Journal of Agricultural and Resource Economics 30(1):94–108

Some Simulation Results for a Green Insurance Mechanism

Kenneth A. Baerenklau

This analysis extends previous work on green insurance by proposing a mechanism that offers a stronger adoption incentive and is applicable to heterogeneous populations and non-binary adoption decisions. Endogenous learning about the new technology is incorporated, and empirically calibrated simulation results are presented for the case of reduced-phosphorus dairy diets. Results show that the mechanism has a significant impact on behavior and may incur no net cost for the regulator when an insurance premium is charged. Conditions under which a green payment mechanism may be preferable to green insurance also are discussed.

Key words: conservation technology adoption, dairy farming, endogenous learning, green insurance, phosphorus, risk preferences, voluntary programs

Introduction

Agricultural nonpoint source (NPS) pollution continues to present challenges to local, state, and federal regulators. In 1998, the U.S. Environmental Protection Agency labeled NPS pollution "the greatest remaining source of water quality problems in the United States today" (USEPA and USDA, 1998) and identified agricultural sources as the largest single class of existing NPS pollution problems.

To date, one of the most effective methods for reducing agricultural NPS pollution has been the adoption of Best Management Practices (BMPs) by agricultural producers. But because producers often expect BMPs to have undesirable effects on their incomes, adoption of BMPs frequently must be encouraged with economic incentives. When the incentive takes the form of a direct subsidy, it commonly is known as a "green payment." For a BMP that truly has a negative impact on producer income, pollution reduction can be achieved either by using a green payment on a permanent basis or on a temporary basis if some type of "lock-in" of the BMP is expected to occur. For a BMP that producers *think* will have a negative impact on their incomes, but which regulators are convinced will not, a green payment can be implemented on a temporary basis to encourage experimentation with the BMP until producers become sufficiently convinced their prior beliefs were incorrect—and thus prefer the BMP even without a subsidy.

The latter scenario is unique because it describes the case of a Pareto-dominant production practice: one that reduces pollution without negatively affecting net farm

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Kenneth A. Baerenklau is assistant professor, Department of Environmental Sciences, University of California–Riverside.
This research was funded by a Science to Achieve Results Fellowship from the U.S. Environmental Protection Agency, by a Hatch grant from the U.S. Department of Agriculture, and by the University of Wisconsin–Madison while the author was a graduate student at that institution. The author thanks Bill Provencher, Brad Barham, Rich Bishop, Dan Bromley, and Fred Buttel for helpful comments and suggestions on previous drafts. Any remaining errors are solely the author's responsibility.

Review coordinated by Paul M. Jakus.

income. While this clearly will not always be the case, advances in scientific knowledge and technological progress continue to generate such scenarios for agriculture. Recent examples include reduced application of nitrogen fertilizer (DeVuyst and Ipe, 1999), reduced application of phosphorus fertilizer (USDA, 2002), and reduced-phosphorus dairy diets (McGraw, 1999; Wu, Satter, and Sojo, 2000). Successful implementation of a voluntary green payment program in cases such as these requires that the subsidy compensates producers for their *anticipated* losses due to adoption of the BMP, regardless of how pessimistic the producers may be. Therefore, when producers are highly skeptical about a proposed BMP, or highly risk averse, total program costs may greatly exceed the actual losses incurred by producers.

To address this issue, DeVuyst and Ipe (DI, 1999) proposed a "green insurance" mechanism. Green insurance is a type of technology insurance which, like a green payment, provides an economic incentive to encourage behavioral change. But whereas the payment mechanism must compensate agents for their *anticipated* losses, the insurance mechanism compensates them only for their *actual* losses. Therefore, when prospective adopters are pessimistic about a truly Pareto-dominant technology, the insurance mechanism may be more cost-effective.

This study extends the previous work of DeVuyst and Ipe by proposing an alternative green insurance mechanism that offers stronger adoption incentives and is applicable to heterogeneous populations and non-binary adoption decisions. Endogenous learning about the new technology is incorporated, and empirically calibrated simulation results are presented for the case of reduced-phosphorus dairy diets in the state of Wisconsin. Results show that the original DI mechanism increases adoption rates only slightly for this case, but the modified mechanism has a significant impact on behavior and may incur no net cost for the regulator when an insurance premium is charged.

Empirical Problem[1]

Dairy cows require adequate levels of phosphorus to maintain high rates of milk production and to avoid reproductive deficiencies. As a consequence, however, these animals excrete excess phosphorus into the environment where it causes a variety of problems including algal blooms, decreased dissolved oxygen levels, and fish kills (Carpenter et al., 1998). Recently, these problems have begun to attract the attention of regulators in Wisconsin and other dairy-intensive states who historically have been more concerned with nitrogen runoff (Connors, 2000; Ritchie, 2001). Two related scientific findings also have been receiving more attention. First, it is well known among animal scientists that phosphorus has a threshold effect in dairy cows. Current data suggest when cows are fed at least 3.3–3.8 grams per kilogram of dry matter (g/kg DM), there appear to be no negative effects on milk production or pregnancy rates; but both decline quickly when phosphorus concentrations drop below this level (Satter, 2000; Wu, Satter, and Sojo, 2000; Satter and Dhiman, 1996). Second, it is well known among Wisconsin agricultural extension agents that most of the state's dairy farmers administer phosphorus concentrations in the neighborhood of 4.8 g/kg DM (McGraw, 1999). On average, this extra phosphorus supplement costs farmers $13 per cow each year (Satter, 2000; Satter and

[1] Additional details regarding the empirical problem can be found in Baerenklau (2004).

Dhiman, 1996). However, despite the possibility of increasing both environmental quality and producer income, most farmers in Wisconsin have not yet begun to adopt reduced-phosphorus dairy diets. The goal of this paper is to assess the ability of a green insurance mechanism to achieve this result.

Green Insurance

As noted previously, green insurance is potentially more cost-effective than green payments for the case of a Pareto-dominant technology. However, two criteria must be met in order to realize these prospective cost savings. First, the regulator must be fairly certain that the technology will leave the agent no worse off. If the regulator is wrong, and the technology produces net losses, then the total cost of a green insurance program could be quite large. Second, for individual insurance contracts, there must exist a reliable signal for determining when the new technique has failed and to what extent. Otherwise, moral hazard would drive up the actual cost of a green insurance program.

For the case of reduced-phosphorus dairy diets, animal scientists are becoming fairly convinced that the true phosphorus threshold for dairy cows is between 3.3 and 3.8 g/kg DM. So perhaps the first criterion is satisfied. But the second criterion is more problematic. Although it is fairly easy to estimate the amount of phosphorus in manure, and therefore the amount in feed, it is not feasible to observe all other aspects of milk production that would influence the two indicators of phosphorus deficiency—milk yield and pregnancy rates. In other words, the opportunity exists for farmers to enroll in a green insurance program for reduced-phosphorus dairy diets, reduce their phosphorus accordingly, but "shirk" in other aspects of their production process to take advantage of this new-found insurance policy.

In cases such as this where a reliable insurance signal does not exist, it may be possible to use a "group incentive" insurance contract instead of individual contracts. Similar to "area yield" insurance, this type of mechanism has been addressed in the agricultural economics literature previously (e.g., Mahul, 1999; Skees, Black, and Barnett, 1997; Miranda, 1991) as a way to indemnify farmers against production losses due to natural events while reducing the moral hazard incentive inherent in an individual insurance contract. Under an area yield insurance policy, each producer receives an indemnity if the average crop yield over the surrounding geographic area (rather than just an individual farm) deviates significantly below some predetermined level. If no single farm is large enough to significantly affect this average yield, then each agent's dominant strategy is to operate his or her farm in good faith; hence there is no moral hazard dilemma. Successful implementation of such an insurance policy, however, requires that producers' yields have strong positive correlation within the designated area (i.e., there must be systematic risk). If a farmer's own yield has only weak positive correlation with the average yield of the surrounding area, that farmer receives very little risk reduction from the insurance, and if the farmer's yield has nonpositive correlation with that of the surrounding area, then no risk reduction is received.[2]

[2] The risk reduction discussed here technically is downside risk reduction. Miranda (1991) shows that weak positive correlation actually can lead to increased risk, but this result appears to derive from increased upside risk.

The green insurance mechanism proposed here is a type of group incentive contract which extends the mechanism proposed previously by DeVuyst and Ipe (DI, 1999). The indemnity schedule is expressed as:

$$(1)\quad \phi_{it}(\psi_{it}) = \min\left\{\left[\frac{I_{it}\cdot(\psi_i^0 - \psi_{it})}{\frac{1}{n_P}\sum_j I_{jt}\cdot(\psi_j^0 - \psi_{jt})}\right]^{\sigma}, K\right\}\cdot \max\left\{\left[\left(\frac{\bar{\pi}_{LR}^P - \bar{\pi}_t^P}{\bar{\pi}_{LR}^P} - \frac{\bar{\pi}_{LR}^N - \bar{\pi}_t^N}{\bar{\pi}_{LR}^N}\right)\cdot \bar{\pi}_{LR}^P\right], 0\right\},$$

where ϕ_t is the per unit indemnity paid in time period t. The "max" term is the original DI mechanism, where $\bar{\pi}$ denotes average per unit profit; the superscripts P and N respectively denote the participant and nonparticipant groups; and the subscripts LR and t respectively denote the long-run and time period t profits. The DI mechanism pays indemnities to participating farmers only when their profits deviate below (above) their long-run group average more (less) than do the profits of nonparticipating farmers who are subject to the same stochastic shocks (i.e., a control group).

To understand the role of the "min" term in (1), consider the problem facing each agent when the adoption decision is continuous and the conservation technology is thought either to reduce the mean or increase the variance of profits, or both. In the absence of any incentive scheme, this (risk-averse) agent will choose some privately optimal adoption level—call this the agent's baseline level. When the DI mechanism is introduced, it establishes new incentives to increase adoption beyond the baseline. Specifically, the expected mean profit level everywhere above the baseline is now larger (because a strictly positive payment is anticipated), and the expected variance of profits is now smaller (because the expected indemnity is negatively correlated with idiosyncratic profit shocks). But the incentive is rather weak. To see this, note that payments are made uniformly to each agent *regardless of his or her individual extent of adoption* (measured relative to the agent's baseline level). Therefore, conditional on all others' choices, the optimal action for an agent who believes further adoption is not privately beneficial is to increase his or her adoption level only slightly beyond the baseline in order to qualify as a "participant," thereby taking advantage of the indemnity created by the other agents while minimizing personal exposure to income loss. If all agents behave similarly, then the average increase beyond the baseline will be very small and the DI mechanism will produce only a minimal change in aggregate behavior.[3]

The "min" term in (1) counteracts this tendency by allowing the incentive to vary with the extent of adoption relative to the group average. In this term, ψ_{jt} is farmer j's input choice in period t; ψ_j^0 is farmer j's baseline input level; I_{it} is an indicator function which takes a value of 1 only if an agent's input choice qualifies for the incentive program; n_P is the total number of qualifying agents; and σ and K are additional parameters chosen by the regulator. For the empirical application considered here, if all farmers reduce phosphorus by the same amount relative to their baseline levels (as would be the case if all adopters were identical), then each receives the same per unit indemnity. Otherwise, farmers who make above-average reductions receive higher indemnities than those

[3] There is another potentially important disincentive implicit in both the DI scheme and the mechanism proposed here. Because the indemnity is based on average group profits, it is not perfectly correlated with any agent's income, and thus there is a positive probability that losses due to adoption will not be compensated. Although the probability of such a false negative declines toward zero as the number of members of each group grows larger, this observation suggests group insurance may be less viable when the sizes of the insured and control groups are relatively small.

who make below-average reductions. This reduces the free-rider incentive by rewarding larger input reductions with larger indemnities.

This scaling term is bounded in various ways to encourage adoption, discourage unwanted behavior, and prevent undesirable outcomes. First, the indicator function (I_{it}) allows the regulator to limit the range of phosphorus input choices qualifying for the incentive program. Agents must reduce their concentrations below their individual baseline level (ψ_t^0) but not below a lower limit (say, $\bar{\psi}$) in order to qualify. This lower limit is analogous to a liability limit in a typical insurance contract and discourages agents from choosing arbitrarily low phosphorus levels to take advantage of the incentive program when beliefs about the technology become more closely aligned with those of the regulator—after all, the regulator does not intend to insure agents against losses for *any* phosphorus input choice. Second, by setting $\sigma > 1$, the regulator introduces curvature into the scaling term that rewards adopters of relatively low phosphorus levels with larger marginal indemnities, thus encouraging these choices and promoting faster learning. And third, the regulator can choose a value for K which places an upper limit on the magnitude of the scaling term. This also serves as a liability limit and prevents agents from receiving unreasonably large payments for moderate reductions when the average reduction is relatively small. These modifications make the group insurance mechanism more akin to an input-reduction subsidy (i.e., a green payment): the "max" term is analogous to the per unit subsidy, and the "min" term is analogous to the total reduction made by each agent; but only *actual* losses are compensated.

Adoption Model[4]

To determine the impact of the green insurance mechanism in (1) on the diffusion rate of reduced-phosphorus diets, a multi-period adoption model incorporating both risk preferences and endogenous learning is utilized. To begin, net farm income is modeled as:

$$(2) \qquad \frac{\pi_{it}}{h_{it}} = \kappa_i + \mathbf{x}_{it}\beta + y_{it}\beta_y + \left[\exp(\mathbf{z}_{it}\gamma + y_{it}\gamma_y)\right]^{1/2} \cdot u_{it} + \nu_t,$$

where the left-hand side, π_{it}/h_{it}, is annual net farm income per cow. The first term on the right-hand side, κ_i, is a farm-specific fixed effect. The second term includes characteristics, $\mathbf{x}_{it}$, which are thought to affect mean farm income. The third term accounts for the technology choice, y_{it}, and its marginal impact on farm income, β_y. If farm-specific phosphorus levels were known, these data would be used as y_{it}. However, these data currently do not exist. Therefore, an alternative adoption scenario (presented below) is used to calibrate the model.

The model also includes two normal i.i.d. error components. The first, u_{it}, is a time- and farm-specific shock to net farm income that exhibits multiplicative heteroskedasticity. Here, $\mathbf{z}_{it}$ is a vector of characteristics thought to influence the variance of farm income. The second term again accounts for the technology choice, y_{it}, and its marginal impact on income variance. The second shock, ν_t, is a time-specific shock which accounts for temporal correlations in farm profits. This shock is assumed to be distributed $N(0, \sigma^2)$.

[4] Additional details regarding the adoption model can be found in Baerenklau (2004 and 2005).

To obtain a reduced-form adoption model for empirical estimation, assume each farmer acts to maximize a nonlinear mean standard deviation utility function (Saha, 1997; Isik and Khanna, 2003; Baerenklau, 2004), given by:

$$(3) \qquad y_{it}^{*} \equiv \arg\max_{y_{it}} \left[\left(\Pi_{it}(y_{it}) \right)^{\alpha_1} - \left(\Sigma_{it}(y_{it}) \right)^{\alpha_2} \right].$$

Here, a farmer's expected wealth is given by $\Pi_{it} \equiv W_{it} + \mathrm{E}[\pi_{it}]$, where W_{it} is the farmer's baseline nonrandom wealth level and $\mathrm{E}[\pi_{it}]$ is expected net farm income. A farmer's expected standard deviation of wealth is given by Σ_{it}. This functional form is very flexible and accommodates heterogeneity in risk preferences quite easily. Here, one set of coefficients $[\hat{\alpha}_1^H, \hat{\alpha}_2^H]$ is estimated for farmers who have completed a post-high school degree program (i.e., higher education) and one set of coefficients $[\hat{\alpha}_1^L, \hat{\alpha}_2^L]$ is estimated for those who have not (i.e., lower education).

The expectation of farm profit, $\mathrm{E}[\pi_{it}]$, is taken over two random vectors: $[u_i, \nu]$ and $[\beta_y, \gamma_y]$. The latter represents farmers' subjective beliefs about the new technology which are assumed to be held commonly and to evolve temporally according to Bayes' theorem as new information about the technology is revealed in each period. Assuming prior beliefs and new information are both normally distributed, the posterior beliefs also are normally distributed with mean and variance given by (Greene, 1997, p. 318):

$$(4) \qquad \beta_{yt+1} = \frac{\tau \cdot \tilde{\sigma}^2_{\beta_{yt}} \cdot \beta_{yt} + \sigma^2_{\beta_{yt}} \cdot \tilde{\beta}_{yt}}{\tau \cdot \tilde{\sigma}^2_{\beta_{yt}} + \sigma^2_{\beta_{yt}}},$$

$$(5) \qquad \sigma^2_{\beta_{yt+1}} = \frac{\tau \cdot \tilde{\sigma}^2_{\beta_{yt}} \cdot \sigma^2_{\beta_{yt}}}{\tau \cdot \tilde{\sigma}^2_{\beta_{yt}} + \sigma^2_{\beta_{yt}}},$$

$$(6) \qquad \gamma_{yt+1} = \frac{\tau \cdot \tilde{\sigma}^2_{\gamma_{yt}} \cdot \gamma_{yt} + \sigma^2_{\gamma_{yt}} \cdot \tilde{\gamma}_{yt}}{\tau \cdot \tilde{\sigma}^2_{\gamma_{yt}} + \sigma^2_{\gamma_{yt}}},$$

and

$$(7) \qquad \sigma^2_{\gamma_{yt+1}} = \frac{\tau \cdot \tilde{\sigma}^2_{\gamma_{yt}} \cdot \sigma^2_{\gamma_{yt}}}{\tau \cdot \tilde{\sigma}^2_{\gamma_{yt}} + \sigma^2_{\gamma_{yt}}},$$

where any quantity denoted by a tilde (~) represents either the new information revealed in time period t or its variance. The parameter τ is an additional scale factor that is needed for the empirical application because estimating the variance of new information is problematic—i.e., although the sample permits unbiased estimation of the signals received in each period ($\tilde{\beta}_{yt}$ and $\tilde{\gamma}_{yt}$), estimating the noise components ($\tilde{\sigma}^2_{\beta_{yt}}$ and $\tilde{\sigma}^2_{\gamma_{yt}}$) would require knowledge of the effective sample size. Therefore, τ accounts for the difference between the noise observed by the agents and the noise perceived by the analyst in each period.

Estimation

Because most Wisconsin dairy farmers have not yet begun to adopt low-phosphorus dairy diets, the parameters in equations (2)–(7) are estimated using a calibration scenario for which data are available. The calibration scenario examines adoption of improved (non-native) forage varieties by 34 Wisconsin dairy farmers from 1996 to 2000. This adoption problem resembles the phosphorus scenario in several important ways: the new technology focuses on animal nutrition, it involves no significant fixed costs, and it is easily reversible. Therefore, it is plausible to assume that the same behavioral models would apply to each scenario. Furthermore, adoption rates in the calibration scenario grew from 11.6% in 1996 to 29% in 2000 as farmers found this new technology to be profitable. This lack of a steady-state adoption level greatly facilitates parameter identification in a model with both risk preferences and endogenous learning.

The adoption model is estimated sequentially.[5] First, a maximum-likelihood method developed by Griffiths and Anderson (1982) is used to obtain consistent estimates for the parameters in equation (2). Then the signals in equations (4)–(7) are estimated by interacting y_{it} in equation (2) with time dummies and rerunning this regression in order to allow the technology to have different observable effects on farm income in each year. Given these signals, the remaining nine coefficients in equations (3)–(7) are then estimated with maximum entropy (Golan, Judge, and Miller, 1996). Details of the maximum entropy method can be found in Baerenklau (2005), but its main advantages are that it facilitates incorporation of ex ante information into the estimation and it guarantees a solution regardless of whether or not the regression system is identified in the traditional sense. Recent applications of this method include Kaplan, Howitt, and Farzin (2003); Fernandez (1997); and Golan, Judge, and Karp (1996).

Variable descriptions and estimation results for equation (2) are given in table 1, estimates for the profitability signals are reported in table 2, and for the risk preference parameters in table 3. The estimates for the net farm income function have the intuitively correct signs and magnitudes, and overall the significance levels are good. The risk preference estimates suggest that agents exhibit increasing absolute and relative risk aversion, but the standard errors are too large to reject other forms of risk aversion at the typical significance levels. However, the model predicts sample average adoption levels well (see table 4), and therefore these estimates are used to calibrate the green insurance simulations.

Calibration

The simulations assume that farmers know the true impact of improved forage varieties on their incomes but are uncertain about the phosphorus threshold level. Therefore, the coefficients in table 1 are used to simulate profits, and $y_{it}\beta_y$ and $y_{it}\gamma_y$ are subsumed by $\mathbf{x}_{it}\beta$ and $\mathbf{z}_{it}\gamma$ for notational simplicity. Next, equation (2) must be modified slightly, as follows:

[5] Other authors have estimated technology and risk preferences jointly (e.g., Kumbhakar, 2002; Isik and Khanna, 2003, and citations therein), but have omitted endogenous learning. Introducing this factor complicates the estimation problem (there are 25 parameters associated with endogenous learning in this model: four initial values, one scale factor, and 20 signals) and motivates the use of a sequential approach.

Table 1. Maximum Likelihood Estimates for Net Farm Income Function (n = 170)

Coeff.	Variable Description	Point Estimate	Standard Error	p-Value
Mean Function:				
β_1	Estimated daily farm revenue per cow from milk sales (price per pound × pounds produced per cow per day)	117.775	12.776	< 0.01
β_2	Acres of farmable land per cow	-31.403	24.696	0.20
β_3	Acres of pasture per cow	22.191	48.139	0.64
β_4	Percent Holsteins × acres of pasture per cow	-154.815	45.771	< 0.01
β_5	Dummy for use of a computerized record keeping system	14.993	50.775	0.77
β_6	Dummy for use of freestall housing	-141.637	53.858	< 0.01
β_7	Percent of farm assets owned by operator	-30.045	113.319	0.79
β_8	Acres of pasture planted with improved grasses per cow	171.889	45.319	< 0.01
Variance Function:				
γ_1	Dummy for farms located in the Southwest region	9.986	0.807	< 0.01
γ_2	Dummy for farms located in the North Central region	9.732	0.816	< 0.01
γ_3	Dummy for farms located in the East region	8.112	0.934	< 0.01
γ_4	Years of experience as a dairy farmer	-0.008	0.014	0.57
γ_5	Pounds of milk produced each day per cow	-0.011	0.015	0.48
γ_6	Acres of farmable land per cow	0.109	0.074	0.14
γ_7	Acres of pasture per cow	0.105	0.256	0.68
γ_8	Percent Holsteins × acres of pasture per cow	-0.506	0.233	0.03
γ_9	Dummy for use of a computerized record keeping system	-0.202	0.257	0.43
γ_{10}	Dummy for use of freestall housing	1.328	0.307	< 0.01
γ_{11}	Percent of farm assets owned by operator	0.443	0.437	0.31
γ_{12}	Acres of pasture planted with improved grasses per cow	0.422	0.339	0.21
σ_v^2	Common variance component	242.531		

Table 2. Estimated Profitability Signals (n = 170)

Year	$\tilde{\beta}_{yt}$	$\tilde{\sigma}^2_{\beta_{yt}}$	$\tilde{\gamma}_{yt}$	$\tilde{\sigma}^2_{\gamma_{yt}}$
1996	228.085	3,395.159	-0.238	0.644
1997	89.701	3,267.265	-0.347	0.568
1998	75.482	6,287.221	1.342	0.385
1999	235.496	2,431.771	0.193	0.307
2000	163.989	1,721.005	0.273	0.172

Notes: $\tilde{\beta}_{yt}$ and $\tilde{\gamma}_{yt}$ are the signals received in each period; $\tilde{\sigma}^2_{\beta_{yt}}$ and $\tilde{\sigma}^2_{\gamma_{yt}}$ are the associated variances.

Table 3. Maximum Entropy Estimates for Adoption Model (n = 170)

Coeff.	Description	Point Estimate	Asymptotic Std. Error
α_1^L	Risk coefficient on mean income for higher education level	0.923	0.231
α_1^H	Risk coefficient on mean income for lower education level	0.838	0.194
α_2^L	Risk coefficient on standard deviation of income for higher education level	1.244	0.369
α_2^H	Risk coefficient on standard deviation of income for lower education level	1.092	0.251

Table 4. Actual and Predicted Annual Mean Adoption Levels in Calibration Scenario

Year	Actual	Predicted	Year	Actual	Predicted
1996	11.6%	10.8%	1999	23.5%	18.9%
1997	14.9%	15.6%	2000	29.0%	24.4%
1998	21.6%	18.0%			

$$\frac{\pi_{it}}{h_{it}} = \kappa_i + x_{1it}(\psi_{it}) \cdot \beta_1 + \mathbf{x}_{it}\beta + \phi_{it}(\psi_{it}) + C(\psi_{it}) + \left[\exp(\mathbf{z}_{it}\gamma)\right]^{1/2} \cdot u_{it} + v_t. \tag{8}$$

The first new term involves farm revenue (the first variable in table 1). In equation (2), this term is calculated as: $x_{1it} = p_{it}w_{it}$, where p_{it} is the price of milk received by agent i in time period t, and w_{it} is the average daily milk production per cow. In equation (8), this term (and its associated coefficient) has been extracted from $\mathbf{x}_{it}\beta$ to emphasize that farm revenue is now a function of phosphorus concentration, ψ_{it}. This function is specified as:

$$x_{1it}(\psi_{it}) = p_{it} \cdot w_{it} \cdot \lambda(\psi_{it}, \theta, \hat{\psi}) \tag{9}$$

and

$$\lambda(\psi_{it}, \theta, \hat{\psi}) = 2 \cdot \left[\min\left\{\frac{\psi_{it} - \hat{\psi}}{\theta - \hat{\psi}}, 1\right\}\right] - \left[\min\left\{\frac{\psi_{it} - \hat{\psi}}{\theta - \hat{\psi}}, 1\right\}\right]^2, \tag{10}$$

where $\lambda(\psi_{it}, \theta, \hat{\psi}) \in [0, 1]$ is a normalized quadratic loss function that depends on the phosphorus concentration (ψ_{it}), the threshold level (θ), and a lower-bound concentration ($\hat{\psi} < \theta$).

Equation (8) also is augmented with $\phi_{it}(\psi_{it})$, the random indemnity payment provided by the insurance program as defined in equation (1), as well as a term to account for the annual cost savings a farmer can earn from reducing the phosphorus concentration fed to his or her herd:

$$C(\psi_{it}) = c_P \cdot \max\left\{\left(\psi_{it}^0 - \psi_{it}\right), 0\right\} - c_R \cdot \left(1 - \lambda(\psi_{it}, \theta, \hat{\psi})\right). \tag{11}$$

Here, c_P is the annual savings per cow per g/kg DM of phosphorus reduction; c_R is the cost to replace a milk cow after a failed pregnancy (to maintain a constant herd size); and ψ_{it}^0 is the farmer's initial phosphorus concentration.

Note, in the absence of any insurance program, equations (8)–(11) specify that phosphorus affects only the first moment of income. When (and if) data become available regarding the impact of phosphorus on the variance of milk production, the model could be extended appropriately. Furthermore, note that the phosphorus-induced declines in both milk production and pregnancies are assumed to be quadratic. The natures of these declines are not yet well known, but the quadratic form has several nice properties. First, it generates a continuously differentiable function for both milk production and pregnancy rates within the relevant range of phosphorus input levels. Second, using a higher order exponent tends to shift the effective threshold level away from (θ), contrary to evidence from the animal science literature. Last, smaller exponents and sigmoid-shaped functions did not have significant effects on the simulation results, so the quadratic specification is retained.

Given these modifications, the optimization problem in equation (3) is now designated by:

$$\psi_{it}^{*} \equiv \arg\max_{\psi_{it}} \left[\left(\Pi_{it}(\psi_{it}) \right)^{\alpha_1} - \left(\Sigma_{it}(\psi_{it}) \right)^{\alpha_2} \right], \tag{12}$$

where ψ_{it}^{*} is the optimal phosphorus concentration for agent i at time t. Compared with equation (3), this expression also differs in terms of its sources of uncertainty. The first random vector $[u_i, v]$ is unchanged. But the second now represents agents' beliefs about the phosphorus threshold, $[\theta]$. As before, this belief is assumed to be normally distributed and commonly held by all agents, and to evolve through time according to Bayes' theorem as new information about the true threshold is revealed through agents' adoption decisions.[6]

A third and new source of uncertainty in equation (12) is the indemnity payment. Because ϕ_{it} is a function of the random profits realized by all producers in time period t, it also is a random variable that affects net income. Furthermore, because each agent's indemnity payment ϕ_{it} is a function of the phosphorus levels chosen by all other agents at time t, determination of ψ_{it}^{*} in (12) requires modeling the strategic interactions between agents that would be expected to occur in a situation like this. Here, the concept of "mutual best response" is employed, requiring solution of a Nash equilibrium in phosphorus decisions in each period.

Policy Simulations

In order to incorporate key features of the low-phosphorus adoption decision and to make the simulations tractable, several additional assumptions are needed. First, it is assumed that the sample farms in the calibration scenario constitute the participant group, and an identical control group (subject to different random income shocks) also exists. Second, the true phosphorus threshold is assumed to be 3.5 g/kg DM, but all farmers initially believe it is higher. Third, the lower-bound concentration, $\hat{\psi}$ in equations (9)–(11), is assumed to be 1.5 g/kg DM (Valk and Šebek, 1999; Call et al., 1987). Fourth, the annual savings per cow from reducing phosphorus by 1 g/kg DM is \$10 (Satter, 2000; Satter and Dhiman, 1996). And fifth, the cost to replace a milk cow after a failed pregnancy is \$335 (Wisconsin Agricultural Statistics Service, 2001).

The first set of simulations presented here characterizes a baseline scenario without any adoption incentive. All simulations are conducted in GAUSS (Aptech Systems, Inc., 2003) and employ the built-in pseudo-random number generators. One hundred repetitions of a 15-year period are simulated with no time trend in profits. A discount factor of 0.96 is used to calculate the present value of program costs. Other simulation parameters that characterize this baseline scenario are summarized in table 5. As shown by this table, prior beliefs are assumed to have a mean of 4.5 g/kg DM and a variance of 0.09 in the baseline simulation. No indemnity is offered in the baseline, and therefore the parameter values and contract length are not applicable. The scale parameter adds

[6] A computational note: equations (4)–(7) are derived from Bayes' theorem but are not directly applicable here because agents are now learning about a threshold. Therefore, if all new observations during a given time period occur above the threshold, the signals used in equations (4)–(7) will not be identified. However, direct application of Bayes' theorem remains possible because it is not necessary to determine these signals in order to calculate the posterior distribution.

Table 5. Simulation Parameters

Parameter	Baseline Scenario	Insurance Scenarios
Initial mean belief about threshold level	4.5 g/kg DM	4.5 g/kg DM
Measure of initial uncertainty about threshold level (variance of initial belief)	0.09	0.09
Insurance parameter $\overline{\psi}$	N/A	3.0 g/kg DM
Insurance parameter σ	N/A	1; 2; 3
Insurance parameter K	N/A	10; 100; 1,000
Number of years incentive is offered	N/A	10
Scale parameter for choice disturbances	0.1	0.1

Note: The parameters $\overline{\psi}$, σ, and K are as defined in the text.

a small random shock to each agent's optimal choice to simulate the unexplained portions of these decisions.

The baseline scenario in table 5 produces realistic initial phosphorus choices that range from a low of 4.26 to a high of 5.24, with an average of 4.73 g/kg DM. Figure 1 shows the subsequent evolution of the threshold belief and the mean choice level for the sample farms. Farmers clearly are learning that the true threshold level is below 4.5 g/kg DM, but their rate of learning is relatively slow. By the end of the fifteenth year, the annual phosphorus load from the group of sample farms has been reduced by 5,035 kg without any adoption incentive.[7]

Green Insurance

Table 5 shows the parameters characterizing three different green insurance scenarios, and figure 1 presents the results graphically for the strongest insurance incentive (i.e., $\sigma = 3$ and $K = 1{,}000$). The incentive contract has two obvious effects. First, it promotes faster learning. From figure 1, beliefs converge toward the true value of the threshold much faster with the incentive. Second, the incentive promotes lower phosphorus choices both during and after the contract window. These expected post-contract choice levels and the associated program costs are of particular interest to a regulator who must meet a mandated load reduction standard within a fixed amount of time. By the end of the simulations, the weakest incentive (i.e., $\sigma = 1$ and $K = 10$) achieves an expected permanent load reduction of 8,793 kg of phosphorus per year for an expected present value cost of $174,082 to the regulator. The medium incentive (i.e., $\sigma = 2$ and $K = 100$) achieves an expected annual load reduction of 11,681 kg of phosphorus for an expected present value cost of $266,107. And the strongest incentive achieves an expected annual load reduction of 12,665 kg of phosphorus for an expected present value cost of $367,049. These results may be compared with the load reductions attainable with the original DI insurance mechanism simply by setting $\sigma = 0$ in the simulations. Not surprisingly, the DI mechanism is not as effective, producing an expected annual load reduction of only 5,353 kg of phosphorus for an expected present value cost of $222,246. Learning also occurs much more slowly with the original DI mechanism; although not shown in figure 1, the belief path is nearly indistinguishable from that in the baseline scenario.

[7] Load reductions are calculated as in Wu, Satter, and Sojo (2000).

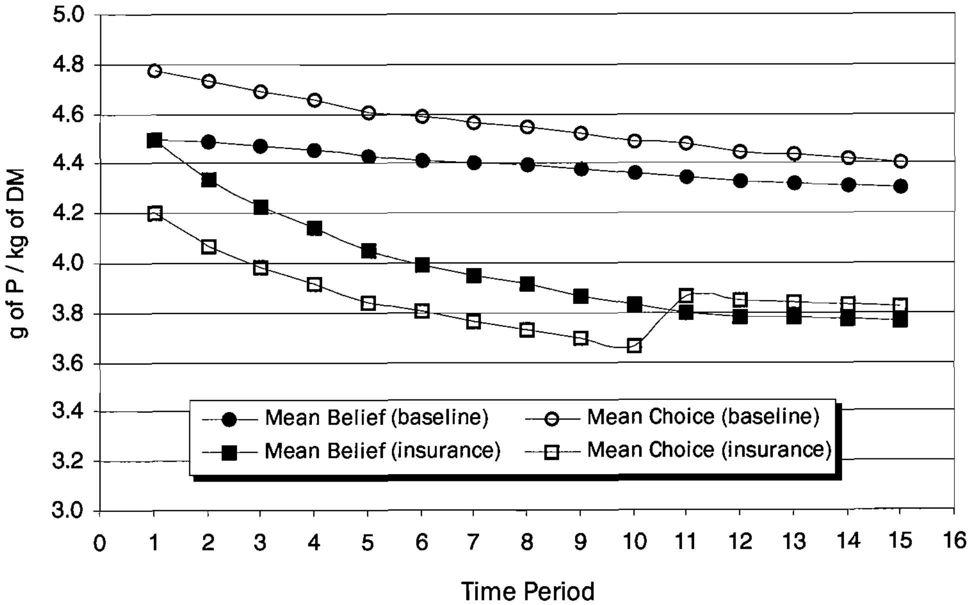

Figure 1. Evolution of mean threshold belief and mean choice level in baseline and insurance scenarios

It is also useful to compare the results for the insurance mechanism with analogous results for a green payment mechanism. Details of the payment simulations are provided in Baerenklau (2004), but the basic setup is as follows. Instead of offering a random indemnity which depends on both phosphorus concentration and realized profits, the regulator offers a certain payment which depends only on phosphorus concentration. The payment takes the form of a uniform input reduction subsidy—it is uniform in the sense that each farmer receives the same per unit payment for phosphorus reductions, but each farmer's total payment depends on his or her total reduction. Total program costs are calculated as they are here.

Results of this comparison are twofold. First, a green payment mechanism tends to incur greater costs for an equivalent load reduction. For example, a 10-year contract for a uniform input reduction subsidy can achieve an expected permanent load reduction of 12,802 kg of phosphorus per year for an expected present value cost of $1,453,624 (versus 12,665 kg and $367,049 for the strongest insurance mechanism examined here). Second, green payments appear better suited for situations where relatively large and/or fast load reductions are desired. For example, a five-year contract for a uniform input reduction subsidy can achieve an expected annual load reduction of 16,247 kg of phosphorus for an expected cost of $3,952,931, but it is not possible to achieve a similar load reduction with a green insurance mechanism.[8]

Finally, it should be noted that the insurance coverage in these simulations is provided to farmers for free; there is no insurance premium. Charging a premium would decrease program costs further because it creates a source of revenue for the regulator

[8] Additional simulations show evidence of rapidly diminishing returns for the insurance mechanism. The additional incentive provided by using $\sigma > 3$ and $K > 1{,}000$ has very little effect on the learning and adoption paths, but program costs continue to increase.

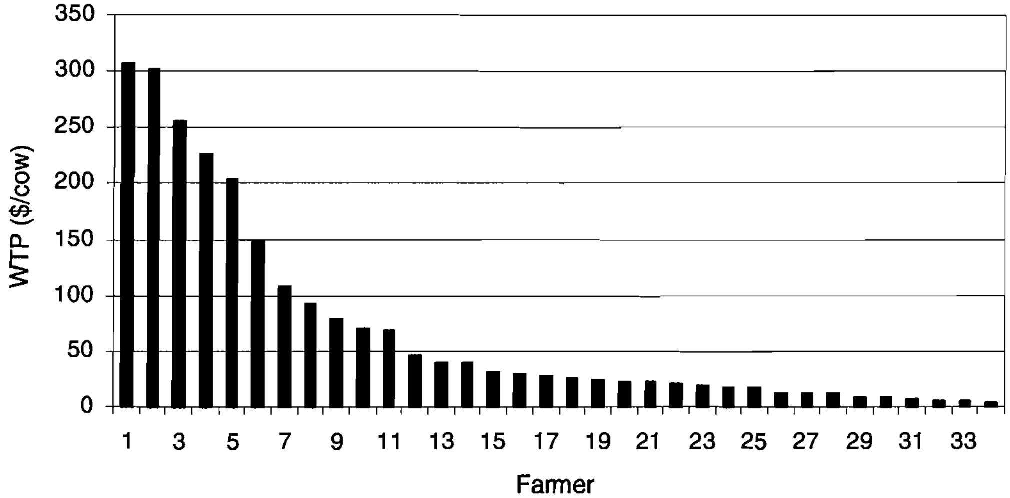

Figure 2. Farmer willingness to pay for one year of insurance coverage at program outset

and tends to reduce program enrollment (and thus total indemnity payments), but it also would increase the expected pollutant load during the program because the uninsured farmers would not reduce their input levels as much as if they were insured. However, provided both insured and uninsured farmers are part of the same information network (as they are in these simulations), post-contract pollutant loadings may be similar to those achievable with complete enrollment because the uninsured farmers will still learn about the true threshold level through time.

To explore the possibility of charging a premium, farmer willingness to pay (WTP) for one year of insurance coverage during the first year of the program is calculated for the strongest insurance mechanism.[9] WTP values range from a high of $307 per cow to a low of $4 per cow with a mean of $68 per cow. Figure 2 presents these results graphically, sorted from highest to lowest WTP. Clearly, charging more than a nominal premium will cause many farmers to exit the program. For example, half of the 34 farmers would choose not to enroll if the premium were only $26 per cow.

To examine the impact of a premium on post-contract pollutant levels, the strongest insurance mechanism is simulated with a premium of $26 per cow. This approach achieves an expected annual load reduction of 12,150 kg and the regulator actually earns a present value profit of $158,227. Clearly, if the regulator is primarily concerned with the long-run pollutant load, this approach is very cost-effective. By pricing the insurance coverage, the regulator can target the mechanism at a subset of polluters, a tactic more difficult to accomplish with a voluntary payment program. Provided farmers who choose not to enroll still receive the information generated by the enrolled farmers and believe them to be a reliable source of information, total program costs can be significantly reduced with only minor increases in long-run pollutant loadings.

[9] I thank a reviewer for suggesting these calculations.

Summary and Conclusion

The simulation results presented here are based on a decision-theoretic model of rational choice under uncertainty which incorporates both risk preferences and endogenous learning. Because data are unavailable for direct estimation of the relevant parameters, the model is calibrated using a structurally similar adoption decision faced by the sample population. The model calibration results generally are good and suggest that both risk aversion and subjective beliefs are important behavioral determinants.

The simulation results reveal that a green insurance mechanism can accelerate learning and produce significant, permanent changes in behavior for a reasonable cost. Although the simulations support ex ante reasoning that pollutant load reductions can be achieved more cost-effectively with green insurance than with green payments when subjective beliefs are limiting adoption, the insurance mechanism appears inadequate for producing relatively large load reductions over relatively short time horizons. Therefore, if significant and rapid behavioral changes are desired, a payment mechanism may be preferable.

Furthermore, implementing green insurance requires that an adequate control group be available and willing to participate. These simulations implicitly assume such a group exists and its members are willing to provide the necessary information without compensation due to the value they place on the information generated by the program participants. To the extent a regulator must compensate the control group, or to the extent a regulator incurs other information collection costs, total program costs would increase. Therefore, if an adequate control cannot be found or if information costs are relatively large, a payment mechanism again may be preferable.

Additional work on green insurance should consider the theoretical properties of the group incentive mechanism. While the mechanism described here may be comparatively simple and practical, it is not necessarily optimal. In other words, it may be possible to derive a green insurance mechanism that provides an even stronger adoption incentive without incurring significant additional costs. Such a mechanism clearly would be beneficial for regulators faced with tight budgets and persistent agricultural NPS pollution problems.

[Received July 2003; final revision received November 2004.]

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