Impacts of Federal Crop Insurance on Land Use and Environmental Quality

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This article integrates economic and biophysical models to assess how federal crop revenue insurance programs 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 and crop choices 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 federal crop insurance has, on average, a small effect on conversions of non-cropland to cropland, and somewhat more significant impacts on crop choice and crop rotation. These changes in cropping systems have, on average, small impacts on agricultural pollution.

Key words: Crop insurance, crop choice, land use, environmental quality.

JEL codes: Q18, Q28.

The focus of U.S. 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 continued with the Agricultural Act of 2014, which eliminated direct government payments and expanded crop insurance. The Congressional Budget Office (2014) estimated that the Agricultural Act of 2014 would increase spending on agricultural insurance programs by $5.7 billion, to a total of $89.8 billion over the next decade (2014–2023).

Crop insurance can alter 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' crop mix and input use (Wu 1999; Goodwin, Vandeveer, and Deal 2004; Babcock and Hennessy 1996; Young, Vandeveer, and Schnepf 2001; Goodwin and Smith 2003; 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

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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 still not fully understood (Walters et al. 2012).

In this paper we integrate economic and biophysical models to quantify 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 (which includes Ohio, Illinois, Indiana, Iowa, Missouri). The Corn Belt 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 (pasture, crop production, and Conservation Reserve Program[1] [CRP] enrollment) and crop choices (e.g., corn vs. soybeans) in the Corn Belt. These models link land use and crop choices on individual parcels to expectation and variance of crop revenues (including the effect of crop insurance and some commodity payments), land quality and topography, climate conditions, and rotational constraints (previous crop or land use) at each site. We estimate these models using a combination of parcel-level data from the National Resources Inventories (NRI), the most comprehensive data available on private land use ever collected in the United States, and county-, state-, and regional-level data on yields, prices, and costs. We use the estimated land use and crop choice models to simulate the effect of federal crop insurance on major land use and crop choices at each parcel. Finally, we link the land use models with biophysical models to estimate the effect of crop insurance on soil erosion, nitrate runoff and leaching, and soil carbon sequestration at each parcel and aggregate the results to the regional level.

Our results suggest that in the Corn Belt federal crop insurance had some impact on crop choice and crop rotation, but rather small effects on conversion from noncropland to cropland. Consequently, federal crop insurance had, on average, very small effects on environmental quality.

The effect of federal crop insurance on land use is an important area of research because of the associated environmental and economic impacts (Knight and Coble 1997). Young, Vandeveer, and Schnepf (2001) simulate changes in acreage, production, price, and net returns induced by crop insurance and find that subsidized crop insurance leads to an increase of only about 0.4% in total crop acreage. Goodwin, Vandeveer, and Deal (2004) examine corn and soybean production in the Corn Belt and wheat and barley production in the Upper Great Plains and find that even in their most extreme scenario (30% decreases in premiums), crop acreage increases by only 0.2%–1.1%.

Some studies have also considered the environmental effect of federal crop insurance programs. Early work focuses on the effect of crop insurance on chemical application rates (Babcock and Hennessy 1996; Young, Vandeveer, and Schnepf 2001; Chambers and Quiggin 2002; Wu 1999; Goodwin, Vandeveer, and Deal 2004). A few more recent studies have measured direct environmental impacts of federal crop insurance. 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 use crop insurance unit-level data to estimate crop acreage share equations for major insured crops or crop groups, and then use the Agricultural Policy – Environmental Extender (APEX) model to simulate effects of crop share changes on several measures of environmental degradation. These authors 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, do 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. These authors also do 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 biophysical models of

[1] Under the CRP, farmers convert environmentally-sensitive land to resource-conserving covers, such as native grasses, trees, and filter strips. In return, farmers receive an annual rental payment from the government for a contract period of 10–15 years. We model CRP enrollment because it has had a major impact on land use over the past 30 years. At the program's peak—36.8 million acres in 2007—roughly 10% of cropland was in CRP. Although the rate of CRP enrollment was smaller in the Corn Belt, CRP is a major factor in land use decisions.

environmental quality indicators to examine the environmental impacts of insurance. We examine how crop insurance affects both the land allocation between crop and non-crop uses, including participation in the 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 combining fine-scale, parcel-level data on land use, crop choice, and parcel characteristics with county-, state-, and region-level data on prices, yields, and costs. 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, but its environmental consequences have not been addressed in existing models.

In the next section we describe the empirical model and approaches for estimating the land use models. The subsequent section describes the data and variable construction, followed by a section that presents and discusses the results from the land use and crop choice models. The next section presents the simulation framework for the land use and crop choice impacts of crop insurance, and discusses the results of the simulation. The subsequent section discusses the environmental impacts, while the final section concludes.

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 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:

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

where U_{ijt} is the utility from land use i on parcel j in year t; $\boldsymbol{\beta_i}$ is a vector of parameters; $\boldsymbol{X}_{ijt}$ is a vector of variables measuring the expected net returns and risk for land use i on parcel j in year t; and υ_{ijt} is a random error term. If the errors υ_{ijt} follow the independently and identically distributed (i.i.d.) extreme value distribution, the probability that utility for land use i exceeds that for other land uses equals

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

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

Major land use is:

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

Crop choices are:

$$(4) \qquad L_{ijt} = L_{jt}(i|i \in C) \cdot L_{jt}(i \in C)$$
$$= \frac{e^{X'_{ijt}\beta_i}}{\sum_{k \in C} e^{X'_{kjt}\beta_k}} \cdot \frac{1}{1 + \sum_{k \in M} e^{X'_{kjt}\beta_k}}, i \in \mathrm{C}.$$

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). Technically, one could estmate the land use and crop choice decisions jointly using equation (2) by treating each crop choice and each noncrop use as an alternative. The advantage of this approach is that it avoids the assumption that major land use and crop choice decisions are made in a sequential fashion, but the disadvantage is that the model would be more difficult to estimate, and estimated coefficients would be harder to interpret.

Most previous land use studies estimate models similar to equations (3) or (4) as a multinomial logit (MNL) or conditional logit (CL) model (Lichtenberg 1989; Wu and Segerson 1995; Hardie and Parks 1997; Wu et al. 2004; Langpap and Wu 2011). 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.

In this paper we estimate equations (3) and (4) as random parameter models to overcome the IIA problem (Train 2009). 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:

$$(5) \quad P_j = \int \left(\prod_t L_{jti_{jt}}(\beta) \right) f(\beta) d\beta$$

where i_{jt} is the selected option at parcel j and time t, $\beta = (\beta_{m_1}, \ldots, \beta_{m_K}; \beta_{c_1}, \ldots \beta_{c_K})$, and $f(\beta)$ is the density function of β.

To specify random parameters using empirical distributions, we use a latent class logit model (LCL), in which 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.

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

$$(6) \quad P_j = \sum_l \left(s_l \prod_t L_{jti_{jt}}(\beta_l) \right)$$

where S_l is the (unconditional) probability that any given parcel belongs to class l.

Train (2009) suggests maximizing the LCL likelihood function via the expectation-maximization (EM) algorithm, which is a method of computing maximum likelihood estimates from incomplete data (e.g., unobserved class membership; Dempster, Laird, and Rubin 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, the expectation to be maximized is:

$$(7) \quad \epsilon(s, \beta) = \sum_j \sum_l h_{jl} \log \left(s_l \prod_t L_{jti_{jt}}(X_{ijt}; \beta_l) \right)$$

where h_{jl} is the parcel-specific (conditional) probability that parcel j belongs to class l:

$$(8) \quad h_{jl} = \frac{s_l \prod_t L_{jti_{jt}}(\beta_l)}{\sum_{l'} s_{l'} \prod_t L_{jti_{jt}}(\beta_{l'})}.$$

Note that weights are not indexed for time—each parcel with multiple observations is given a single weight.

Starting values are calculated by randomly dividing the NRI parcels into L groups. The initial class probabilities are $s_l^0 = 1/L$. Starting values for each set of class-specific parameters (β_l^0) are estimated by a conditional logit using the data associated with the NRI parcels assigned to each of the L groups. The initial parcel- and class-specific weights are calculated using equation (8). The class probabilities, parameter vectors, and the parcel- and class-specific weights (h_{jl}) are updated sequentially until they converge (do not change with several updates). The class probabilities are updated using the observation-specific weights: $s_c^l = \frac{\sum_j h_{jl}^0}{\sum_j \sum_{l'} h_{jl'}^0}$. Each of L class-specific parameter vectors are updated using a conditional logit model estimated from all of the data (not a subset as in the starting value estimation) weighted with the parcel- and class-specific weights (h_{jl}^1), yielding β_l^1. Finally, the parcel- and class-specific weights are updated for use in the next iteration using s_l^0 and β_l^1 in equation (8). The variance-covariance matrix and the marginal effects are given in 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). Both BIC and CAIC are related to Akaike's Information Criterion, but use penalty functions that increase more rapidly as the number of model parameters increases. The AIC $= -2\epsilon + 2B$, where the expectation, ϵ, is evaluated at the maximum and B is the total number of estimated parameters. The B IC $= -2\epsilon + \epsilon BJ$ and CAIC $= -2\epsilon + B(1+ \log(J))$, where J is the number of 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.

Data and Variable Construction

Our analysis is conducted at the NRI parcel level, but estimation of the land use and crop choice models requires a substantial amount of data, which must be integrated from multiple sources at various levels of aggregation. We combine parcel-level NRI data on land use, crop choices, and parcel characteristics (such as soil quality), county-level data on yields, revenues, soil rental rates, and coverage of insurance products, state-level information on rental rates and prices, and regional data on production costs. In this section we describe the data sources and construction of the variables used to estimate the econometric models.

The annual, parcel-level data on land use and crop choices from 1997 to 2010 were obtained from the NRI. The 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. Both the core and non-core NRI points are randomly selected to ensure statistical inference at the regional level. Our data set, which is limited to the Corn Belt states and excludes counties (mostly in southern Missouri) that lack data on crop yields, includes 7,187 NRI points and a total of 90,994 observations, or, on average, roughly 12.6 observations per NRI point. One observation is lost on every point because the previous year's land use is an explanatory variable; other observations are lost because of missing or incomplete information. Over our study period, on average, 75% of land is in crop production, 18% in pasture, and 7% is in CRP. Of land in crop production, an average of 42% was in corn, 40% in soybeans, 4% in wheat, and 14% in hay, although these percentages changed over time.

The availability of parcel-level data on land use and crop mix is valuable because it allows us to control for rotation effects. We include dummy variables indicating the crop grown (for the crop model) or land use (for the land use model) on the site in the previous year. Parcel-specific data on land quality also help capture variation in mean and variance of net returns to various crops and land use among NRI sites—variation that cannot be captured with the data available for measuring returns. High-quality land ("good 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 ("bad land") is a dummy variable set equal to one if a site has a land capability of 6–8, and set to zero otherwise. Land Capability Classification (LCC) is a multidimensional measure of the suitability of land to crop production such as soil productivity, soil erosion hazard, and wetness (USDA-SCS 1961). Land in LCC 1 and 2 has few limitations to crop production, while land in classes 6–8 can have severe limitations to crop production. In our sample, an average of 85% of "good land" was used for crops between 1997 and 2010; only 36% of "bad land" was used for crops. The model also includes land slope measured as a percentage.

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.[2] Summary statistics for all variables used in the analysis are presented in table 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. Thus,

$$(9) \quad E(R_{ct}) = \sum\nolimits_i w_{it}[E(G_{it}) - C_{it}]$$

where $E(G_{it})$ is expected gross revenue for crop i at time t, (see equation [19]) C_{it} is operating cost for crop i at time t, and w_{it} is the acreage weight for crop i at time t, derived

[2] 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.

Table 1 Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
	Land Use–CRP eligible			Land Use–Not CRP eligible			Crop Choice		
Expected net return to crops	24,547	199.58	69.82	66,447	229.96	113.42			
Variance, net return to crops	24,547	4,444.98	2,594.60	66,447	6,296.27	5,397.75			
Expected net return to pasture	24,547	32.38	7.03	66,447	33.56	7.79			
Variance, net return to pasture	24,547	45.44	30.77	66,447	48.77	34.37			
Expected net return to CRP	24,547	90.86	22.52						
Variance, net return to CRP	24,547	0.00	0.00						
Expected revenue, corn							72,457	471.75	146.51
Variance, corn revenue							72,457	13,152.18	11,799.69
Expected revenue, soybeans							72,457	355.80	106.92
Variance, soybean revenue							72,457	7,061.89	5,817.66
Expected revenue, wheat							72,457	280.55	105.25
Variance, wheat revenue							72,457	10,696.22	10,691.24
Expected revenue, hay							72,457	396.07	117.93
Variance, hay revenue							72,457	7,534.41	5,952.91
Goodland	24,547	0.43	0.49	66,447	0.63	0.48	72,457	0.65	0.48
Badland	24,547	0.06	0.24	66,447	0.05	0.22	72,457	0.03	0.16
Slope (percent)	24,547	5.48	4.47	66,447	3.66	4.57	72,457	3.31	3.63
Mean max. temperature, corn season	24,547	79.58	2.38	66,447	80.16	2.54	72,457	79.83	2.46
Mean precipitation, corn season	24,547	0.13	0.02	66,447	0.13	0.02	72,457	0.13	0.02
Std. dev. precipitation, corn season	24,547	0.32	0.03	66,447	0.32	0.04	72,457	0.32	0.04
Mean precipitation, wheat season	24,547	0.10	0.06	66,447	0.10	0.08	72,457	0.10	0.07
Std. dev. precipitation, wheat season	24,547	0.26	0.05	66,447	0.27	0.07	72,457	0.27	0.06
Previously cropland	24,547	0.81	0.39	66,447	0.78	0.41			
Previously pasture	24,547	0.04	0.20						
Previously corn							72,457	0.44	0.50
Previously soybeans							72,457	0.42	0.49
Previously wheat							72,457	0.04	0.20

from a rolling average of county 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. Use of the rolling average reduces the impact of temporary departures from a typical mix of crops (e.g., weather-induced departures from the typical mix of corn and soybeans) on expected returns.

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

$$(10) \quad V(R_{ct}) = \sum\nolimits_i \sum\nolimits_{i'} w_{it} w_{i't} V(G_{it}, G_{i't})$$

where $V(G_{it}, G_{i't})$ is the covariance between gross revenue for crops i and i'. Crop costs are not included in the variance calculation because they are assumed to be known at the beginning of year t, while expectations about the variability of revenue are based on past revenue (see next section). Therefore, costs are not stochastic and are not correlated with past revenues used to form expectations about the deviation of revenues.

The only pasture rental rate data available going back to the mid-1990s are at the state level. Even with data at the state level, 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 pasture rental rates, county average hay revenue is used as an indicator of county-level variation in forage revenue on pasture land. Ideally, these variations would be based on grass (non-alfalfa) hay, but the only reliable county-level data is for total hay production. Thus,

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

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 (see 18); $\bar{G}_{ht}$ 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:

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

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

Production costs for corn, soybeans, and wheat are based on USDA Economic Research Service (ERS) cost and return data for 1997–2010. While crop production cost estimates are regional (based on ERS Farm Resource Regions), costs can vary across counties based on the exact mixture of crops grown. Production costs for hay are based on establishment and harvest cost guidelines in Barnhart, Duffy, and Smith (2008). Establishment costs include tillage, herbicide, seed, fertilizer, and planting. Ongoing costs include mowing/raking, baleing, hauling, and annual fertilizer application. Seed and fertilizer prices are from USDA-NASS. Machinery costs are based on custom farming rates indicated in Barnhart, Duffy, and Smith (2008), adjusted for earlier and later years using various sources of information on custom hire rates (e.g., Anderson and Noyes 2004; Aakre 2005; Jose and Bek 2008). Costs of mowing-conditioning are based on three cuttings per year. Bailing and hauling costs are estimated from per-ton custom rates.

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. The 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 nationwide. 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.[3] Because annual CRP payments are fixed, the variance of CRP net return is zero.

The NRI indicates CRP enrollment, but only when land was enrolled through CRP "General Signup."[4] 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% of CRP acreage; in 2010 General Signup still accounted for 83% of land in CRP.[5] General Signup 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 (i) have been previously in crop production or enrolled in CRP and (ii) 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 October 1, so land that we observe "entering" CRP in 2002 was actually enrolled on October 1, 2001).

Once an NRI parcel is in CRP, we include a variable indicating previous enrollment. Over the period of the CRP contract, land is likely to stay in the program. The next decision point comes when the CRP contract expires. While CRP land is automatically eligible for re-enrollment, producers may or may not choose to re-enroll. Because NRI provides no information on CRP contracts, however, it is impossible to accurately determine the expiration date for any specific NRI parcel. The CRP contracts can vary in length (10–15 years). Moreover, the 2006 Reenrollment and Extension (REX) program offered new contracts (10–15 years) or contract extensions (2–5 year) on 28 million acres set to expire in 2007–2010. A total of 23 million acres were included in new or extended contracts. So the date land entered CRP (implied by the year when NRI first indicates CRP enrollment) effectively contains no information on the contract expiration date.

Mean and Variance of Revenue from Individual Crops

To estimate the mean and variance of returns to individual crops and the effect of crop insurance on returns, we develop a joint distribution of yields and prices. Yield distributions are based on NASS county average yields. For corn, soybeans, wheat, and hay, the expected yield for crop i and year t, $E(y_{it})$, is an Olympic average of yields for the most recent five years (the average with the high and low values removed). Next, for each year 1997–2010, a linear trend was fitted using yield data for the most recent 22 years. Yield deviations are the difference between the observed yields and a linear trend:

$$(13) \quad \Delta y_{i,t-z} = (y_{i,t-z} - y^T_{i,t-z})/y^T_{i,t-z}$$

where $z \in \{1,\ldots,22\}$, $\Delta y_{i,t-z}$ is the yield deviation for year t-z,$y_{i,t-z}$is the realized yield, and $y^T_{i,t-z}$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 (2007), the absolute value of the yield deviations are increased by a constant multiplier until expected losses based on a yield guarantee of 65% equal yield-based crop insurance premium rates for 65% coverage. The yield distribution vector for crop i, at time t, denoted $\hat{\mathbf{y}}_{it}$, contains Z elements with the zth element defined by:

$$(14) \quad \hat{y}_{it,t-z} = E(y_{it})(\alpha_i \Delta y_{i,t-z} + 1)$$

where $\alpha_i$is the inflation factor, which is chosen so that

$$(15) \quad \min_{\alpha_i} \left\{ \left(\omega(\bar{y}_i) - Z^{-1} \sum_z \max \left(\frac{(0.65\bar{y}_i - \hat{y}_{it,t-z}(\alpha_i))}{0.65\bar{y}_i}, 0 \right) \right)^2 \right\}$$

where $\omega(\bar{y}_i)$is the premium rate for 65%

[3] The 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.

[4] Note that CRP participation does not determine which observations are part of our sample. Rather, NRI parcels are randomly selected, and some of them are enrolled in CRP.

[5] 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.

coverage (excluding the fixed rate load), calculated from Risk Management Agency (RMA) county actuarial data for 2010, and $\bar{y}_i$is the average county yield for 2000–2009 (which approximates the APH yield for the representative farm in 2010).[6,7] The first terms in the bracket $(\omega(\bar{y}_i))$ represent the expected loss based on the crop insurance continuous rating model, and the second term represents the expected loss calculated from our yield distribution for 65% coverage. The vast majority of inflation factors are in the range 1–3. An inflation factor of 2 would indicate that roughly half of farm-level yield variation is averaged out in county yields.

Price distributions are based on futures market and cash price data. To specify expected and realized prices, we use procedures established by RMA for the crop insurance program. 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 (one element for each of the past years used to derive the distribution), with the zth element defined by:

$$(16)\quad \hat{p}_{it,t-z} = E(p_{it})(\Delta p_{i,t-z} + 1)$$

where $E(p_{it})$ is the expected price, $\Delta p_{i,t-z} = \frac{p_{i,t-z} - E(p_{i,t-z})}{E(p_{i,t-z})}$ is the price deviation for year t-z, and p_{it} 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). Further, prices are adjusted to reflect county conditions using the ratio of the national average loan rate to the county loan rate. Inter-county variation in loan rates is designed to reflect county-level variation in cash prices.

The effect that federal crop insurance has on expected revenue and revenue variance is estimated by adding estimated net indemnity to crop revenue for each point 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 price [planting time] or the harvest time [realized] price). For a single point in the price-yield distribution, the RP indemnity is

$$(17)\quad \hat{I}_{it,RP,t-z} = \max\left((\theta_{i,RP,t}\max(\hat{p}_{it,t-z}, E(p_{it}))\bar{y}_{it} - \hat{p}_{it,t-z}\hat{y}_{it,t-z}), 0\right)$$

where $\theta_{i,RP,t}$ is the coverage level selected by the producer. Because the type of crop insurance purchased by producers evolved significantly in the late 1990s, we also model revenue protection insurance with the harvest price exclusion, yield protection, and catastrophic coverage. In our study region, for example, revenue insurance accounted for 25% of insured acreage in 1998 but grew to 88% by 2010. 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, by year, was obtained from the RMA 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. Coverage levels used in the analysis reflect the liability-weighted average coverage level by county, insurance type, and year based on RMA Summary of Business data.

We assume that crop insurance is actuarially fair, as required by law, so the total

[6] The year 2010 is selected because premium rates are based on loss histories that cover the period of relatively broad crop insurance participation after premium subsidy increases in 1994 and 2001.

[7] We did not exclude the reserve factor loading. The reserve factor is designed to build reserves in anticipation of unusually large losses, increasing unloaded premium rates by 13.6%. Thus, yield variances may be a bit over-inflated.

Table 2 Information Criterion for the Latent Class Logit Crop-pasture-CRP Model

# Classes	BIC	CAIC	LL
2	**5,624.5**	**5,661.5**	**-2,660.7**
3	5,696.5	5,752.5	−2,618.8

premium, including the premium actually paid by farmers and premium subsidies from the government, equals the expected indemnity.[8] Premium subsidy rates are based on coverage level and assuming basic crop insurance units.[9] For each point in the empirical distribution, gross revenue per acre for crop i, including crop insurance, is

$$(18)\quad \hat{G}_{it,t-z} = \hat{p}_{it,t-z}\hat{y}_{it,t-z} + L_{it,t-z} + \sum_{q} a_{iqt}(\hat{I}_{itq,t-z} - (1-\gamma(\theta_{iqt}))E(I_{itq}))$$

where q indexes the insurance plan (e.g., revenue protection), a_{iqt} is the share of crop i insured under plan q at time t, γ is the premium subsidy rate, and $E(I_{itq}) = Z^{-1}\sum_z \hat{I}_{itq,t-z}$ and $L_{it,t-z}$represent the marketing loan benefit $(L_{it,t-z} = \max\ ((p_i^{loan} - \hat{p}_{it,t-z})\hat{y}_{it,t-z}, 0))$, where $p_i^{loan}$is the commodity loan rate. We model marketing loan benefits because they depend directly on crop acreage and, therefore, provide a direct incentive to maintain crop acreage. Although crop prices have been well above commodity loan rates for more than decade, marketing loan benefits were important in the late 1990s and early 2000s.

Given market and insurance returns, expected revenue for crop i at time t is:

$$(19)\quad E(G_{it}) = Z^{-1}\sum_{z} \hat{G}_{it,t-z}$$

and the variance of revenue is

$$(20)\quad V(G_{it}) = Z^{-1}\sum_{z} (\hat{G}_{it,t-z} - E(\hat{G}_{it,t-z}))^2.$$

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.

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, and 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 parcels eligible for the CRP, information criteria reported in table 2 support a two-class latent class logit model.[10] The estimates of elasticities for the two-class 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. Estimated class-conditional land use probabilities are also shown in appendix C. It is noteworthy that all own-net return elasticities are positive and cross-net return elasticities are negative. These results suggest that landowners respond to increasing returns 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 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

[8] 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, Schnitkey, and Sherrick (2011) all note that losses are consistently larger in the Great Plains when compared to the Corn Belt. Across crops, regions, and time, however, total crop insurance premiums exceeded indemnities, with an average loss ratio of 0.88 for 1995–2007 (Woodward, Schnitkey, and Sherrick 2011).

[9] Subsides are higher for some unit types but data on unit type is not available in the Summary of Business data. As such, our analysis may underestimate the level of net return to crop insurance purchase.

[10] Predicted land use probabilities and insurance-induced acreage changes are very similar for a three-class model.

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

	Change in Net Return:			Change in Variance:		
Change in Probability:	Cropland	Pasture	CRP	Cropland	Pasture	CRP
Class Conditional Elasticities						
Class 1:						
Cropland	0.0690**	−0.0041**	−0.0221**	−0.0061	0.0000	0
Pasture	−0.3461**	0.0628**	−0.0221**	0.0284	−0.0003	0
CRP	−0.3461**	−0.0041**	0.1690**	0.0284	0.0000	0
Class 2:						
Cropland	0.4497**	−0.0414**	−0.1100**	−0.0822**	0.0004**	0
Pasture	−2.4735**	0.4303**	−0.1100**	0.4101**	−0.0045**	0
CRP	−2.4735**	−0.0414**	1.2364**	0.4101**	0.0004**	0
Unconditional Elasticities						
Cropland	0.2008**	−0.0216**	−0.0389**	−0.0331	0.0002*	0
Pasture	−1.0725**	0.1834**	−0.0389**	0.1577	−0.0017	0
CRP	−1.0725**	−0.0216**	0.5441**	0.1577	0.0002*	0

Note: Asterisks ** indicates $p \leq 0.01$; *indicates $p \leq 0.05$

Table 4 Elasticities for Crop-pasture Logit Model

	Change in Net Return:		Change in Variance:	
Change in Probability:	Cropland	Pasture	Cropland	Pasture
Cropland	0.1620**	−0.0271**	−0.0127	0.0001
Pasture	−0.7727**	0.1094**	0.0590	−0.0005

Note: Asterisks ** indicate $p \leq 0.01$; * indicates $p \leq 0.05$.

production will increase the probability of a parcel being allocated to crop production by 0.069% for class 1 landowners, compared with 0.450% 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 (compare values in table 4 to "unconditional" elasticities reported in table 3).

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.[11] Table 6 reports the unconditional elasticities of crop choices with respect to changes in the expected revenue and variance of revenue for alternative crops. Table 7 reports the elasticities of crop choices for each of the six classes of landowners. The coefficient estimates are reported in appendix C. Estimated class-conditional crop probabilities are also shown in appendix C. The average class-conditional

Table 5 Information Criterion for the LCL Crop Choice Model

# Classes	BIC	CAIC	LL
4	90,471.6	90,614.6	−44,613.0
5	89,827.8	90,006.8	−44,134.2
6	***89,438.0***	***89,653.0***	***-43,782.6***
7	89,657.4	89,908.4	−43,735.5

[11] While we would not expect differently specified models to necessarily yield the same results, we checked the sensitivity of our results to estimating 5- and 7-class crop choice models. The implications of these models are quite similar to those of the 6-class model.

Table 6 Unconditional Elasticities for the LCL Crop Choice Model

	Change in Revenue to:				Change in Revenue Variance:			
Change in Probability:	Corn	Soy	Wheat	Hay	Corn	Soy	Wheat	Hay
Corn	0.951**	−0.616**	−0.031*	−0.083**	−0.184**	0.072**	0.009*	0.016**
Soy	−0.984**	0.846**	−0.031*	−0.083**	0.129**	−0.097**	0.009*	0.016**
Wheat	−0.984**	−0.616**	1.105**	−0.083**	0.129**	0.072**	−0.244**	0.016**
Hay	−0.984**	−0.616**	−0.031*	1.529**	0.129**	0.072**	0.009*	−0.154**

Note: Asterisks ** indicate p ≤ 0.01; * indicates p ≤ 0.05.

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

	Change in Revenue:				Change in Revenue Variance:			
Change in Probability:	Corn	Soy	Wheat	Hay	Corn	Soy	Wheat	Hay
Class 1:								
Corn	0.241**	−0.137**	−0.002**	−0.045**	−0.175**	0.067**	0.002**	0.019**
Soy	−0.162**	0.168**	−0.002**	−0.045**	0.112**	−0.088**	0.002**	0.019**
Wheat	−0.162**	−0.137**	0.236**	−0.045**	0.112**	0.067**	−0.230**	0.019**
Hay	−0.162**	−0.137**	−0.002**	0.290**	0.112**	0.067**	0.002**	−0.140**
Class 2:								
Corn	0.619**	−0.288**	−0.026	−0.166**	−0.105**	0.033**	0.006	0.017**
Soy	−1.256**	1.130**	−0.026	−0.166**	0.196**	−0.130**	0.006	0.017**
Wheat	−1.256**	−0.288**	1.078**	−0.166**	0.196**	0.033**	−0.237**	0.017**
Hay	−1.256**	−0.288**	−0.026	1.389**	0.196**	0.033**	0.006	−0.150**
Class 3:								
Corn	2.220**	−1.410**	−0.081**	−0.200**	−0.532**	0.232**	0.026**	0.029**
Soy	−0.865**	0.923**	−0.081**	−0.200**	0.183**	−0.154**	0.026**	0.029**
Wheat	−0.865**	−1.410**	1.736**	−0.200**	0.183**	0.232**	−0.553**	0.029**
Hay	−0.865**	−1.410**	−0.081**	2.360**	0.183**	0.232**	0.026**	−0.368**
Class 4:								
Corn	0.300**	−0.131**	−0.044**	−0.041**	−0.145**	0.044**	0.029**	0.013**
Soy	−0.076**	0.153**	−0.044**	−0.041**	0.038**	−0.055**	0.029**	0.013**
Wheat	−0.076**	−0.131**	0.177**	−0.041**	0.038**	0.044**	−0.120**	0.013**
Hay	−0.076**	−0.131**	−0.044**	0.270**	0.038**	0.044**	0.029**	−0.090**
Class 5:								
Corn	2.573**	−1.888**	−0.064**	−0.056**	−0.158**	0.086**	0.006**	0.003**
Soy	−3.370**	2.606**	−0.064**	−0.056**	0.227**	−0.122**	0.006**	0.003**
Wheat	−3.370**	−1.888**	3.436**	−0.056**	0.227**	0.086**	−0.305**	0.003**
Hay	−3.370**	−1.888**	−0.064**	4.876**	0.227**	0.086**	0.006**	−0.211**
Class 6:								
Corn	0.448**	−0.301**	−0.024	−0.010*	−0.095**	0.045**	0.006	0.002
Soy	−0.326**	0.283**	−0.024	−0.010*	0.064**	−0.041**	0.006	0.002
Wheat	−0.326**	−0.301**	0.431**	−0.010*	0.064**	0.045**	−0.122**	0.002
Hay	−0.326**	−0.301**	−0.024	0.631**	0.064**	0.045**	0.006	−0.086**

Note: Asterisks ** indicate p ≤ 0.01; * indicates p ≤ 0.05.

probabilities reveal that class formed to accommodate a wide range of crop allocations. For example, class 3 producers are focused on soybean production. Class 4 producers grow more wheat than any other producers. In classes 1 and 6 (which make up about 50% of land) the predicted probabilities of corn and soybeans are closest, suggesting that these farms use something like a corn-soybean rotation.

Consistent with economic theory, all own-revenue elasticities 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 0.951%, and decreases the probability of a cropland parcel being allocated to soybeans by 0.616%, to wheat by 0.031%, and to hay by 0.083%. 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 0.184%, but the probability that a cropland parcel is used for soybeans, wheat, or hay increases by 0.072%, 0.009%, and 0.016%, respectively.

The results in table 6 indicate that the probabilities of crop choices, on average, are inelastic to changes in economic variables. These results are consistent with previous findings (e.g., Wu et al. 2004), and may be explained by agronomic (rotational) constraints and the relatively few crops grown in the study region. However, there is a large variation among the landowners in their responses to changes in expected net returns and variances of net returns. Landowner in groups 3 and 5 are highly responsive, while landowners in the other groups are relatively less responsive. These results suggest that the effects of crop insurance, which are discussed in the next section, also vary among landowners.

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 federal crop 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 federal crop insurance programs. 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. 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 predict continuous corn at that site. Finally, the corresponding acreage is calculated using the NRI's xfactor, which is the weight assigned to each NRI parcel to indicate the acreage it represents.

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.[12] The results indicate that federal crop insurance, on average, would have small impacts on land use. Cropland acreage increases by only 0.06%, whereas pasture and CRP acreage decrease by 0.28% and 0.42%, 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, Vandeveer, and Schnepf 2001; Goodwin, Vandeveer, and Deal 2004). The impact of crop insurance on crop choices are relatively larger. The acreage of cropland devoted to continuous corn increases by 3.72%, whereas less land is

[12] Some simulated rotations with small predicted acreage, mainly those including wheat, which is very unusual in the Corn Belt, are not reported here.

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

Land Use Type	No Insurance (1,000 acres)	Insurance (1,000 acres)	% Change from the No-Insurance Baseline: All parcels	% Change from the No-Insurance Baseline: Class 3 parcels
Land Use				
Acres of cropland	13,478	13,485	0.06%	
Acres of pasture land	1,812	1,807	−0.28%	
Acres of CRP land	625	622	−0.42%	
Acres of corn (3 year average)	4,229	4,302	1.71%	7.55%
Acres of soybeans (3 year average)	3,806	3,789	−0.43%	−2.35%
Acres of wheat (3 year average)	358	329	−8.16%	−7.53%
Acres of hay (3 year average)	713	687	−3.65%	−6.19%
Cropping Systems				
Continuous corn	2,245	2,329	3.72%	12.27%
Continuous soybeans	1,618	1,616	−0.15%	0.62%
Corn-Soybeans	2,655	2,695	1.51%	27.86%
Corn-Corn-Soybeans	530	535	0.91%	0.00%
Soybeans-Soybeans-Corn	593	559	−5.87%	−23.82%
Corn-Corn-Hay	658	641	−2.46%	−3.92%

planted with continuous soybeans, which decrease by 0.15%.

Table 8 also reports the effect of federal crop insurance on class 3 landowners, who are most responsive to changes in revenue variance among the six classes of landowners (according to elasticities reported in table 7). Crop insurance indeed has larger effects on land use and crop choice in terms of percentage changes. For example, acres in corn-soybean rotation increases by 28% for class 3 landowners compared with 1.5% for all landowners. Percentage changes for some rotation systems are also larger for class 5 landowners. For example, acres of hay decreases by 26% under crop insurance for class 5 landowner, compared with 3.7% for all landowners. However, because hay accounts for only about 8% of total cropland, the change in total hay acreage for class 5 landowners is relatively small. Generally speaking, acreage changes are relatively small for land use types that experience large percentage changes under federal crop insurance programs.

We also repeated the entire simulation procedure for subsamples defined by county percentage of dominant cropping systems (predominantly corn, predominantly soybean, or mixed). We found some variation in the magnitude of crop choice impacts of crop insurance across these categories. For instance, the increase in corn-corn-soybean acreage is meaningfully larger than the reported average in counties with corn-dominant systems. Similarly, continuous corn acreage increases by significantly more than the reported average in areas characterized by a mixed cropping system. Again, acreage changes are generally small for land use types that experience large percentage changes.

Impacts of Crop Insurance on Environmental Quality

The changes in land use may 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). Specifically, 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 estimated by regressing simulated environmental data (e.g., measures of nitrate runoff and leaching) on the vector of crop

Table 9 Estimated Impacts of Crop Insurance on Environmental Quality

Indicator	No Insurance	Insurance	% Change from the No-Insurance Baseline	
			All Parcels	Class 3 parcels
Nitrogen Runoff (1,000s lbs.)	474.39	474.37	0.00%	0.82%
Nitrogen Percolation (1,000s lbs)	869.54	872.37	0.33%	2.39%
Loss of Soil Organic Carbon (1000s metric tons)	865.18	868.42	0.37%	1.12%
Wind Erosion (1,000s tons)	6.80	7.05	3.65%	6.74%
Water Erosion (1,000s tons)	174.78	175.15	0.21%	0.31%

management practices and site characteristics using appropriate econometric methods.[13] 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). Metamodeling is particularly appealing when it is infeasible to simulate environmental impacts at all sites and for all sets of conditions that arise in a large regional analysis such as that 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. 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, Babcock, and Ogg (1996) and Mitchell et al. (1998), respectively.[14]

The land use, crop choice, and environmental quality models described thus far collectively form an assessment framework. We apply this framework to evaluate how federal crop insurance might affect agricultural nonpoint source pollution in the Corn Belt. Levels of fertilizer and pesticide use are calculated using average application rates for each crop rotation and state. 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 scenarios. The site- and rotation-specific measures of environmental impacts are aggregated to the entire sample using the expansion factor and the probability of each rotation system. 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, on average, 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 3.65%. Other impacts are small or negligible: nitrogen percolation is predicted to go up by 0.33%, and nitrogen runoff, loss of soil carbon, and water erosion are all predicted to increase by less than 0.5% with crop insurance. These results suggest that the environmental impacts of crop insurance in our study region are small, on average.

Table 9 also reports estimated environmental impacts for class 3 landowners who are most responsive to changes in revenue variance. Even though the impacts are relatively larger for class 3 landowners, the impacts are still quite modest. For example, wind erosion increases by 6.7% for class 3 landowners, compared with the 3.7% average. We also checked the robustness of these results by repeating the entire simulation procedure for subsets of counties defined by county

[13] 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.

[14] If re-estimated, the environmental production functions would change only if the production technologies have changed (e.g., no-till is now practiced in a different way than in the late 1990s) because soil characteristics and long-run climate conditions have not changed much since then. Although the number of farmers adopting different crop management practices have changed in the Corn Belt, the ways in which these practices are implemented have not changed much since the late 1990s because they are mature technologies. Our simulated environmental impacts capture the effects of changes in crop management practices across farmers on the environmental outcomes.

percentage of dominant cropping systems (predominantly corn, predominantly soybean, or mixed).[15] Although we also find some heterogeneity in environmental impacts across these subgroups of counties, the differences are small in magnitude relative to the reported averages except for nitrogen leaching and soil wind erosion. Finally, we simulated environmental impacts separately for each crop rotation category.[16] We find that crop insurance has relatively larger, but still modest, effects for some rotations. In particular, insurance-induced changes in nitrogen runoff, nitrogen percolation, loss of soil carbon, and water erosion are larger than the aggregates reported in table 9 (increases range from roughly 2% to 5%) for corn-intensive rotations such as continuous corn, corn-soybean, and corn-corn-soybean. This suggests some potential heterogeneity in impacts for regions where these rotations are more prevalent, such as Illinois, Indiana, and Iowa.

Note that a small percentage increase in non-point source pollution could potentially result in large environmental impacts, particularly when the increase occurs in areas where water quality is already a major problem. In fact, more than 1,200 water bodies appear on the U.S. Environmental Protection Agency listing of impaired waterways in the Upper Mississippi River Basin, which largely overlap the Corn Belt (Helmers et al. 2007). In some cases, concentrations are already high enough to be of concern for human or ecosystem health (U.S. Geological Survey 1999). In those watersheds, even a small increase in nitrogen loadings could exacerbate the problem. For example, further increases in nitrogen cocentrations can accelerate algal production in receiving surface water, resulting in a variety of problems including clogged pipelines, fish kills, and reduced recreational opportunities. Increased suspended sediment can increase the cost of water treatment for municipal and industrial water uses and degrade aquatic wildlife habitat (U.S. Geological Survey 1999).

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 Latent Class Logit econometric models and a combination of parcel-, county-, and state-level data to predict land use, crop choices, and crop rotations at the parcel level based on expectations and variances of revenues, as well as land quality, weather conditions, and other physical characteristics at each parcel. We account for crop choice history, which allows us to explicitly simulate specific crop rotation choices. 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 federal crop insurance on nitrate runoff and leaching, soil water and wind erosion, and carbon sequestration at each NRI site.

Our results suggest that federal crop insurance, on average, does not result in significant conversion of pasture or CRP land to cropland in the U.S. Corn Belt. A more meaningful impact of federal crop insurance will be on crop choice and therefore on crop rotation patterns. Total acreage of corn is predicted to increase by roughly 1.7%, whereas the amount of acres planted with wheat will decrease by about 8%. Accordingly, the acreage planted with most crop rotations involving corn increases, by about 4% for continuous corn and 1% for corn-corn-soybeans. On the other hand, acres of continuous wheat decline by almost 6%. These changes in cropping systems will have small effects on agricultural runoff and environmental quality, on average, with the largest predicted impact being a roughly 4% increase in wind erosion for the region. Although the impacts are generally small, the negative correlation between crop insurance and environmental quality suggests that insurance premium costs likely do not reflect the full social costs or benefits of crop insurance.

Our results suggest that the effects of federal crop insurance on land use and environmental quality may vary across the landscape and by land use type. However, confidentiality of NRI sample locations prevents us from identifying the spatial patterns of the impacts within the Corn Belt. In addition, the results from this study may not apply to regions with different crop systems and climate and soil conditions. Theoretically, crop insurance is likely to have a larger impact on land use decisions in regional with marginal growing conditions. An important topic for future research is to identify the spatial patterns of land use change and

[15] NRI sample locations are confidential; county is the smallest geographic identifier revealed to the user.

[16] Results are not reported due to space constraints. They are available upon request.

environmental impacts under federal crop insurance. In areas where federal crop insurance has a large effect on land use and crop choice, moral hazard may be a concern because federal crop insurance could lead farmers to grow riskier crops. Such moral hazard effects may cause poor actuarial performance and increase the governmental cost of federal crop insurance programs. In addition, the large change in land use and crop choice may lead to greater environmental impacts. Thus, identifying the "hot spots" or "high-impact areas" can inform the design of policy for improving both the economic and environmental performance of the federal crop insurance program.

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Appendix A: Variance-covariance Matrix for Latent Class Logit

Train (2009) shows that the derivatives of the expectation to be maximized in equation (7) are equal to those of the log-likelihood function when both are evaluated at the maximum. Therefore, the derivatives of the expectation can be used to estimate the variance-covariance matrix via BHHH method in the same way the derivatives of the log-likelihood function would be used:

$$\mathrm{VC} = \begin{bmatrix} \frac{\partial\epsilon}{\partial\beta_{lb}}\frac{\partial\epsilon}{\partial\beta_{lb'}} & \frac{\partial\epsilon}{\partial\beta_{lb'}}\frac{\partial\epsilon}{\partial s_l} & \cdots & 0 & 0 \\ \frac{\partial\epsilon}{\partial\beta_{lb}}\frac{\partial\epsilon}{\partial s_l} & \frac{\partial\epsilon}{\partial s_l}\frac{\partial\epsilon}{\partial s_l} & & 0 & \frac{\partial\epsilon}{\partial s_l}\frac{\partial\epsilon}{\partial s_{l'}} \\ \vdots & & \ddots & \vdots & \\ 0 & 0 & & \frac{\partial\epsilon}{\partial\beta_{l'b}}\frac{\partial\epsilon}{\partial\beta_{l'b'}} & \frac{\partial\epsilon}{\partial\beta_{l'b'}}\frac{\partial\epsilon}{\partial s_l} \\ 0 & \frac{\partial\epsilon}{\partial s_{l'}}\frac{\partial\epsilon}{\partial s_l} & \cdots & \frac{\partial\epsilon}{\partial\beta_{l'b'}}\frac{\partial\epsilon}{\partial s_{l'}} & \frac{\partial\epsilon}{\partial s_{l'}}\frac{\partial\epsilon}{\partial s_{l'}} \end{bmatrix}^{-1}$$

where ϵ is the expectation, s_l is the probability that any member of the population is a member of class l, $\boldsymbol{\beta_l}$ is the parameter vector for class l, and b indexes individual parameters (which may appear in more than one equation).

The derivatives of ϵ, with respect to any specific parameter, β_{lb}, vary based on where an individual parameter appears in the alternative-specific utility functions. For parameters that appear only in the utility for the observed land use (denoted i_{jt}) the derivatives are defined as

$$\frac{\partial\epsilon}{\partial\beta_{lb}} = \sum_j h_{jl} \sum_t (1 - L_{jti_{jt}}) x_{jti_{jt}b}$$

where h_{jl} is the point-specific class probability, $L_{i_{jt}}$ is the logit function for the observed land use at point j and time t, $x_{jti_{jt}b}$ is an explanatory variable associated with land use i_{jt} and parameter b. For parameters that appear in one utility function but not for the observed land use (denoted i'), the derivatives are defined as

$$\frac{\partial\epsilon}{\partial\beta_{lb}} = \sum_j h_{jl} - \sum_t L_{jti'} x_{jti'b}.$$

For parameters that appear in all of the utility functions (expected net revenue and revenue variance), the derivatives are defined as:

$$\frac{\partial\epsilon}{\partial\beta_{lb}} = \sum_j h_{jl} \sum_t \sum_t (y_{jti} - L_{ijt}) x_{jtib}$$

where $y_{jti} = 1$ when alternative i is selected, and zero otherwise. Finally, the derivatives of class shares are defined as:

$$\frac{\partial\epsilon}{\partial s_l} = \sum_j h_{jl} s_l^{-1}.$$

The zero terms in the cross-class portions of the variance-covariance matrix recognize that the β parameters in different classes are independent of each other (i.e., $\frac{\partial^2\epsilon}{\partial\beta_{lb}\partial\beta_{l'b'}} = 0$).

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 l is $P_{ijtl} = L_i(x_{jt}; \beta_l)$, where $L_i(x_{jt}; \beta_l)$ is the logit function for land use i, $\boldsymbol{x_{jt}}$ is the vector of independent variables at time t and parcel j, and $\boldsymbol{\beta_l}$ is the parameter vector for class l.

Class-conditional, Observation-specific Marginal Effects

$$\text{Own effect}: \quad \frac{\partial P_{jtli}}{\partial x_{jtib}} = L_i(1 - L_i)\beta_{lib}$$

$$\text{Cross effect}: \quad \frac{\partial P_{jtli}}{\partial x_{jti'b}} = (-L_l L_i)\beta_{li'b}$$

Here, $x_{jti'b}$ is a single element of x_{jt} associated with the ith alternative and the bth parameter and β_{lib} is a single element of β_l.

Class-conditional, Observation-specific Elasticities

$$\text{Own}: \quad \eta_{bii}^{jtl} = \frac{\partial P_{jtli}}{\partial x_{jtib}} \frac{x_{jtib}}{P_{jtli}} = (1 - L_i)\beta_{lib} x_{jtib}$$

$$\text{Cross}: \quad \eta_{bii'}^{jtl} = \frac{\partial P_{jtli}}{\partial x_{jti'b}} \frac{x_{jti'b}}{P_{jtli}} = (-L_j)\beta_{lkj} x_{jti'b}$$

Class-conditional Average Elasticities

$$\text{Own}: \quad \eta_{bii}^{l} = \sum_j \sum_t w_j \eta_{bii}^{jtl} \left(T_j \sum_j w_j\right)^{-1}$$

$$\text{Cross}: \quad \eta_{bii'}^{l} = \sum_j \sum_t w_j \eta_{bii'}^{jtl} \left(T_j \sum_j w_j\right)^{-1}$$

Here, w_j is the NRI weight for point j and T_j is the number of time periods.

Unconditional, Observation-specific Elasticities

$$\text{Own}: \quad \eta_{kii}^{jt} = \sum_l h_l \eta_{kii}^{jtl}$$

$$\text{Cross}: \quad \eta_{kii'}^{jt} = \sum_l h_l \eta_{kii'}^{jtl}$$

Here, h_{jl} is the probability of class membership for NRI point j.

Unconditional, Average Elasticities:

$$\text{Own}: \quad \eta_{kii} = \sum_j \sum_t w_j \sum_l h_l \eta_{kii}^{jtl} \left(T_j \sum_j w_j\right)^{-1}$$

$$\text{Cross}: \quad \eta_{kii'} = \sum_j \sum_t w_j \sum_l h_l \eta_{kii'}^{jtl} \left(T_j \sum_j w_j\right)^{-1}$$

Appendix C

Table C.1. Latent Class Logit Parameter Estiamtes for Cropland-pasture-CRP Model

Equation	Variable	Class 1	Class 2
		Estimate	Estimate
All	Expected Return	0.00210**	0.01479**
All	Variance of Return	−0.00001	−0.00011**
Cropland	Goodland (LCC 1-2)	0.38985*	0.86677**
Cropland	Badland (LCC 6-8)	0.28917	−1.69268**
Cropland	Slope (percentage)	−0.10365**	−0.01910
Cropland	Mean max. temperature, corn season	−0.04060**	−0.09969**
Cropland	Mean precipitation, corn season	10.32591	6.49213
Cropland	Std. dev. precipitation, corn season	−6.42747	15.57560**
Cropland	Previous Use Cropland	9.08302**	7.44232**
Cropland	Previous Use Pasture	6.47119**	2.93442**
Pasture	Goodland (LCC 1-2)	1.25580**	−0.41249
Pasture	Badland (LCC 6-8)	−0.77495*	−0.82904*
Pasture	Slope (percent)	−0.05410*	0.03969
Pasture	Mean max. temperature, corn season	−0.05433**	−0.06044**
Pasture	Mean precipitation, corn season	17.40511	22.11196
Pasture	Std. dev. precipitation, corn season	−7.90952	−3.17410
Pasture	Previous Use Cropland	3.59307**	5.55621**
Pasture	Prevous Use Pasture	8.27983**	9.33889**
	Unconditional Pr(Class)	0.66**	0.34**

Table C-2 Latent Class Logit Parameter Estiamtes for Crop Choice Model

Equation	Variable	Class1	Class2	Class3	Class4	Class5	Class6
All	Expected Crop Revenue	0.001**	0.004**	0.007**	0.001**	0.013**	0.002**
All	Variance Crop Revenue	−0.000022**	−0.000023**	−0.000055**	−0.000014**	−0.000030**	−0.000012**
Corn	Goodland (LCC=1, 2)	0.315**	−0.390**	0.131	0.408**	18.352**	−2.830**
Corn	Badland (LCC=6-8)	0.157	0.648**	−1.024**	3.159**	2.618**	−7.455**
Corn	Slope (percent)	−0.054**	−0.109**	−0.070**	−0.110**	−0.158**	0.050**
Corn	Mean max. temperature, corn season	−0.051**	−0.001	0.088**	−0.060**	−0.020**	0.067**
Corn	Mean precipitation, corn season	17.166**	−29.884	−26.216**	−35.006**	242.745**	−42.534**
Corn	Std. dev. precipitation, corn season	−0.832	−2.313	−12.817**	7.040**	−103.892**	33.472**
Corn	Mean precipitation, wheat season	6.431**	−14.679**	−42.530**	−14.699**	−185.771**	−125.687**
Corn	Std. dev. precipitation, wheat season	−6.674**	22.382**	14.742**	25.677**	90.538**	27.448**
Corn	Previous crop corn	5.387**	4.942**	3.182**	2.781**	3.849**	3.788**
Corn	Previous crop soybeans	9.026**	5.206**	4.451**	4.119**	4.277**	4.688**
Corn	Previous crop wheat	4.124**	2.152**	3.692**	3.690**	0.882**	2.202**
Soy	Goodland (LCC=1, 2)	0.415**	−0.719**	−0.316**	−0.176*	18.490**	−3.671**
Soy	Badland (LCC=6-8)	0.020	0.882**	−2.401**	3.384**	2.686**	−7.496**
Soy	Slope (percent)	−0.047**	−0.245**	−0.222**	−0.096**	−0.133**	−0.062**
Soy	Mean max. temperature, corn season	−0.024**	−0.037**	0.062**	0.007	0.014**	0.051**
Soy	Mean precipitation, corn season	23.301**	−36.270**	−33.519**	−42.833**	255.951**	−71.699**
Soy	Std. dev. precipitation, corn season	−14.271**	0.504	4.408	19.208**	−104.367**	42.114**
Soy	Mean precipitation, wheat season	4.260**	−20.519**	0.735	8.778**	−138.784**	−74.266**
Soy	Std. dev. precipitation, wheat season	−2.131**	33.212**	−2.075	−13.426**	62.208**	22.800**
Soy	Previous crop corn	9.001**	5.776**	3.812**	5.010**	4.707**	5.767**
Soy	Previous crop soybeans	5.965**	4.540**	3.672**	4.254**	1.355**	2.772**
Soy	Previous crop wheat	4.321**	2.025**	2.878**	3.806**	0.106	0.488**
Wheat	Goodland (LCC=1, 2)	−1.116**	−1.567**	−0.553**	−0.004	16.895**	−2.219**
Wheat	Badland (LCC=6-8)	−35.208**	1.401**	−37.257**	2.542**	−25.385**	−7.531**
Wheat	Slope (percent)	−0.206**	−0.269**	−0.269**	−0.091**	−0.127**	0.116**
Wheat	Mean max. temperature, corn season	−0.018	−0.037**	−0.053**	−0.074**	−0.012	0.174**
Wheat	Mean precipitation, corn season	−16.088	−16.699	−22.527**	−38.924**	143.808**	−138.063**
Wheat	Std. dev. precipitation, corn season	−3.030	−31.816**	5.032	13.764**	−52.369**	45.292**
Wheat	Mean precipitation, wheat season	3.526	−40.279**	−13.909**	−11.489**	−77.889**	22.225*
Wheat	Std. dev. precipitation, wheat season	−0.890	62.992**	24.284**	20.146**	29.409**	−40.642**
Wheat	Previous crop corn	5.510**	5.332**	3.576**	3.958**	3.070**	3.985**
Wheat	Previous crop soybeans	6.599**	5.243**	3.603**	5.351**	4.649**	5.344**
Wheat	Previous crop wheat	3.708**	2.188**	4.400**	2.734**	0.547	−0.173
Shares		0.296	0.124	0.098	0.093	0.191	0.198

Table C.3. Logit Parameter Estimates for Cropland-pasture Model

	Estimate
Expected Return	0.00411**
Variance of Return	−0.00001
Good land (LCC 1-2)	0.26959**
Bad land (LCC 6-8)	−0.54178**
Slope (percentage)	−0.04336**
Mean max. temperature, corn season	−0.04721**
Mean precipitation, corn season	−14.26363*
Std. dev. precipitation, corn season	4.74811*
Previous Use Cropland	8.84361**

Table C.4. Average Probability of Crop by Class (2010)

Crop	1	2	3	4	5	6
	Pr (Class) (conditional)					
Corn	0.41	0.70	0.31	0.20	0.62	0.43
Soy	0.44	0.19	0.59	0.46	0.36	0.51
Wheat	0.01	0.02	0.03	0.20	0.01	0.05
Hay	0.14	0.10	0.07	0.13	0.01	0.01
Pr(Class) (unconditional)	0.30	0.12	0.10	0.09	0.19	0.20

Table C.5. Average Probability of Land Use for CRP-eligible Land (2010)

Land Use	1	2
	Pr (Class)	(conditional)
Crop	0.79	0.81
Pasture	0.07	0.09
CRP	0.14	0.10
Pr(Class) (unconditional)	0.66	0.34