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Crop Insurance, Land Allocation, and the Environment

Cory G. Walters, C. Richard Shumway, Hayley H. Chouinard, and Philip R. Wandschneider

Government programs that help agricultural producers manage risk may have environmental consequences. In recent years, premium subsidies for crop insurance have been increased substantially to encourage greater producer participation. Using detailed, producer-level crop insurance contract data in four regions, we investigate whether adverse environmental effects have resulted from these increased subsidies. We find some association between environmental effects and insurance contracts. On average, however, we find that environmental effects are generally small and as often beneficial as adverse. More importantly, we find that results are specific to local conditions and to particular environmental indicators and may be hidden in aggregate analysis.

Key words: acreage decision, crop insurance, environment

Introduction

The unintended consequences of governmental policies are always of great interest to taxpayers, especially when potentially large financial and environmental effects are at stake. Agricultural policy involves both, and considerable attention has been given to the environmental impacts of agriculture. For instance, soil erosion caused by agricultural production represents the leading cause of negative water quality impacts on rivers and lakes in the United States (U.S. Environmental Protection Agency, 2002). Agricultural related soil erosion transports nutrients and chemicals, reducing soil quality and degrading waterways. Environmental degradation associated with agricultural production fosters concerns about how government programs designed to support agricultural producers impact the environment.

Crop insurance now constitutes one of the primary risk management programs administered and subsidized by the U.S. government. The total premium base associated with crop insurance increased from less than \$1 billion in 1994 to over \$8.6 billion in 2009.[1] Insured cropland increased from 100 million acres to 265 million acres over the same time period (U.S. Department of Agriculture, Risk Management Agency, 2010). Beginning with legislative actions in 1994, premium subsidies have risen substantially. The Agricultural Risk Protection Act (ARPA) of 2000 applied subsidies as a percentage of premium and increased subsidy rates across all coverage levels. The average subsidy

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Cory G. Walters is Assistant Professor in Agricultural Economics, University of Kentucky. and former Graduate Research Assistant, School of Economic Sciences, Washington State University; C. Richard Shumway is Regents Professor, Hayley H. Chouinard is Associate Professor, and Philip R. Wandschneider is Professor, School of Economic Sciences, Washington State University.
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[1] These figures exclude premiums generated from CAT coverage. CAT did not exist in 1994 and generated \$0.4 billion in premiums in 2009.

rate (subsidy dollars divided by total premium) at the 65% coverage level was 42% in 1995; by 2009 the subsidy rate for this coverage level had increased to 59%. At the 80% coverage level the subsidy increased nearly threefold—from 17% under the 1994 legislation to 48% under the ARPA legislation. The current practice of applying subsidy to premiums on a percentage basis tends to favor relatively high risk areas—both across the country and on individual farms—just as Ricardo (1817) postulated in his explanation of the extensive margin. Thus, increased premium subsidy rates may have increased crop insurance participation in general, with disproportionate increases in relatively risky areas. What is not clear is how much crop insurance participation may be influencing acreage decisions (i.e., the crop mix) and, consequently, may result in secondary (external) environmental effects. Although there are reasons to expect potentially large negative effects, the magnitude and even the direction of these environmental effects are yet to be definitively determined.

Producers use crop insurance to manage production risk, but reductions in risk associated with crop insurance are unlikely to be symmetric across crops. Since crops differ in their agronomic and environmental characteristics, changes in risk will inevitably affect production decisions. Hence, the change in risk from insurance adoption will affect acreage decision, such as production plans among crops (e.g., corn vs. soybeans vs. sunflower or wheat vs. barley vs. lentils).[2] Therefore, whereas the primary purpose of crop insurance policies concerns farm income and government expenditures, one must ask whether crop insurance may have impacted the acreage decision, causing substantive environmental effects. Potential positive environmental effects, if present, would also be of interest, because they could be seen as offsets to the cost of crop insurance programs.

We first investigate whether crop insurance participation and selected insurance characteristics have affected acreage allocation decisions. Second, we examine whether these reallocations may have contributed to environmental degradation.[3] We quantify the impact of crop insurance on the environment by region, insurance characteristic, and environmental domain (i.e., wind erosion, other soil erosion, nitrogen flux, and soil organic carbon). We then examine how different insurance contract characteristics affect the environment and how land heterogeneity changes the environmental impact of crop insurance.

The relationships among risk, farm production decisions, and environmental effects are such that there are inevitable environmental consequences to any policy that changes these relationships. Farming is, after all, a kind of environmental activity—inescapably bound to soil, water and air quality (and, of course, changing ecosystems). However, the direction and magnitude of external environmental effects of agricultural activity are empirical questions. Previous research has identified relationships with potential for environmental consequences among government programs and acreage allocations. Serra et al. (2009) found that decoupling crop production and government payments resulted in land being shifted away from government program crops towards non-program crops. More specific to the current study, Goodwin and Vandeveer (2004) provided evidence that increased participation in crop insurance programs resulted in statistically significant but modest acreage responses. They also found that the acreage response from crop insurance varied by crop type and region. Wu and Adams (2001) determined that revenue insurance affected cropping patterns by altering production risk-expected return relationships and could increase use of environmentally sensitive land for crop production. Finally, Wu (1999) showed that crop insurance in the Central Nebraska Basin shifted land away from hay and pasture production to corn, increasing chemical use.

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[2] It will also affect cropping decisions between insurable and uninsurable crops. We are unable to address these decisions at this time due to the lack of data.

[3] More generally, crop insurance can affect two distinct types of farm decisions—the land use decision at the extensive margin (i.e., the amount of land devoted to a crop) and the output-impacting, enterprise management decision at the intensive margin (i.e., the amount and organization of other inputs used on the land given the crop choice). We analyze the decision at the extensive margin for two reasons. First, it is likely that crop insurance has more impact on land use decisions than on other management decisions; and second, the land use decision is likely to have greater effect on total chemical use and environmental quality than the intensive margin impact of crop insurance (Wu and Adams, 2001).

Studies suggest that land allocation decisions as a result of changes in insurance arrangements have potential for statistically significant environmental effects; economic reasoning suggests that these effects are likely to be negative. For instance, insurance—induced reallocation—either toward more intensive use of environmentally sensitive land types or toward crops associated with higher environmental damages—may cause negative environmental impacts, but the existence and size of any such environmental impacts is not currently well known. Past empirical studies have been limited in number, methods, and findings. In fact, it is difficult to obtain and use the detailed information necessary to assess these complex relationships.

Our study of the environmental effects of crop insurance contributes to the current literature in three important ways. First, detailed producer-level data allows us to directly analyze the relationship between firm-level crop insurance and acreage allocation decisions. Most prior studies examining the effects of government programs on acreage decisions suffer from potential information loss by either aggregating to county-level or by relying on a relatively small number of survey responses. In contrast, our study uses comprehensive producer-level crop insurance contract information and performance data, allowing us to directly capture the impact of two producer-selected crop insurance decisions—coverage level and insurance type—on acreage allocations. Second, we extend the current literature by identifying and quantifying four specific environmental effects associated with crop insurance participation (wind erosion, other soil erosion, nitrogen loss, and change in total organic carbon held in the soil) in four diverse production regions. Third, our empirical results do not find that crop insurance programs have large, broadly distributed, adverse environmental effects. Rather, we find a mix of environmental effects specific to crops and regions.

A Model of Acreage Decisions

We examine the environmental impact of producer acreage responses (i.e., land allocation) from crop insurance participation and insurance characteristic selection. Conceptually, we consider a multi-output technology represented by the implicit function G:

$$G(\boldsymbol{y},\boldsymbol{x},\boldsymbol{E}) = 0. \tag{1}$$

where $\boldsymbol{E}$ is a vector of environmental inputs and outputs, $\boldsymbol{y}$ is a vector of crop production levels, and $\boldsymbol{x}$ is a vector of production inputs. Specific inputs may vary with crops produced. Production outputs and inputs are embedded in the agricultural-environmental technology, G, which also embodies a transformation between $\boldsymbol{y}$ and $\boldsymbol{x}$. This model assumes that production decisions may affect environmental outputs and may be affected by environmental inputs (e.g., soil quality), $\boldsymbol{E}$. Additionally, it allows environmental effects to have either (or both) positive or negative signs and to be small or large. Agricultural producers are assumed to be price takers and act as utility-maximizing, risk-averse firms.

Conceptually, we begin with utility-maximizing agricultural producers, where the agent's utility function includes a vector of final market goods, $\boldsymbol{z}$, and a vector of environmental goods, $\boldsymbol{q}$. For simplicity, we restrict the environmental goods to local, farm-related effects that matter directly to the agent and are a subset of $\boldsymbol{E}$. Hence, the farmer's direct utility function is:

$$\psi = \psi(\boldsymbol{z},\boldsymbol{q}). \tag{2}$$

We can further modify this function by representing the market portion of utility in indirect utility fashion as a function of prices, p, variance of profit, $V(\pi)$, and income, M, where $z = z[p,V(\pi),M]$. We suppress price impacts and assume that all income is earned on the farm. However, we retain the direct effects of $\boldsymbol{q}$. The revised utility function is:

$$U = U(\pi,V(\pi),\boldsymbol{q}), \tag{3}$$

where π is a function of revenue and, hence, of yields. Yields are determined by transformation technologies involving both market inputs, x, and environmental effects, e, where e is the subset of environmental inputs affecting production, such as soil type. Therefore, utility is both directly and indirectly a function of environmental effects. The environmental effects comprise three overlapping subsets: the first subset, e, is environmental inputs into the production process. Examples of q could include local concerns such as safe drinking water and clean air and global concerns such as greenhouse gas emissions and carbon sequestration. The second subset, q, is environmental outputs directly affecting the utility of the agent (such as soil quantity), and the third subset, Q, is the set of observed environmental outputs and inputs.

The role of environmental effects q and e implies a complicated decision model.[4] In the model observed environmental effects may include some environmental outputs, q, of concern to the decision-maker's utility as well as some environmental inputs, e, affecting the production process. Ideally we would like to model more of the decision process and recover direct values of environmental effects. However, to recover the latter, we would have to parameterize the environmental domain to obtain a "hedonic" value of environmental goods, and our data do not allow us to obtain such estimates. While explicitly valuing environmental effects might be desirable, it is beyond our present reach. We observe only the effects of production and insurance decisions on agricultural outputs and infer some environmental outputs and develop a two-stage empirical model that treats environmental effects as byproducts of the production decision. Hence, for purposes of this study, the production technology equation can be re-written as:

$$Q = G(\boldsymbol{y}, \boldsymbol{x}), \tag{4}$$

where tracing the utility effects of environmental inputs and outputs alert us to the potentially complex role of environmental effects in the production decision. We observe production choices and the (modeled) environmental effects, but we do not observe whether or how a producer might weigh environmental effects while making production decisions. Hence, while our intuition is that subsidized insurance will lead to planting crops with higher risk and that high risk crops will be more likely to carry negative environmental effects, we recognize the opposite is also possible. For instance, an alternative behavioral hypothesis is that the opportunity to reduce risk will allow farmers to choose more environmentally benign crops that would otherwise be financially too risky.

We specify our model following Coyle's (1992) linear mean-variance model of utility maximization, which incorporates price uncertainty into a utility maximization framework.[5] We extend this model to include the yield risk faced by producers. Hence, we include the possibility that producers may participate in crop insurance programs to mitigate yield or revenue risk. Following Coyle, we specify utility as:

$$U = E(\pi) - (\alpha/2)V(\pi) \tag{5}$$

where $E(\pi)$ is expected profit, $V(\pi)$ is the variance of profit, and the risk aversion measure, Îś, is constrained to be strictly positive. We include the opportunity to purchase crop insurance, so expected profit is defined as:

$$E(\pi) = E(p,y) - \boldsymbol{w}x + Indem(p,y,\hat{p},\hat{y},cl,ins,u) - Prem(\hat{p},\hat{y},cl,ins,u), \tag{6}$$

where $E(p,y)$ is expected revenue with stochastic output prices p and stochastic yield y; w is the vector of nonstochastic input prices; $Indem(p,y,\hat{p},\hat{y},cl)$ is the indemnity payment from crop

[4] There is an important body of literature supporting the idea that some agricultural producers have land stewardship motives that lead them to care about environmental issues beyond those implied by profit or risk motives (e.g., Bishop, Shumway, and Wandschneider, 2010; Chouinard et al., 2008; Kalinowski, Lynne, and Johnson, 2006; Hayes and Lynne, 2004).

[5] While convenient for empirical analysis, this model is somewhat restrictive in that it implicitly assumes there are no income effects.

insurance which depends on expected output prices and yield, insurance-determined prices ($\hat{p}$), insured yield ($\hat{y}$), coverage level (cl), insurance type (ins) (i.e., yield or revenue), and unit type (u) (i.e., size of insured parcel); and $Prem(\hat{p}, \hat{y}, cl, ins, u)$ is the producer-paid premium. Crop yields are uncertain and input quantities depend on the crop mix.

Assuming a normalized quadratic dual utility function as a 2nd order approximation to a representative farmer's unknown utility function that is dual to equation (5) (Coyle, 1992, p. 852), the structure of the implied output supply equations guides our specification of acreage share equations. We estimate an acreage share equation for each major crop or crop group in each region: [6]

$$
\begin{aligned}
z_{ik} \quad = \quad & \delta_i + \sum_m \mu_{im} \boldsymbol{I}_{ikm} + \sum_{j=1}^{n} \theta - ij\overline{CV}_j + \sum_{j=1}^{n} a_{ij} E(p_j) + \\
& \sum_{j=1}^{n} b_{ij} Var(p_j) + \sum_{j=1}^{n-1} \sum_{j+1}^{n} \gamma_{ijl} Cov(p_j, p_l) + e_{ik},
\end{aligned} \tag{7}
$$

where z_{ik} represents the ratio of crop i ($i = 1, \ldots, n$) acres to total insured acres on farm k; $\boldsymbol{I}$ is an m-vector of crop insurance characteristics; $\overline{CV}_j$ is the expected coefficient of variation of crop j yield (measuring yield risk); $Var(p_j)$ is the price variance of crop j; $Cov(p_j, p_l)$ is the covariance of crop prices j and l; δ_i, μ_{im}, θ_{ij}, a_{ij}, b_{ij}, and γ_{ijl} are parameters to be estimated; and e_{ik} is the error term which, after accounting for producer and temporal heterogeneity, is assumed to be distributed $N(0, \sigma_{ii} I)$. State-level expected crop prices, crop price variance, and crop price covariance are normalized by an index of input prices paid by producers. This normalization maintains zero homogeneity of the acreage share equations in these variables, as implied under the linear mean-variance specification of equation (5).[7] We estimate crop acreage share equations because the average subsidy level and formula changed substantially over the data period; both of these changes may have affected total insured acreage. Focusing on acreage share equations enables us to estimate the asymmetric changes in crop acreage due to crop insurance choices. The time subscript t is dropped to reduce notational clutter.

The vector of crop insurance characteristics includes the decision to purchase insurance as well as type and level of insurance coverage. When deciding to purchase crop insurance, agricultural producers make decisions about coverage level and insurance type to reduce yield or revenue risk. Selecting a higher coverage level with a higher guarantee reduces risk but increases premium costs. Because of reduced production risk, producers may shift acreage to more risky crops—with concomitant impacts on the use of inputs and cultivation strategies.

Producers also select insurance type (yield or revenue) for each crop. We analyze the most widely used insurance plans, including three revenue-based plans—Crop Revenue Coverage (CRC), Income Protection (IP), Revenue Assurance (RA)—and two yield-based plans—(Multiple Peril Crop Insurance (MPCI) and catastrophic insurance (CAT). Table 1 describes these five plans. The CRC, IP, and RA plans protect against low yield, low price, and a combination of both; MPCI and CAT insure only against low yield. We consider CAT insurance as a special form of MPCI for which the government pays 100% of the premium.[8] Selecting an insurance type will depend upon the producer's information about yield and price distributions. Profit-minded and risk-averse producers select insurance type based on perceived production risk or revenue risk and insurance costs. Choosing revenue insurance over yield insurance increases premium costs but provides additional price risk protection.

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[6] The normalized quadratic utility function implies linear output supply equations. We depart from this implication in the structure of our estimation equations since we estimate crop acreage equations rather than crop supply equations and divide individual crop acreage by total acreage for the reason noted below.

[7] Zero homogeneity implies that a proportional increase in all output and input prices and output price variances and covariances does not affect optimal acreage shares.

[8] We refer to yield insurance options except CAT as MPCI.

Table 1: Description of Insurance Programs

Policy	Description	Risk Protection (Insurance Type)	Available Coverage Levels[a]
Crop Revenue Coverage (CRC)	Protection is based on revenue (yield × price). Two prices are used - the base price (minimum guaranteed price) and the harvest price. Indemnity is based on loss below the revenue guarantee using the higher price.	Revenue (Yield × Price)	50% to 85% in 5% increments
Income Protection (IP)	Protection is based on revenue using the base price. Indemnity is based on loss below the revenue guarantee.	Revenue	50% to 75% in 5% increments
Revenue Assurance (RA)	Protection is based on revenue using the base price, unless the fall harvest price option is selected. Then RA functions like the CRC.	Revenue	65% to 85% in 5% increments
Multiple Peril Crop Insurance (MPCI)	Protection is based on yield. Insures at a percentage of a specified price.[b] Indemnity is based on yield loss only.	Yield	50% to 85% in 5% increments
Catastrophic Coverage (CAT)	Protection is based on yield. Insures at 50% of yield at 55% of specified price, so it effectively insures 27.5% of guarantee. Indemnity is based on yield loss only. [b] Entire premium is paid by Federal Government. Producer pays $100 administration fee.	Yield	50%

Notes: [a] Available coverage levels are specific to crop type.
[b] Yield-based insurance plans are multiplied by a price established by the Federal Crop Insurance Corporation to represent the dollar value of each bushel.

Following Chavas and Holt (1996) and Saha and Shumway (1998), we use an adaptive expectations formulation to calculate expected prices. This specification assumes that the random output price is "characterized by a Markov process, which implies that all available and relevant information about the next periods expected price is contained in the current period's realization" (Saha and Shumway, 1998, p. 44). It is also consistent with the findings of several studies that found that the lagged output price outperformed several alternatives, including futures prices, in empirical tests of expected crop price when using annual data (e.g., Houck et al., 1976; Chavas, Pope, and Kao, 1983; Lim, 1989; Chavas and Holt, 1990). Because government programs changed over the data period (1995 to 2002), expected price at time t is calculated for each crop as a function of its lagged overall price (cash price plus per-unit government payments) plus a drift parameter δ:

$$E(p_t) = \delta + \beta p_{t-1}, \tag{8}$$

where p is the price at time t, and δ is the mean of the first difference.

Following (Chavas and Holt, 1996), we use a three-year weighted average (with declining weights) of differences between actual and expected crop prices to specify price variances and covariances. We specify the variance of a crop's price as:

$$\begin{aligned} Var(p_t) \quad = \quad & 0.50(p_{t-1} - E_{t-2}(p_{t-1}))^2 + 0.33(p_{t-2} - E_{t-3}(p_{t-2}))^2 + \\ & 0.17(p_{t-3} - E_{t-4}(p_{t-3}))^2. \end{aligned} \tag{9}$$

The variance can be interpreted as the sum of squared prediction errors for the previous three years, with declining weights of 0.50, 0.33, and 0.17. Using the same declining weights, the covariance between prices for crops j and l is:

$$
\begin{aligned}
Cov(p_{jt}, p_{lt}) \;=\; & 0.50(p_{j,t-1} - E_{t-2}(p_{j,t-1}))(p_{l,t-1} - E_{t-2}(p_{l,t-1})) + \\
& 0.33(p_{j,t-2} - E_{t-3}(p_{j,t-2}))(p_{l,t-2} - E_{t-3}(p_{l,t-2})) + \\
& 0.17(p_{j,t-3} - E_{t-4}(p_{j,t-3}))(p_{l,t-3} - E_{t-4}(p_{l,t-3})).
\end{aligned} \tag{10}
$$

We estimate equation (7) for each region and for each major insured crop or crop group. Although our data and model allow us to empirically examine insured producers' crop allocation decisions, there are several important econometric issues that must be addressed in the estimation procedure. First, because the acreage allocation and the insurance (and insurance contract) decisions are made simultaneously, we use an instrumental variables procedure to estimate the acreage share equations. Instruments include yield lagged one and two years, lagged loss ratio (i.e., indemnity/premium), lagged insurance decision, current and lagged producer premium, lagged indemnity, year fixed effect, producer fixed effect, and all exogenous variables in equation (7).[9] Second, the insurance decision and each insurance contract decision, I_{ikm}, are represented by binary choice variables. Predicting these $\hat{I}$'s from the instruments in the first stage of the instrumental variables procedure yields a continuous variable. We convert the $\hat{I}$'s back to a binary variable by sorting them from small to large and assign a value of zero to observations below the mean $\hat{I}$ and a value of one to observations above the mean. Third, we account for unobserved producer heterogeneity by including producer fixed effects. Temporal heterogeneity is accounted for by including time fixed effects.[10] Fourth, because not all producers purchase crop insurance every year, we use unbalanced panel estimation procedures in each region to assure that variances and statistical tests are computed properly. Following estimation of the instrumental variables, equation (7) is estimated for each acreage allocation equation in each region using XTREG with the fixed effects option in STATA.[11]

There are two econometric issues that we do not address in our estimation procedure. First, contemporaneous correlations across equations are not accounted for; however, the large number of observations in each region likely obviates any potential inefficiencies in parameter estimates. Second, we do not have acreage allocation data for producers who did not enroll in the crop insurance program. Consequently, our data are subject to selectivity bias. Because we are unable to disentangle the effects of selectivity bias, we use producers who select the CAT insurance option as a proxy for non-participants. Because of the low coverage provided by CAT, these participants (and those who do not purchase crop insurance at all) are not likely to alter cropping patterns.[12]

Environmental Impacts Due to Acreage Decisions

We hypothesize that crops with greater yield or revenue risk create greater environmental damage because of added fertilizer and chemical applications and/or more intensive cultivation. Uncertain growing conditions and the additional protection offered by more expensive crop insurance contracts may induce insured farmers to allocate more acres to riskier crops, which could cause additional environmental damage. We note that crops themselves do not cause environmental damage. That is, such damage is the result of management decisions that are often tied to specific crops and

[9] We found no evidence of weak instruments using Staiger and Stock's (1997) testing method.

[10] Based on the Hausman test, fixed effects was deemed more appropriate than a random effects estimation.

[11] To alleviate high collinearity among variables, we dropped the covariance variables as regressors.

[12] With CAT coverage, producers pay no insurance premium, only an administrative fee of \$100 for each crop produced in each county. CAT coverage insures against yields below 50% of Actual Production History (APH) at 55% of the government set price, thus providing insurance at 27.5% of revenue. In contrast, the next lowest available insurance contract is yield insurance at 50% of APH and 100% price, providing 50% insurance coverage (or 50% of revenue). CAT coverage was originally developed for producers who needed to insure because of the mandatory insurance participation rule for producers to participate in government programs. Enacted by the government in 1995, the mandatory participation rule was dropped in 1996 but CAT coverage remains an available crop insurance option. The term "revenue" is used here only to describe the revenue guarantee associated with the yield insurance since only yield is insured and the government-set price is fixed.

regions. For instance, crops vary in terms of fertilizer needs, ground cover, and post-harvest residue. Although we expect changes in land use due to crop insurance to lead to negative environmental impacts based on cultivation intensity, insurance-induced land reallocation could lead to improved environmental outcomes if a riskier crop has more benign environmental implications. The same possibility exists with regard to the intensity of fertilizer and chemical inputs. Whether a riskier crop is more likely to induce environmental damage depends on the specific production technology associated with the crop. Consequently, the possibility of induced environmental damage is an empirical question.

To test whether insurance participation affects the environment via acreage decisions, we use the estimation results obtained from the acreage allocation equations together with the National Nutrient Loss and Soil Carbon Database (NNLSC) developed by soil scientists to predict environmental impacts of estimated input reallocations due to crop insurance (Potter et al., 2006). The NNLSC data are used in the Agriculture Policy/Environment eXtender (APEX) model to simulate the effect of a cropping change on the environment (Williams and Izaurralde, 2007). The APEX model assesses effects of crop type, erosion, and related agronomic models at the whole farm and small watershed level (Williams, 1995).

We use the APEX model and the NNLSC database to assess the impact of changes in crop acreages on four specific environmental variables: total nitrogen loss, change in total organic carbon, sediment loss due to wind erosion, and soil erosion due to other causes. Each is an important and distinctly different intermediate indicator of environmental health. Nitrogen loss through water-borne sediment impacts ecosystems by contaminating streams (and groundwater) and results in eutrophication by enriching water with nitrates while reducing nitrogen available for crop production. Carbon sequestration, the change in total organic carbon stored in the soil, is one of the most promising ways to reduce the buildup of greenhouse gases in the atmosphere (U.S. Department of Energy, 2007). Soils contain more carbon than is contained in vegetation and the atmosphere combined. This makes soil a major reservoir for carbon (Swift, 2001; Lal et al., 1998). Wind and other types of soil erosion adversely impact soil productivity as well as environmental quality (Lal, 2001; U.S. Department of Agriculture, Natural Resource Conservation Service, 2003a,b).

The per-acre damage for each environmental indicator is calculated for each crop in each region for the crop insurance decision and for individual crop insurance characteristic decisions. The simulation results give us point estimates of how much alternative insurance decisions affect the environment, but derivation of confidence intervals is impractical if not infeasible due to the number of individual simulated data points. Consequently, we are limited to drawing non-stochastic assessments of the test results.

We first base the NNLSC simulations on the predicted acreage allocation shares with and without crop insurance. For this test, the vector of crop insurance characteristics, $\boldsymbol{I}$, in equation (7) is a single binary variable with a value of 1 if any crop insurance contract other than CAT is purchased and 0 if CAT is selected. As previously noted, we treat acreage allocations under CAT coverage as representing uninsured producers and test whether purchase of another crop insurance contract has adverse environmental impact.

We next examine whether different insurance characteristics result in different environmental impacts. We test whether revenue insurance and higher coverage levels have larger adverse environmental impacts than yield insurance and lower coverage levels. Producer-selected crop insurance options such as revenue insurance and higher coverage are expected to have greater adverse effects on the environment by promoting larger reallocation of acreage to more environmentally harmful crops in environmentally sensitive areas. For this test, the vector $\boldsymbol{I}$ in equation (7) includes four binary variables—RHC_{ik}, RLC_{ik}, MHC_{ik}, and MLC_{ik}—where RHC is 1 if the producer selected revenue insurance with a high level of coverage (i.e., greater than 70%), RLC is 1 if the producer selected revenue insurance with a low level of coverage (i.e., 70% and below), MHC is 1 if the producer selected MPCI insurance with a high level of coverage, and MLC is 1 if the producer selected MPCI insurance with a low level of coverage. The purchase of CAT coverage is considered the base coverage. We determine whether a significant difference exists between the coefficients for revenue and MPCI insurance and between higher and lower coverage.

To determine whether crop insurance participation, revenue insurance, or high coverage level has a greater impact on the environment, we require that there be statistically significant differences in the relevant parameters of equation (7). In addition, we require that the value from the NNLSC for a measure of environmental degradation be at least 1% higher (which we subjectively define as a "meaningful" difference).

We also examine the possibility that crop insurance might have greater adverse environmental impacts in regions with greater within-county land resource heterogeneity. Intuition suggests that, because of the yield risk protection offered by crop insurance, crop insurance participation may lead to larger changes in land use in regions with high land heterogeneity compared to regions with less land heterogeneity. More heterogeneous regions have more scope for environmental damage scenarios because: (a) heterogeneous circumstances allow more "gaming" of the system by farm operators with respect to their acreage allocations; (b) heterogeneous areas may have a higher probability that both environmentally sensitive and non-sensitive land exist on the same farm; and (c) heterogeneous areas may tend to have thicker risk tails and thus more environmental risk, because insurance favors riskier crops given how subsidies are applied. However, these causal pathways are speculative. For example, it is possible that more homogeneous regions have fewer, but larger, shifts in farm operations, which lead to larger environmental effects. Consequently, this is an empirical question that could have policy implications.

We test the effects of land heterogeneity by examining whether larger environmental impacts from crop insurance and particular crop insurance characteristics occur in regions with greater land resource heterogeneity. We examine four growing regions: two relatively homogeneous regions with more uniform land quality characteristics (Iowa and North Dakota in the Midwest), and two more heterogeneous regions (Eastern Washington in the Pacific Northwest and Eastern Colorado in the Northern Great Plains).

To determine whether land heterogeneity leads to greater adverse environmental impact from crop insurance, we require that the average of all significantly different environmental effects for an indicator be at least 1% greater for regions with greater within-county land resource heterogeneity than for regions with less within-county land resource heterogeneity.

Data

We use a detailed actuarial data set from the Risk Management Agency of the United States Department of Agriculture. The data consist of producer-level crop insurance contracts and acreage allocations for 1993 to 2002.[13] We use 1995 to 2002 data because 1995 is the first year CAT coverage, which we use as a proxy for uninsured producers, was available.[14] The data set includes information from the Federal Crop Insurance Corporation for each crop insurance contract, including indemnity amount, premium paid by producer, subsidy amount, crop type, number of acres in crop, coverage level, insurance type, year, and county location of field. All four regions produce at least three of six primary crops: wheat, corn, soybeans, barley, sunflower, and dry peas. We also include an "other crops" category that represents additional crops commonly produced and insured in the region.[15]

For a producer to be included in our analysis, s/he had to have purchased crop insurance for at least six of the eight years of the study period and to have grown each of the region's primary

[13] Due to the producer detail in this data set, confidentiality requirements have limited its accessibility for analysis as well as the years of data we were permitted to use.

[14] The 1994 Crop Insurance Reform Act authorized catastrophic coverage or CAT coverage. The years 1993 and 1994 were used in the instrumental variables specification.

[15] The "other" category includes canola and dry beans in North Dakota, oats in Iowa, dry beans and barley in Eastern Colorado, and canola, oats, and dry beans in Eastern Washington.

crops at least once during the study. The latter criterion assures that each producer has the ability to produce each of the region's primary crops and so has the capacity to reallocate land resources among those crops.[16]

State-level output and input prices are calculated using data described in Ball, Hallahan, and Nehring (2004). Output price is the sum of cash price plus distortion-creating government payments per bushel.[17] Thus, government commodity programs are explicitly incorporated into the analysis through the price variables.

The coefficient of variation (CV) for each crop is used as a proxy for yield risk and is calculated based on crop reporting district yield data from 1950 to 1995. Crop reporting districts represent an average yield from multiple counties. Each state has five to seven crop reporting districts. The de-trended crop reporting district coefficients of variation clearly underestimate yield risk faced by individual producers, but they are the best proxy available due to the lack of yield data prior to 1995 for our producers.

Environmental data were obtained from the National Nutrient Loss and Soil Carbon Database simulation model (NNLSC). The NNLSC uses 1997 National Resources Inventory (NRI) data collected on U.S. farmland along with Cropping Practice Survey data and Area Studies data to simulate physical processes pertaining to soil, water, and other natural resources (Potter et al., 2006). A Unique Resource Unit (URU) was developed by the NNLSC from NRI data points, state, crop type, climate type, soil type, irrigation type, and conservation practice. Each URU was treated as a field, which averaged 12,000 acres in size and represented different types of tillage practices, fertilizer application methods, and manure applications. Several model runs were conducted for each URU. Each model run provided a data point in the nutrient loss database, resulting in over 1.4 million individual data points. Simulation results from the NNLSC represent thirty years of production.

The NNLSC data does not contain environmental data on every crop we analyze. Where we do not have crop data, we used the next best crop based on plant type characteristics as a proxy. For example, corn was used as a proxy for canola, and soybeans were used as a proxy for both dry beans and dry peas in Eastern Washington; sorghum was used as a proxy for both sunflower and canola, and soybeans were used as a proxy for dry beans in North Dakota; soybeans and sorghum were used as proxies for dry beans and sunflower, respectively, in Eastern Colorado.[18]

Results

Tables 2, 3, 4 reports the estimated coefficients for the regional systems of acreage share equations (7) with an insurance binary variable.[19] The constant in each equation represents a producer who selected CAT insurance and is treated as a proxy for uninsured producers. Seven of the eight own-price parameters are positive, as expected. In nearly all equations, we found evidence of both substitute and complementary outputs; that is, at least one cross-price parameter was negative (substitute) and at least one was positive (complement).

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[16] No producers were excluded by these criteria in North Dakota or Eastern Colorado; 499 were excluded in Eastern Washington and 2,327 in Iowa. Excluded producers account for 5.8% of observations in Eastern Washington and 7.7% in Iowa.

[17] Commodity-related government subsidies (deficiency payments, diversion payments, and sugar beet support payments) to producers of the commodity are added to state-level market receipts and divided by state-level production (Ball et al., 1999). 1996 Farm Bill subsidies were centered on the Agricultural Market Transition Act.

[18] While the NNLSC database and Apex model make it possible to assess the environmental effects of changing management practices, we do not have management practice information for individual producers with insurance contracts. Consequently, we are only able to examine the extensive margin environmental impacts of crop insurance and not the intensive margin effects.

[19] Although they were estimated as part of the regional systems, we do not report estimated coefficients for two crops with very small acreage shares. They include sunflower (2.0% in Eastern Colorado and 6.2% in North Dakota) and dry peas (2.2% in Eastern Washington).

Table 2: Effect of Crop Insurance Participation on Wheat Acreage Share

	Region			
Parameter	**Iowa**	**North Dakota**	**Eastern Colorado**	**Eastern Washington**
Insurance	—	0.017	−0.004	0.004
		(0.009)	(0.004)	(0.008)
P Wheat	—	0.655**	0.040**	0.119
		(0.091)	(0.013)	(0.0874)
P Corn	—	—	0.283**	—
			(0.015)	
P Barley	—	0.355**	—	−0.079
		(0.038)		(0.051)
P Sunflower#	—	0.789**	−0.173**	0.003
		(0.088)	(0.015)	(0.020)
P Other	—	−1.495**	−0.114**	−0.046
		(0.175)	(0.006)	(0.040)
V Wheat	—	0.048**	0.073**	−0.007
		(0.006)	(0.006)	(0.008)
V Corn	—	—	−0.021**	—
			(0.002)	
V Barley	—	−0.252**	—	−0.011
		(0.032)		(0.013)
V Sunflower#	—	−0.099**	−0.089**	−0.002
		(0.011)	(0.006)	(0.003)
V Other	—	—	—	—
Time	—	−0.011**	−0.013**	0.002**
		(0.001)	(0.001)	(0.001)
CV		0.810	0.124	−0.136
		(0.461)	(0.080)	(0.141)
Constant	—	0.592**	0.831**	0.912**
		(0.119)	(0.031)	(0.044)
# Obs.	27994	10472	15023	7931

Notes: Standard errors are shown in parentheses, P is price, V is variance, and # indicates dry peas in Eastern Washington. Double asterisks (**) represent significance at the 5% level. Although equations were also estimated for sunflower in North Dakota and Eastern Colorado and for dry peas in Eastern Washington, their estimated coefficients are not reported in this table because their acreage shares were so small.

Acreage Decisions

We found statistically significant impacts of crop insurance on acreage allocations at the 5% level only for corn (negative) in Eastern Colorado and barley (positive) in North Dakota. In both regions acreage allocations were impacted by 4%. Our results lend support to results from Goodwin and Vandeveer (2004), who found that crop insurance participation results in some statistically significant acreage responses. In our case they are few: only 25% of all insurance participation parameter estimates are significant. Half of the own-price parameters, 47% of cross-price parameters, 46% of variance parameters, all of the time and constant parameters, and half of the coefficient of variation parameters were statistically significant.

Table 5 reports the insurance contract characteristic portion of the estimation results for the system of acreage share equations with crop insurance characteristic variables in equation (7). Price and variance parameter estimates were similar in magnitude and statistical significance to those in

Table 3: Effect of Crop Insurance Participation on Corn Acreage Share

	Region			
Parameter	**Iowa**	**North Dakota**	**Eastern Colorado**	**Eastern Washington**
Insurance	−0.003	—	−0.039**	—
	(0.006)		(0.004)	
P Wheat	—	—	0.002**	—
			(0.001)	
P Corn	0.001	—	−0.003**	—
	(0.001)		(0.001)	
P Barley^	−0.001	—	—	—
	(0.001)			
P Sunflower	—	—	—	—
P Other	—	—	—	—
V Wheat	—	—	0.0003	—
			(0.0002)	
V Corn	0.001	—	−0.0001	—
	(0.0006)		(0.0001)	
V Barley^	−0.00003	—	—	—
	(0.0002)			
V Sunflower	—	—	0.0003**	—
			(0.0001)	
V Other	−0.001**	—	—	—
	(0.0003)			
Time	−0.005**	—	0.005**	—
	(0.0004)		(0.0004)	
CV	−0.043		0.361**	
	(0.089)		(0.004)	
Constant	−0.562**	—	0.030**	—
	(0.060)		(0.002)	
# Obs.	27994	10472	15023	7931

Notes: Standard errors are shown in parentheses, P is price, V is variance, and ^ indicates soybeans in Iowa. Double asterisks (**) represent significance at the 5% level. Although equations were also estimated for sunflower in North Dakota and Eastern Colorado and for dry peas in Eastern Washington, their estimated coefficients are not reported in this table because their acreage shares were so small.

tables 2, 3, and 4, so they are not reported in table 5. The statistically significant effects of crop insurance contract characteristics on acreage shares varied between -1% and +6% for wheat, -8% and +9% for corn, -4% and +5% for barley, and +1% for soybeans.[20] A total of 63% of the insurance characteristics had a statistically significant impact on crop acreage allocations in all regions except Eastern Washington.

To test whether a significant difference exists between revenue and yield insurance and between high and low coverage level, we computed Wald Chi-square test statistics. Results from these tests are reported in table 6. We found a significant difference in all regions except Eastern Washington

[20] Because the insurance decision and the insurance characteristic binary variables were estimated using instrumental variable procedures without imposing adding-up restrictions, the sum of the insurance characteristic variables do not necessarily equal the insurance decision variable. Consequently, the insurance parameter estimates reported in tables 2, 3, and 4 do not all lie within the bounds of the insurance characteristic parameter estimates for the respective region and crop reported in table 5.

Table 4: Effect of Crop Insurance Participation on Barley^ Acreage Share

	Region			
Parameter	**Iowa**	**North Dakota**	**Eastern Colorado**	**Eastern Washington**
Insurance	0.004**	0.044**	—	−0.011
	(0.003)	(0.005)		(0.010)
P Wheat	—	0.068	—	−0.056
		(0.050)		(0.050)
P Corn	0.043**	—	—	—
	(0.008)			
P Barley^	0.028**	0.040	—	0.054
	(0.005)	(0.021)		(0.035)
P Sunflower#	—	0.088	—	−0.009
		(0.048)		(0.014)
P Other	−0.073**	−0.163	—	0.013
	(0.013)	(0.097)		(0.027)
V Wheat	—	0.005	—	−0.001
		(0.003)		(0.006)
V Corn	0.002**	—	—	—
	(0.001)			
V Barley^	0.005**	−0.027	—	0.002
	(0.001)	(0.017)		(0.009)
V Sunflower#	—	−0.011	—	−0.001
		(0.006)		(0.002)
V Other	−0.003**	—	—	—
	(0.0006)			
Time	0.006**	−0.003**	—	0.002**
	(0.0003)	(0.001)		(0.001)
CV	0.559**	0.762**		0.275**
	(0.0057)	(0.017)		(0.011)
Constant	0.015**	0.029**	—	0.010**
	(0.0036)	(0.003)		(0.004)
# Obs.	27994	10472	15023	7931

Notes: Standard errors are shown in parentheses, P is price, V is variance, ^ indicates soybeans in Iowa, and # indicates dry peas in Eastern Washington. Double asterisks (**) represent significance at the 5% level. Although equations were also estimated for sunflower in North Dakota and Eastern Colorado and for dry peas in Eastern Washington, their estimated coefficients are not reported in this table because their acreage shares were so small.

between revenue and yield insurance. Only in Iowa did we find a significant difference between high and low coverage levels. These findings support the hypothesis that producers' acreage allocation decisions are not entirely independent of their selection of type and coverage level of insurance contract and are consistent with Wu and Adams' (2001) finding that revenue insurance altered cropping patterns.

Environmental Impacts

Using the estimated impacts of crop insurance on acreage allocations, we now consider the environmental impacts from land allocation effects associated with crop insurance. To consider the effect on different dimensions of the environment, we analyze four different environmental indicators–total nitrogen loss, change in soil organic carbon, wind erosion, and other soil erosion–using the simulation techniques described above. The expected environmental damage caused by

Table 5: Effects of Various Crop Insurance Contract Characteristics on Acreage Shares

		Region			
Crop	**Parameter**	**Iowa**	**North Dakota**	**Eastern Colorado**	**Eastern Washington**
Wheat	Revenue and	—	0.063**	−0.013**	0.013
	High Coverage Level	—	(0.010)	(0.006)	(0.008)
	Revenue and	—	0.014**	−0.010**	0.002
	Low Coverage Level	—	(0.007)	(0.004)	(0.013)
	Yield and	—	−0.022	0.011	−0.006
	High Coverage Level	—	(0.016)	(0.018)	(0.008)
	Yield and	—	−0.007	−0.006	−0.007
	Low Coverage Level	—	(0.007)	(0.004)	(0.009)
Corn	Revenue and	−0.052**	—	0.063**	—
	High Coverage Level	(0.004)	—	(0.006)	—
	Revenue and	−0.005**	—	0.087**	—
	Low Coverage Level	(0.002)	—	(0.004)	—
	Yield and	−0.076**	—	0.031	—
	High Coverage Level	(0.004)	—	(0.032)	—
	Yield and	−0.065**	—	0.047**	—
	Low Coverage Level	(0.003)	—	(0.004)	—
Barley^	Revenue and	0.0001	−0.024	—	−0.012
	High Coverage Level	(0.003)	(0.017)	—	(0.018)
	Revenue and	0.007**	−0.037**	—	0.024
	Low Coverage Level	(0.003)	(0.007)	—	(0.075)
	Yield and	0.0002	0.049**	—	−0.002
	High Coverage Level	(0.003)	(0.015)	—	(0.006)
	Yield and	0.002	0.027**	—	−0.010
	Low Coverage Level	(0.003)	(0.004)	—	(0.008)

Notes: Standard errors are shown in parentheses, îndicates soybeans in Iowa. Double asterisks (**) represent significance at the 5% level.

each planted acre of a crop was weighted by the crop's share of total crop acreage in the region. All crops were accounted for, so the sum of acreage shares is equal to 1.0 in each region. With no formal method to test for statistically significant adverse environmental impacts from crop insurance, we conservatively treat a 1% increase in the absolute value of an environmental indicator as being a "meaningful" difference. All assessments of meaningful differences are relative to the environmental impact with CAT (a proxy for no) insurance.

Table 7 presents estimated environmental effects of crop insurance due to acreage reallocation among all crops in each region. In North Dakota we found that the decision to purchase crop insurance had a "meaningful" environmental impact (i.e., the environmental effect differed from the "No Insurance" effect by at least 1%) in all four environmental indicators. However, the effect was adverse for total nitrogen loss. In Eastern Colorado the decision to purchase crop insurance had a meaningful environmental impact in three environmental indicators, two of which were adverse: wind erosion and soil organic carbon. In Eastern Washington, the decision to purchase crop insurance had meaningful environmental impact in all four environmental indicators, only one of which—wind erosion—was adverse; however, as previously noted, the crop insurance decision did not have a significant effect on the crop allocation decision in this region. In Iowa, the decision to purchase crop insurance had no meaningful environmental impact, adverse or beneficial, and no significant effect on the crop allocation decision.

Table 6: Wald Test Statistics for Revenue vs. Yield Insurance and High vs. Low Coverage Level on Acreage Share

		Region			
Crop	**Parameter**	**Iowa**	**North Dakota**	**Eastern Colorado**	**Eastern Washington**
Wheat	Revenue Insurance	—	29.20**	1.98	2.10
		—	(0.00)	(0.16)	(0.15)
	High Coverage	—	3.09	0.43	0.45
		—	(0.08)	(0.51)	(0.51)
Corn	Revenue Insurance	184.32**	—	44.83**	—
		(0.00)	—	(0.00)	—
	High Coverage	57.31**	—	0.06	—
		(0.00)	—	(0.81)	—
Barley^	Revenue Insurance	0.99	34.18**	—	0.09
		(0.32)	(0.00)	—	(0.77)
	High Coverage	3.91**	2.38	—	0.13
		(0.05)	(0.12)	—	(0.72)

Notes: P-values are in parentheses, ^indicates soybeans in Iowa. Double asterisks (**) represent significance at the 5% level.

Table 7: Environmental Impacts of Crop Insurance Participation

Environmental Indicator	Region	No Insurance	Insurance
Wind Erosion	North Dakota	1.60	1.58
	Iowa	0.50	0.50
	Eastern Colorado	0.99	1.09*
	Eastern Washington	0.004	0.004*
Soil Erosion	North Dakota	0.47	0.46*
	Iowa	2.82	2.82
	Eastern Colorado	0.21	0.21
	Eastern Washington	1.38	1.35*
Total Nitrogen Loss	North Dakota	29.96	30.37*
	Iowa	51.74	51.66
	Eastern Colorado	15.99	15.38*
	Eastern Washington	30.53	30.17*
Change in Soil Organic Carbon	North Dakota	−3.34	−3.22*
	Iowa	−6.36	−6.37
	Eastern Colorado	−0.86	−0.88*
	Eastern Washington	−0.25	−0.24*

Notes: Wind erosion, soil erosion, and change in soil organic carbon values are in tons per acre. Total nitrogen losses are in lbs. per acre. Nitrogen loss is computed as the sum of nitrate in runoff, leachate, subsurface lateral flow, organic nitrogen in water- and wind-borne sediment, and volatilized nitrogen. Single asterisk (*) indicates a difference greater than 1% in absolute value from no insurance.

Estimated environmental effects from crop insurance contract characteristics for each region are presented in table 8. They represent the contribution to environmental damage from acreage reallocation among all crops in the region under each of four crop insurance contract options. Among the specific insurance contract options, all had meaningful adverse environmental impacts.

Table 8: Environmental Impacts of Crop Insurance Contract Characteristics

Environmental Indicator	Region	Crop Insurance Contract: No Insurance[a]	Revenue High Coverage	Revenue Low Coverage	Yield High Coverage	Yield Low Coverage
Wind Erosion	North Dakota	1.58	1.51*	1.58	1.56*	1.60
	Iowa	0.52	0.49*	0.52	0.478*	0.48*
	Eastern Colorado	0.96	1.00*	1.07*	0.92*	1.25*
	Eastern Washington	0.003	0.003*	0.003*	0.004*	0.003*
Soil Erosion	North Dakota	0.48	0.47*	0.48	0.47*	0.48
	Iowa	2.91	2.83*	2.92	2.83*	2.83*
	Eastern Colorado	0.208	0.208	0.216*	0.204*	0.221*
	Eastern Washington	1.299	1.301	1.301	1.288	1.295
Total Nitrogen Loss	North Dakota	28.99	27.80*	28.79	29.45*	29.60*
	Iowa	53.36	50.88*	53.53	49.92*	50.38*
	Eastern Colorado	15.69	17.44*	18.43*	16.45*	18.11*
	Eastern Washington	31.56	30.62*	30.57*	31.78	30.67*
Change in Soil Organic Carbon	North Dakota	−3.36	−3.31*	−3.38	−3.20*	−3.21*
	Iowa	−6.52	−6.42*	−6.56	−6.46	−6.44*
	Eastern Colorado	−0.87	−0.85*	−0.88*	−0.84*	−0.91*
	Eastern Washington	−0.35	−0.20*	−0.23*	−0.39*	−0.27*

Notes: Wind erosion, soil erosion, and change in soil organic carbon values are in tons per acre. Total nitrogen losses are in lbs. per acre. Nitrogen loss is computed as the sum of nitrate in runoff, leachate, subsurface lateral flow, organic nitrogen in water- and wind-borne sediment, and volatilized nitrogen. Single asterisk (*) indicates a difference greater than 1% in absolute value from no insurance.
[a] The "no insurance" environmental effects are based on the estimated intercepts in equation (7) and thus differ in this table from table 7. This equation was estimated separately for the insurance contract decision and for the contract characteristics decision since combining them would have resulted in a singular covariance matrix.

However, only fifteen of the sixty-four specific contract-state-environmental indicators examined had meaningful adverse environmental impacts, and only seven of those had an impact in excess of 5%. Applying the same criterion in the other direction, half of the sixty-four had meaningful beneficial environmental impacts, eleven of which had an impact in excess of 5%. Among the forty-eight impacts for regions with significant acreage reallocations, thirteen were meaningfully adverse, six were adverse with more than 5% impact, twenty-three were meaningfully beneficial, and five were beneficial with more than 5% impact. Thus, for all regions and just those with statistically significant acreage reallocations, the number of meaningful beneficial environmental impacts far exceeded the number of meaningful adverse environmental impacts. Only in regions with statistically significant acreage reallocations and for impacts in excess of 5% did the number of adverse impacts exceed the number of beneficial impacts.

We next examined whether the crop insurance and crop insurance contract characteristic decisions had greater adverse environmental impact in regions with greater within-county land resource heterogeneity using the results reported in tables 7 and 8. Results show a total of nineteen meaningful adverse environmental indicators, three in North Dakota and none in Iowa (the more homogenous regions) as well as thirteen in Eastern Colorado and three in Eastern Washington (the more heterogeneous regions). Thus, there was considerably more evidence of adverse environmental impact in regions with greater within-county land resource heterogeneity. This conclusion also holds when only those states with significant acreage reallocation effects are considered (i.e., Eastern Colorado vs. North Dakota in table 5 and Eastern Colorado vs. North Dakota and Iowa in table 6).

Table 9: Average Percentage Environmental Impact from Crop Insurance

Region	Insurance	Revenue High Coverage	Revenue Low Coverage	Yield High Coverage	Yield Low Coverage
North Dakota	1.47	−4.42	−2.32	2.13	2.77
Iowa	−0.01	−4.93	0.29	−6.95	−5.98
Eastern Colorado	0.33	11.26	17.77	4.62	16.75
Eastern Washington	−2.81	−2.44	−2.36	0.52	−2.52
Average	−0.03	−0.13	3.35	0.08	2.76
Average for regions with significant acreage reallocations[b]	0.90	0.64	5.25	−0.07	4.51

Notes: A positive impact is adverse, and a negative impact is beneficial. [rma] These regions include North Dakota and Eastern Colorado for the crop insurance selection decision, and North Dakota, Iowa, and Eastern Colorado for the contract characteristics decisions.

Among the meaningful beneficial environmental impacts, eleven were in North Dakota, eleven in Iowa, five in Eastern Colorado, and twelve in Eastern Washington. Consequently, the evidence suggests that greater land heterogeneity also results in less beneficial environmental impact from crop insurance decisions. The evidence for this conclusion is stronger for regions with statistically significant acreage reallocations.

Finally, we examined the overall environmental impact of crop insurance in each region and computed the average across regions in order to assess impact on the environment. We assessed whether insurance generally has adverse impact on the environment, whether revenue insurance has greater adverse impact than yield insurance, and whether selecting higher coverage insurance has greater adverse impact than lower coverage insurance. Without other strong priors, we weighted the percentage change in each environmental indicator equally. The calculated environmental impacts in percentages are reported by region, for the average, and for the average of regions with significant acreage reallocations in table 9. We interpret the average indicator as a measure of overall environmental health.

The insurance selection decision had an adverse overall environmental impact in two regions: 1.5% in North Dakota and 0.3% in Eastern Colorado. In Eastern Washington the selection decision had a strong beneficial impact of -2.8%, and in Iowa its impact was almost neutral. Across the four regions, the selection decision had an average beneficial environmental impact of -0.3%. Across the two regions with statistically significant acreage reallocations, the selection decision had an average adverse environmental impact of 0.9%. Thus, we conclude that the decision to purchase crop insurance did not have a meaningful overall adverse environmental impact on average but was meaningful with statistically significant acreage reallocations in one-half of the regions.

The environmental impact of specific insurance characteristics varied considerably more among regions than did the impact of the decision to insure.[21] Adverse environmental impacts were found for each insurance characteristic and were most evident in North Dakota and Eastern Colorado; both regions had statistically significant acreage reallocations. For revenue insurance, higher coverage resulted in meaningfully different and less adverse (or more beneficial) environmental impacts than lower coverage in three regions. For yield insurance, higher coverage resulted in meaningfully different and more adverse environmental impact than lower coverage in one region and meaningfully different and less adverse impact in another region. For both yield and revenue insurance, higher coverage resulted in meaningfully different and less adverse environmental impacts on average both for all regions and for those with significant acreage reallocations. Thus, contrary to expectations, selection of high coverage insurance had generally less adverse environmental impact than low coverage insurance.

[21] As previously noted, the estimated impacts of insurance characteristics do not necessarily bound the estimated impact of the insurance decision in each region because of the instrumental variables estimation procedure used.

Conclusions

We analyze potential unintended consequences of crop insurance purchases – the extensive-margin (land allocation) environmental effects of crop insurance and insurance contract characteristics among regions and crops. We consider a spectrum of environmental effects by using four different environmental indicators. Our results identify regions where the environment is harmed and where it is improved in specific environmental characteristics as a result of crop insurance purchases.

We conduct our investigation by asking two questions. First, does crop insurance policy affect production decisions, particularly land allocation decisions? Second, do land allocation changes tend to generate negative environmental effects? We find statistically significant acreage allocation impacts of the crop insurance selection decision in only two of the four regions we studied. We find statistically significant differences in acreage allocation impacts among insurance contract characteristics in three of the regions. In summary, we find evidence of the expected impact of changes in crop insurance on production decisions, specifically the land allocation decision, but the detected impacts are relatively few and generally modest.

Our results support neither extreme in a debate about whether these changes in cropping patterns induced by crop insurance have adverse environmental effects. We find a small, but not universal, tendency for increased crop insurance participation to create "noticeable" environmental effects. Our evidence shows both positive and negative environmental effects as cropping patterns change. On average, the contribution of crop insurance to adverse environmental effects is slightly less than 1% in regions with statistically significant acreage reallocations.

While we find small and not always negative environmental effects, our results should not be interpreted as supporting a "no negative environmental impact" generalization. We do not have data to investigate the very real possibility that insurance changes influenced other, non-land (within-crop) production decisions, with their own environmental effects. Although we do not find evidence on average (across regions and environmental indicators) of meaningful adverse environmental impact from crop insurance participation (via changes in cropping patterns), there is evidence of adverse impact in specific environmental indicators in three of the four regions. The adverse impacts occur with respect to three of the four environmental indicators (wind erosion, total nitrogen loss, and change in soil organic carbon). Conversely, we find instances of beneficial environmental impact from crop insurance participation among all four environmental indicators and in three of the four regions.

Among the specific crop insurance contracts, we find meaningful environmental impacts, both adverse and beneficial, from each of four insurance contract characteristics. Contrary to our *a priori* expectation, selecting high coverage insurance has meaningfully lower adverse environmental impact on average than selecting low coverage insurance. Consistent with our *a priori* expectation, greater within-county land heterogeneity has greater adverse environmental impact and less beneficial impact. However, mixed environmental effects are consistent with the larger decision model we outlined in our theory section. One can speculate on at least two systematic mechanisms to explain the positive environmental effects. First, perhaps contrary to earlier empirical work and our intuition, production technology tends to be fairly unbiased with regard to the interaction between the environment and risky production technologies. Second, farmers could be more environmentally sensitive than many have thought, and thus inclined to adopt "greener technologies" when the risks associated with those crops can be reduced. These possibilities seem ripe for further research.

Our study suggests that, from a regional perspective, environmental effects of crop acreage reallocation due to crop insurance are subtle but potentially locally important. Although often modest, the generally positive correlation between crop insurance and environmental damage supports the policy implication that insurance premium costs do not always reflect the full social cost or benefit of crop insurance and that the gap is location sensitive.

These results and implications are based on analysis of detailed farm-level data for a large number of farms in several production regions. Because our data are not a representative sample, we cannot generalize the results. However, the importance of this study hinges on this point. In general, as studies become larger in scale, detail is lost. Studies of farm decisions demand the kind of detailed data and model specificity we have employed. Given the relatively modest environmental impacts we find, it is not surprising that the results of past studies have been inconclusive. Our study, which is highly detailed for a small number of regions, finds varied and relatively modest effects. This explains why a large-scale aggregate study may find no impacts, but that detailed studies may find location and crop specific environmental effects, suggesting that a true aggregate reckoning of the total environmental effects of crop insurance would require both enormous detail and a broad geographically distributed sample area. What appears to be statistical noise may, in fact, hide locally important effects.

Results of this study warn us against generalizing local research results to recommendations for uniform national policies. Furthermore, our results speak to the importance of national policies being locally flexible and suggest a focus on locally important environmental impacts in further research. From a policy perspective, this study provides support for a moderately optimistic view about the environmental effects of crop insurance programs with the caveat that local adverse effects may be significant.

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References

Ball, V. E., F. M. Gollop, A. Kelly-Hawke, and G. P. Swinand. "Patterns of State Productivity Growth in the U.S. Farm Sector: Linking State and Aggregate Models." *American Journal of Agricultural Economics* 81(1999):164–179.

Ball, V. E., C. Hallahan, and R. Nehring. "Convergence of Productivity: An Analysis of the Catch-up Hypothesis within a Panel of States." *American Journal of Agricultural Economics* 86(2004):1315–1321.

Bishop, C. P., C. R. Shumway, and P. R. Wandschneider. "Agent Heterogeneity in Adoption of Anaerobic Digestion Technology: Integrating Economic, Diffusion, and Behavioral Innovation Theories." *Land Economics* 86(2010):585–608.

Chavas, J. P. and M. T. Holt. "Acreage Decisions Under Risk: The Case of Corn and Soybeans." *American Journal of Agricultural Economics* 72(1990):529–538.

———. "Economic Behavior Under Uncertainty: A Joint Analysis of Risk Preferences and Technology." *Review of Economics and Statistics* 78(1996):329–335.

Chavas, J. P., R. D. Pope, and R. S. Kao. "An Analysis of the Role of Futures Prices, Cash Prices and Government Programs in Acreage Response." *Western Journal of Agricultural Economics* 8(1983):27–33.

Chouinard, H. H., T. Paterson, P. R. Wandschneider, and A. M. Ohler. "Will Farmers Trade Profits for Stewardship? Heterogeneous Motivations for Farm Practice Selection." *Land Economics* 84(2008):66–82.

Coyle, B. T. "Risk Aversion and Price Risk in Duality Models of Production: A Linear Mean-Variance Approach." *American Journal of Agricultural Economics* 74(1992):849–859.

Goodwin, B. K. and M. L. Vandeveer. "An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Progam." *American Journal of Agricultural Economics* 86(2004):1058–1077.

Hayes, W. M. and G. D. Lynne. "Towards a Centerpiece for Ecological Economics." *Ecological Economics* 49(2004):287–301.

Houck, J. P., M. E. Abel, M. R. Ryan, P. W. Gallagher, R. G. Hoffman, and J. B. Penn. "Analyzing the Impact of Gevernment Programs on Crop Acreage." Technical Bulletin 1548, U.S. Department of Agriculture, Economic Research Service, Washington, D.C., 1976.

Kalinowski, C. M., G. D. Lynne, and B. Johnson. "Recycling as a Reflection of Balanced Self-Interest: A Test of the Metaeconomics Approach." *Environment and Behavior* 38(2006):333–355.

Lal, R. "Soil Degradation by Erosion." *Land Degradation & Development* 12(2001):519–539.

Lal, R., J. M. Kimble, R. F. Follett, and C. V. Cole. *The Potential of U.S. Cropland to Sequester Carbon and Mitigate the Greenhouse Effect*. Ann Arbor, MI: Sleeping Bear Press, 1998.

Lim, H. *Profit Maximization, Returns to Scale, Separability, and Measurement Error in State-Level Agricultural Technology*. PhD dissertation, Texas A & M University, College Station, TX, 1989.

Potter, S. R., J. D. Andrews, J. D. Atwood, R. L. Kellogg, J. Lemunyon, L. Norfleet, and D. Oman. *Model Simulation of Soil Loss, Nutrient Loss, and Change in Soil Organic Carbon Associated with Crop Production*. Washington, D.C.: U.S. Department of Agriculture, Natural Resource Conservation Service, Conservation Effects Assessment Project (CEAP), 2006.

Ricardo, D. *Principles of Political Economy and Taxation*. London: J. Murray, 1817.

Saha, A. and C. R. Shumway. "Refutable Implications of the Firm Model Under Risk." *Applied Economics* 30(1998):441–448.

Serra, T., D. Zilberman, J. M. Gil, and A. Featherstone. "The Effects of Decoupling on Land Allocation." *Applied Economics* 41(2009):2323–2333.

Staiger, D. and J. H. Stock. "Instrumental Variables Regression with Weak Instruments." *Econometrica* 65(1997):557–586.

Swift, R. S. "Sequestration of Carbon by Soil." *Soil Science* 166(2001):858–871.

U.S. Department of Agriculture, Natural Resource Conservation Service. *Soil Erosion*. Washington, D.C.: U.S. Department of Agriculture, Natural Resource Conservation Service, 2003a.

———. "Soil Quality." Agronomy Technical Note No. 16, U.S. Department of Agriculture, Natural Resource Conservation Service, Washington, D.C., 2003b.

U.S. Department of Agriculture, Risk Management Agency. "Summary of Business Reports and Data." 2010. Available online at: http://www.rma.usda.gov/data/sob.html.

U.S. Department of Energy. *Carbon Sequestration*. Washington, D.C.: U.S. Department of Energy, 2007.

U.S. Environmental Protection Agency. "Water Quality Conditions in the United States: A Profile from the 2000 National Water Quality Inventory." Report EPA-841-F-02-003, U.S. Environmental Protection Agency, Washington, D.C., 2002. Available online at: http://water.epa.gov/lawsregs/guidance/cwa/305b/upload/2002_09_09_305b_2000report_factsheet.pdf.

Williams, J. R. "The EPIC Model." In V. P. Singh, ed., *Computer Models of Watershed Hydrology,* Highlands Ranch, CO: Water Resources Publications, 1995, 909–1000.

Williams, J. R. and R. C. Izaurralde. "The APEX Model." Tech. rep., Texas Agricultural Experiment Station, Temple, TX, 2007.

Wu, J. J. "Crop Insurance, Acreage Decisions, and Nonpoint-Source Pollution." *American Journal of Agricultural Economics* 81(1999):305–320.

Wu, J. J. and R. M. Adams. "Production Risk, Acreage Decisions, and Implications for Revenue Insurance Programs." *Canadian Journal of Agricultural Economics* 49(2001):19–35.