley and Burt 1973; Yakowitz 1982; Pandey and Medd 1991). Many have used SDP for modeling commodity storage problems and for agricultural, biological, and ecological modeling (Kennedy 1986; Williams and Wright 1991; Deaton and Laroque 1992). But the literature has generally been slow and reluctant to use SDP to model planting decisions more broadly, especially as a positive model to describe farmer behavior. To our knowledge, this article is first to explicitly consider the consequences of price uncertainty on sequential crop planting decisions using an SDP framework.

Crop rotations have been incorporated into some linear programming models (El-Nazer and McCarl 1986; Musser et al. 1985; Johansson, Peters, and House 2007), but these models do not account for the sequential nature of planting decisions, or for option values related to price uncertainty. That is, these models take multiyear rotation rules as a single decision, with future prices assumed known in advance, as if the problem were static, nonsequential, and nonstochastic. There are, of course, great computational advantages to these alternative approaches. In some earlier models of aggregate supply, current supply is sometimes conditioned on past aggregate plantings, which may proxy for rotational effects, but there is no explicit account of parcel-specific choices (Eckstein 1984; Burt and Worthington 1988). Recent work by (Song, Zhao, and Swinton 2011) considers option values connected to changing land use from crop production to perennial energy crops. This work, like ours, is partly motivated by recent biofuel policies.

Given the importance of crop rotations has long been widely acknowledged, it is natural to ask why there has been so little modeling of rotational decisions using an SDP framework. The most obvious answer is that SDP modeling with more than one or two continuous state variables can be computationally expensive. But time and rapidly advancing computer technology have lowered the computational expense of larger scale SDP problems. Also, methods in computational economics have matured, with several contributors making their computer code publicly available, further lowering the costs of implementing SDP models. While computational limits still constrain the complexity of these models, with a few simplifying assumptions, we are able to develop a model that captures the most salient aspects of the corn versus soybeans planting decisions that govern a significant share of highly productive cropland in the midwestern United States.

In the next section we describe the parameterization of the model. We then report econometric estimates of the key parameters, followed by a description of the algorithm used to solve the SDP. We then compare profits and crop choices of the optimal infinite-horizon policy to policies derived from assuming maximization over 1- and 2-year horizons rather than the infinite horizon SDP, as well as a policy that optimizes input use conditional on an "always rotate" rule of thumb. To explore the potential effects of recent ethanol expansion on planting decisions, we consider the effect of premium corn prices that have been documented for fields located near ethanol plants. Finally, we compare predictions from the infinite horizon model and alternative objectives to actual crop choices observed on parcels sampled by the National Resources Inventory.

A Stochastic Dynamic Model of Crop Choice

Consider planting decisions for a standardized unit of land. At a sufficiently small scale, crop choice is discrete, even though when aggregated across all units for a given farm, county, or state, the decision will approximate a continuous decision. To focus squarely on the issue of rotational dynamics, we assume no time or capital allocation constraints, spatial interaction effects, or farm-level capital or liquidity constraints that would force us to model planting decisions at the farm level. Instead, each unit of land is regarded as an independent "profit center," and by maximizing profit from harvesting crops on each unit of land, each farm maximizes its value as a whole.

There is some arbitrariness about how big or small an individual unit of land may be. It should usually be treated as a contiguous parcel of land that is typically growing only one crop per season. We might think of this as a "field" where, for agronomic reasons, it would not make sense for a farmer to plant different crops on the same field. If this is not the case, then the "field" should be conceptually subdivided into smaller parcels for which the farmer almost always plants only one crop or the other. For this analysis, we will abstract away from the size of the unit even though in a more general model unit size may be chosen simultaneously with crop choice. As such, we also abstract away from portfolio considerations that have been a traditional focus of planting decisions under uncertainty. The data to which we compare our model's predictions refer to specific points where the discrete crop choice is indicated. We report values and output on a per-acre basis.

Our yield data on crop rotations and input use, which we use to calibrate the model, are from an experiment station in northeast Iowa. As such, the model we develop is most relevant to that region of the country and nearby regions with similar soils and climate. Iowa, being the largest corn and soybean producer in the United States, and likely the highest concentration of corn and soybean production in the world, is a salient focus.

The main features we want the model to be capable of predicting are (1) the pattern of planting, (2) the relative frequency of corn versus soybean plantings, and (3) the sensitivity of optimal planting decisions to exogenous changes in commodity or input prices. There are two ways in which we examine the question of price sensitivity. First, prices change over time in a stochastic fashion. Second, evidence in previous research shows that corn prices are higher near recently established ethanol plants. A key focus will be on how decision rules differ depending on the planning horizon of the farmer, and which best predicts actual planting decisions.

A key simplifying assumption is to model crop revenues per acre, price multiplied by yield, rather than keeping prices and yields separate. This simplification accounts for price-yield correlations stemming from spatially-correlated weather and pest outcomes. Historical revenue-per-acre data also appear strongly stationary, despite a significantly increasing trend in yields and decreasing trend in real prices. Stationarity is necessary for describing the stochastic autoregressive processes for our state variables that we discuss below. This one simplification therefore solves both the problem of price-yield covariance and the problem of nonstationarity.

In general, a long history of crop choices and soil management choices may influence current expectations for yield and revenue. Incorporating a long crop history for a large number of possible crops would greatly increase the state space and render a solution computationally infeasible. Thus, to simplify the problem, we consider economically efficient choice among just two crops, corn or soybeans, together with the optimal continuous application of nitrogen fertilizer, where we denote crop choice, i_t, and nitrogen fertilizer use, n_t, for a field of arable land, on which either soybean, $i_t = 0$, or corn, $i_t = 1$, may be produced. Although just two crop choices limits the scope of the model, these two particular crops are exclusively planted, or nearly so, on a large share of the nation's most productive cropland.

We consider models in which up to 3 years of crop history may affect current revenues. Crop choices more than 3 years past are not economically or statistically significant in regression analysis of yields from experimental field plots (we show this below). To account for this history, we denote a crop-specific adjustment factor $a^i(\mathbf{I}_t, n_t)$, where $\mathbf{I}_t$ denotes crop history at planting time in year t. This function gives a proportional adjustment to expected revenues for each crop i that depends on past plantings and nitrogen fertilizer application in the current year (n_t).

Field-level expected revenues are also tied to the stochastic evolution of prices and to the broader covariance between prices and yield. To account for both autocorrelation of prices and current-period covariances between prices and yields, we model current expected revenues for any given field as being tied to expectations about *state-level* revenues per acre. State-level revenues, like prices, are observed, publicly available, and exogenous to field-level decisions. State-level revenues per acre equal the average price received in Iowa multiplied by the realized state-level yield. We denote these state-level revenues by r_t^c and r_t^s for corn and soybeans, respectively. State-level revenues per acre, like prices, display strong autocorrelation, so that past revenues strongly influence expectations about current revenues. "Field-level" revenues are given by the crop-specific adjustment factor multiplied by state-level revenues. The idea is that an individual farmer's planting and fertilizer application decisions will affect his or her own revenues by the same proportion that it affects the farmer's yield. In other words, we assume field-level marginal yield effects are too small to affect price or yield at the state level.

$$\text{(1)} \qquad \text{Field Revenues} = r_t^i a^i(\mathbf{I}_t, n_t).$$

The other critical factor affecting profits of corn relative to soybeans is nitrogen fertilizer prices, which are autocorrelated and show strong association with state-level corn and soybean revenues per acre (this is shown in an online appendix). Unlike revenues per acre, however, fertilizer prices, denoted f_t, are observed at the time of the planting decision.

We assume expectations about current and future profits are a function of past state-level revenues per acre for corn, past state-level revenues per acres for soybeans, current fertilizer prices, and planting history. The farmer makes optimal planting and fertilizer decisions while anticipating how current decisions affect both current and future profit opportunities.

To evaluate these expectations, we assume these three state variables follow a 1^{st}-order vector autoregressive process:

$$\text{(2)} \qquad \mathbf{p}_{t+1} = \mathbf{a} + \mathbf{p}_t^T \mathbf{B} + \mathbf{u}_{t+1}$$

where $\mathbf{p_t}$ is a vector composed of lagged corn and soybean state-level revenues per-acre and current-period fertilizer prices:

$$\text{(3)} \qquad \mathbf{p}_t = \begin{bmatrix} \log(r_{t-1}^c) \\ \log(r_{t-1}^s) \\ \log(f_t) \end{bmatrix}$$

$\mathbf{a}$ and $\mathbf{B}$ are a vector and matrix of parameters, and $\mathbf{u}_{t+1}$ is a vector of random innovations with a variance-covariance matrix equal to $\boldsymbol{\Omega}$. We assume multivariate normal random innovations, which approximately fits the data. We use a first-order model because standard model selection criteria (AIC and BIC) strongly preferred a first-order model.[1] No higher-order terms showed statistical significance. This is fortunate because each additional lag in the vector autoregressive process would have added three continuous state variables to the SDP,

[1] These are standard model selection criteria. AIC is the "Akaike information criterion" (Akaike 1974) and BIC is the "Bayesian information criteria" (Schwarz 1978). Both criteria score models based on the likelihood function minus a penalty for the number of parameters, with BIC using a larger penalty than AIC.

which would be prohibitively expensive from a computational standpoint. (We describe the data below.)

To calculate current profits, we simply subtract costs from revenues. The only costs we explicitly consider are nitrogen fertilizer expenditures. While other costs and inputs surely matter for field-level profits, nitrogen fertilizer inputs are the largest single variable expenditure that interacts strongly with the corn-or-soybeans crop choice. For one, nitrogen fertilizer is not typically applied to soybeans but is almost universally applied to corn. Also, there are strong substitution possibilities between fertilizer applications and rotational decisions. For example, corn monoculture requires greater levels of fertilizer to achieve the same yield as compared to corn following soybeans. Other inputs are generally of lesser expense or are typically similar regardless of whether corn or soybeans are planted. These other inputs include phosphorus, potassium, labor, land, and capital utilization. The current profit function is thus given by:

$$\pi(i_t, n_t|\mathbf{I}_t, \mathbf{p}_t]) = r_t^i a^i(\mathbf{I}_t, n_t) - i_t f_t n_t. \tag{4}$$

The producer's objective is to maximize the expected present value of profit (4) over an infinite time horizon (we also consider shorter horizons), subject to the stochastic evolution of state-level revenues and fertilizer prices (2). We can write this infinite horizon problem using the recursive Bellman equation that relates the current value function to the future value function:

$$\begin{aligned} V(\mathbf{I}_t, \mathbf{p}_t) = \max_{i_t n_t} \mathbb{E}[\pi(i_t, n_t|\mathbf{I}_t, \mathbf{p}_t) \\ + \theta V(\mathbf{I}_{t+1}, \mathbf{p}_{t+1})] \end{aligned} \tag{5}$$

where V is the maximum expected present value of the field over an infinite horizon of optimal corn and soybean plantings. It is a function of one discrete and three continuous state variables: the crop history, past unadjusted (state-level) soybean and corn revenues, and current nitrogen fertilizer prices. We assume these variables provide all the information necessary to form expectations about end-of-season profit and the next period's discounted value function, where θ is the discount factor.

To briefly formalize the option values described in the introduction, consider a second-order Taylor expansion around expected prices conditional on past prices. Because current profits are linear in prices, this expansion simplifies to:

$$\begin{aligned} V(\mathbf{I}_t, \mathbf{p}_t) \approx \max_{i_t n_t} \pi(i_t, n_t|\mathbf{I}_t, \mathbb{E}[\mathbf{p}_t]) \\ + \theta V(\mathbf{I}_{t+1}, \mathbb{E}[\mathbf{p}_{t+1}]) \\ + \underbrace{\theta \mathrm{vec}(\mathbf{H_p})^T \mathrm{vec}(\Omega_\mathbf{p})}_{\text{optionvalue}} \end{aligned} \tag{6}$$

where $\mathbf{H_p}$ is the Hessian matrix of V with respect to $\mathbf{p}$, $\mathbf{\Omega_p}$ is the covariance matrix of $\mathbf{p}_{t+1}$ conditional on information in time t, and vec() vectorizes these matrices. This last term embodies option values.[2]

Given parameters for the autoregressive process of revenues, a functional form for the agronomically based, revenue-adjustment functions, $a^i(\mathbf{I}_t, n_t)$, and a discount factor, θ, the dynamic optimization problem is fully defined. The solution to the model is a policy function that gives crop choice and nitrogen fertilizer applications as a function of the state variables: $i(\mathbf{I}_t, n_t)$ and $n(\mathbf{I}_t, n_t)$. These policy functions are the choices that satisfy the Bellman equation (5). Because the value function does not have an analytical representation, the model must be solved numerically. We use value function iteration to find these policy functions.

Solving the Model

Here we describe the numerical methods used to solve the SDP models. For readers uninterested in the technical details of how these problems are solved, this section may be of little interest and may be skipped without significant loss of applied content. Similarly, readers familiar with these techniques are unlikely to learn new methods. We provide these details for completeness and to aid replication. Miranda and Fackler (2002) provide an in-depth discussion of the numerical methods we use. In addition, the computer code we use to approximate functions and perform quadrature to evaluate integrals was written by Paul Fackler, which

[2] Note that $\mathbf{I}_{t+1}$is a deterministic function of $\mathbf{I}_t$ and crop choice in i, and thus not random. However, subsequent values of $\mathbf{I}_{t+i}$are uncertain, and this uncertainty ultimately affects the shape of the value function.

can be downloaded from his website. Our code is available upon request.

Each model we examine includes three or four state variables. The three state variables included in all models are crop history, which embodies from one to three previous years of plantings; the previous year's average revenue received per corn acre, r^c_{t-1}; and the previous year's average revenue received per soybean acre, r^s_{t-1}. In models with just three state variables, the fertilizer price is assumed fixed. In other versions of the model, the current year's nitrogen fertilizer price, f_t, is the fourth state variable.

To solve the model numerically, we first divide the state space into a discrete number of points. The value function is approximated at each discrete point, and we interpolate values in-between points using a linear spline. The vector **s** denotes the discrete evaluation points and $V(\mathbf{s})$ the associated points in the value function. The vector **s** thus spans all combinations of evaluation points across all possible states.

Because crop choice is an integer that can take only two values, 0 if soybean is planted and 1 if corn is planted, approximating functions that return continuous values are not well suited to approximate optimal crop choices. To account for this, we used a simple nearest-neighbor approach to simulate optimal crop choices. Lagged soybean and corn revenues are simulated for each growing season, and for each lagged soybean and corn revenue pair, we find the nearest pair of soybean and corn revenue nodes that were used to find each decision rule. With the nearest soybean and corn revenue and the crop history state in hand, we set the current crop choice equal to the crop choice that solved the optimization problem underlying the decision rule. This approximation method works well when simulating crop choices as long as the number of soybean and corn revenue nodes is at least 20.

Computational cost is tied to the size of **s**. In a model with 1 year of crop history, the crop-choice state variable, $\mathbf{I}_t$, may assume one of two values: zero if soybeans were planted in year $t-1$ and one if corn was planted. In the model with 2 years of crop history, $\mathbf{I}_t$ may assume one of four values: one for continuous soybean (SS), two for soybean followed by corn (SC), three for continuous corn (CC), and four for corn followed by soybean (CS). Similarly, in the model with 3 years of crop history, the crop-choice state variable may assume one of eight feasible crop histories.

We divide the three continuous state variables (the vector **p**) into 20 equally spaced evaluation points that range between \$100 and \$1,600 per acre, \$100 and \$1,700 per acre, and \$0.05 and \$1.60 per pound, for state-level corn revenues, soybean revenues, and fertilizer prices, respectively. These ranges are somewhat larger than those observed in the data (described below). When the crop history includes a single year, the previous year's crop choice can assume only two values. Multiplying out the set of feasible evaluation points, we have a minimum of $2 \times 20 \times 20 \times 20 = 16{,}000$ evaluation points in vector **s**. The number of evaluation points then doubles for each additional year of crop history considered.

Increasing the number of evaluation points for the continuous state variables involves a delicate balance between accuracy and computational expense. If we choose 30 points rather than 20 for each of the three continuous state variables, the dimension of the state vector increases from 16,000 to 54,000 (2×30^3) for a single-year crop history. If we solve the model using 2 years of history, then we need to allocate 4 evaluation points for the first state variable, which again doubles the memory requirements. Though expensive, in some applications the number of evaluation points can significantly influence how well the overall model approximates the true solution.[3] Our computational constraint makes it impossible to solve models with more than 20 evaluation points when we use all four state variables.[4] If we fix fertilizer

[3] For example, a recent article by Cafiero et al. (2009) reconciled a long-standing puzzle about the amount of autocorrelation in storable commodity prices by simply increasing the number of evaluation points in the tochastic dynamic programming model. Approximating the inverse demand function with just 20 evaluation points smoothes over a critical kink in the policy function where stockout occurs. This seemingly minor computational issue leads to a spurious implication that commodity prices should have little autocorrelation (Deaton and Laroque 1992, 1996). In a model with 1,000 evaluation points, the numerical solution accurately recovers the kink in the demand curve and predicts commodity prices with a high degree of autocorrelation, which is what we observe in commodity price data. Since we do not expect there to be non-smooth kinks in our policy functions (except for crop choice, which is explicitly discrete), the relative coarseness of our policy function approximation should be a less severe problem.

[4] To solve the largest model, we used a Linux workstation with a Xeon E5, 3.1Ghz processor with 16 cores, 128G of RAM, running a multicore package of Matlab. It required one to two days for a single model to converge.

prices and thereby reduce the number of continuous state variables to two, we are able to increase the number of evaluation points to 30, but we found this made little difference.

The dynamic program is solved recursively. It begins by solving the terminal condition of the dynamic programming model, which is a static expected profit function (equation [4]) conditional on each of the 16,000+ evaluation points in the state vector **s**. This decision involves finding the optimal crop to plant and, if corn is planted, how much nitrogen fertilizer to apply. In this initial step, the longer-run consequences of these decisions are ignored. We store the expected profit-maximizing crop choices and per-acre profit levels and then compute the coefficients of a four-dimensional linear spline so that we may evaluate expected profits in-between the evaluation points. This spline function is the first estimate of the value function (or terminal condition) which we denote $V_T(\mathbf{I}, \mathbf{p})$.

The next step involves substituting the first estimate of the value function into the right-hand side of the Bellman equation (5) and solving the two-period problem: maximize current profits plus the discounted expected value of $V_T(\mathbf{I}, \mathbf{p})$. This optimization depends on the current state, $(\mathbf{I}_{T-1}, \mathbf{p}_{T-1})$. To trace out the whole value function, we therefore perform this optimization for each evaluation point in the state vector **s**. Optimization requires that we integrate $V_T(\mathbf{I}, \mathbf{p})$ over the probability distribution of future states, conditional on each $s_j \in \mathbf{s}$. While crop choice affects the future state space in a deterministic way, the distribution of the vector $\mathbf{p}_T$ conditional on s_j is given by the vector autoregressive process described above (2) and its assumed trivariate normal distribution of innovations, which have mean zero and an estimated covariance matrix $\boldsymbol{\Omega}$ (reported below).[5]

Having stored optimal values and optimal choices for each $s_j \in \mathbf{s}$), we again compute the coefficients of a four-dimensional linear spline so that we may approximate expected values in-between the evaluation points in **s**. This spline function gives the next iteration's estimate of the value function, which we denote $V_{T-1}(\mathbf{I}, \mathbf{p})$.

By substituting $V_{T-1}(\mathbf{I}, \mathbf{p})$ into the right-hand side of the Bellman equation, we can repeat this process until either a given planning horizon has been considered or until the value function converges to very similar values between iterations. Full convergence satisfies the Bellman equation and gives the solution to the infinite-horizon problem. We therefore repeat the procedure until the maximum absolute value of the change in the value function at each state vector was less than \$1e^{-6}, which typically occurred around 350 iterations. We also considered 1- and 2-year horizon problems.

Data and Parameter Estimates

The main parameters are the agronomic revenue adjustment functions $a^i(\mathbf{I}, n_t)$ and the matrix of autoregressive coefficients $\mathbf{B}'$s from equation (2). Estimation of the adjustment cost function comes from analysis of experimental plot data from northeastern Iowa that was generously provided by David Hennessy. Estimation of the autoregressive coefficients comes from analysis of historical data on Iowa corn and soybean prices and yields that are publicly available from USDA's National Agricultural Statistical Service (NASS) and from USDA data on nitrogen fertilizer prices.

Revenue Adjustment Functions

The experimental plots are composed of seven large plots with 12 subplots in each large plot. One of the four fertilizer application rates (0, 80, 160, and 240 lbs/acre) are applied and held constant over time for a specific subplot.[6] Nitrogen fertilizer was only applied to corn, and the effect on subsequent soybean yields turns out to be statistically small, as we show below.

The data from the experimental plots, including yields and controlled fertilizer usage, are summarized in table 1. Note that fertilizer application rates are balanced via the experimental design across rotation

[5] In solving the model, the error terms and weights are drawn following the multivariate normal distribution using a Gaussian quadrature rule (Miranda and Fackler 2002). We provide evidence in an online appendix to show that the normal-distribution assumption appears reasonable in this case.

[6] The fact that fertilizer application rates are held constant over time in the experimental plot data is one reason why our adjustment function does not include past application rates. Another reason is computational feasibility: including past application rates in the production function would add yet another state variable to the dynamic programming model.

Table 1. Summary Statistics from Experimental Field Plots

	(**C** ≡ Corn and **S** ≡ Soybeans)							
Past Plantings:	**C-C-C** (1)	**C-C-S** (2)	**C-S-C** (3)	**C-S-S** (4)	**S-C-C** (5)	**S-C-S** (6)	**S-S-C** (7)	**S-S-S** (8)
	Corn Yields (bushels/acre)							
Mean	106.9	105.5	107.9	na	135.5	137.6	na	na
SD	42.8	42.0	43.8	na	36.2	36.6	na	na
N	300	300	600	na	600	300	na	na
	Nitrogen Applications on Corn (current or previous, lbs./acre)							
Mean	120.0	120.0	120.0	na	120.0	120.0	na	na
SD	89.5	89.5	89.5	na	89.5	89.5	na	na
N	300	300	600	na	600	300	na	na
	Soybean Yields (bushels/acre)							
Mean	49.8	48.3	45.2	na	na	na	na	38.5
SD	11.5	11.0	11.4	na	na	na	na	9.8
N	300	300	300	na	na	na	na	300

Note: The table reports average yields and nitrogen application rates for different rotations in the experimental data. Column headings give different rotation histories. For example, **C-S-S** means corn was planted in the immediately preceding year and soybeans were planted both years preceding the last. Not all feasible rotation histories are present in the data, as indicated by "na." Nitrogen fertilizer was not applied to soybeans, and the level of fertilizer applied on corn rotated with soybeans had no statistically significant effect on yield.

treatments, so that differences in average yields, conditional on sampling error, can be interpreted as causal.

The data show that corn yields following soybean plantings average about 28 percent greater than corn yields following corn plantings.[7] Planting decisions in years prior to the immediately preceding year appear to have little influence on yield. For soybeans, yields following corn plantings average about 25 percent greater than yields cultivated in soybean monoculture. In comparison to corn, average soybean yields are more sensitive to plantings 2 and 3 years past. The greater the frequency and more recent prior corn plantings, the greater the current soybean yield. Average yield for soybeans following 3 years of corn is about 9 percent greater than average yield in continuous corn-soybean rotation.

We use regression analysis and the data summarized in table 2 to calibrate the adjustment cost functions $a^i(\mathbf{I}, n)$. We report several specifications so readers can judge the trade-off between parsimony and goodness of fit. Using a longer crop history improves the fit slightly, but accounting for it requires a larger state space in our dynamic programming model. We also experiment with different kinds of interactions between fertilizer applications and rotation history. The regressions show that the fit improves little after an account of the previous year's plantings and fertilizer use. We also find a strong interaction effect between past plantings and nitrogen use for corn: the marginal productivity of fertilizer is uniformly greater when corn is planted after corn rather than after soybeans.

The regression models have the form:

$$\log(Y_{pt}) = +a_t + \mathbf{I}_{pt}\beta + \gamma_1 \log(n_p + 1) + \gamma_2 log^2(n_p + 1) + \varepsilon_{pt} \quad (7)$$

where Y_{pt} is yield on plot p in year t, a_t is a year fixed effect, n_p is nitrogen application rate in pounds per acre (fixed across years), $\mathbf{I}_{pt}$ is a vector of 0–1 dummy variables indicating the rotation history, and ε_{pt} is the model error. Note that while the experimental data include only four discrete levels of nitrogen application, we treat it as a continuous variable in the regression analysis. This treatment allows us to infer yield and revenue effects over a continuum of application levels in our dynamic programming model. Separate models were estimated for corn and soybeans. For soybean yields, nitrogen is not applied and the applicable terms in equation (7) are dropped.

Because the regressions account for rotation history using dummy variables, and

[7] This figure comes from comparing the weighted average of columns 1–3 relative to the weighted average of columns 5–6, the weights equal to the square root of N.

Table 2. Regressions Predicting Crop Yield Conditional on Planting History and Fertilizer Use

	Log Corn Yield			Log Soybean Yield			
Crop History:	1 (1)	2 (2)	3 (3)	1 (4)	2 (5)	3 (6)	3 (7)
	Estimate/(Standard Error)						
C, CC, or CCC	3.79	3.79	3.79	3.72	3.75	3.77	3.77
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
CCS			3.78			3.74	3.74
			(0.03)			(0.02)	(0.02)
CS or CSC		3.80	3.80		3.67	3.67	3.67
		(0.03)	(0.03)		(0.02)	(0.02)	(0.02)
S, SC, or SCC	4.47	4.47	4.46	3.50	na	na	na
	(0.03)	(0.03)	(0.03)	(0.02)			
SCS			4.48			na	na
			(0.03)				
SS or SSS		na	na		3.50	3.50	3.48
					(0.02)	(0.02)	
$\log(n+1) \times$ C	0.10	0.10	0.10				6.97#
	(0.02)	(0.02)	(0.02)				(10.9)
$\log^2(n+1) \times$ C	14.8#	14.8#	14.8#				−1.30#
	(3.14)	(3.14)	(3.14)				(2.08)
$\log(n+1) \times$ S	0.07	0.07	0.07				−6.10#
	(0.02)	(0.02)	(0.02)				(18.9)
$\log^2(n+1) \times$ C	1.37#	1.37#	1.37#				2.47#
	(3.62)	(3.62)	(3.62)				(3.61)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	2100	2100	2100	1200	1200	1200	1200
Adjusted R^2	0.81	0.81	0.81	0.82	0.84	0.84	0.84

Note: (#) indicates numbers multiplied by 1,000. Crop history indicates how many years of past plantings used in the regression. For one year, the history is either C or S; for two years, the history is CC, CS, SC or SS; for three years, the history is indicated by a three-letter sequence. Histories "SSC" and "CSS" are not present in the data. Missing rotations are not shown in the table (e.g., SSC) or are indicated by "na" if the rotation exists for corn but not for soybeans. n represents fertilizer applications, in pounds per acre, and takes on one of four distinct values: 0, 80, 160, and 240. We use $n+1$ to make the log operator well defined at $n=0$. $log(n+1) \times$ S measures the effect of the nitrogen application rate on corn when soybeans were planted in the last period. Although nitrogen was not applied to soybeans, column 7 investigates how nitrogen application rates on corn rotated with soybeans affect soybean yield.

because some feasible crop histories are not present in the data, we must interpolate to make yield predictions for the unobserved histories. We do this by combining regression coefficients from similar nonmissing histories. For example, an SSC history is not in our data of soybean yields, but SSS is in our data, as are CCC and CCS. We therefore approximate the soybean yield for SSC with that for SSS, plus the difference between yields for CCC and CCS, because this difference is akin to the difference between SSC and SSS. We make similar interpolations for all missing rotation histories. Results from these interpolations are shown in table 3. Holding fertilizer applications fixed at 130 pounds for corn yields, and taking the average of year fixed effects, the table reports average predicted yield for each feasible rotation history.

To parameterize the revenue adjustment functions ($a^i(\mathbf{I}, n)$) from the yield regressions, we divide the regression-predicted yield (with necessary interpolations described above) by the average state-level yield observed in Iowa, which is 127.96 bushels per acre of corn and 31.36 bushes per acre (see table 3) of soybeans in the 1-year history case. Thus, assuming farmers optimize, the typical value of the adjustment function should be approximately 1. The resulting estimated adjustment functions for corn are shown in figure 1.

State-Level Revenues and Fertilizer Prices

We use a vector autoregressive model to characterize the stochastic evolution of state-level revenues per acre and fertilizer prices, which are key state variables in the stochastic dynamic programming

Table 3. Yield Predictions for Different Rotation Histories.

History:	1 Year		2 Years		3 Years	
Current Crop:	S	C	S	C	S	C
Rotation						
S, SS, or SSS	33.4	131.7	33.4	132.6	33.4*	133.7*
SSC					34.8	130.7*
SC or SCS			37.0*	131.7	37.7*	133.0
SCC					39.0*	131.1
C, CS, or CSS	41.8	106.8	39.4	107.3	40.7*	106.9*
CSC					39.4	107.3
CC or CCS			43.0	106.4	43.6	106.2
CCC					42.3	106.6

Note: The table reports average predicted yields based on the regression models reported in table 2, fixing fertilizer at 130 pounds per acre and using the average of year fixed effects. A (*) indicates a rotation history that is missing in the data and a prediction that has therefore been interpolated. Interpolation is done by combining similar non-missing rotations. For example, a SSC history is not in our data of soybean yields, but SSS is in our data. We therefore approximate the soybean yield for SSC with that for SSS, plus the difference in yields for CCC and CCS.

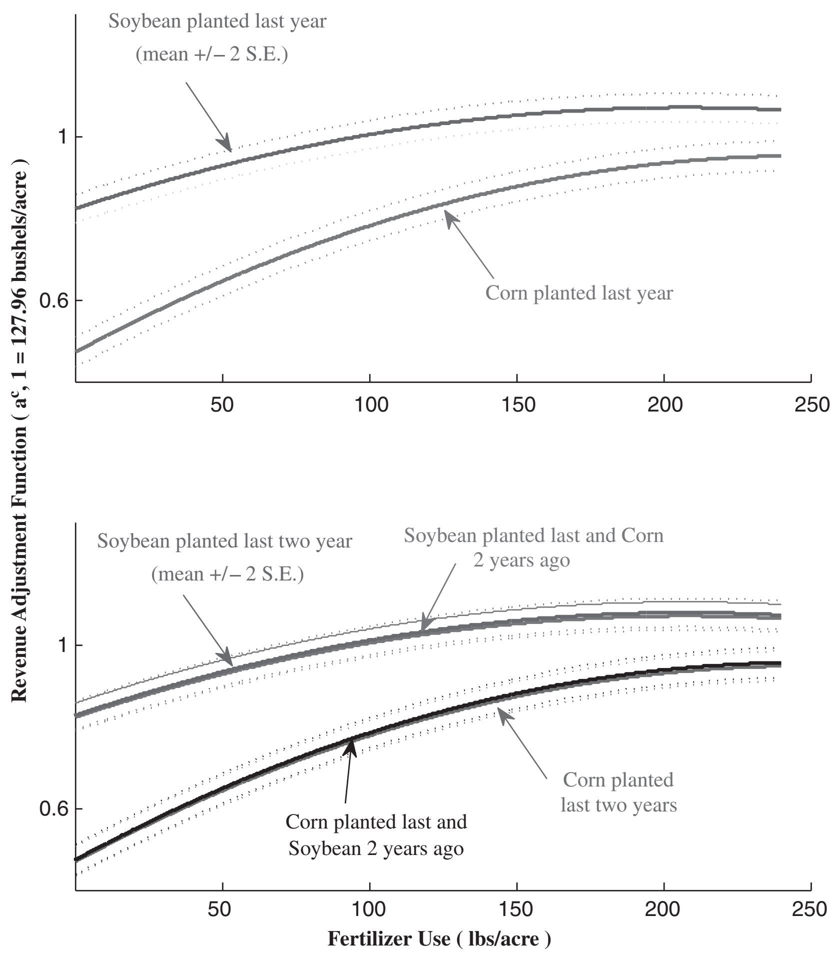

Figure 1. Estimated revenue adjustment functions for corn

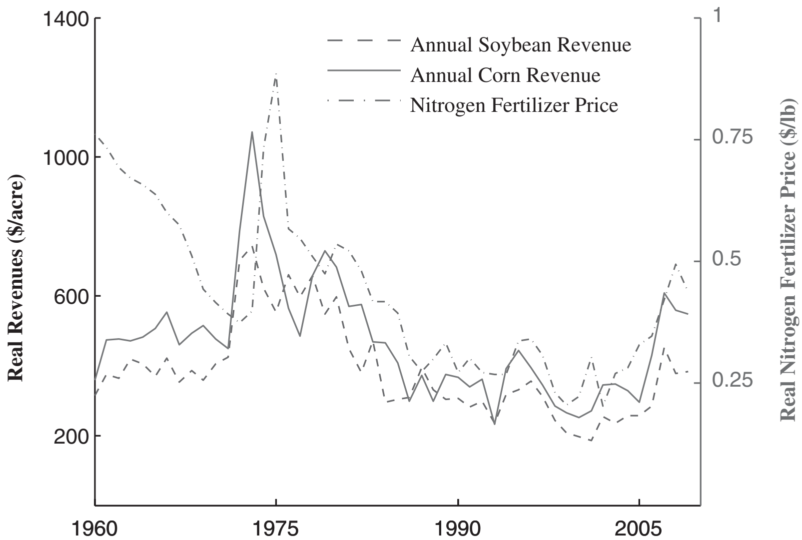

Figure 2. Historical Iowa corn and soybean revenues and fertilizer prices

Table 4. Vector Autoregression Models of State-Level Revenues

	Corn Revenue Log r_t^c		Soybean Revenue Log r_t^s	
	(1)	(2)	(1)	(2)
	Estimates/(Standard Errors)			
Intercept	1.09	1.21	0.75	0.70
	(0.52)	(0.54)	(0.48)	(0.51)
$\log(r_{t-1}^c)$	0.48	−0.31	0.16	−0.14
	(0.19)	(0.22)	(0.17)	(0.20)
$\log(r_{t-2}^c)$		0.61		0.20
		(0.21)		(0.19)
$\log(r_{t-1}^s)$	0.35	0.22	0.71	0.22
	(0.19)	(0.22)	(0.17)	(0.21)
$\log(r_{t-2}^s)$		0.30		0.59
		(0.22)		(0.21)
Sample size	49	48	49	48
Adjusted R^2	0.66	0.71	0.71	0.71
	Variance-Covariance of Innovations (AR1)			
	u^c		u^s	
u^c	3.61		2.34	
u^s	2.34		3.13	

Note: The table reports estimates of first-order and second-order vector regressive models. The first-order coefficients (columns 1 and 3) comprise our estimate of the matrix **B** in equation (2) and the variance-covariance matrix comprise the estimate of **Ω**, all for the case when fertilizer price is assumed fixed. The models were estimated using ordinary least squares.

model. The revenue data come from USDA's National Agricultural Statistics Service for the state of Iowa and are adjusted to year 2000 dollars using the consumer price index. The fertilizer price data were obtained from USDA's Economic Research Service (http://www.ers.usda.gov/data/fertilizerUse/, table 7).These data are plotted in figure 2.

In tables 4 and 5, we report results from first- and second-order autoregressive models. The first table reports regression models without fertilizer prices, which are used for

Table 5. Vector Autoregression Models of State-Level Revenues and Fertilizer Prices

	Corn Revenue Log r_t^c		Soybeans Revenue Log r_t^s		Fertilizer Price f_{t+1}	
	(1)	(2)	(3)	(4)	(5)	(6)
			Estimates/(Standard Errors)			
Intercept	1.71	2.22	1.65	1.84	-2.21	-2.30
	(0.76)	(0.92)	(0.69)	(0.88)	(0.60)	(0.74)
$\log(r_{t-1}^c)$	0.42	-0.39	0.07	-0.23	0.30	-0.03
	(0.20)	(0.21)	(0.18)	(0.20)	(0.16)	(0.17)
$\log(r_{t-2}^c)$		0.46		0.11		0.34
		(0.22)		(0.21)		(0.17)
$\log(r_{t-1}^s)$	0.33	0.19	0.67	0.21	0.14	-0.13
	(0.19)	(0.22)	(0.17)	(0.21)	(0.21)	(0.17)
$\log(r_{t-2}^s)$		0.42		0.64		0.14
		(0.23)		(0.22)		(0.19)
$\log(f_t)$	0.11	-0.23	0.16	-0.07	0.68	-0.07
	(0.10)	(0.17)	(0.09)	(0.16)	(0.08)	(0.14)
$\log(f_{t-1})$		0.37		0.25		0.72
		(0.20)		(0.19)		(0.16)
Sample size	49	48	49	48	49	48
Adjusted R^2	0.66	0.68	0.73	0.72	0.82	0.82

	Variance-Covariance Matrix of Innovations (AR1)		
	u^c	u^s	u^f
u^c	3.51	2.20	0.60
u^s	2.20	2.92	−0.15
u^f	0.60	−0.15	2.21

Note: The table reports estimates of first-order and second-order vector regressive models of fertilizer prices and state-level corn and soybean revenues per acre. The first-order coefficients (columns 1, 3, and 5) comprise the estimate of the matrix **B** in equation 2, and the variance-covariance matrix gives the estimate of **Ω**. The models were estimated using OLS.

models with fixed fertilizer price.[8] The second table reports models with fertilizer prices. Although a second-order model would be computationally infeasible if used in our dynamic program, we report the regression results to show that earlier lags have little or no predictive power, which suggests the first-order model is sufficient. AIC and BIC selection criteria also prefer a first-order process. We chose the first-order model for these reasons plus the fact that adding additional continuous state variables greatly increases computational expense. One hundred years of simulated revenues and fertilizer prices, based on the first-order model in table 5, are plotted in the online appendix. The online appendix also reports various residual plots and Kolmolgorov-Smirnoff test statistics, which fail to reject the null hypothesis that each error is distributed normal.

[8] We use models with fixed fertilizer price to explore the sensitivity of results to the number of grid points used to approximate the value function.

National Resources Inventory

We use data from National Resources Inventory (NRI), a survey administered by USDA's Natural Resources Conservation Service (NRCS), to obtain data on actual rotations for comparison with model predictions. The NRI is a survey that repeatedly samples approximately a million points across the United States in order to track parcel-specific land use change. The key advantages of the NRI in comparison to other surveys is that land units rather than farms are sampled, and the land units are fixed over time. Until 1997, the survey was conducted every 5 years; however, on cultivated cropland, the survey also obtained crop choices for the 4 years prior to each sampled year. Combining surveys from 1982, 1987, 1992, and 1997 gives a panel of crop choices running from 1979 through 1997 with only the years 1983, 1988, and 1993 missing. Since 1997 the survey has become annual. Although the point data are not publicly available since 1997, we were able to analyze these data on site at USDA's Economic Research Service.

For our analysis, we limit the data set to 6,513 parcels in Iowa from 1979 to 2007 that planted either corn or soybeans. Observations are not available for 1983, 1988, and 1993. These data are summarized in the online appendix table 2. The table shows the frequency of every possible 3-year rotation in available years since 1981 (with prior rotations stretching back to 1979). Looking over time, there are a several interesting features. The frequency of corn ranges from 50%–60% of sampled parcels. Corn and soybeans are planted in rotation (corn after soybean or vice versa) on 67%–91% of the parcels. Corn is planted after corn from 3% to 15%, and the frequency of soybeans after soybeans ranges from just 0.1% to 1.6%.

It is also interesting that, beginning in 1996, the frequency of corn after corn dropped sharply. This year coincides with the Federal Agricultural Improvement and Reform Act (FAIR, colloquially called the Freedom to Farm Act). This bill largely “decoupled” government payments from farmer planting decisions. Since, prior to this Act, payments depended to some extent on how much corn farmers planted relative to their historical baseline, the policy change likely encouraged greater efficiency via greater crop rotation. Also, corn-soybean rotations were least prevalent, and corn after corn most prevalent, in 1987, which happened to be a year of remarkably low commodity prices. This low rotation incidence also might have been policy related, since pre-Act payments were connected to the amount by which market prices fell below established target prices. Although we do not formally address these policy considerations in this article, they are useful to keep in mind when considering its predictive accuracy.

Finally, it is interesting to note the marked increase in corn-after-corn plantings in 2007, when corn prices climbed sharply with the rapid rise of ethanol production.

Results

Scenarios Considered

Here we report rotation decisions, fertilizer applications, average profits, and profit variability under a series of different modeling assumptions and decision rules based on four planning horizons:

(i) *1-Year Horizon*: A farmer that optimizes current expected profits conditional on past plantings (e.g., a cash renter who believes he or she is unlikely to be farming the same parcel next year).

(ii) *2-Year Horizon*: A farmer that maximizes the expected sum of current and subsequent year’s profits conditional on past plantings (e.g., a cash renter who has a 2-year contract or at least believes there is a strong possibility that he or she will be farming the same parcel for at least 2 years).

(iii) *Infinite Horizon*: A fully optimizing farmer that maximizes the present discounted value over an infinite horizon (e.g., a landowner who is farming on his or her own land).

(iv) *Always Rotate*: A rule-of-thumb farmer that rotates corn after soybeans and vice versa, regardless of prices, but applies fertilizer optimally conditional on planting decisions.

Comparing results over these different objectives allows us to evaluate the economic costs associated with less-than-optimal or rule-of-thumb decision criteria. These cost margins are an important consideration because real option values, which could be implicit in rotational decisions of forward-looking farmers, tend to be small in size even when they have a large influence on decisions. It would not be surprising to find farmers using simpler decision rules. Thus, in addition to simulated outcomes, we also examine how well the models predict actual plot-level decisions.

We also consider optimal decisions of a “risk-averse” farmer that maximize the present value of log profits rather than raw profits.[9] Our goal is simply to examine whether decisions are particularly sensitive to tastes about profit variability. Because farm-level profits will sum outcomes across many parcels of land, and because consumption is likely to be much smoother than profits, maximizing the expected present value of log profit for a single acre of production implicitly assumes both risk

[9] For these specifications, we add \$350 to profits ($u = \ln(350 + \pi)$) to ensure we never take the log of a negative number. We put “risk-averse” in quotes because using the natural log of profit is a crude approximation of diminishing marginal utility of wealth or consumption.

aversion and large degree uninsurable risk.

Next, we compare solutions with observed price and revenue processes with one in which corn plantings receive an additional premium of $20 acre. This premium approximately equals the premium received by farmers selling corn to nearby ethanol plants, which now consume a significant share of Iowa corn production.[10] This also gives some indication of planting response to a permanent change in relative prices of corn relative to soybeans.

All of the above assumptions are considered in models with one, two, and three-year histories, but we report results for 3-year histories in the online appendix. For each objective and history length, we consider models with fertilizer price fixed at $0.42/lb and a model in which fertilizer price evolves stochastically according to the vector-auto regression model reported above. We chose a fixed fertilizer price of $0.42/lb because it is close to the recent high prices of nitrogen, and it best predicts actual planting decisions reported in the National Resources Inventory. For the model with a fixed fertilizer price, we have one less continuous state variable, which greatly reduces computational expense. These different modeling strategies are used to evaluate the robustness of predicted choices to various modeling assumptions.

After solving the infinite-horizon and shorter-horizon objectives, we simulate 100 years of the estimated stochastic generating process of prices and revenues and evaluate decisions and profits for each solved model. We then replicate this 100-year simulation 1,000 times using the same pseudo-random outcomes across all models so that differences across models cannot be attributed to sampling error. For each simulation we evaluate average profits, the standard deviation of profits, the present value of profits, average fertilizer applied to corn, the average frequency of corn plantings, and the average frequency of corn after corn. For each measure, we report the average over the 1,000 simulations.

[10] McNew and Griffith (2005) estimate a corn price premium of 12.5 cents per bushel near ethanol plants, which amounts to $20/acre if yield is expected to be 160 bushels per acre, which is typical in recent years in Iowa.

Policy Functions

Figure 3 shows solved policy functions for risk-neutral objectives with fixed fertilizer prices, 1 year of planting history, and no corn price premium. Each line in figure 3 represents a threshold for planting corn or soybeans under a given planning horizon (naive, 2 year, or infinite) and planting history (**C** last year or **S** last year). If a revenue pair falls below the curve, the policy function indicates soybeans should be planted; if a revenue pair falls above the curve, the policy function indicates corn should be planted. The points on each line indicate node locations. Dots indicate actual historical revenue pairs.

There are three notable features about the threshold curves: First, for the most part, the longer the planning horizon, the wider the region wherein it is optimal to rotate (plant corn after soybeans and vice versa), which reflects the real option values embodied in rotations. The exception (discussed below) is that corn after corn is less likely for a 2-year planning horizon than an infinite horizon. Second, nearly all observed revenue pairs lie between the threshold curves, regardless of the planning horizon. The one exception being the year 1971, when only the naive farmer plants corn after corn. Third, observed historical revenue pairs generally appear closer to the corn-soybean threshold following corn as compared to following soybeans, especially for shorter planning horizons. Thus, while our model would predict the nearly identical land use choices (i.e., always rotate) for all planning horizons, the model suggests that corn after corn plantings may be more likely than soybean after soybean plantings. Note that we indicate revenue pairs from a few recent years so they can be placed in historical context.

We have only illustrated policy functions with 1 year of planting history and fixed fertilizer prices. Plots showing policy functions for 2- and 3-year histories require multiple panels for clear presentation, so we have placed these in an online appendix. Policy functions for 2- and 3-year histories show patterns similar in spirit to figure 3, but the curves tend to shift up or down depending on earlier crop history. The more corn was planted in years prior to the previous one, the more the threshold curves shift up favoring soybeans, and vice versa. These patterns make sense given documented rotational

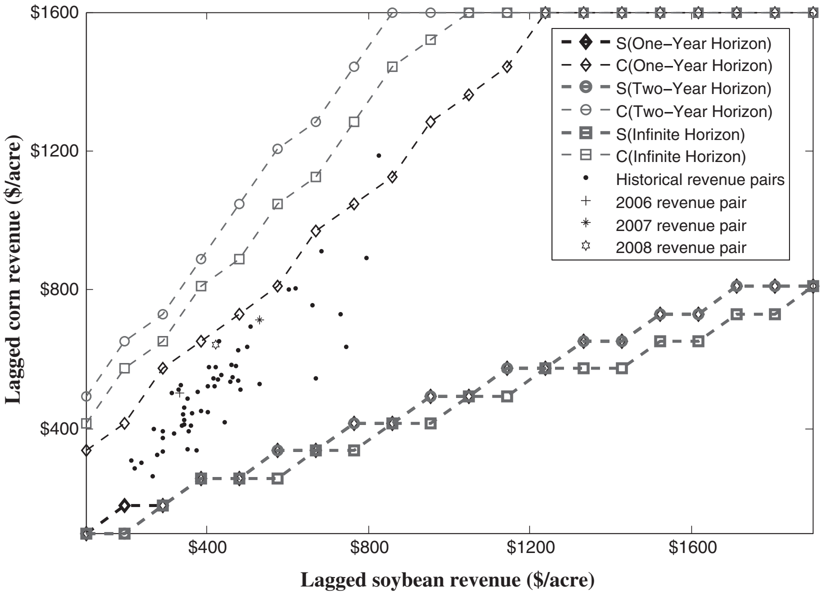

Figure 3. Threshold curves for optimal corn and soybean plantings conditional on past state-level revenues

Notes: The figure illustrates solved policy functions for risk-neutral objectives with fixed fertilizer prices, one-year of planting history, and no corn price premium. Each line gives an threshold curve for planting corn or soybeans under a given planning horizon (naive or infinite) and planting history (**C** last year or **S** last year). If a revenue pair falls below the threshold curve, the policy function indicates soybeans should be planted; if a revenue pair falls above the threshold curve, the policy function indicates corn should be planted. The points on each line indicate node locations. Dots indicate historical revenue pairs. Threshold curves for models using longer crop histories are shown in an online appendix.

benefits, and suggest monoculture, while unlikely, is even less likely to persist. Interestingly, the model with 3-year rotations show that if past rotations were relatively balanced, the threshold curves move slightly toward the center relative to the single-year case.[11] Thus, all else the same, more rotation in past planting increases the likelihood of future monoculture, a pattern that makes intuitive sense.

It is interesting that the 2-year planning horizon is less likely to engage in monoculture than the infinite planning horizon. This pattern likely results from the nature of revenue autocorrelation. Corn and soybean price movements are strongly correlated, as indicated by the autocorrelations and covariance matrix in table 4. But while revenues are strongly autcorrelated, they are mean reverting within a few years (the sum of the lagged coefficients are 0.83 and 0.87 for corn and soybean, respectively, while innovations have a correlation of 0.70). As a result, the option value of preserving land disposition for future monoculture is likely to be greatest for the subsequent year, since in the long run the relative benefits of monoculture revert to the mean. Corn monoculture is thus most likely when current profits are maximized, least likely with a two-year horizon, and in between with an infinite horizon. This pattern becomes more exaggerated with longer planting history, mainly because corn monoculture favors subsequent soybean yields, an issue discussed in more detail below.

The next section considers simulations of these models as well as those with stochastic fertilizer prices. Policy functions for models with stochastic fertilizer choice have too many dimensions for graphical presentation. And because policy functions for risk-averse objectives look nearly identical to those for the risk-neutral objective, we do not display them.

Simulation Results

Results for models with a single year of crop history (tables 6 and 7) show similar

[11] To ease comparison between one-year histories and two- and three-year histories, we plot policy functions for the single-year case in the background of the two- and three-year figures (again, see the online appendix).

Table 6. Simulation Results for Fixed Fertilizer Price and One-Year Crop History

Objective	PV Annuity ($/acre)	Percentage (%) Corn	Percentage (%) Corn-Corn	Mean Profit ($/acre) Corn	Mean Profit ($/acre) Soybean	Fertilizer (lbs/acre) Mean	Fertilizer (lbs/acre) Std
			Risk neutral, no premium on corn				
One-Year	473.87	52.28	5.09	462.77	418.42	135.32	29.49
Two-Year	477.46	50.00	0.00	464.30	422.48	128.94	20.39
Infinite	477.47	50.01	0.10	464.36	422.34	129.07	20.64
Always Rotate	477.45	50.00	0.00	464.30	422.49	128.93	20.38
			Risk neutral, $20 premium on corn				
One-Year	481.80	56.58	13.73	474.04	417.23	147.53	33.55
Two-Year	487.58	50.00	0.01	484.98	422.50	132.45	18.61
Infinite	487.60	50.03	0.22	485.32	422.16	132.71	19.18
Always Rotate	487.58	50.00	0.00	485.02	422.49	132.43	18.58
			Risk averse, no premium on corn				
One-Year	474.24	51.62	3.79	464.45	418.19	132.12	28.31
Two-Year	477.45	50.00	0.00	464.29	422.48	127.23	20.61
Infinite	477.46	50.00	0.06	464.27	422.42	127.32	20.77
Always Rotate	477.45	50.00	0.00	464.29	422.49	127.22	20.61
			Risk averse, $20 premium on corn				
One-Year	482.87	54.84	10.24	480.62	414.05	142.83	32.93
Two-Year	487.58	50.00	0.01	484.97	422.48	130.92	18.79
Infinite	487.59	50.03	0.22	485.32	422.16	131.18	19.35
Always Rotate	487.58	50.00	0.00	485.01	422.49	130.89	18.75

Note: The table summarizes results from 1,000 replicates of 100-year simulations, wherein a one-acre field is managed using each of four different management strategies: (1) Maximization of current profits conditional on the state variables. (2) Maximization of the current plus discounted subsequent year's profits. (3) Maximization of the expected net present value using the solution to the full, infinite-horizon SDP with discount factor $\beta = 0.95$. (4) Maximization of current profits subject to always rotating. All values are means taken across the 1,000 series. *PV Annuity* gives the annual perpetual annuity which, if discounted, results in the same expected present value as the objective. Risk-neutral farmers maximize the expected present value of profits and risk-averse farmers maximize the expected present value of log profits. The $20 premium accords with evidence on the price premium that corn receives near ethanol plants. All simulations assume the same stochastic evolution of state variables (the first-order autoregressive model reported in table 5 and use the same sequence of pseudo random draws in order to minimize differences stemming from chance error.

decisions across modeling assumptions. In the great majority of states, it is optimal to rotate regardless of the planning horizon, or whether farmers are risk averse, fertilizer prices are stochastic, or corn plantings receive a $20 per acre premium. This result is more striking when only one year of crop history is considered (table 6). In this case, excepting very rare circumstances, only naive current-year maximizing farmers ever plant corn after corn regardless of prices or state-level revenues. Even naive one-year maximizers plant corn 51.6% to 62.0% of the time, depending on the corn premium, risk aversion, and whether fertilizer prices are fixed or stochastic.

Fertilizer application rates on corn vary from an average of 129 to 161 pounds per acre, depending on modeling assumptions. Differences derive mainly from the incidence of corn monoculture, with higher application rates the greater the frequency of corn after corn. Fertilizer application rates also vary with expected corn prices conditional on corn being planted. This conditional price expectation also tends to be higher the greater the incidence of corn after corn. This pattern highlights the substitutability of rotation for fertilizer applications.

Present values are slightly higher and fertilizer applications and corn plantings slightly lower with a fixed fertilizer price as opposed to stochastic fertilizer prices. Corn plantings increase for naive farmers because occasionally low fertilizer prices reduce the cost of monoculture. But since fertilizer prices are positively correlated with corn prices, these opportunities do not happen often, and profits from the highest revenue years are diminished from typically higher fertilizer costs in those years. Fertilizer applications are likely higher with stochastic fertilizer prices because corn monoculture is more frequent.

Table 7. Simulation Results for Stochastic Fertilizer Price and One-Year Crop History

Objective	PV Annuity ($/acre)	Percentage (%) Corn	Percentage (%) Corn-Corn	Mean Profit ($/acre) Corn	Mean Profit ($/acre) Soybean	Fertilizer (lbs/acre) Mean	Fertilizer (lbs/acre) Std
			Risk neutral, no premium on corn				
One-Year	463.73	54.41	9.37	441.76	420.01	141.19	30.90
Two-Year	466.78	50.00	0.05	453.07	414.82	130.08	17.03
Infinite	466.80	50.04	0.28	452.92	414.92	130.39	17.64
Always Rotate	466.78	50.00	0.00	453.15	414.75	130.01	16.85
			Risk neutral, $20 premium on corn				
One-Year	471.16	61.96	24.54	443.58	431.65	157.80	35.99
Two-Year	476.88	50.02	0.14	473.64	414.97	133.44	16.53
Infinite	476.86	50.43	1.26	471.98	415.87	134.87	19.27
Always Rotate	476.88	50.00	0.00	473.91	414.75	133.26	16.14
			Risk averse, no premium on corn				
One-Year	464.11	52.92	6.37	446.88	415.90	136.48	29.00
Two-Year	466.77	50.00	0.05	453.06	414.82	128.39	17.39
Infinite	466.76	50.08	0.42	452.40	415.25	128.88	18.30
Always Rotate	466.78	50.00	0.00	453.14	414.75	128.31	17.21
			Risk averse, $20 premium on corn				
One-Year	472.64	58.04	16.66	454.80	421.49	150.10	34.76
Two-Year	476.87	50.15	0.50	472.79	415.54	132.37	17.70
Infinite	476.85	50.46	1.32	471.90	415.87	133.45	19.76
Always Rotate	476.87	50.00	0.00	473.90	414.75	131.73	16.47

Note: The table summarizes results from 1,000 replicates of 100-year simulations, wherein a one-acre field is managed using each of four different management strategies: (1) Maximization of current profits conditional on the state variables. (2) Maximization of the current plus discounted subsequent year's profits. (3) Maximization of the expected net present value using the solution to the full, infinite-horizon SDP with discount factor $\beta = 0.95$. (4) Maximization of current profits subject to always rotating. All values are means taken across the 1,000 series. *PV Annuity* gives the annual perpetual annuity which, if discounted, results in the same expected present value as the objective. Risk-neutral farmers maximize the expected present value of profits and risk-averse farmers maximize the expected present value of log profits. The $20 premium accords with evidence on the price premium that corn receives near ethanol plants. All simulations assume the same stochastic evolution of state variables (the first-order autoregressive model reported in table 5 and use the same sequence of pseudo random draws in order to minimize differences stemming from chance error.

Interestingly, there is almost no economic cost for farmers having planning horizons of just two years of using the always-rotate rule, amounting to an annuity value of one to three cents per acre per year as compared to the infinite-horizon case. Even farmers who maximize only current-year profits only sacrifice the equivalent of $3–$5 per acre annually relative to the optimal decision rule.

When we consider models with a two-year crop history, larger differences in planting decisions emerge (tables 8 and 9). Interestingly, naive farmers now fare better than farmers with a two-year planning horizon and farmers that always rotate, and have decision rules that appear remarkably similar to the infinite-horizon case. Naive farmers plant corn 54.6%–63.2% of the time while infinite-horizon farmers plant corn 53.6%–58.4% of the time depending on other modeling assumptions; two-year horizon farmers always plant corn less than 50% of the time. We did not expect this result. Plantings prior to the last year have no significant influence on corn yields. The most logical explanation comes from the additional boost soybean yields receive (about 8%) after two years of corn versus a single year of corn (see column 5 of table 2). Planting corn after corn is thus less costly for farmers with planning horizons of three years or more. Similar long-term effects on soybean yields resulting from corn monoculture emerge when we consider three-year crop histories (see column 6 of table 2), and the simulation results look similar to those for the two-year history (see online appendix).

Like the model with a single year of planting history, differences in present values across planning horizons are small. Farmers who always rotate rather than plant optimally sacrifice about $2 per acre annually without a corn premium and just $3.23 with the corn price premium. This difference seems

Table 8. Simulation Results for Fixed Fertilizer Price and Two-Year Crop History

Objective	PV Annuity ($/acre)	Percentage (%) Corn	Corn-Corn	Mean Profit ($/acre) Corn	Soybean	Fertilizer (lbs/acre) Mean	Std
			Risk neutral, no premium on corn				
One-Year	466.05	58.57	17.74	450.53	406.71	148.33	37.44
Two-Year	463.68	47.68	0.63	470.88	393.56	131.17	21.27
Infinite	466.50	55.45	11.64	460.17	398.43	142.71	36.15
Always Rotate	464.15	50.00	0.00	464.30	398.49	128.93	20.38
			Risk neutral, $20 premium on corn				
One-Year	477.42	60.02	20.62	469.64	404.47	154.03	37.21
Two-Year	473.47	47.70	0.63	491.68	393.46	134.53	19.59
Infinite	478.20	58.24	17.21	470.78	407.23	151.00	35.66
Always Rotate	474.28	50.00	0.00	485.02	398.49	132.43	18.58
			Risk averse, no premium on corn				
One-Year	466.33	54.55	9.69	462.45	396.66	139.03	35.20
Two-Year	463.81	47.84	0.94	470.80	393.71	129.88	22.23
Infinite	466.48	53.63	7.99	463.23	397.19	137.23	33.61
Always Rotate	464.15	50.00	0.00	464.29	398.49	127.22	20.61
			Risk averse, $20 premium on corn				
One-Year	477.73	59.12	18.82	470.01	406.14	151.02	36.64
Two-Year	474.13	48.85	0.95	488.89	395.53	133.07	20.46
Infinite	478.19	58.36	17.31	470.55	407.44	149.65	35.98
Always Rotate	474.28	50.00	0.00	485.01	398.49	130.90	18.75

Note: The table summarizes results from 1,000 replicates of 100-year simulations, wherein a one-acre field is managed using each of four different management strategies: (1) Maximization of current profits conditional on the state variables. (2) Maximization of the current plus discounted subsequent year's profits. (3) Maximization of the expected net present value using the solution to the full, infinite-horizon SDP with discount factor $\beta = 0.95$. (4) Maximization of current profits subject to always rotating. All values are means taken across the 1,000 series. *PV Annuity* gives the annual perpetual annuity which, if discounted, results in the same expected present value as the objective. Risk-neutral farmers maximize the expected present value of profits and risk-averse farmers maximize the expected present value of log profits. The $20 premium accords with evidence on the price premium that corn receives near ethanol plants. All simulations assume the same stochastic evolution of state variables (the first-order autoregressive model reported in table 5 and use the same sequence of pseudo random draws in order to minimize differences stemming from chance error.

small given the considerable difference in plantings and fertilizer applications. Two-year horizon farmers plant even less corn and have higher present values than farmers who always rotate. There could be important policy implications from this result. If farmers actually behave in accordance with the one-year or infinite-horizon model, they might be enticed into planting much less corn and less fertilizer per acre for as little as $2 to $3 per acre. Given well-known environmental consequences of nutrient applications on water quality, it would appear that considerable reduction in nitrogen applications might be achieved with relatively small incentive payments that encourage rotation and discourage monoculture. Such incentive payments might take the form of a fertilizer tax, for example.

The main observation from comparing risk-averse and risk neutral farmers is that differences are extremely small. It therefore seems unlikely that farmers' risk preferences might be discerned from observed planting decisions. Although we only consider log profit, the amount of implied risk aversion is actually quite substantial, because this measure considers only a single acre and precludes availability of insurance or credit to smooth consumption in the face of volatile profits. Nevertheless, we find risk-averse farmers rotate more and apply slightly less nitrogen fertilizer. Somewhat surprisingly, risk-averse farmers with a short time horizon have a higher present value of returns than risk-neutral farmers maximizing current profits. Thus, risk aversion partially compensates for lack of foresight. This result occurs because rotation slightly reduces profit variability relative to monoculture, and this decision also happens to have greater future returns. Comparison between risk-averse and risk-neutral objectives suggest that crop insurance likely increases

Table 9. Simulation Results for Stochastic Fertilizer Price and Two-Year Crop History

Objective	PV Annuity ($/acre)	Percentage Corn (%)	Percentage Corn-Corn (%)	Mean Profit Corn ($/acre)	Mean Profit Soybean ($/acre)	Fertilizer Mean (lbs/acre)	Fertilizer Std (lbs/acre)
Risk neutral, no premium on corn							
One-Year	455.47	57.51	15.35	435.64	406.43	147.82	34.83
Two-Year	454.29	48.71	2.39	455.58	389.35	134.44	22.94
Infinite	455.72	55.69	11.98	441.24	401.17	144.54	32.98
Always Rotate	453.70	50.00	0.00	453.16	391.19	130.01	16.85
Risk neutral, $20 premium on corn							
One-Year	466.21	63.20	26.46	442.29	419.83	160.06	36.51
Two-Year	463.18	48.88	1.22	474.05	391.56	135.76	18.98
Infinite	467.02	57.09	14.58	458.31	403.42	150.13	33.84
Always Rotate	463.79	50.00	0.00	473.91	391.19	133.26	16.14
Risk averse, no premium on corn							
One-Year	455.56	56.17	12.74	439.21	402.97	143.71	34.27
Two-Year	454.38	48.96	2.56	454.93	389.96	132.92	23.57
Infinite	455.73	55.59	11.81	441.40	401.12	142.80	33.34
Always Rotate	453.69	50.00	0.00	453.15	391.19	128.31	17.21
Risk averse, $20 premium on corn							
One-Year	466.44	62.23	24.56	444.60	417.16	157.28	36.86
Two-Year	464.94	49.84	2.91	472.56	392.48	136.39	23.01
Infinite	466.99	57.08	14.54	458.16	403.62	148.71	34.23
Always Rotate	463.79	50.00	0.00	473.90	391.19	131.73	16.47

Note: The table summarizes results from 1,000 replicates of 100-year simulations, wherein a one-acre field is managed using each of four different management strategies: (1) Maximization of current profits conditional on the state variables. (2) Maximization of the current plus discounted subsequent year's profits. (3) Maximization of the expected net present value using the solution to the full, infinite-horizon SDP with discount factor $\beta = 0.95$. (4) Maximization of current profits subject to always rotating. All values are means taken across the 1,000 series. *PV Annuity* gives the annual perpetual annuity which, if discounted, results in the same expected present value as the objective. Risk-neutral farmers maximize the expected present value of profits and risk-averse farmers maximize the expected present value of log profits. The $20 premium accords with evidence on the price premium that corn receives near ethanol plants. All simulations assume the same stochastic evolution of state variables (the first-order autoregressive model reported in table 5 and use the same sequence of pseudo random draws in order to minimize differences stemming from chance error.

fertilizer applications, but implications would be clearer with a more careful study that considered the asymmetric nature of indemnities and evolution of premiums in response to yield surprises.

Implied Long-Run Supply Response

By comparing average plantings and yields with and without the $20 per acre premium for corn, we can obtain long-run price supply elasticities for corn and cross-price elasticities for soybeans. These calculations are summarized in table 10. Note that these elasticities only account for crop substitution between corn and soybeans and yield effects, not other kinds of land use conversion. For most models with one year of crop history, the implied long-run elasticities are small, in the range of 0.11–0.14, and even smaller (and mostly negative) for soybeans. Since crop choices hardly change, the main response to price is greater fertilizer applications, which shows up in higher average corn yields and near zero response for soybeans. The exceptions are for naive one-year objectives, which have elasticities greater than 2 for corn and larger (but negative) elasticities for soybeans. Substitution toward more corn monoculture increases corn output, but lowers corn yield, thereby causing a smaller increase for corn than reduction in soybeans.

For two- and three-year crop histories, the results are more varied. These varied responses connect to the discussion above about the benefits of corn monoculture on subsequent soybean yields. Since one-year maximizers and always-rotate outcomes are, almost by definition, similar to the one-year history case, the interesting results are those for two-year and infinite-horizon objectives. These objectives give somewhat different planting rules than the one-year history case and also have different supply elasticities,

Table 10. Long-Run Supply Elasticities to Corn Price Change

	One-Year Crop History				Two-Year Crop History				Three-Year Crop History			
Fertilizer Price:	*Fixed*		*Stochastic*		*Fixed*		*Stochastic*		*Fixed*		*Stochastic*	
Crop:	Corn	Soybean	Corn	Soybean	Corn	Soybean	Corn	Soybean	Corn	Soybean	Corn	Soybean
	(%Δ Production/%Δ Corn Price)											
Objective	*Risk Neutral*											
One-Year	1.96	−2.24	2.55	−2.34	2.46	−2.26	1.76	−1.34	2.54	−2.57	2.00	−1.69
Two-Year	0.11	−0.0002	0.13	−0.04	0.31	−0.20	0.61	−0.52	0.15	−0.03	0.17	−0.06
Infinite	0.13	−0.03	0.12	−0.02	1.42	−1.10	0.98	−0.78	0.94	−0.89	0.47	−0.43
Always Rotate	0.11	0	0.11	0	0.11	0	0.11	0	0.12	0	0.11	0
	Risk Averse											
One-Year	2.30	−2.67	1.47	−1.59	2.43	−2.19	1.96	−1.53	2.31	−2.29	2.60	−2.29
Two-Year	0.12	0.0005	0.14	−0.03	0.39	−0.27	0.72	−0.60	0.19	−0.05	0.19	−0.08
Infinite	0.14	−0.03	0.13	−0.02	1.43	−1.10	1.04	−0.83	1.22	−1.20	0.48	−0.42
Always Rotate	0.12	0	0.11	0	0.12	0	0.11	0	0.13	0	0.12	0

Note: Long-run supply elasticities are calculated by comparing average plantings and yield with and without a $20 per acre premium for corn. Define P_x as average percent corn plantings, Y_x^C and Y_x^S as average yield for corn and soybeans respectively, where $x=1$ is with price premium and $x=0$ is without. Each corn (own-price) elasticity is calculated as $(\log(P_1)+\log(Y_1^C)-\log(P_0)-\log(Y_0^C))/\Delta\log(\text{average price})$. Each soybean (cross-price) elasticity is calculated as $(\log(1-P_1)+\log(Y_1^S)-\log(1-P_0)-\log(Y_0^S))/\Delta\log(\text{average price})$. $\Delta\log(\text{average price})$ is calculated as $\log(R_0+20)-\log(R_0)$, where R_0 is the average corn revenue per acre without the price premium.

ranging from 0.3 to 1.5 for corn and −0.03 to −1.2 for soybeans. The larger magnitude elasticities are for the infinite-horizon model with fixed fertilizer prices with smaller elasticities for the two-year objective. With a two-year history and stochastic fertilizer prices, the elasticities are near the middle of these ranges for both two-year and infinite-horizon objectives. With a three-year history, the two-year objective again gives very inelastic responses regardless of whether fertilizer prices are fixed or stochastic, but for infinite-horizon objectives, responses are much more elastic when fertilizer prices are fixed rather than stochastic.

Comparison of Models to Observed Rotations

To test how different models predict actual planting decisions of individual farmers, we matched predictions conditional on historical state variables to actual rotations observed in the NRI data. For the models with fixed fertilizer price and one-year of crop history, all but one of the observations are in the rotation region of the state-space that lies between the two sets of threshold curves. The one exception (1975) is a year not observed in the NRI data, so all models predict the same planting behavior and have the same prediction accuracy (figure 4). Prediction accuracy is no better, and sometimes worse, in the model with stochastic fertilizer price (figure 5). It is mainly worse for naive, current-year maximizing farmers. Note that for this field-level model, always rotate turns out to have the best possible prediction accuracy, since this is the most frequent land use choice in every year, and we assume the same field-experiment-based productivity for all parcels. Prediction accuracy for two-year and three-year histories are similar to the one-year model.

While these results provide some illustration of the importance of rotation, there simply is not enough data to differentiate between models. To differentiate between models requires considerably longer time series to span the full distribution of prices and revenues. Other idiosyncratic factors, like early season moisture and ability to plant, presumably influence rotation decisions and might explain residual shortfall in predictive accuracy.

Discussion and Conclusions

This article develops a new dynamic model of crop planting decisions built around the agronomic benefits of crop rotations and price uncertainty. Where the effects of price uncertainty on planting decisions has long been a focus in agricultural economics, that traditional focus has been built primarily around a static model with risk aversion, wherein planting allocation decisions are

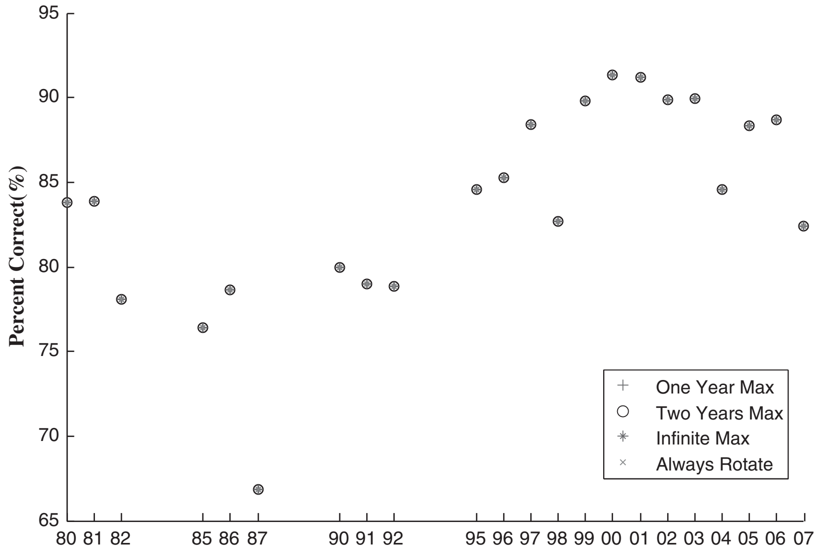

Figure 4. Prediction accuracy of fixed nitrogen fertilizer price models compared to NRI data

Notes: This graph summarized the prediction accuracy of different revenue maximization models given one year rotation history with no premium on corn price and fixed nitrogen fertilizer price. The prediction accuracy is almost the same for every model.

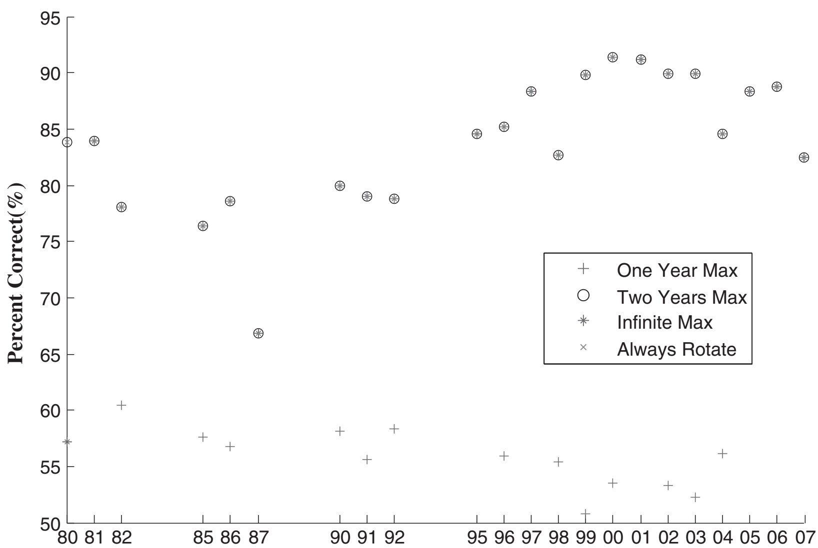

Figure 5. Prediction accuracy of stochastic nitrogen fertilizer price models compared to NRI data

Notes: This graph summarized the prediction accuracy of different revenue maximization models given one year rotation history with no premium on corn price and stochastic fertilizer price. The prediction results are the same for two year horizon models and always rotating models.

treated as a portfolio problem (Sandmo 1971; Feder 1980; Just and Zilberman 1983; Chavas and Holt 1990; Pope and Just 1991). In a static model with risk aversion, a farmer plants a mix of corn and soybeans to reduce profit risk, not because they are complements in a dynamic production process. In this traditional approach, the effect of uncertainty is driven by curvature of a utility function and a motive to diversify, not by production complementarities and option values associated with longer-run price uncertainty. While both the static portfolio approach and stochastic-dynamic views are likely important, there has been relatively little attention paid to the latter, and this article develops a first attempt to address that gap.

It may be interesting to note a fundamental difference between the portfolio/allocation and the option-value/rotation approach taken here: where effects of risk aversion in agriculture follow mainly from imperfect insurance markets, real option values exist even in perfect markets. A nearly obvious corollary of this observation is that an absence of monoculture does not constitute *prima facie* evidence of market failure. Indeed, within the context of rotational decisions, risk aversion appears to be of relatively minor importance for planting decisions and fertilizer applications.

Calibration of our model using data from experimental field trials, as well as historical price and yield data from Iowa, indicates a powerful incentive to rotate. Even in locations near ethanol plants, which are assumed to receive a $20 per acre premium for producing corn, the model shows farmers rotating nearly as often as farmers without such a premium. Indeed, always rotating with or without the premium is imperceptibly different from the optimal decision rule, at least when a single year of crop history is considered. This finding suggests highly inelastic supply response to both temporary (stochastically evolving) and permanent price shocks.

When we consider longer crop histories in the decision rules, the results are more varied and somewhat surprising. Although rotation remains the dominant outcome, the solution to the infinite horizon model looks closer to the naive (single-year maximizing) farmer than the always-rotating or two-year maximizing farmer. This result follows from an additional gain to soybean yields after two and/or three years of continuous corn. This additional gain does not show up when a single year of planting history is considered. As a result, farmers with a long planning horizon, like naive farmers, are more likely to deviate from corn-soybean rotation when corn prices are relatively high.

An interesting and potentially important observation for policy considerations is that the market does not harshly punish sub-optimal actors. Shortsighted farmers, who maximize only current-year or two-year profits, as well as those who always rotate, do nearly as well over the long run as fully forward-looking stochastic dynamic optimizers. At the same time, the different objectives and modeling assumptions can sometimes give markedly different decision rules in response to temporary and permanent price movements. Given remaining uncertainties about the agronomic benefits of rotations and the likelihood that farmers hold heterogeneous expectations about the future, a fairly wide range of supply responses might be rationalized by these results.

A potentially more interesting implication is that farmers who, for one reason or another, choose to plant corn after corn at any significant frequency, might be persuaded to always rotate with a fairly small incentive payment of $4 per acre or less. Such incentive payments could be desirable given water pollution and vast dead zones (e.g, Gulf of Mexico and Chesapeake Bay) have been linked to fertilizer from agriculture (Malakoff 1998; Donner and Kucharik 2008), which is predominantly corn. Always rotating would reduce corn plantings, fertilizer applications connected with corn plantings, and simultaneously reduce application rates on remaining corn acreage. In a similar vein, it might be interesting to consider the influence of a fertilizer tax on both planting decisions and application rates.

Our approach to modeling crop choice could otherwise be extended to consider subsidized crop insurance. At present, crop insurance premiums depend on a ten-year yield history but are not adjusted for past plantings, so that premiums are set too low if a farmer who typically rotates decides to plant corn after corn or soybeans after soybeans. Premiums would subsequently be too high if the farmer were to return to rotation. Such mispricing might discourage rotation in favor of monoculture, a potentially avoidable form of dynamic moral hazard (Vercammen and van Kooten 1994). By discouraging rotations, insurance might also encourage greater chemical use and lead to worse environmental outcomes. Horowitz and Lichtenberg (1993) found insurance increased chemical use if inputs were "risk-increasing." While we do find some limited evidence of this phenomenon in our model, perhaps a more natural explanation is substitutability of inputs (fertilizer and/or pesticides) with rotations that insurance might discourage.

There may also be implications for introduction of genetically modified seed with pest resistance, like Bt corn. Given adoption of genetically modified crops has grown simultaneously with corn ethanol production, and corn expansion has come at least partly at the expense of reduced soybean plantings, future research might investigate the degree to which these new seed varieties substitute for rotation benefits.

Future work might also consider a multiple-field setting. Because diversification would presumably be maximized or nearly so with an even split of corn and soybean plantings, and the present value of profits from always rotating is nearly optimal, the always-rotating rule of thumb would seem to nearly maximize both average profits and diversification, so long as the initial condition of the land was half corn and half soybeans. However, given corn and soybean returns are highly correlated, the risk-return tradeoffs may be subtle and likely small. Nevertheless, it may be interesting for future work to explicitly consider the portfolio problem simultaneously with rotations. Given the computational burden and limited stakes suggested by this article, we leave this inquiry for future research.

Supplementary Material

Supplementary online appendix is available at http://oxfordjournals.org/our_journals/ajae/ online.

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