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Nutrient Best Management Practice Insurance and Farmer Perceptions of Adoption Risk

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This paper explores the effect farmer perceptions concerning how best management practice (BMP) adoption changes the profit distribution have on BMP adoption incentives and the potential for insurance to increase these incentives. Adoption indifference curves illustrate the effect of farmer perceptions on BMP adoption incentives and the potential for insurance to expand the set of perceptions consistent with adoption. Empirical analysis quantifies these conceptual results for nutrient BMP insurance, a new policy available to corn farmers as part of a USDA–Risk Management Agency pilot program in four states. Results indicate that nutrient BMP insurance can have economically relevant effects on farmer adoption incentives.

Key Words: adoption indifference curves, crop insurance, fertilizer, green insurance

JEL Classifications: D8, Q12, Q16, Q21

The Federal Crop Insurance Corporation (FCIC) Board of Directors at its August 12, 2002, meeting approved a 3-year pilot program for Nutrient Management/Best Management Practice Insurance (USDA-RMA). The pilot program began in the 2003 crop year in four states—Iowa, Minnesota, Pennsylvania, and Wisconsin. This endorsement authorizes the U.S. Department of Agriculture's Risk Management Agency (RMA) to provide premium subsidies to encourage farmer participation. The RMA further indicated its commitment to the policy's success by awarding an education grant to a group of stakeholders to promote the policy in Iowa, Minnesota, and Wisconsin (Montgomery). Unfortunately, finalizing the policy details was delayed, so effective marketing did not take place in 2003, whereas industry uncertainty is likely to slow marketing in 2004 (Buman).[1]

Nutrient management/best management practice insurance (nutrient BMP insurance) helps corn farmers manage the actual and perceived risks associated with adoption of nutrient BMPs. Risk is commonly reported as a major reason why farmers do not adopt profit-

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[1] The USDA-RMA has several publications concerning policy provisions available on-line: http://www.rma.usda.gov/policies/2003n-bmp.html; http://www.rma.usda.gov/FTP/Policies/2003/n-bmp/pdf/CRC_BMP_Endorsement.pdf; and http://www.rma.usda.gov/FTP/Policies/2003/n-bmp/pdf/MPCI_BMP_Endorsement.pdf (Accessed November 12, 2003).

enhancing BMPs (Feather and Cooper; Hrubovcak, Vasavada, and Aldy; Nowak). Nutrient BMP insurance is intended to directly address risk as an impediment to adoption of nutrient BMPs by corn farmers. The policy requires insured farmers to plant a check strip that receives the status quo nutrient management practice, whereas the majority of the field receives the approved nutrient BMP. At harvest, an indemnity is paid if the yield difference between the check strip and the adjacent BMP rows exceeds the deductible.

Nutrient BMP insurance is "green insurance," a type of insurance receiving renewed attention as a policy tool to increase adoption of BMPs (Mitchell and Hennessy). Ideas for potential green insurance policies are not lacking. Huang et al. analyze a nitrogen fertilizer insurance policy that insures against excessive rainfall preventing side-dress nitrogen applications on corn. Huang analyzes a different nitrogen insurance policy to encourage farmers to switch to growing season-only fertilizer application as opposed to a before-plant application. Mitchell et al. examine Bt corn refuge insurance, which insures against yield loss due to insect damage, as a means to encourage farmers to plant refuge acres for managing insect resistance to Bt corn. Section 522(d)(3)(B) of the Agricultural Risk Protection Act of 2000 mandates the RMA "to develop a multifaceted approach to pest management and fertilization to decrease inputs, decrease environmental exposure, and to increase application efficiency." As a result, other specific risk insurance policies like nutrient BMP insurance are likely to be developed.

This paper develops a conceptual model to explore how farmer perceptions concerning the effect of BMP adoption on the distribution of profit affect farmer incentives to adopt a BMP and how insurance changes these incentives. Next, an empirical model is developed for nutrient BMP insurance to verify and quantify the conceptual model and to determine the economic relevance of the conceptual model for nutrient BMP insurance. Empirical results suggest that a potential role does exist for nutrient BMP insurance to substantially increase nutrient BMP adoption incentives.

Conceptual Model

Farmers who have never used a specific BMP likely do not know all the risks associated with using the BMP or the extent of these risks. However, farmers do have prior knowledge and perceptions of these risks developed from their previous experience with other technologies; discussions with neighbors, extension personnel, and other specialists; and exposure to information in the farm media. When farmers make their BMP adoption decision, they use the subjective probabilities associated with their knowledge and perceptions to estimate the profitability of a specific BMP. As a rational farmer gains experience with the BMP, eventually these subjective probabilities should converge to the objective probabilities. However, initially these subjective probabilities are what rational farmers use to make their adoption decisions.

Economic analysis of technology adoption uses the increase in expected utility or the associated increase in the certainty equivalent to measure farmer incentives to adopt new technologies (Huang; Huang et al.; Mitchell et al.). Typically such studies use data to estimate the objective probability distribution of returns with the new technology and then determine adoption incentives. The role of farmer perceptions is ignored, yet these perceptions are important for understanding farmer behavior when faced with uncertainty. Expected utility and certainty equivalents should be calculated using the subjective distribution of returns with the BMP, which may not be the same as the objective distribution (Sri Ramaratnam et al.).

To formalize this concept, let $u(\pi_i)$ be a risk-averse farmer's utility function, where $u' > 0$, $u'' < 0$, and π_i is random per acre profit when the farmer uses technology i. For simplicity, assume two technologies exist—the status quo technology ($i = sq$) and the best management practice ($i = bmp$). Let $EU_i = E[u(\pi_i)]$ be the farmer's expected utility with technology i, and let CE_i implicitly defined by

$u(CE_i) = EU_i$ be the associated certainty equivalent, where $E[\cdot]$ is the expectation operator. Because the farmer has experience with the status quo technology, the farmer's subjective distribution of profit π_{sq} is the same as the objective distribution. However, for the BMP, the subjective distribution of profit π_{bmp} is not necessarily the same as the objective distribution. To denote this difference, let EU_{bmp} and CE_{bmp} be expected utility and the associated certainty equivalent when the objective distribution is used and $E\tilde{U}_{bmp}$ and $C\tilde{E}_{bmp}$ when the farmer's subjective distribution is used. The increase in a farmer's certainty equivalent is a monetary measure of the farmer's benefit from adopting the BMP technology, or equivalently, the farmer's adoption incentive. The farmer's perceived adoption benefit is $\tilde{W} = C\tilde{E}_{bmp} - CE_{sq}$. The actual adoption benefit, after the farmer has used the BMP long enough for subjective perceptions to converge to the objective distribution, is $W = CE_{bmp} - CE_{sq}$.

A farmer uses the perceived benefit $\tilde{W}$ to determine adoption, not the actual benefit W, since the farmer does not know W at the time of the decision. Thus, a rational farmer will not adopt the BMP if the perceived adoption benefit $\tilde{W}$ is negative, even if the actual adoption benefit W is positive. Hence, economic analyses conducted by those with specialized skills and access to scientific data may find that a certain BMP is welfare enhancing ($W > 0$), yet despite widespread communication of the results through extension/outreach and research channels, many farmers do not adopt the BMP. Thus, although analyses find it profitable to adopt different practices that reduce fertilizer use and these studies have been widely disseminated, farmer perceptions, and hence behavior, are not consistent with these results (Babcock and Blackmer; Sri Ramaratnam et al.). When surveys find that farmers do not adopt BMPs because of risk, the risk is not necessarily the objective risk as measured by specialists, but rather the risk as perceived by the farmers. BMP insurance is one policy tool intended to overcome this impediment to BMP adoption by reducing the perceived risks associated with adoption.

Figure 1 illustrates how farmer perceptions of risk affect BMP adoption incentives, assuming preferences are defined over perceived changes (not actual changes) in the mean and standard deviation of profit due to BMP adoption relative to the status quo. In this context, a farmer's perception is defined as a pair ($\Delta\mu$, $\Delta\sigma$), where $\Delta\mu$ is the farmer's belief of the effect of BMP adoption on mean profit, and $\Delta\sigma$ is the farmer's belief of the effect of BMP adoption on the standard deviation of profit. More specifically, $\Delta\mu = E[\pi_{bmp}] - E[\pi_{sq}]$ and $\Delta\sigma = [\mathrm{Var}(\pi_{bmp})]^{0.5} - [\mathrm{Var}(\pi_{sq})]^{0.5}$, where $\mathrm{Var}(\cdot)$ denotes variance and both $\Delta\mu$ and $\Delta\sigma$ are calculated using the farmer's subjective probabilities. An adoption indifference curve is the set of perceptions for which the farmer has constant BMP adoption incentives, where adoption incentives are calculated using the farmer's subjective probabilities. Hence, all points on an indifference curve have equal values for $\tilde{W}$. As examples, the curves in Figure 1 show cases for $\tilde{W} = 0$ with and without nutrient BMP insurance. The horizontal axis measures the farmer's perception of how BMP adoption will change mean profit (i.e., $\Delta\mu$), and the vertical axis measures the farmer's perception of how BMP adoption will change the standard deviation of profit (i.e., $\Delta\sigma$). Points below and right of an indifference curve have higher BMP adoption incentives, since moving down implies a perceived decrease in the standard deviation of profit and moving right implies a perceived increase in mean profit, both of which increase adoption incentives.

The bottom indifference curve for $\tilde{W} = 0$ without BMP insurance passes through the origin because if the farmer believes that BMP adoption will not change the profit mean or standard deviation relative to the status quo, the farmer is indifferent between adopting the BMP and using the status quo. Farmers with perceptions represented by points in the southeast (northwest) quadrant will (will not) adopt the BMP, since the farmers believe that BMP adoption will increase (decrease) mean profit and decrease (increase) the standard deviation of profit. However, a tradeoff exists for perceptions represented by points in the northeast and the southwest quadrants. If a farmer be-

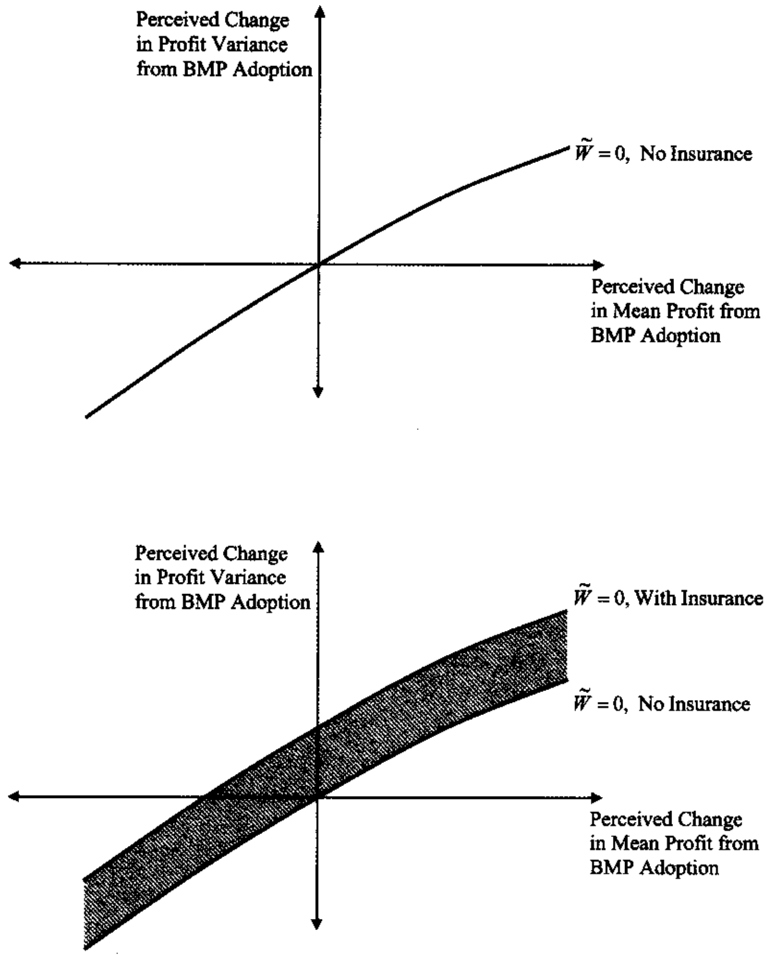

Figure 1. Adoption Indifference Curves with and without Insurance to Illustrate the Effect of the Perceived Risks of BMP Adoption and of BMP Insurance on Adoption Incentives

lieves that BMP adoption will increase (decrease) mean profit, then the perceived standard deviation of profit must also increase (decrease) to maintain constant adoption incentives. Hence, indifference curves have a positive slope. However, the curvature of indifference curves for mean-variance preferences is *a priori* unclear (Meyer).

The bottom plot in Figure 1 shows how BMP insurance encourages BMP adoption by reducing the perceived risks associated with adoption. Note that the axes again measure the perceived change in the mean and standard deviation of profit due to BMP adoption, not the perceived change in the mean and standard deviation of profit due to BMP adoption in conjunction with BMP insurance. The indifference curve for $\tilde{W} = 0$ shifts left and upward because although along the new curve farmers believe that BMP adoption will decrease mean profit and/or increase the standard deviation of profit relative to the indifference curve without insurance, they also believe that the insurance will offset these changes.

This shift of the indifference curve expands the set of farmer perceptions that are consistent with BMP adoption to include the gray area between the two indifference curves. Farmers with perceptions in this newly added area will adopt the BMP, although they believe that BMP adoption without insurance will result in lower welfare than the status quo technology. They rationally adopt the BMP because they believe the insurance will offset these effects and increase their welfare. BMP insurance not only reduces actual risks as impediments to adoption, but also encourages adoption among farmers who believe the BMP will decrease their welfare. This induced adoption by this latter group of farmers will give them experience with the BMP so they can realize that their perceptions were incorrect—that despite their original perceptions, the BMP is actually welfare-improving.

The conceptual analysis argues that, conceptually, nutrient BMP insurance can encourage BMP adoption by expanding the set of perceptions consistent with adoption. Empirically verifying this hypothesis requires developing an empirical model to estimate the shift in adoption indifference curves due to insurance and to determine whether it is economically relevant. This paper focuses specifically on nutrient BMP insurance for its empirical analysis. What follows is first analysis of experimental data to determine how nutrient BMP adoption changes the distribution of corn yield, and hence profit. Next an empirical model of nutrient BMP insurance is specified, including farmer preferences and returns, and then numerical methods are used to develop empirical adoption indifference curves.

Empirical Model of Nutrient BMP Insurance

The current nutrient BMP insurance requires insured farmers to plant a check strip that receives the status quo nutrient management practice, whereas the rest of the field receives the approved nutrient BMP. At the end of the season, an indemnity is paid if the yield difference between the check strip and the adjacent BMP rows exceeds the deductible. The policy contains several provisions to reduce fraud by denying indemnities if evidence exists that the check strip was differentially managed relative to the BMP portion of the field.[2]

For notation, Y_{bmp} is yield on the BMP portion of the field, Y_{chk} is yield on the check strip that received the status quo nutrient treatment, and Y_{aph} is the actual production history (APH) yield used for determining multiple-perils crop insurance (MPCI) premiums and indemnities. Since Y_{bmp} is the realized yield used for determining MPCI indemnities, $Y_{aph} = E[Y_{bmp}]$. This assumption maintains focus on the effect of BMP insurance, since incorporating farmer perceptions concerning differences between APH yield and the true expected yield would confound the analysis.

Nutrient BMP insurance and MPCI do not compensate farmers for the same loss. An MPCI indemnity is paid when actual yield (Y_{bmp}) falls below the yield guarantee βY_{aph}, where β is the MPCI coverage level. Thus, BMP yield for determining nutrient BMP insurance indemnities is capped from below at $Y_{bmp} = \beta Y_{aph}$, and the remaining loss is covered by MPCI. To limit liability and reduce farmer incentives to differentially manage the check strip and BMP portions of the field, the check strip yield is capped at $(1 + \alpha)Y_{aph}$. Using these caps, define $\hat{Y}_{bmp}$ as the BMP yield capped from below at βY_{aph}:

$$(1) \quad \hat{Y}_{bmp} = \max\{Y_{bmp}, \beta Y_{aph}\},$$

and define $\hat{Y}_{chk}$ as the check strip yield capped from above at $(1 + \alpha)Y_{aph}$:

$$(2) \quad \hat{Y}_{chk} = \min\{Y_{chk}, (1 + \alpha)Y_{aph}\}.$$

Before a nutrient BMP insurance indemnity is paid, proportional yield loss $(\hat{Y}_{chk} - \hat{Y}_{bmp})/\hat{Y}_{chk}$ must exceed the deductible δ. Thus, the indemnity I_{nbmp} is

$$(3) \quad I_{nbmp} = P_g \max\{0, (1 - \delta)\hat{Y}_{chk} - \hat{Y}_{bmp}\},$$

where P_g is the nonrandom MPCI price guarantee. The fair insurance premium M_{nbmp} is the expected value of this indemnity:

$$(4) \quad M_{nbmp} = P_g E[\max\{0, (1 - \delta)\hat{Y}_{chk} - \hat{Y}_{bmp}\}].$$

Empirically analyzing the effect of nutrient BMP insurance on adoption incentives requires implementing Equations (3) and (4), which entails specifying the insurance parameters (the deductible δ, the MPCI coverage

[2] For more information, see references in Footnote 1.

level β, and the liability limit parameter α), as well as the joint distribution of Y_{bmp} and Y_{chk}.

Effect of Nutrient BMP Adoption on the Mean and Variance of Yield

To focus on technology risk, as opposed to risks that do not change with adoption, the empirical model of nutrient BMP adoption focuses only on how nutrient BMP adoption affects the mean and variance of corn yield. Table 1 summarizes the available experimental data. Two types of data were available: (i) yield data from replicated plot experiments in which nitrogen fertilizer rates were experimentally varied, and (ii) yield data from side-by-side comparisons of different nutrient BMPs and standard practices.

The replicated plot data were generated following standard experimental design methods. A field was separated into numerous plots, each plot randomly assigned a nitrogen fertilizer treatment (e.g., 0, 25, . . . , 200 lbs./ac), and harvested yield for each plot measured. Most experiments used 10 nitrogen rates with three replicates, giving 30 observations for each site-year. For more detail concerning experiments of this sort, see Binford, Blackmer, and Cerrato; Blackmer et al.; and Cerrato and Blackmer.

For this analysis, yields for each site-year combination were normalized by dividing each observed yield by the maximum observed yield for that site-year, regardless of the nutrient application rate. This normalization converted yield to a proportion between zero and one and allowed comparison across different locations, years, and hybrids. Single-factor analysis of variance (ANOVA) is the typical statistical analysis method to test whether the mean yield for different treatments are statistically different, since only the nitrogen application rate differed between treatments (Snedecor and Cochrane). Similarly, a two-sample F-test is an appropriate test to determine whether yield variances differ by the nitrogen application rates (Snedecor and Cochrane).

Yield data from the side-by-side comparisons consisted of a status quo and BMP yield for each site, with many sites around the state in any given year. As a result, yields were not normalized, since only two observed yields were available for each site. Statistical analysis grouped all observations for each state to test whether the mean yield or the variance of yield for the BMP strips statistically differed from the mean yield for the status quo strips.

Tables 2 and 3 summarize the mean and standard deviation of normalized yields for the nitrogen data from some of the states. The tables do not include the Illinois data, since variable rates were used, which prevents summarizing the data in this manner. Similarly, data from side-by-side field trials in Iowa, Nebraska, and Wisconsin are not included, since nutrient rates were not experimentally controlled.

Tables 2 and 3 report the results of single-factor ANOVA for each data set. Means followed by the same letter do not significantly differ at the 5% level. No statistically significant difference in mean yields exists for the Pennsylvania data or for the Indiana data for rates at or above 80 lbs./ac. For the Morris, MN, data, mean yield does not statistically differ for a rate of 120 and 160 lbs./ac, or for 80 and 120 lbs./ac, but does significantly differ between 80 and 160 lbs./ac. For the Iowa data, no significant mean yield difference exists for 125 and 150 lbs./ac and for 200, 250, and 300 lbs./ac, but mean yields do differ significantly between these groups. For the Waseca, MN, data, all mean yields statistically differ at the different application rates. Although not reported, single-factor ANOVA for the side-by-side data from Iowa, Nebraska, and Wisconsin indicates no statistically significant difference in mean yields.

Tables 2 and 3 also report results of two sample F-tests for different variances—Standard deviations followed by the same letter imply that the variances do not differ statistically at the 5% level. The yield variances for the Iowa data fall into three different groups: 0 and 25 lbs./ac; 50, 75, 100, 125, and 200 lbs./ac; and 150, 250, and 300 lbs./ac. The yield variances for the Indiana data also show a grouping, since the variances at 40, 120, and 200 lbs./ac do not statistically differ, nor do

Table 1. Summary of Available Experimental Data[a]

State	Observations	Rates (lbs./ac)	Sites	Years	Previous Crops
Nitrogen					
Illinois[b]	450	0–274	18	1990–92	Corn, soybeans, alfalfa, wheat
Indiana[b]	940	0–200	21	1991–92, 1994–95	Corn
Iowa[b]	2,220	0–300	13	1986–91	Corn, soybeans
Iowa[c]	78	NA	Several	1999	Corn, soybeans, alfalfa
Minnesota[b]	1,857	0–200	2	1981–89	Corn
Nebraska[d]	58	NA	Several	1987–88, 1992–93, 1996	Corn
Pennsylvania[b]	178	95–175	Unknown	1976–80	Corn, legume
Wisconsin[c]	160	NA	Several	1989–98	Corn, soybeans, alfalfa
Phosphorus					
Iowa[b]	100	0–67	20	1989–90	Corn, soybeans

[a] Agricultural Conservation Innovation Center personnel obtained data from several academic researchers at land grant schools in each state. In some cases, publications were identifiable: Illinois (Brown); Iowa (Binford, Blackmer, and Cerrato; Cerrato and Blackmer; Blackmer et al.); and Minnesota (Olness, Evans, and Moncrief).

[b] Replicated plot experiments with experimentally varied nitrogen application rate.

[c] Side-by-side on-farm trials of status quo versus nutrient BMP.

[d] Side-by-side experimental trials of status quo versus nutrient BMP.

Table 2. Mean and Standard Deviation of Corn Yield (As a Proportion of the Observed Site-Year Maximum) for Indiana and Iowa Data for Different Nitrogen Application Rates (lbs./ac)

State	Rate	Mean	Standard Deviation	Observations
Indiana	0	0.778a	0.170a	158
	40	0.821b	0.139b	152
	60	0.763	0.162	8
	80	0.856c	0.111c	152
	120	0.842bc	0.141b	159
	160	0.856c	0.110c	151
	180	0.779	0.091	8
	200	0.851c	0.135b	152
Iowa	0	0.491a	0.168a	222
	25	0.570b	0.160a	222
	50	0.663c	0.149b	222
	75	0.742d	0.141b	222
	100	0.798e	0.140b	222
	125	0.833f	0.141b	222
	150	0.843f	0.125c	222
	200	0.874g	0.141b	222
	250	0.900g	0.118c	222
	300	0.878g	0.116c	222

Means followed by the same letter do not significantly differ at the 5% level. Standard deviations followed by the same letter imply that the variances do not differ statistically at the 5% level.

those at 80 and 160 lbs./ac. The data for 60 and 180 lbs./ac were not included, since only eight observations were available. The yield variances do not statistically differ by application rate for the Pennsylvania and the Morris, MN, data. For the Waseca, MN, data, the variance shows a decreasing trend from 80 to 200 lbs./ac, with each variance statistically differing from the others. Although not reported, two sample F-tests of the side-by-side data from Iowa, Nebraska, and Wisconsin indicate no statistically significant difference in yield variance.

As an alternative to test for differences in the mean and variance, least squares regression was conducted for the data with nitrogen application rates of at least 100 lbs./ac. Regressors were the nitrogen application rate and its square, as well as an intercept. Results are not reported, but estimated parameters were insignificant at the 5% level for all data sets, except the Iowa data. Both the Breusch-Pagan and the White heteroscedasticity tests were insignificant at the 5% level for all data sets, except the Waseca, MN, data. These results imply that for most locations, no statistically significant difference in the mean and variance of yield can be found. The side-by-side nutrient BMP trial data from Iowa, Nebraska, and

Table 3. Mean and Standard Deviation of Corn Yield (As a Proportion of the Observed Site-Year Maximum) for Pennsylvania and Morris and Waseca, MN, Data for Different Nitrogen Application Rates (lbs./ac)

State	Rate	Mean	Standard Deviation	Observations
Pennsylvania	95	0.807a	0.121a	59
	130	0.820a	0.132a	59
	175	0.832a	0.125a	59
Waseca, MN	0	0.566a	0.127a	170
	40	0.748b	0.116a	170
	80	0.854c	0.120a	170
	120	0.924d	0.072b	170
	160	0.951e	0.058c	170
	200	0.962f	0.049d	170
Morris, MN	0	0.383a	0.152a	168
	40	0.609b	0.162a	167
	80	0.693c	0.161a	168
	120	0.705cd	0.163a	167
	160	0.731d	0.153a	168

Means followed by the same letter do not significantly differ at the 5% level. Standard deviations followed by the same letter imply that the variances do not differ statistically at the 5% level.

Wisconsin also support this conclusion, since no statistically significant difference in the mean or variance of yield was found, although a variety of nutrient BMPs were evaluated under a variety of conditions.

Mitchell reports the results for a similar, although less data extensive, analysis of the effect of phosphorus fertilizer on corn yield and reaches a similar conclusion. Single-factor ANOVA and two sample F-tests imply that the mean and variance of corn yields do not statistically differ over the wide range of phosphorus application rates tested. These results do not imply that nitrogen and phosphorus have no impact on the mean and variance of corn yield. Rather the interpretation is that at optimal or near optimal application rates, statistically identifying the impact of nitrogen and phosphorus on yield is very difficult. This difficulty arises because at these application rates, other uncontrollable factors overwhelm the relatively small effect of nitrogen and phosphorus, if such an effect exists. Alternatively, the interpretation is that with optimal or near optimal nutrient application rates, the data generally support a von Liebig production function with yield at its plateau and a constant variance.

Agronomists and economists commonly estimate von Liebig functions for the response of corn yield to nitrogen and phosphorus (Babcock and Blackmer; Binford, Blackmer, and Cerrato; Cerrato and Blackmer; Frank, Beattie, and Embleton; Huang; Paris; Paris and Knapp). The linear von Liebig function can be written as

$$Y = \begin{cases} A + BN & N < N_c \\ Y_p & N \geq N_c, \end{cases}$$

where Y is harvested yield, Y_p is the maximum yield or the yield plateau, N is the nutrient application rate, N_c is the critical nutrient level, and A and B are parameters. As nutrients N increase, mean yield increases according to the function $A + BN$ until the nutrient application rate reaches the critical level N_c, above which mean yield no longer responds to additional nutrients, but remains at the plateau Y_p. The results of the statistical analysis are generally consistent with the conclusion that yield has a mean following a von Liebig production function with both the BMP and status quo application rates above the critical rate, plus an additively separable homoscedastic error.

This analysis finds no consistent, statistically significant effect of BMP adoption on the mean and variance of yield—the effects are too small relative to total yield variability. How yield varies between adjacent strips in a field due to uncontrolled factors is more important for determining the yield difference between the BMP and check strip than the impact of BMP adoption. As a result, this analysis assumes that Y_{bmp} and Y_{chk} have the same mean and variance, the same fundamental assumption used to develop premiums for the current nutrient BMP insurance policy (Mitchell). Therefore, the correlation between BMP and check strip yields in adjacent strips becomes a pertinent factor for specifying the joint distribution of Y_{bmp} and Y_{chk}.

Joint Distribution of Nutrient BMP and Check Strip Yields

A beta distribution is used for corn yield, a common assumption for crop yields (see Goodwin and Ker's review). Based on the previous analysis, both the BMP and check strip yields have the same mean and variance. To approximate yield conditions in nutrient BMP pilot states, mean yield is 150.0 bu/ac, and the yield coefficient of variation is 0.30 (Coble, Heifner, and Zuniga; Hennessy, Babcock, and Hayes; USDA-NASS). Following Babcock, Hart, and Hayes, minimum yield is zero and maximum yield is the mean plus two standard deviations.

Following Mitchell, a random correlation coefficient is used for the correlation between the BMP and check strip yields. Mitchell describes the data analysis supporting this assumption. In brief, the data from the side-by-side experiments indicate the level and uncertainty in the correlation coefficient. Estimated semivariograms from published papers provide similar results, plus indicate the large variability for within-field yield correlation between years. This year-to-year and location-to-location variability for the yield correlation within a field is important for determining appropriate premiums, but it cannot be controlled or accurately predicted. Hence, assuming a random correlation coefficient is a useful approach when this critical parameter is not known with certainty (Davis and Espinoza).

A beta density is a good choice for the correlation coefficient, since it has strict upper and lower limits like the correlation and can take a variety of shapes (Evans, Hastings, and Peacock). Following Mitchell, a mean of 0.90 and a standard deviation of 0.04 are used for the correlation coefficient, with a minimum and maximum of -1 and 1. The lower and upper limits of the 95% confidence interval are 0.808 and 0.963 for the correlation coefficient with these parameters.

Farmer Returns and Preferences

To focus on yield risk and insurance, the analysis uses a nonrandom cost of production C = \$181.25/ac and a nonrandom corn price of \$2.00/bu for both the market price and the price guarantee P_g used for paying indemnities. All other sources of income and wealth are ignored. The constant cost of production for both the status quo and the nutrient BMP technology implies that the cost saving from reduced input use with the BMP equals the cost of developing and implementing the crop-consultant certified BMP. Cost differences likely exist, but the assumption is convenient for this analysis, so that the farmer adoption decision depends only on changes in the mean and standard deviation of profit resulting from changes in yield risk and insurance, not cost changes. Negative-exponential utility is used, so that wealth effects can be ignored and the cost of production does not affect BMP adoption incentives.

Following previous results, the yield distribution does not change with BMP adoption. Thus, BMP yield (Y_{bmp}) is the harvested yield for calculating returns with the status quo technology and when the farmer adopts the BMP. BMP yield is also used to determine MPCI indemnities for both the status quo and the BMP. As a result, returns (\$/ac) for the status quo with MPCI and when the farmer adopts the BMP with MPCI are

$$(5) \quad \pi_{sq} = \pi_{bmp} = P_g Y_{bmp} - M_{mpci} + I_{mpci} - C,$$

where M_{mpci} and I_{mpci} are the MPCI premium and indemnity, a fair premium is used ($M_{mpci} = E[I_{mpci}]$), and $I_{mpci} = P_g \max\{0, \beta Y_{aph} - Y_{bmp}\}$. The check strip yield (Y_{chk}) is used to determine nutrient BMP insurance indemnities, so returns with the BMP and nutrient BMP insurance are

$$(6) \quad \pi_{ins} = P_g Y_{bmp} - M_{nbmp} + I_{nbmp} - M_{mpci} + I_{mpci} - C,$$

where M_{nbmp} and I_{nbmp} are the nutrient BMP insurance premium and indemnity defined by Equations (3) and (4).

With negative exponential utility, expected utility is $EU_i = E[1 - \exp(-R\pi_i)]$ for each specification $i = \{sq, bmp, ins\}$, where R is the coefficient of absolute risk aversion. The certainty equivalent is $CE_i = -\ln(1 - EU_i)/R$, and the willingness to pay to switch technologies is the difference in certainty equivalents. Following Babcock, Choi, and Feinerman, the coefficient of absolute risk aversion R is chosen so that the risk premium is approximately 20% and 40% of the standard deviation of profit for moderate and high levels of risk aversion, respectively. Specific values for R were 0.00549 and 0.0120.

Simulations

Calculating fair insurance premiums, expected utility, and the change in expected profit and the standard deviation of profit is analytically intractable for the empirical model. Thus, Monte Carlo integration is used to solve integrals numerically (Greene, pp. 192–195). A C++ program using numerical algorithms described in Press et al. generated the random variables. First, 1,000 correlation coefficients were drawn from the appropriate beta density for the BMP and check strip yield correlation. For each correlation, 50,000 pairs of BMP and check strip yields were drawn from beta densities with the appropriate mean and standard deviations using the weighted linear combination method of Johnson and Tenenbein to obtain the required correlation.[3] The average indemnity for the 50,000 yield pairs over all 1,000 correlation coefficients is the Monte Carlo estimate of the fair premium. Similarly, the average utility for each profit specification is the expected utility for calculating the certainty equivalent and willingness to pay, and the change in the average and standard deviation profit gives the change in the profit mean and standard deviation. Following the current pilot program, a check strip yield cap of 35% ($\alpha = 0.35$) and a 5% deductible ($\delta = 0.05$) were used. The MPCI coverage level β was varied between 50% and 85% in 5% increments, the available MPCI coverage levels.

Simulations were conducted over a wide range of beliefs for the BMP yield mean and coefficient of variation, keeping the check strip yield distribution with a mean of 150.0 bu/ac and a coefficient of variation of 0.30. Mean BMP yield was varied from 130 to 160 bu/ac in 1 bu/ac increments, and the yield coefficient of variation was varied from 0.05 to 0.61 in 0.02 increments. For each of these beliefs concerning the effect of the BMP on the yield distribution, the perceived change in the mean and standard deviation of profit was calculated, as well as the willingness to pay for the BMP with and without nutrient BMP insurance. Mitchell reports actuarially fair nutrient BMP premiums and the results of extensive sensitivity analysis indicating how premiums change with different parameter assumptions.

Adoption Indifference Curves and Nutrient BMP Insurance

To determine adoption indifference curves with and without nutrient BMP insurance, the simulation data were used to estimate the willingness to pay $\tilde{W}$ as a function of the perceived change in the mean and standard deviation of profit ($\Delta\mu$ and $\Delta\sigma$). Polynomial approximations were estimated using maximum likelihood, sequentially adding terms until they were no longer significant. The final function for the willingness to pay without nutrient BMP insurance was

$$(7)\quad \begin{aligned}\tilde{W}_{bmp} = {} & (a_0 + a_1\beta + a_2\beta^2)\Delta\mu \\ & + (b_{10} + b_{11}\beta + b_{12}\beta^2)\Delta\sigma \\ & + (b_{20} + b_{21}\beta + b_{22}\beta^2)(\Delta\sigma)^2 \\ & + (b_{30} + b_{31}\beta + b_{32}\beta^2)(\Delta\sigma)^3 \\ & + (h_0 + h_1\beta + h_2\beta^2)\varepsilon,\end{aligned}$$

where β is the MPCI coverage level; $\Delta\mu$ and $\Delta\sigma$ are the perceived changes in the mean and standard deviation of profit; $\varepsilon \sim N(0, 1)$ is the error term; and the a_i, b_{ij}, and h_i are estimated parameters. With nutrient BMP insurance, the function was the same as without nutrient BMP insurance, except that an intercept term was needed, since the indifference curve no longer passed through the origin:

$$(8)\quad \begin{aligned}\tilde{W}_{ins} = {} & (k_0 + k_1\beta + k_2\beta^2) \\ & + (a_0 + a_1\beta + a_2\beta^2)\Delta\mu \\ & + (b_{10} + b_{11}\beta + b_{12}\beta^2)\Delta\sigma \\ & + (b_{20} + b_{21}\beta + b_{22}\beta^2)\Delta\sigma^2 \\ & + (b_{30} + b_{31}\beta + b_{32}\beta^2)\Delta\sigma^3 \\ & + (h_0 + h_1\beta + h_2\beta^2)\varepsilon,\end{aligned}$$

where all variables are as in Equation (7) and the k_i are additional parameters to estimate.

To determine empirical BMP adoption indifference curves for the case when $\tilde{W}_i$ is zero for a given MPCI coverage level β and $\Delta\mu$, the cubic formula was used with the estimated coefficients to solve the resulting cubic equation for the three values for $\Delta\sigma$ at which $\tilde{W} = 0$.[4] This process was used to find the adoption indifference curves with and without nutrient BMP insurance for both levels of risk aversion and all MPCI coverage levels.

[3] Since the method of Johnson and Tenenbein approximates draws from the implied joint distribution, draws are not guaranteed to match higher order and cross moments of the joint density (Goodwin and Ker).

[4] Many versions of the cubic formula are available on the Internet. The version used for this analysis was found at http://planetmath.org/encyclopedia/CubicFormula.html (Accessed November 12, 2003).

Results and Discussion

Figures 2 and 3 report the empirical adoption indifference curves for select cases. Nutrient BMP insurance shifts the adoption indifference curves left and upward to expand the set of perceptions consistent with BMP adoption, as the conceptual model predicts (Figure 1). The magnitude of this shift varies greatly, depending on the MPCI coverage and farmer risk aversion.

Figure 2 shows that nutrient BMP insurance causes a large shift when the farmer has 50% MPCI coverage and a small shift when the farmer has 85% MPCI coverage. The vertical distance between the curves is the additional increase in the profit standard deviation due to BMP adoption that nutrient BMP insurance allows the farmer to believe will occur and still have a positive incentive to adopt the BMP. With 50% MPCI coverage, this additional perceived increase in the profit standard deviation ranges from \$9 to \$75/ac. With 85% MPCI coverage, this additional perceived increase ranges from \$31/ac on the left end, to almost zero near the origin, to over \$9/ac on the right end. The effect of nutrient BMP insurance on adoption incentives decreases as MPCI coverage increases, because at high coverage levels MPCI becomes a more effective substitute for nutrient BMP insurance.

With 50% MPCI coverage, the shift of the indifference curve due to nutrient BMP insurance is even more pronounced in the northeast quadrant, where the farmer believes the BMP increases both the mean and standard deviation of profit. Thus in this case nutrient BMP insurance provides the greatest incentive to adopt the BMP when it is needed—when the farmer believes the BMP is profit enhancing, but riskier.

Figure 3 shows the effect of farmer risk aversion on the shift of adoption indifference curves due to nutrient BMP insurance with 65% MPCI coverage. The top plot with moderate risk aversion (as in Figure 2) shows a relatively large shift in the adoption indifference curve, especially in the northeast quadrant. The bottom plot shows that with higher risk aversion (a risk premium about 40% of the profit standard deviation), the indifference curves become flatter. This occurs because for any given perceived increase in mean profit, a smaller perceived increase in the profit standard deviation is needed to maintain constant utility with higher risk aversion. Alternatively, for any given perceived increase in profit standard deviation, a larger perceived increase in mean profit is needed to maintain constant utility with higher risk aversion.

This effect of risk aversion on adoption indifference curves causes the noticeably smaller shift in the adoption indifference curve due to nutrient BMP insurance with higher risk aversion in Figure 3. For any given perceived increase in mean profit, a more risk-averse farmer needs a smaller perceived increase in the profit standard deviation for the willingness to pay for the BMP to equal zero, even with BMP insurance. Thus, the adoption indifference curves with and without insurance move closer together as risk aversion increases. This smaller shift with higher risk aversion does not imply that a more risk-averse farmer finds the nutrient BMP insurance less valuable. Rather, with greater risk aversion, it takes a smaller perceived increase in profit standard deviation to reduce a farmer's willingness to pay for the BMP to zero.

For the curves in Figure 3, the additional perceived increase in the profit standard deviation allowed by nutrient BMP insurance ranges from \$4 to \$35/ac with moderate risk aversion (top plot) and \$1.50 to \$6/ac with high-risk aversion (bottom plot). Moving from moderate to high-risk aversion decreases the additional perceived increase in the profit standard deviation allowed by nutrient BMP insurance 60%–80% depending on the perceived change in mean profit.

Results reported here for nutrient BMP insurance are generally consistent with the findings of Huang and Huang et al., who analyze specific nutrient BMPs (split or growing season–only nitrogen application) and insurance for specific risks (excessive rainfall preventing application). The analysis here and these analyses find that BMP insurance can increase farmer adoption incentives but use different approaches to measure this effect. For the

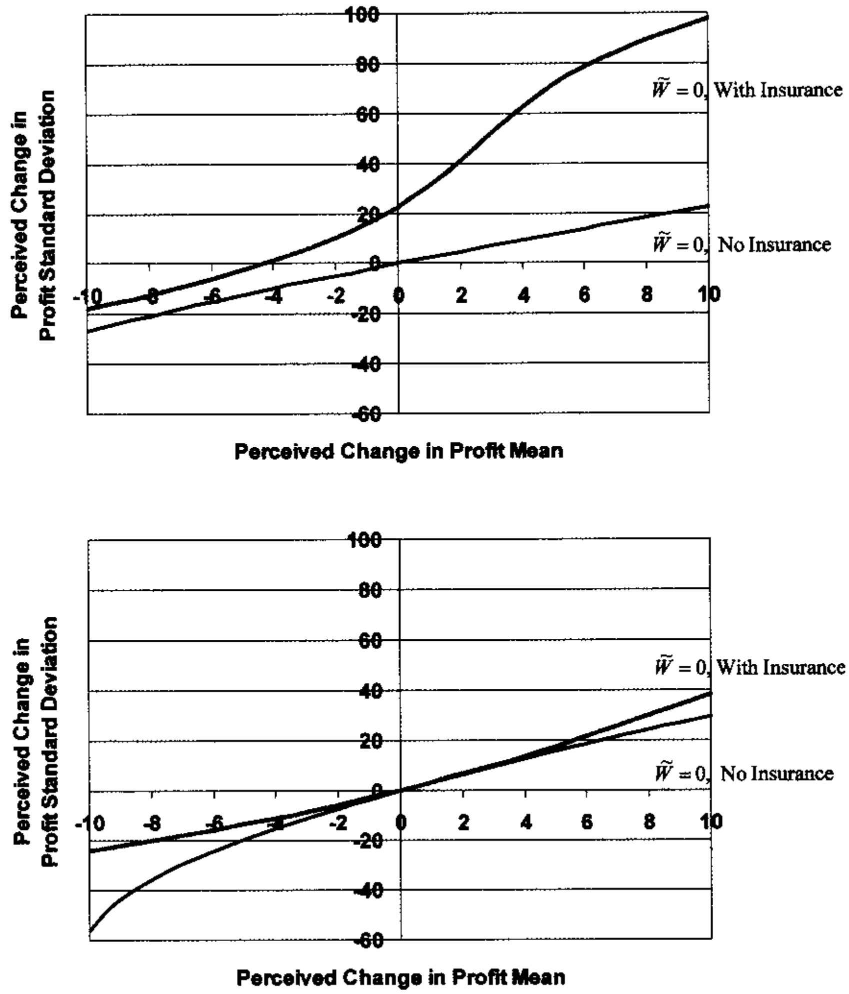

Figure 2. Effect of Nutrient BMP Insurance on Nutrient BMP Adoption Indifference Curves ($\tilde{W}$=0) under Moderate Risk Aversion with a 50% (top) and 85% (bottom) Coverage Level for Multiple Peril Crop Insurance

analysis here, the willingness to pay is held fixed and the perceived changes in the mean and standard deviation of profit due to BMP adoption are derived with and without BMP insurance. Huang and Huang et al. determine the change in the mean and standard deviation of profit due to BMP adoption and then derive the willingness to pay with and without insurance. For a general Iowa example, Huang finds that insurance can increase the willingness to pay from $1.76/ac to $15.55/ac depending on the probability of excessive rainfall and the production function used, which are consistent with the empirical findings here.

Specific results are reported here only for a few cases to illustrate the general effects of nutrient BMP insurance. Nutrient BMP insurance has the greatest effect on moderately risk-averse farmers with low levels of MPCI coverage who believe that the nutrient BMP increases both the mean and standard deviation of profit. Effects are smaller for highly risk-averse farmers with high levels of MPCI coverage. For a reasonable set of parameter values, empirical results show that actuarially fair nutrient BMP insurance can have a substantially positive effect on BMP adoption incentives. These qualitative results would not change if the analysis were conducted with a

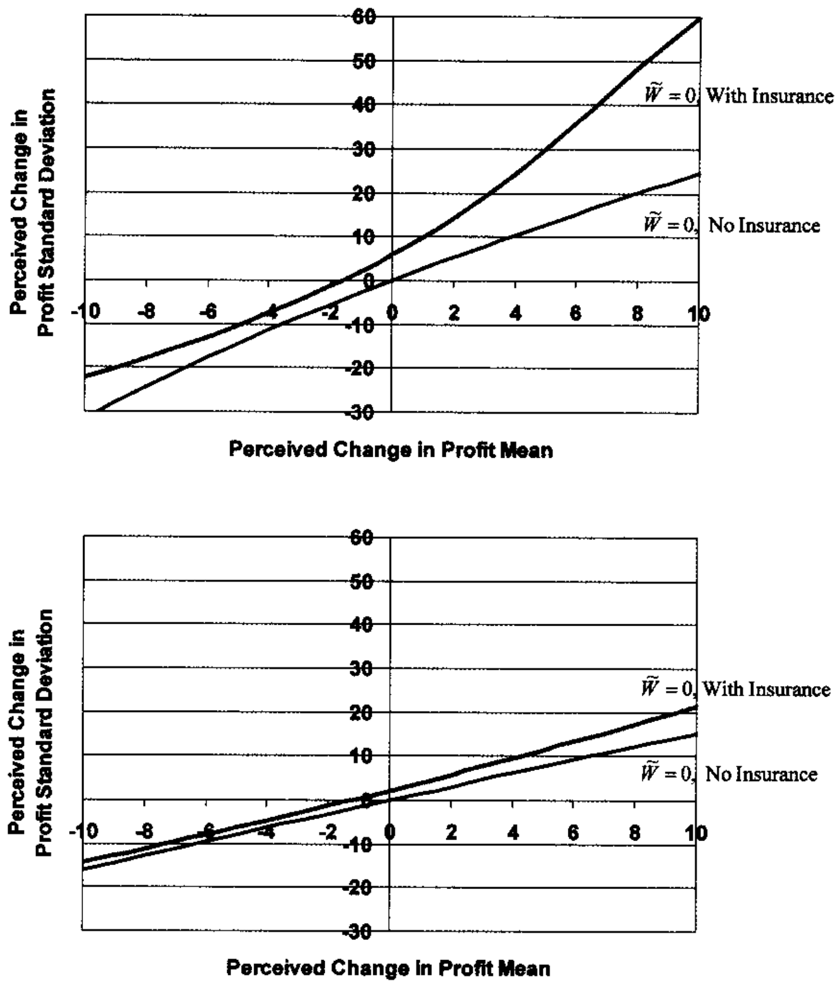

Figure 3. Effect of Nutrient BMP Insurance on Nutrient BMP Adoption Indifference Curves ($\tilde{W}=0$) under Moderate Risk Aversion (top) and High Risk Aversion (bottom) with a 65% Coverage Level for Multiple Peril Crop Insurance

wider range of assumptions for the mean and standard deviation for the status quo yield, or different price and cost assumptions; only the quantitative results would change. Sensitivity analysis has instead focused on the MPCI coverage level and farmer risk aversion.

The purpose of nutrient BMP insurance in the case analyzed here is not to reduce the risks associated with nutrient BMP adoption, since no statistically identifiable risk was found, but to encourage adoption by reducing perceived risks associated with nutrient BMP adoption. Farmers who adopt because of the insurance will gain experience with the BMP and update their perceptions until they learn the actual effect of the BMP on the mean and standard deviation of corn yields. If the BMP truly has no discernible effect on the distribution of corn yield, eventually these farmers will find little value in purchasing nutrient BMP insurance, but should still find the BMP valuable if it generates cost savings. Nutrient BMP insurance accomplishes its goal as "green insurance" by increasing the number of farmers trying and learning about these alternative technologies.

Conclusion

This paper explored the role that perceptions concerning how BMP adoption affects the distribution of profit have on farmer incentives to adopt a nutrient BMP and how insurance changes these incentives. A conceptual model developed adoption indifference curves to understand the effect of perceptions and BMP insurance on BMP adoption incentives. At least conceptually, nutrient BMP insurance expands the set of perceptions that are consistent with BMP adoption. However, an empirical model of an existing nutrient BMP insurance policy was developed to determine if the effects of the insurance were economically relevant and to evaluate its potential to encourage BMP adoption.

Analysis of extensive experimental data from a variety of locations found that at optimal or near optimal application rates, identifying a statistically significant impact of nitrogen fertilizer on corn yield is difficult because the relatively small effects, if they exist, are overwhelmed by other factors. Empirical analysis of an existing nutrient BMP insurance policy finds that the insurance does indeed expand the set of perceptions consistent with nutrient BMP adoption for corn. In one example, the allowable perceived increase in the profit standard deviation with BMP adoption increases \$9–\$75/ac because of the effect of nutrient BMP insurance. In general, the magnitude of this effect depends on several factors, including MPCI coverage, farmer risk aversion, and the perceived change in mean profit due to BMP adoption. Nevertheless, nutrient BMP insurance can substantially increase BMP adoption incentives in some cases, particularly for moderately risk-averse farmers purchasing low MPCI coverage.

Nutrient BMP insurance raises interesting moral hazard and adverse selection issues not formally addressed here. Farmers have an obvious incentive to differentially manage the check strip in order to maximize its yield. The policy includes several provisions to mitigate this moral hazard, including documentation requirements, requiring a certified crop consultant to develop the nutrient BMP, as well as denying claims when evidence of differential weed or insect management is apparent. Also, because a single premium is used for each state, the existing policy likely suffers from adverse selection. Sensitivity analysis finds that fair premiums increase with average yield (Mitchell). Because the premium is based on the state average yield, farmers with lower average yields pay premiums that are too high. Conversely, farmers with higher average yields pay premiums that are too low, and so have a greater incentive to buy the insurance, since on average they are likely to receive more in indemnities than paid in premiums. The RMA premium subsidy partially mitigates this adverse selection problem, since farmers with lower average yields still obtain benefits from the insurance, and so will participate. In addition, developing nutrient BMP premiums that are based on MPCI rates, and therefore will vary with average yield and yield variability, would reduce the adverse selection problem.

Farmer participation is likely to be low in the early years of the nutrient BMP insurance pilot, which should limit losses due to adverse selection and moral hazard. Actuarial data from these pilot years will provide useful data to improve the policy so that policy provisions and premiums can be updated to address these and other problems that may arise. Making improvements and developing methodologies is important, since other green insurance policies are likely to be endorsed by the RMA as it pursues goals mandated by the Agricultural Risk Protection Act.

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