Impacts of Federal Crop Insurance on Land Use and Environmental Quality

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Abstract

This paper integrates economic and physical models to assess how federal crop revenue insurance programs might affect land use, cropping systems, and environmental quality in the U.S. Corn Belt region. The empirical framework includes econometric models that predict land conversion, crop choices, and crop rotations at the parcel-level based on expectation and variance of crop revenues, land quality, climate conditions, and physical characteristics at each site. The predictions are then combined with site-specific environmental production functions to determine the effect of revenue insurance on nitrate runoff and leaching, soil water and wind erosion, and carbon sequestration. Results suggest that crop insurance will have small impacts on conversions of non-cropland to cropland, and somewhat more significant impacts on crop choice. These changes in crop mix have small impacts on agricultural pollution.

Key Words: Crop Insurance; Revenue Insurance; Crop Choice; Environmental Quality

JEL Codes: Q18, Q28,

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1. Introduction

The focus of federal agricultural policy has shifted from direct payments towards risk management, and federal crop insurance has become a cornerstone of U.S. agricultural policy (Woodard 2013). More than 265 million acres were enrolled in the crop insurance program in 2011, with $114 billion in estimated total liability. The corresponding costs to the federal government in 2011 were estimated at over $11 billion (Glauber 2013). The shift of agricultural policy focus continues with the Agricultural Act of 2014, which eliminates direct government payments and significantly expands crop insurance. The Act establishes the Supplemental Coverage Option (SCO), which provides additional protection to producers of covered commodities beyond traditional crop insurance policies. It expands the Noninsured Crop Assistance Program (NAP) to allow additional "buy-up" coverage above catastrophic loss levels. There has never been a farm bill with such a robust crop insurance program combined with price-sensitive commodity programs (Olen and Wu 2014).

Crop insurance alters producers' incentives in two broad ways. First, premium subsidies based on the "fair" premium, by definition, add to expected revenue for crop production. As such, subsidized crop insurance may create incentives for farmers to expand crop production to marginal lands. Second, crop insurance reduces the riskiness of growing covered crops relative to other crops, thus potentially affecting farmers' choice of land use, crop mix, input use (Wu 1999; Goodwin et al. 2004; Babcock and Hennessy 1996; Young et al. 2001; Goodwin and Smith 2013; Walters et al. 2012).

Changes in land use and crop mix under crop insurance could lead to unforeseen secondary effects on environmental quality. Converting grassland to crop production may mean increased use of fertilizers, pesticides, and other chemicals in vulnerable areas, thus potentially leading to additional runoff and water pollution. Changes in crop mix towards more erosive and chemical-intensive crops, such as from hay to corn, may also lead to increased runoff and leaching and water contamination (Goodwin and Smith 2003). On the other hand, if riskier crops have less damaging environmental effects, insurance-induced crop mix changes could improve environmental outcomes. However, the extent to which changes in federal crop insurance policy may affect land use and crop mix, as well as the magnitude of the accompanying environmental impacts, is not clear (Walters et al. 2012).

In this paper we integrate economic and biophysical models to examine the potential effects of federal crop insurance on land use and cropping patterns, as well as the resulting impacts on environmental quality in the U.S. Corn Belt region (Ohio, Illinois, Indiana, Iowa, Missouri). The region accounts for over one third (35%) of total liability in the U.S. crop insurance program (USDA Risk Management Agency 2013). We estimate a set of latent class logit models (LCL) to assess the effects of federal crop insurance programs on farmers' major land use decisions (e.g., pasture vs. crop production), crop choices (e.g. corn vs. soybeans or wheat), and crop rotations (e.g. continuous corn vs. corn-soybean) in the Corn Belt. These models link land use and crop choices on individual parcels to the means, variances, and covariances of revenues from alternative crops, production costs, land characteristics of the parcel, weather conditions at the parcel, and rotational constraints. We estimate these models using data from the National Resources Inventories (NRI), the most comprehensive data on private land use ever collected in the United States. We use the estimated land use and crop choice models to simulate the effect of federal crop insurance on major land use, crop choices, and crop rotations in the region. Finally, we link the land use models with physical models to estimate the effect of crop insurance on soil erosion, nitrate runoff and leaching, and soil carbon sequestration.

Our results suggest that the most significant impacts of federal crop insurance in the study region would be on crop choice and therefore on crop rotation patterns, whereas the effects on conversion from non-cropland to cropland would be small. Changes in crop rotation patterns, in turn, will have modest detrimental effects on environmental quality.

Several previous studies have examined the effects of the federal crop insurance on land use without examining its potential environmental impact. Wu and Adams (2001) examine the relationship between production risk, cropping patterns, and alternative revenue insurance programs in the Corn Belt. Young et al. (2001) examine the nationwide market impacts of crop insurance by simulating changes in acreage, production, price, and net returns induced by crop insurance. Most previous studies find statistically significant but modest impacts of crop insurance participation on crop acreage allocations. For instance, Young et al. (2001) report that subsidized crop insurance leads to an increase of only about 0.4% in total crop acreage. Similarly, Goodwin et al. (2004) find that even in their most extreme scenario (a 30% drop in insurance premiums), corn acreage increases by only 0.3 - 0.5%.

Some previous studies have considered the environmental effect of federal crop insurance programs. Most of these studies focus on the effect of crop insurance on chemical application rates without examining its effect on crop mix and land use (Babcock and Hennessy 1996; Young et al. 2001; Chambers and Quiggin 2002; Coble et al. 1997). Wu (1999) examines the effects of crop insurance on cropping patterns and chemical use in the Central Nebraska Basin and finds that providing crop insurance for corn will shift land from hay and pasture to corn, which will lead to increased chemical use at the extensive margin. This extensive effect dominates the effect of insurance on the chemical application rate, leading to an increase in total chemical use. Goodwin et al. (2004) use a structural model of acreage, insurance and conservation program participation, and input usage decisions to examine the effects of increased participation in crop insurance programs in the Corn Belt and Upper Great Plains, including the effect on chemical use. Goodwin and Smith (2003) develop econometric models to estimate the effect of crop insurance programs on soil erosion and find no large measurable increases in erosion as a result of increased insurance participation. Walters et al. (2012) is the closest in spirit to this paper. They first use producer-level data from Iowa, North Dakota, Washington, and Colorado to estimate crop acreage share equations for major insured crops or crop groups and then use the APEX (Agricultural Policy – Environmental Extender) model to simulate effects of crop share changes on several measures of environmental degradation. They find modest effects of insurance on crop choice as well as small, positive and negative, environmental effects of changing cropping patterns. Walters et al. (2012), however, does not explicitly explore separate effects of insurance on the amount of land converted to crops from other uses and, given the amount of cropland, the impact on crop choice. It also does not account for crop rotation patterns and the limitations imposed by these patterns on crop choice, or the distinct environmental effects of different crop rotations.

This paper contributes to this literature by integrating economic models of land use and crop choice with physical models of environmental quality indicators to examine the environmental impacts of insurance. We examine how risk affects both the land allocation between crop and non-crop uses, including participation in the Conservation Reserve Program (CRP), and, conditional on land use, the crop choice decision. In contrast to most previous studies, which use county-level data, we conduct our analysis using fine-scale parcel-level land use and crop choice data. Our model also accounts for crop choice history, thus allowing us to explicitly simulate specific crop rotation choices. This is an important aspect of the crop choice decision and its environmental consequences have not been addressed in existing models. Simulated crop rotations are then combined with environmental production functions to assess the effect of federal crop insurance on nitrogen runoff and leaching, soil carbon loss, and soil erosion.

In the next section we describe the empirical model and approaches for estimating the land use models. Section 3 describes the data and variable construction. Section 4 presents and discusses the results from the land use and crop choice models. Section 5 presents the simulation framework for the land use and crop choice impacts of crop insurance and discusses the results of the simulation. Section 6 discusses the environmental impacts. Finally, section 7 concludes.

2. The Empirical Model

Consider a landowner who makes land use decisions to maximize utility. Land use decisions may involve major land uses and crop choices. Major land uses include whether to allocate a parcel to crop production or a non-crop use such as pasture, or enrolling the parcel in the Conservation Reserve Program (CRP) if it is eligible. If a parcel is allocated to crop production, the landowner must decide which crop to grow. Suppose a landowner can choose among *n* crops, with $i \in C \equiv \{c_1, c_2, \ldots, c_n\}$ indicating the crop choices, and $i \in M \equiv \{m_1, m_2, \ldots, m_K\}$ indicating K non-crop alternatives. For each use, utility is a function of variables affecting the expected net returns and risk:

(1) $$U_{ijt} = X'_{ijt}\beta_i + \varepsilon_{ijt}, \quad i \in M \cup C,$$

where U_{ijt} is the utility from land use *i* on parcel *j* in year *t*; β_i is a vector of parameters; X_{ijt} is a vector of variables measuring the expected net returns and risk for land use *i* on parcel *j* in year *t*; and ε_{ijt} is a random error term. If the errors ε_{ijt} follow the *i.i.d.* extreme value distribution, the probability that utility for land use *j* exceeds that for other land uses equals

$$L_{ijt} = \frac{e^{X'_{ijt}\beta_i}}{\sum_{k \in M \cup C} e^{X'_{kjt}\beta_k}}, i \in M \cup C. \tag{2}$$

For estimation purposes, it is convenient to rewrite the probability as follows:

(3) Major land use: $$L_{ijt} = \frac{e^{X'_{ijt}\beta_i}}{1 + \sum_{k \in M} e^{X'_{kjt}\beta_k}}, \; i \in M$$

(4) Crop choices: $$L_{ijt} = L_{jt}(i \mid i \in C) \times L_{jt}(i \in C) = \frac{e^{X'_{ijt}\beta_i}}{\sum_{k \in C} e^{X'_{kjt}\beta_k}} \times \frac{1}{1 + \sum_{k \in M} e^{X'_{kjt}\beta_k}}, \; i \in C.$$

This decomposition is convenient as it means that we can separately study the major land use decision (crop vs. noncrop) and the crop choice decision (which crop to grow, conditional on the parcel being allocated to crop production).

Most previous land use studies estimate models like (3) or (4) as a multinomial logit (MNL) or conditional logit (CL) model (Lichtenberg 1989; Wu and Segerson 1995; Hardie and Parks 1997; Plantinga, Mauldin, and Miller 1999; Wu et al. 2004; Langpap and Wu 2012). An often-cited limitation of MNL or CL is the assumption of independence of irrelevant alternatives (IIA). This assumption is convenient for estimation, but not legitimate if there are omitted variables in estimation, as omitted variables correlated across choices may result in its violation (Train 2009).

In this paper, we follow Claassen et al. (2013) to estimate equations (3) and (4) as random parameter models to overcome the IIA problem. When parameters follow parametric distributions (and are constant across all observations for a specific parcel), the probability of the observed sequence of land uses choices at parcel *j* is:

(5) $$P_j = \int \left(\prod_t L_{ijt}(b) \right) f(b) db,$$

where $b = (b_{m_1},...,b_{m_K};b_{c_1},...,b_{c_n})$, and $f(b)$ is the density function of b.

To specify random parameters using empirical distributions, we use a latent class logit model (LCL) solved via an expectation-maximization (EM) algorithm (Train 2009). LCL allows us to fully relax IIA without splitting the data and estimating multiple models, as in Lubowski, Plantinga, and Stavins (2008) and Rashford, Walker, and Bastian (2010), or determining how land uses should be nested, as in Gardner, Parks, and Hardie (2010). In the LCL model each individual is assumed to belong to a given class, although class membership is not observed. Classes represent groups of relatively homogenous individuals (in terms of behavior) or parcels of land (in terms of unobservable attributes) and each class has its own set of parameters. Heterogeneity in response to economic or policy change is captured by class membership and class-specific parameters. The probability of class membership is estimated unconditionally (as the probability that any given individual belongs to class *c*) for individual parcels, conditional on the observed choices, although the number of classes is selected by the researcher.

Suppose each land parcel falls into one of *L* classes. The probability of the observed sequence of land use choices at parcel *j* is:

(6) $$P_j = \sum_l \left(s_l \prod_t L_{ijt}(b_l) \right),$$

where s_l is the probability that any given parcel belongs to class *l*.

Maximizing the LCL likelihood function using standard techniques can be difficult. Train (2009) suggests maximizing the likelihood function via the expectation-maximization (EM) algorithm. The EM algorithm is a method of computing maximum likelihood estimates from incomplete data, e.g., unobserved class membership (Dempster et al. 1977). Repeated maximization of a specific expectation, which is closely related to the log-likelihood function, converges to the maximum of the log-likelihood function. For the LCL model, Train (2009) shows that the expectation to be maximized is:

(7) $$\varepsilon(s, \beta) = \sum_l \sum_i h_{il} log\left(s_l \prod_t L_{ijt}\left(X_{ijt}; \beta_l\right)\right),$$

where h_{il} is the observation-specific probability that parcel *i* belongs to class *l*:

(8) $$h_{il} = \frac{s_l \prod_t L_{ijt}(X_{ijt};\beta_l)}{\sum_{l'} s_{l'} \prod_t L_{ijt}(X_{ijt};\beta_{l'})}\,.$$

Claassen et al. (2013) provide a detailed description of the EM algorithm. Specifically, starting values are calculated by randomly dividing the sample into *L* parts. The initial class probabilities are equal to 1/*L*. Starting values for each set of class-specific parameters are estimated by conditional logit using the data assigned to each of *L* subsets. The initial parcel- and class-specific weights are calculated using (8). The class probabilities, parameter vectors, and the parcel- and class-specific weights (h_{il}) are updated sequentially until they converge (do not change with several updates). The class probabilities are updated using the parcel- and class-specific weights. The variance-covariance matrix and the marginal effects are given in the appendices A and B, respectively.

To determine the number of classes (and, implicitly, the number of parameters) to be used in an LCL model, Pacifico and Yoo (2013) recommend using the Bayesian Information Criterion (BIC) or the Consistent Akaike's Information Criterion (CAIC). BIC and CAIC are related to AIC, but use penalty functions that increase more rapidly as the number of model parameters increases. Specifically, AIC $= -2lnL + 2m$, were lnL is the log-likelihood and m is the total number of estimated parameters, while BIC $= -2lnL + mlnN_i$ and CAIC $= -2lnL + m(1 + lnN_i)$, where N_i is the number of individuals or (in our case) parcels of land, each of which may have repeated observations. Different criteria sometimes support different models, leading to uncertainty about which criterion is the most trustworthy (Dziak et al. 2012). In our application, both criteria lead to the same model, as shown below.

3. Data and Variable Construction

The land use and crop choice models require a substantial amount of data for estimation, which must be integrated from multiple sources. These data include land use and crop choices, expected returns and variance of returns to alternative crops, and land characteristics (soil properties, topographic features, climate conditions). In this section we describe the data sources and construction of the variables used to estimate the models.

The annual, parcel-level data on land use and crop choices from 1997 to 2010 were obtained from the Natural Resources Inventories (NRI). NRI inventories are conducted by the USDA Natural Resources Conservation Service (NRCS) to determine the status, condition, and trend of the nation's soil, water, and related resources. Information on land use, land quality and many other attributes was collected at more than 800,000 points at 5-year intervals beginning in 1982. For a subsample of roughly 110,000 “core” points, annual land use observations are available for 1997-2010. Our dataset, which is limited to the Corn Belt states (Illinois, Indiana, Iowa, Missouri, and Ohio) and excludes counties (mostly in Southern Missouri) that lack data on crop yields, includes 7,787 NRI points and a total of 97,929 observations, or on average roughly 12.4 observations per NRI point. One observation is lost on every point because the previous year land use is an explanatory variable; other observations are lost because of missing or incomplete information. Roughly 75 percent of land is in crop production, 18 percent in pasture, and 7 percent is in CRP. Each NRI site was assigned a weight to indicate the acreage it represents.[1] The sampling design ensures that inferences at the national, regional, state, and sub-state levels can be made in a statistically reliable manner.

3.1. Mean and variance of net returns to alternative land uses

The key explanatory variables for our major land use model are the expected net returns and variance of net returns to alternative land uses in the region. Net returns to crop production are estimated as the difference in revenue and operating costs. Specifically, expected net crop return is the acre-weighted average revenue less operating cost for four crops: Corn, soybeans, wheat, and hay.

$$E(R_{ct}) = \sum_i w_{it}(E(G_{it}) - C_{it}), \tag{9}$$

where $E(G_{it})$ is expected gross revenue for crop *i* at time *t*, C_{it} is operating cost for crop *i* at time *t*, and w_{it} is the acreage weight for crop *i* at time *t* and is derived from a rolling average of acreage in the three most recent years: $w_{it} = \frac{\bar{A}_{it}}{\sum_j \bar{A}_{jt}}$, where $\bar{A}_{it} = (A_{i,t-1} + A_{i,t-2} + A_{i,t-3})/3$, and $A_{i,t-1}$ is the number of acres in crop *i* at time *t*-1. For example, acreage weights for 2005 were derived from average acreage for 2002-04.

Crop revenue variance is based on the variances for individual crops and covariance across crops:

$$V(R_{ct}) = \sum_i \sum_j w_{it} w_{jt} V\left(G_{it}, G_{jt}\right), \tag{10}$$

where $V\left(G_{it}, G_{jt}\right)$ is the covariance between gross revenue for crops *i* and *j*.

[1] For example, the sum of weights at all NRI sites planted to corn gives an estimate of corn acreage in the region.

The only pasture rental rate data available going back to the mid-1990s are at the state level. Even with state data, data for Indiana and Ohio had to be imputed for some years. Missing rents were imputed by calculating the ratio of rents in Indiana and Ohio to the average rent for Illinois, Iowa, and Missouri for years when data are available. For both states the ratio is 1.2. For years when data are not available for Ohio and Indiana, pasture rents are imputed as 1.2 times the average rent for Illinois, Iowa, and Missouri.

To approximate county-level rates, county average hay revenue is used as an indicator of county-level variation in forage revenue on pastureland. Ideally, these variations would be based on grass (non-alfalfa) hay, but the only reliable county-level data is for total hay production.

$$E(R_{pt}) = R_{spt}\left(1 + \frac{E(G_{ht}) - \bar{G}_{ht}}{\bar{G}_{ht}}\right) \tag{11}$$

where R_{pt} is the estimated county-level pasture rental rate for year t; R_{spt} is the state-average pasture rental rate in year t; $E(G_{ht})$ is county-average expected gross revenue for hay in year t (based on 5-year Olympic average yield (high and low yield removed) and a three year average (state-level) price); $\bar{G}_{ht}$ is the state average expected gross revenue for hay (state average of $E(G_{ht})$).

The variance of pasture return is also based on variance of hay revenue:

$$V(R_{pt}) = \frac{R_{spt}^2}{\bar{G}_{ht}^2} V(G_{ht}) \tag{12}$$

where $V(G_{ht})$ is the county-level variance of hay revenue.

A government program that has a major effect on agricultural land use is the Conservation Reserve Program (CRP). Under the CRP, farmers convert environmentally sensitive land to resource-conserving covers, such as native grasses, trees, and filter strips. In return, they receive an annual rental payment from the government for a contract period of 10–15 years. CRP enrollment reached its historical high of 36.8 million acres in 2007, and declined to 24.2 million acres in 2014, at an annual cost of $1.8 billion. At the end of fiscal year 2010 (September 30, 2010) there were 4.68 million acres of land enrolled in CRP in the five Corn Belt states (Illinois, Indiana, Iowa, Missouri, and Ohio) and a total of 26.66 million acreage nation-wide.

As a measure of return to Conservation Reserve Program (CRP) participation, we use the county-average Soil Rental Rate (SRR) used by the Farm Service Agency (FSA) in establishing CRP annual payments.[2] Because annual CRP payments are fixed, the variance of CRP net return is zero.

The NRI data captures only "General Signup" CRP enrollments. Under General Signup, landowners can enroll whole fields or whole farms for a period of 10-15 years. In 2007, at the peak of CRP acreage enrollment, general signup accounted for 91 percent of CRP acreage; in 2010, general signup still accounted for 83 percent of land in CRP.[3] General Sign-up enrollment was available only on land meeting eligibility criteria and only in years when the USDA enrolled land under General Signup. To be eligible for CRP enrollment, land must (1) have been previously in crop production or enrolled in CRP and (2) be highly erodible or located in a CRP-designated conservation priority area. Based on the timing of signup periods, little or no land entered the CRP through continuous signup in 2002, 2003, or 2008-10 (land enters CRP on

[2] FSA uses a soil productivity indicator to adjust the county average SRR to field-specific conditions. We use the county average SRR because it is consistent with our use of county data to represent crop and pasture returns. We use site-specific data on soil quality and topography to account for intra-county variation in returns to land.

[3] The balance of CRP enrollment is based on Continuous Signup which largely supports the adoption of "partial field" practices including filter strips, riparian buffers, grass waterways and other "buffer" practices. These practices require very little land compared to the whole fields or farms enrolled through General Signup. For more information see the FY2010 CRP annual summary report available at https://www.fsa.usda.gov/Internet/FSA_File/annual2010summary.pdf.

October 1, so land that we observe "entering" CRP in 2002 was actually enrolled on October 1, 2001.)

3.2. Mean and variance of revenue from individual crops

To estimate the mean and variance of returns to individual crops, we need to estimate yield and price distributions. Yield distributions are based on NASS county average yields. For corn, soybeans, wheat, and hay, the expected yield for crop $i, E(y_i)$, is an Olympic average of yields for the most recent five years (the average with the high and low values removed). Yield deviations are the difference between the observed yields and a linear trend fitted using yields for the most recent 22 years:

(13) $$\Delta y_{iz} = (y_{iz} - y_{iz}^T) / y_{iz}^T ,$$

where Δy_{iz} is the yield deviation in year *z*, y_{iz} is the realized yield, and y_{iz}^T is the trend yield.

Because farm-level yield variation is typically larger than the variation in county-average yields, the county yield deviations are inflated using crop insurance actuarial data. Following Coble, Dismukes, and Thomas (2008), the absolute value of the yield deviations are increased by a constant multiplier until expected losses based on a yield guarantee of 65 percent, equal yield-based crop insurance premium rates for 65 percent coverage. The yield distribution vector for crop *i* denoted $\hat{y}_i$, contains *Z* elements (one element for each of the past yields used to derive the distribution) are defined as:

(14) $$\hat{y}_{iz} = E(y_i)(\alpha_i \Delta y_{iz} + 1) ,$$

where α_i is the inflation factor, which is chosen so that:

(15) $$\min_{\alpha_i}\left\{\left(\omega(\bar{y}_i) - Z^{-1}\sum_z \max\left(\frac{(0.65\bar{y}_i - E(y_i)\alpha_i \Delta y_{iz})}{0.65\bar{y}_i}, 0\right)\right)^2\right\},$$

where $\omega(\bar{y}_i)$ is the premium rate for 65 percent coverage (excluding the fixed rate load), calculated from RMA county actuarial data for 2010 and $\bar{y}_i$ is the average county yield for 2002-2011 (the APH yield for the representative farm). The first terms in the bracket ($\omega(\bar{y}_i)$) is the expected loss based on the crop insurance continuous rating model and the second term is the expected loss given 65 percent coverage, yield deviations calculated from county yield data, and the variance inflation factor, α_i .

Price distributions are based on futures market and cash price data. Expected prices for corn, soybeans, and wheat are planting time prices for the harvest month futures contract. For example, the expected price of corn is the average of daily closing prices in February for the December CME Group corn contract. The realized price is the average of daily closing prices during October for the CME Group December corn contract. Expected and realized soybean prices are based on the February and October prices, respectively, for the December CME Group soybean contract. For winter wheat, expected and realized prices are based on August 15-September 14 and June prices, respectively, for the Kansas City Board of Trade (KCBOT) July contract. For hay, expected prices are an average of state-level prices for the previous three years.

The price distribution vector for crop *i* at time *t*, denoted $\hat{p}_{it}$, contains *Z* elements defined as:

(16) $$\hat{p}_{iz} = E(p_i)\left(\Delta p_{iz} + 1\right),$$

where $E(p_i)$ is the expected price, $\Delta p_{iz} = \dfrac{p_{iz} - E(p_{iz})}{E(p_{iz})}$ is the price deviation, and p_{iz} is the realized price. Each element of the price distribution is adjusted for expected basis, estimated as the 5-year average difference between the harvest month futures price (October for corn) for a post-harvest futures contract (December for corn) and the harvest month cash price (October for corn). To approximate local cash prices, each element of price distribution vector is multiplied by the ratio of the county crop loan rate to the national average loan rate.

The revenue distribution vector for crop *i* contains *Z* elements defined as $\hat{G}_{iz} = \hat{p}_{iz}\hat{y}_{iz}$. Expected revenue is:

(17) $$E(G_i) = Z^{-1}\sum_z \hat{G}_{iz}.$$

Revenue variance/covariance is

(18) $$V(G_{ij}) = Z^{-1}\sum_z \left(\hat{G}_{iz} - E(R\hat{G}_{iz})\right)\left(\hat{G}_{jz} - E(\hat{G}_{jz})\right).$$

3.3. Variables capturing differences among parcels

The most detailed data available for measuring the mean and variance of net returns and revenue are at the county level. To capture the differences in mean and variance of net returns and revenue among NRI sites, we include several physical variables reflecting both land quality and weather condition at individual sites. Slope is a continuous variable measured as a percentage. High quality land is a dummy variable set equal to one if the parcel has a land capability class of 1 or 2, and set equal to zero otherwise. Similarly, low-quality land is a dummy variable set equal to one if a site has a land capability class above 4, and set to zero otherwise.

We also control for the effect of weather on land use and crop choices. We use historical weather data from weather stations across the study region, which were obtained from the

Midwestern Climate Center. For each NRI site, we used data from the nearest weather station to estimate the mean and standard deviations of maximum daily temperature as well as means and standard deviations of precipitation during the corn and wheat growing seasons.[4] To capture rotational constraints we include dummy variables indicating the crop grown on the site in the previous year.

3.3. The effect of federal crop insurance

The effect of federal crop insurance on expected revenue and revenue variance is estimated by adding estimated net indemnity to crop revenue for each point, *z*, in the empirical distribution. Farmers can choose from a wide range of insurance products, although a handful of products dominate the market for major crop commodities. In recent years the most common is Revenue Protection (RP), which covers producers against yield loss, intra-season price declines, or intra-season price increases (the revenue guarantee is based on the higher of the base (planting time) price or the harvest-time (realized) price). The RP indemnity is:

$$I_{i,RP,z} = \max((\theta \max(\hat{p}_{iz}, p_i^b) y_i^{aph} - \hat{p}_{iz}\hat{y}_{iz}), 0) \quad , \tag{19}$$

where θ is the coverage level selected by the producer, p_i^b is the Risk Management Agency base price (we use this as the expected price), and y_i^{aph} is the farm's Actual Production History (APH) yield.

We assume that crop insurance is actuarially fair, as required by law, so the total premium equals the expected indemnity.[5] Premium subsidies depend only on the coverage level

[4] Because the long-run average of weather conditions changes little over time, farmers' expectations of weather conditions were assumed to be constant and were represented by the averages of the means and variances of temperatures and precipitation during the corn and wheat growing seasons from 1975 to 1994.

[5] There is evidence that premiums are higher than actuarially fair for some producers while they are lower than actuarially fair for others. Glauber (2004), Babcock (2008), and Woodward et al. (2011) all note that losses are consistently larger in the Great Plains when compared to the Corn Belt. Across crops, regions, and time, however,

selected by producers. So the crop insurance indemnity, net of the producer-paid premium, is specified as

(20) $$N = I_{iq} - (1-\gamma(\theta))E(I_{iq}),$$

where I_{iq} is the indemnity paid for crop *i* and insurance product *q* and $\gamma(\theta)$ is the premium subsidy rate. We also model revenue protection insurance with the harvest price exclusion, yield protection policies, and catastrophic coverage.

For each county in our data, the share of each crop covered by each of these four crop insurance products and the associated coverage level is based on Risk Management Agency county-level Summary of Business data. Insured acreage reported by RMA is compared to crop acreage data collected by the National Agricultural Statistics Service (NASS) to determine the level of uninsured acreage. We assume that each farm's insurance purchases reflect the county-level mix of insurance products. Coverage levels for each product represent the most popular coverage level (by county and year) for each product modeled. These assumptions ensure that our revenue estimate reflect shift in the crop insurance market during the study period (1997-2010). During this period, farmers shifted from traditional yield products, to revenue products, and, in recent years, to revenue products that also insurance against intra-season price declines (e.g., Revenue Protection). The summary statistics for all variables used in the analysis are presented in Table 1.

4. Results for Land Use and Crop Choice Models

We start by discussing results for the major land use models and then focus on the crop choice models.

total crop insurance premiums exceeded indemnities, with an average loss ratio of 0.88 for 1995-2007 (Woodward et al. 2011).

4.1. Major land use models

As already noted, some parcels are eligible for the CRP and others are not. Even on eligible parcels, General Signup enrollment was not available in every year of our study period. Thus, we estimate two major land use models. One is a three-alternative LCL model (crop, pasture, CRP) for CRP-eligible NRI sites and years when eligible land could have entered CRP under General Signup. The other model is a simple logit model (crop or pasture) for NRI sites that are ineligible for the CRP and for all NRI sites during years when land could not have entered the CRP through General Signup.

For the LCL model for NRI sites eligible for the CRP, information criteria reported in Table 2 supports a two latent classes logit model. The estimates of elasticities for the two latent classes model with respect to changes in net returns and variance of net returns to alternative land uses are reported in Table 3. The estimated coefficients are reported in appendix C. It is noteworthy that all own-net return elasticities are positive and cross-net return elasticities are negative. In addition, all own net-return-variance elasticities are negative and all cross net-return-variance elasticities are positive. These results suggest that landowners respond to increasing return or decreasing risk for a land use by increasing land allocation to the use and decreasing land allocation to other uses.

The class-conditional elasticities indicate that there are considerable differences between the two classes in their response to changes in expected net returns or variance of net returns. Specifically, class 1 landowners are much less responsive to changes in the economic variables than class 2 landowners. For example, a 1% increase in the net return to crop production will increase the probability of a parcel being allocated to crop production by 0.154% for class 1 landowners, compared with 0.232% for class 2 landowners. On the other hand, if the variance of net return for crop production goes up by 1%, the probability that a parcel is used for crop production decreases by 0.038% for class 1 landowners, compared with 0.034% for class 2 landowners.

The results for the crop-pasture logit model for NRI sites ineligible for the CRP are reported in Table 4. Both the elasticities with respect to the expected net returns and variance of net returns have signs consistent with economic theory. Compared with land parcels eligible for CRP, land parcels ineligible for CRP are less responsive to changes in the economic variables on average.

4.2. Crop choice model

Results for the LCL crop choice model are reported in Tables 5-7. Specifically, Table 5 reports the information criteria, which support a LCL model with six classes. Table 6 reports the unconditional elasticities of crop choices with respect to changes in the expected revenue and variance of revenue for alternative crops. The coefficient estimates are reported in the appendix.

Consistent with economic theory, all own-revenue elaticities are positive, and all cross-revenue elasticities are negative. In addition, all own revenue variance elasticities are negative, while cross-variance revenue elasticities are positive. These results suggest that an increase in the expected revenue for a crop increases the likelihood that the crop is planted, and decreases the likelihood that other crops are planted. In contrast, the own revenue variance elasticities are negative and cross revenue variance elasticities are positive, suggesting that more variability in revenues for a crop reduces the likelihood that the crop is planted, but increases the likelihood that other crops are planted. For example, a 1% increase in the expected revenue for corn increases the probability of a cropland parcel being allocated to corn by 0.974%, and decreases the probability of a cropland parcel being allocated to soybeans by 0.664%, to wheat by 0.031%, and to hay by 0.055%. On the other hand, if the variance of revenue for corn goes up by 1%, the probability that a cropland parcel is used for corn decreases by 0.147%, but the probability that a cropland parcel is used for soybeans, wheat and hay increases by 0.063%, 0.008% and 0.009%, respectively.

The results indicate that the probabilities of crop choices are generally inelastic to changes in economic variables. These results are consistent with previous finding (e.g., Wu et al. 2004), and may be explained by agronomic (rotational) constraints and the relatively few crops grown in the study region.

5. The Effect of Crop Insurance on Land Use

In this section we use the estimated land use and crop choice models to evaluate the impact of crop revenue protection insurance on land use and crop choice. We compare a no-insurance baseline with an insurance scenario by modifying the expected revenue and variance of revenue variables to reflect the effects of a revenue protection crop insurance plan. Specifically, we estimate the value of insurance using a simulation model in which the distribution of revenue or yield is truncated at the crop insurance guarantee level. We use expected revenue and variance of revenue from the truncated distribution to simulate the insurance case, and expected revenue and variance without the truncation to simulate the no-insurance case.

We establish land use and crop rotations at each NRI point in both scenarios using the following procedure. First, we use the data and the estimated coefficients for the land use choice models to predict the probability that each NRI parcel in our sample will be used for crops. Then we use these predicted probabilities and a random number generator to determine land use (crop, pasture, or CRP) at each parcel. Next, for the parcels designated as cropland, we use the data and the estimated coefficients from the crop choice model to calculate the probabilities of choosing alternative crops in the first baseline year. Based on these predicted probabilities, we again use a random number generator to determine crop choice at each NRI site in the first baseline year. Once the crop choice in the first year is determined, we repeat the process for a second and then a third year, because environmental impacts of land use depend on crop rotations rather than simply on crop choice. For example, a continuous corn rotation uses between 175% and 250% more nitrogen fertilizer than corn following soybeans. Similarly, the corn-corn-soybean rotation and the corn-soybean rotation may have different environmental impacts. Finally, based on the crop choices in the three baseline years, we determine the crop rotation at each NRI site. For example, if a choice of corn is predicted in each of the three years at a site, we have continuous corn at that site.

The land use and crop choice simulation results are presented in table 8. Results show land use (acreage in crop, pasture, and CRP), the three-year average of acres of the various crops, and total acreage of land in various crop rotations. The results indicate that revenue protection insurance would have small impacts on land use. Cropland acreage increases by only 0.18%, whereas pasture and CRP acreage decrease by 1.07% and 0.23%, respectively. This result is consistent with existing literature on the effects of crop insurance, which has found similarly small impacts on crop acreage (e.g. Young et al. 2001; Goodwin et al. 2004). The results suggest that the meaningful impact of crop insurance might be on crop choice and thus on crop rotations. The acreage of cropland devoted to continuous corn and continuous soybeans increases by 4.07% and 3.29%, respectively, whereas less land is planted with continuous wheat, which decreases by 14.4%.

6. Impacts of Crop Insurance on Environmental Quality

The changes in land use can in turn affect environmental quality. In this section we use environmental production functions to predict changes in agricultural externalities resulting from cropping changes induced by crop revenue insurance. The environmental production functions are estimated using a metamodeling approach (Wu and Babcock 1999).[6] For a sample of NRI points, the Erosion Productivity Impact Calculator (EPIC) (Sharpley and Williams 1990) is used to simulate environmental impacts based on crop management practices (crop rotation, tillage, and conservation practices), soil characteristics, and climatic factors at that site. Environmental production functions are then estimated by regressing simulated environmental data (e.g., measures of nitrate runoff and leaching) on the vector of crop management practices and site characteristics using appropriate econometric methods.[7] The estimated environmental production functions are then used to predict environmental impacts. These functions use the same information as the simulation model, but they eliminate the need to conduct model simulations for all input combinations, since they predict the outcome of such simulations (Wu et al. 2004). The nitrate runoff and percolation production functions are taken from Wu and Babcock (1999). The methodologies used to develop the erosion and carbon sequestration production functions, similar to those used in this analysis, are described in Lakshminarayan et al. (1996) and Mitchell at al. (1998), respectively.

The land use, crop choice, and environmental quality models described thus far collectively form an assessment framework. We apply this framework to evaluate how crop insurance might affect agricultural nonpoint source pollution in the Corn Belt. Levels of fertilizer

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[6] Metamodeling is required because it is not feasible to simulate environmental impacts at all sites and for all sets of conditions that arise in a large regional analysis such as performed here. Furthermore, metamodels simplify the analysis of changes in crop management practices because instead of conducting new simulations, regression coefficients can reveal how changes affect predicted outcomes.

[7] For example, Wu and Babcock (1999) use a generalized Tobit model to estimate the nitrate-N runoff and percolation production functions to account for heteroskedasticity and censoring problems.

and pesticide use are calculated using average application rates for each crop rotation and state (U.S. Department of Agriculture 1998). Then we substitute the predicted crop rotations and the corresponding level of nitrogen application at each NRI site for each of the two scenarios into the environmental production functions. This allows us to predict levels of nitrate runoff, nitrate percolation, soil water erosion, soil wind erosion, and carbon sequestration at each NRI site for the no-insurance and insurance scnearios. The site-specific measures of environmental impacts are aggregated to the entire sample using the expansion factor to facilitate presentation of the results. We compare the results under both scenarios to determine the impacts of crop revenue insurance.

The simulated environmental impacts are presented in table 9. The results suggest that changes in cropping patterns under crop insurance would have rather modest detrimental impacts on environmental quality in our sample area. The largest effect is on wind erosion, which is predicted to increase by 6.82%. Other impacts are small or negligible: nitrogen percolation is predicted to go up by 1.1%, and nitrogen runoff, loss of soil carbon, and water erosion are all predicted to increase by less than 1% with crop insurance. These results suggest that the environmental impacts of crop insurance in our study region are modest.

7. Conclusions

This study develops an empirical modeling framework to assess the effects of federal crop insurance on land use and agricultural non-point source pollution. We use econometric models to predict land use, crop choices, and crop rotations at the parcel level based on expectations and variances of agricultural revenues, as well as land quality, weather conditions, and other physical characteristics at each parcel. We then combine the data on crop rotations, nitrogen application rate, land quality and other physical characteristics with site-specific environmental production functions to determine the effect of crop revenue insurance on nitrate runoff and leaching, soil water and wind erosion, and carbon sequestration at each NRI site.

Our simulation suggests that crop insurance does not result in significant conversion of pasture or CRP land to cropland in the U.S. Corn Belt region. This result is consistent with the existing literature. Our results indicate that the more meaningful impact of revenue insurance will be on crop choice and therefore on crop rotation patterns. Total acreage of corn is predicted to increase by roughly 3%, whereas the amount of acres planted with wheat will decrease by about 16%. Accordingly, the acreage planted with most crop rotations involving corn increases, by about 4% for continuous corn and 9% for corn-corn-soybeans. On the other hand, acres of continuous wheat decline by as much as 14%. These changes in cropping systems will have small effects on agricultural runoff and environmental quality, with the largest predicted impact being a roughly 7% increase in wind erosion. In sum, we find that crop insurance has likely had small effects on land use, and modest impacts on crop rotation systems and therefore on environmental quality in the U.S. Corn Belt region.

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Table 1. Summary Statistics for the Explanatory Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Mean and variance of net return for major land uses					
Expected net return for crop production	24780	204.39	65.10	-2.29	441.89
Variance of net return for crop production	24780	4449.24	2599.26	402.91	20552.85
Expected net return for pasture	24780	32.38	7.03	14.89	52.16
Variance of net return for pasture	24780	45.44	30.83	2.73	183.32
Expected net return for CRP	24547	90.86	22.52	26.00	154.00
Variance of net return for CRP	24547	0.00	0.00	0.00	0.00
Mean and variance of revenue from alternative crops					
Expected corn revenue	77973	469.86	141.97	234.76	992.38
Variance of corn revenue	77973	13117.23	11560.73	1598.01	131318.60
Expected soybean revenue	77973	358.51	104.19	140.02	765.72
Variance of soybean revenue	77973	7312.78	5793.20	795.80	67622.82
Expected wheat revenue	77973	278.85	102.38	125.46	778.20
Variance of wheat revenue	77973	10664.32	10389.05	561.67	106451.40
Expected hay revenue	77973	398.28	117.51	110.90	824.09
Variance of hay revenue	77973	7560.87	5904.89	172.35	49827.98
Land quality and weather variables					
Goodland	77973	0.65	0.48	0.00	1.00
Badland	77973	0.03	0.16	0.00	1.00
Slope	77973	3.30	3.62	0.10	40.00
Mean of maximum temperature during corn growing season	77973	79.83	2.46	70.84	86.67
Mean precipitation during corn growing season	77973	0.13	0.02	0.04	0.19
Standard deviation of precipitation during corn growing season	77973	0.32	0.04	0.13	0.51

Mean precipitation during wheat growing season	77973	0.10	0.07	0.07	1.58
Standard deviation of precipitation during wheat growing season	77973	0.27	0.06	0.19	1.21
Dummy variables for previous year's crop					
Previous crop is corn	77973	0.41	0.49	0.00	1.00
Previous crop is soybeans	77973	0.39	0.49	0.00	1.00
Previous crop is wheat	77973	0.04	0.19	0.00	1.00
Previous crop is hay	77973	0.07	0.26	0.00	1.00

Table 2. Information Criterion for the Latent Class Logit Major Land Use Model

# Classes	BIC	CAIC	LL
2	***5,698.9***	***5,735.9***	***-2,697.9***
3	5,768.3	5,824.3	-2,654.7

Table 3. Estimates of Elasticities for the LCL Crop-Pasture-CRP Model

		Change in Net Return to:			Change in Return Variance:		
	Change in Probability:	Cropland	Pasture	CRP	Cropland	Pasture	CRP
Class-conditional Elasticities							
Class 1:	Cropland	0.154**	-0.009**	-0.046**	-0.038	0.0001	0
	Pasture	-0.718**	0.128**	-0.046**	0.172	-0.0019	0
	CRP	-0.718**	-0.009**	0.346**	0.172	0.0001	0
Class 2:	Cropland	0.371**	-0.029**	-0.094**	-0.034	0.0001	0
	Pasture	-2.161**	0.369**	-0.094**	0.187	-0.0020	0
	CRP	-2.161**	-0.029**	1.042**	0.187	0.0001	0
Unconditional Elasticities							
	Cropland	0.232**	-0.019**	-0.056**	-0.039	0.0001	0
	Pasture	-1.242**	0.213**	-0.056**	0.176	-0.0020	0
	CRP	-1.242**	-0.019**	0.605**	0.176	0.0002	0

** indicates p≤0.01; *indicates p≤0.05

Table 4. Estimates of Elasticities for the Crop-Pasture Logit Model

	Change in Net Return to:		Change in Variance of:	
Change in Probability:	Cropland	Pasture	Cropland	Pasture
Cropland	0.1782**	-0.0276**	-0.0249**	0.0002**
Pasture	-0.8242**	0.1137**	0.1181**	-0.0009**

** indicates p≤0.01; *indicates p≤0.05

Table 5. Information Criterion for the Latent Class Logit Crop Choice Model

# Classes	BIC	CAIC	LL
2	107,892.3	108,053.3	-53,681.3
3	104,530.9	104,637.9	-51,798.4
4	102,822.7	102,965.7	-50,787.2
5	101,924.9	102,103.9	-50,181.1
6	**101,539.6**	**101,754.6**	**-49,831.4**
7	*101,724.2*	*101.975.2*	*-49,766.6*

Table 6. Unconditional Elasticities for the Latent Class Logit Crop Choice Model

	Change in Revenue:				Change in Revenue Variance:			
Change in Probability:	Corn	Soybeans	Wheat	Hay	Corn	Soybea	Wheat	Hay
Corn	0.974**	-0.664**	-0.031	-0.055**	-0.147**	0.063**	0.008	0.009**
Soybeans	-1.036**	0.876**	-0.031	-0.055**	0.111**	-0.081**	0.008	0.009**
Wheat	-1.036**	-0.664**	1.136**	-0.055**	0.111**	0.063**	-0.200**	0.009**
Hay	-1.036**	-0.664**	-0.031	1.650**	0.111**	0.063**	0.008	-0.136**

** indicates p≤0.01; *indicates p≤0.05

Table 7. Class-conditional Elasticities for the LCL Crop Choice Model

	Change in Probability:	Change in Revenue:				Change in Revenue Variance:			
		Corn	Soybeans	Wheat	Hay	Corn	Soyb	Wl	Hay
Class 1:	corn	0.061*	-0.016	-0.003	-0.029	-0.039	0.007	0.002	0.011
	soy	-0.106	0.111*	-0.003	-0.029	0.055	-0.046	0.002	0.011
	wheat	-0.106	-0.016	0.095	-0.029	0.055	0.007	-0.073	0.011
	hay	-0.106	-0.016	-0.003	0.110*	0.055	0.007	0.002	-0.041
Class 2:	corn	1.122**	-0.808**	-0.022	-0.035**	-0.132**	0.069**	0.004	0.003**
	soy	-1.010**	0.823**	-0.022	-0.035**	0.120**	-0.072**	0.004	0.003**
	wheat	-1.010**	-0.808**	1.231**	-0.035**	0.120**	0.069**	-0.200**	0.003**
	hay	-1.010**	-0.808**	-0.022	1.752**	0.120**	0.069**	0.004	-0.138**
Class 3:	corn	0.199**	-0.088**	-0.012**	-0.053**	-0.112**	0.034**	0.009**	0.018**
	soy	-0.076**	0.123**	-0.012**	-0.053**	0.040**	-0.052**	0.009**	0.018**
	wheat	-0.076**	-0.088**	0.150**	-0.053**	0.040**	0.034**	-0.115**	0.018**
	hay	-0.076**	-0.088**	-0.012**	0.178**	0.040**	0.034**	0.009**	-0.067**
Class 4:	corn	0.726**	-0.353**	-0.122**	-0.053**	-0.168**	0.059**	0.038**	0.007**
	soy	-0.285**	0.420**	-0.122**	-0.053**	0.069**	-0.074**	0.038**	0.007**
	wheat	-0.285**	-0.353**	0.472**	-0.053**	0.069**	0.059**	-0.153**	0.007**
	hay	-0.285**	-0.353**	-0.122**	0.794**	0.069**	0.059**	0.038**	-0.125**
Class 5:	corn	1.421**	-0.945**	-0.053**	-0.129**	-0.113**	0.056**	0.007**	0.007**
	soy	-2.858**	2.328**	-0.053**	-0.129**	0.239**	-0.142**	0.007**	0.007**
	wheat	-2.858**	-0.945**	2.461**	-0.129**	0.239**	0.056**	-0.278**	0.007**
	hay	-2.858**	-0.945**	-0.053**	3.457**	0.239**	0.056**	0.007**	-0.190**
Class 6:	corn	1.352**	-0.953**	-0.057**	-0.010**	-0.333**	0.167**	0.018**	0.002**
	soy	-0.521**	0.480**	-0.057***	-0.010**	0.119**	-0.086**	0.018**	0.002**
	wheat	-0.521**	-0.953**	1.044**	-0.010**	0.119**	0.167**	-0.348**	0.002**
	hay	-0.521**	-0.953**	-0.057**	1.560**	0.119**	0.167**	0.018**	-0.252**

** indicates p≤0.01; *indicates p≤0.05

Table 8. Estimated Impacts of Crop Insurance on Land Use and Cropping Systems

	Baseline: No Insurance (1000 acres)	Insurance (1000 acres)	% Change
Land Use			
Acres of cropland	13,095	13,119	0.18%
Acres of pasture land	2,069	2,047	-1.07%
Acres of CRP land	750	748	-0.23%
Acres of corn (3 year average)	4,282	4,410	2.99%
Acres of soybeans (3 year average)	3,891	3,877	-0.36%
Acres of wheat (3 year average)	367	308	-15.90%
Acres of hay (3 year average)	661	618	-6.42%
Cropping Systems			
Continuous corn	2,278	2,370	4.07%
Continuous soybeans	1,670	1,725	3.29%
Continuous wheat	216	185	-14.40%
Corn-Soybeans	2,849	2,865	0.54%
Corn-Corn-Soybeans	502	549	9.41%
Corn-Soybeans-Wheat	2	1	-13.33%
Soybeans-Soybeans-Corn	512	461	-9.88%
Wheat-Soybeans	115	105	-8.81%
Corn-Corn-Hay	609	579	-4.96%

Table 9. Estimated Impacts of Crop Insurance on Environmental Quality

Indicator	Baseline: No Insurance	Insurance	% Change
Nitrogen Runoff (1000s lbs.)	484.26	488.58	0.89%
Nitrogen Percolation (1000s lbs)	885.29	894.99	1.10%
Loss of Soil Organic Carbon	873.22	873.49	0.03%
Wind Erosion (1000s tons)	6.97	7.45	6.82%
Water Erosion (1000s tons)	177.96	179.19	0.69%

Appendix A: Variance-Covariance Matrix for Latent Class Logit

The probability of land use i on parcel j at time t and, conditional on membership in class c is $P_{ijtc} = L_i(\beta_c; x_{jt})$, where $L_i(x_{jt}; \beta_c)$ is the logit function for land use i , x_{jt} is the vector of independent variables at time t and location j, and β_c is the parameter vector for class c.

Using the BHHH method to estimate VC matrix gives:

$$\mathrm{VC} = \begin{bmatrix} \frac{\partial\varepsilon}{\partial\beta_{ck}}\frac{\partial\varepsilon}{\partial\beta_{ck\prime}} & \frac{\partial\varepsilon}{\partial\beta_{ck\prime}}\frac{\partial\varepsilon}{\partial s_c} & \cdots & 0 & 0 \\ \frac{\partial\varepsilon}{\partial\beta_{ck}}\frac{\partial\varepsilon}{\partial s_c} & \frac{\partial\varepsilon}{\partial s_c}\frac{\partial\varepsilon}{\partial s_c} & & 0 & \frac{\partial\varepsilon}{\partial s_c}\frac{\partial\varepsilon}{\partial s_{c\prime}} \\ \vdots & & \ddots & \vdots & \\ 0 & 0 & & \frac{\partial\varepsilon}{\partial\beta_{c\prime k}}\frac{\partial\varepsilon}{\partial\beta_{c\prime k\prime}} & \frac{\partial\varepsilon}{\partial\beta_{c\prime k\prime}}\frac{\partial\varepsilon}{\partial s_c} \\ 0 & \frac{\partial\varepsilon}{\partial s_{c\prime}}\frac{\partial\varepsilon}{\partial s_c} & \cdots & \frac{\partial\varepsilon}{\partial\beta_{c\prime k\prime}}\frac{\partial\varepsilon}{\partial s_{c\prime}} & \frac{\partial\varepsilon}{\partial s_{c\prime}}\frac{\partial\varepsilon}{\partial s_{c\prime}} \end{bmatrix}^{-1},$$

where β and s are elements of θ, k indexes individual parameters (parameters can appear in more than one equation) and

$$\frac{\partial\varepsilon}{\partial\beta_{ck}} = \sum_j h_{jc}\frac{\partial\log\left(\prod_t L_{i_{\square}t}(x_{jt};\beta_c)\right)}{\partial\beta_{ck}}$$

$$\frac{\partial\varepsilon}{\partial s_c} = \sum_j h_{jc}s_c^{-1}$$

where

$\frac{\partial\log\left(\prod_t L_{i_{jt}}(x_{jt};\beta_c)\right)}{\partial\beta_{ck}} = \sum_t(1 - L_{i_{jt}})x_{jti_{jt}k}$ for parameters that appear only in the utility for the selected option

$\frac{\partial\log\left(\prod_t L_{i_{jt}}(x_{jt};\beta_c)\right)}{\partial\beta_{ck}} = -\sum_t L_{ijt}x_{jti_{jt}k}$ for parameters that appear in one utility function but not for the selected option

$\frac{\partial \log\left(\prod_t L_{i_{jt}}(x_{jt};\beta_c)\right)}{\partial \beta_{ck}} = \sum_t \sum_l (y_{ljt} - L_{ljt}) x_{jtlk}$ for parameters that appear in all of the utility functions (expected net revenue and revenue variance), where $y_{ljt} = 1$ when alternative *l* is selected, zero otherwise.

The zero terms in the cross-class portions of the VC matrix recognize that $\frac{\partial^2 \varepsilon}{\partial \beta_{ck} \partial \beta_{c'k'}} = 0$.

Appendix B: Marginal Effects and Elasticities for the Latent Class Logit Model

Marginal effects and elasticities are calculated for individual observations then aggregated. The probability of land use *i* on parcel *j* at time *t*, conditional on membership in class *c* is $P_{ijtc} = L_i(\beta_c; x_{jt})$, where $L_i(x_{jt}; \beta_c)$ is the logit function for land use *i* , x_{jt} is the vector of independent variables at time *t* and parcel *j* and β_c is the parameter vector for class *c.*

Class-conditional, observation-specific, marginal effects:

Own effect: $\frac{\partial P_{jtci}}{\partial x_{jtki}} = L_i(\beta_c; x_{jt})\left(1 - L_i(\beta_c; x_{jt})\right)\beta_{cki}$

Cross effect: $\frac{\partial P_{jtci}}{\partial x_{jtkl}} = \left(-L_l(\beta_c; x_{jt}) L_i(\beta_c; x_{jt})\right)\beta_{ckl}$

x_{jtki} is a single element of x_{jt} and β_{cki} is a single element of β_c where *k* indexes individual covariates and *i* indexes the equation in which they appear.

Class-conditional, observation-specific, elasticities:

Own: $\eta_{kii}^{jtc} = \frac{\partial P_{jtci}}{\partial x_{jtki}} \frac{x_{ki}}{P_{jtci}} = \left(1 - L_i(\beta_c; x_{jt})\right)\beta_{cki} x_{jtki}$

Cross: $\eta_{kij}^{jtc} = \frac{\partial P_{jtci}}{\partial x_{jtkj}} \frac{x_{kj}}{P_{jtci}} = \left(-L_j(\beta_c; x_{jt})\right)\beta_{ckj} x_{jtkj}$

Class-conditional average elasticities:

Own: $\eta_{kii}^{c} = \sum_j \sum_t w_j \eta_{kii}^{jtc} \left(\sum_j \sum_t w_j\right)^{-1}$

Cross: $\eta_{kij}^{c} = \sum_j \sum_t w_j \eta_{kij}^{jtc} \left(\sum_j \sum_t w_j\right)^{-1}$

w_j is the NRI weight

Unconditional, observation-specific, elasticities:

Own: $\eta_{kii}^{jt} = \sum_c h_c \eta_{kii}^{jtc}$

Cross: $\eta_{kij}^{jt} = \sum_c h_c \eta_{kij}^{jtc}$

h_{jc} is the posterior probability of class membership for NRI point j .

Unconditional, average elasticities:

Own: $\eta_{kii}^{jt} = \sum_j \sum_t w_j \sum_c h_c \eta_{kii}^{jtc} \ \left(\sum_j \sum_t w_j\right)^{-1}$

Cross: $\eta_{kij}^{jt} = \sum_j \sum_t w_j \sum_c h_c \eta_{kij}^{jtc} \ \left(\sum_j \sum_t w_j\right)^{-1}$

Appendix C

Table C-1. Latent Class Logit Parameter Estimates for Cropland-Pasture-CRP Model

Equation	Variable	Class1		Class2	
		Estimate		Estimate	
All	Expected Return	0.00430	**	0.01249	**
All	Variance of Return	-0.00005		-0.00005	
Cropland	Goodland (LCC=1, 2	0.32850		1.14028	**
Cropland	Badland (LCC=6-8)	-0.16726		-1.51909	**
Cropland	Slope (percent)	-0.11944	**	-0.00264	
Cropland	Avg. Max. Temp	-0.04257	**	-0.11031	**
Cropland	Avg, Precip.	8.33340		10.40074	
Cropland	Std. Dev. Precip.	-5.62609		15.45405	**
Cropland	Previous Use Cropland	9.32834	**	7.42487	**
Cropland	Prevous Use Pasture	6.37483	**	7.65312	**
Pasture	Goodland (LCC=1, 2	1.54705	**	-0.73510	
Pasture	Badland (LCC=6-8)	1.45039	**	-7.20241	**
Pasture	Slope (percent)	-0.03403		0.01040	
Pasture	Avg. Max. Temp	-0.05034	**	-0.07526	**
Pasture	Avg, Precip.	12.39873		25.24859	
Pasture	Std. Dev. Precip.	-8.18315		0.22386	
Pasture	Previous Use Cropland	4.21501	**	5.09734	**
Pasture	Prevous Use Pasture	8.31504	**	13.39265	**
	Class Share	0.364	**	0.636	**

Table C-2. Logit Parameter Estimates for Cropland-Pasture Model

	Estimate	
Expected Return	0.00430	**
Variance of Return	-0.00002	**
Goodland (LCC=1, 2	0.35538	**
Badland (LCC=6-8)	-0.87830	**
Slope (percent)	-0.09780	**
Avg. Max. Temp	-0.02347	**
Avg, Precip.	-10.09286	**
Std. Dev. Precip.	1.78281	
Previous Use Cropland	6.31634	**

Table C-3. Latent Class Logit Parameter Estimates for Crop Choice

Equation	Variable	Class1		Class2		Class3		Class4		Class5		Class6	
All	Expected Crop Revenue	0.00036		0.00456	**	0.00059	**	0.00216	**	0.00915	**	0.00400	**
All	Variance Crop Revenue	-0.00001		-0.00002	**	-0.00001	**	-0.00002	**	-0.00003	**	-0.00003	**
Corn	Goodland (LCC=1, 2	1.53650	**	1.81917	**	0.18283	**	0.57642	**	0.96759	**	0.24912	**
Corn	Badland (LCC=6-8)	0.77279	**	-1.28166	**	3.50433	**	0.27067		-6.30983	**	1.71731	**
Corn	Slope (percent)	0.00389		-0.08769	**	-0.09952	**	-0.31371	**	-0.29482	**	0.24647	**
Corn	Avg. Max. Temp (corn)	0.01455		0.07110	**	-0.00826		0.05363	**	-0.03123	**	-0.07640	**
Corn	Avg, Precip. (corn)	8.24797		-16.43661	**	-20.26399	**	-105.80730	**	-63.49595	**	47.86373	**
Corn	Std. Dev. Precip. (corn)	-90.08988	**	-0.90503		5.03338	*	-4.81539	*	48.48307	**	16.04172	**
Corn	Avg, Precip. (wheat)	-258.59140	**	-96.32451	**	5.34969	**	-43.78834	**	2.18268	**	1.23528	
Corn	Std. Dev. Precip. (wheat)	190.04850	**	31.47584	**	-3.08515	**	68.60491	**	-3.43016	**	-6.30281	**
Corn	Previous crop corn	4.38017	**	1.35041	**	2.97551	**	1.80522	**	3.71536	**	0.47433	**
Corn	Previous crop soybeans	3.44583	**	4.64030	**	4.11688	**	2.97565	**	5.61848	**	1.85722	**
Corn	Previous crop wheat	1.72760	**	1.31333	**	2.38251	**	1.65483	**	0.35940	**	-0.56785	**
Soy	Goodland (LCC=1, 2	1.59216	**	1.64049	**	-0.02123		-0.34186	**	0.97563	**	-0.13221	
Soy	Badland (LCC=6-8)	1.58358	**	-1.57504	**	4.64800	**	-3.37156	**	-4.81032	**	1.31532	**
Soy	Slope (percent)	-0.09269	**	-0.11496	**	-0.14146	**	-0.32411	**	-0.34556	**	0.09181	**
Soy	Avg. Max. Temp (corn)	0.03795	**	0.06910	**	-0.01733	**	0.12869	**	-0.04650	**	-0.09595	**
Soy	Avg, Precip. (corn)	-61.23530	**	-16.71993	**	-17.25841	**	-117.07360	**	-56.78893	**	51.58368	**
Soy	Std. Dev. Precip. (corn)	-93.35084	**	-1.62056		6.07997	**	0.86650		49.33816	**	24.65954	**
Soy	Avg, Precip. (wheat)	-216.35880	**	-70.02289	**	4.24385	**	-27.32821	**	3.17991	**	0.56190	
Soy	Std. Dev. Precip. (wheat)	199.86280	**	25.38336	**	-1.69310		41.24083	**	-3.27282	**	-6.10467	**
Soy	Previous crop corn	4.60146	**	4.12687	**	4.41031	**	3.78880	**	4.78059	**	1.51463	**
Soy	Previous crop soybeans	2.61243	**	2.27090	**	3.55202	**	2.51257	**	3.92316	**	1.69155	**
Soy	Previous crop wheat	0.67626	*	0.77358	**	2.19086	**	0.99575	**	0.02577		-0.48254	**
Wheat	Goodland (LCC=1, 2	1.24244	**	1.36299	**	-0.06933		0.22757	**	-0.65345	**	0.09656	
Wheat	Badland (LCC=6-8)	0.28561		-1.77308	**	5.28079	**	-3.02660	**	-4.05999	**	1.48011	**
Wheat	Slope (percent)	-0.04143		-0.11345	**	-0.19042	**	-0.34908	**	-0.38517	**	0.12521	**
Wheat	Avg. Max. Temp (corn)	-0.10185	**	0.08757	**	-0.00701		0.06997	**	0.03136	**	-0.19895	**
Wheat	Avg, Precip. (corn)	-24.42634		-72.84136	**	-63.34625	**	-116.80570	**	-91.49550	**	72.83481	**
Wheat	Std. Dev. Precip. (corn)	-125.64520	**	14.61743	**	16.88038	**	-2.24881		37.49138	**	28.02539	**
Wheat	Avg, Precip. (wheat)	-136.85920	**	5.76236		-1.97522		-42.34171	**	-3.56848		-25.39980	**
Wheat	Std. Dev. Precip. (wheat)	219.93810	**	-9.97402	*	1.84588		66.14657	**	3.46788		10.72222	**
Wheat	Previous crop corn	5.63862	**	1.34008	**	3.10396	**	1.88466	**	3.01635	**	0.69588	*
Wheat	Previous crop soybeans	2.19192	**	3.96321	**	4.33121	**	3.54635	**	5.03629	**	1.69665	**
Wheat	Previous crop wheat	0.99415	**	-0.16207		2.50328	**	-0.64816	**	-0.41929		0.98513	**
	Shares	0.061	**	0.463	**	0.11	**	0.098	**	0.175	**	0.093	**