ELSEVIER

Agricultural Economics 11 (1994) 159–170

AGRICULTURAL
ECONOMICS

Role of information in the adoption of best management practices for water quality improvement

Peter M. Feather [a,*], Gregory S. Amacher [b]

[a] *Natural Resources and Environment Division, Economic Research Service, U.S. Department of Agriculture, Washington, DC, USA*
[b] *Virginia Polytechnic Institute and State University, Blacksburg, VA, USA*

Accepted 19 April 1994

Abstract

This study investigates the role of information in influencing the adoption of improved farm management practices. A lack of producer information regarding both the profitability and the environmental benefits of adopting improved practices may be a reason why widespread adoption of these practices has not occurred. Compared to direct regulation or financial incentives, raising producer information levels may be a more cost-effective method of increasing adoption. The United States Department of Agriculture has recently established and begun implementing a program based on this idea. To test the validity of the program, a two-stage adoption model is specified and estimated using data from a survey of producers in the program area. The results indicate that producer perceptions play an important role in the decision to adopt. Changing these perceptions by means of an educational program may be a reasonable alternative to financial incentives in encouraging BMP adoption.

1. Introduction

Best management practices (BMPs) are agronomically sound practices that protect or enhance water quality and are at least as profitable as existing practices. Producer ignorance of their existence and misperceptions of their effect on farm profitability may result in reduced adoption rates of these practices. Financial incentives such as cost sharing or tax exemptions, where the government 'shares' in the risk of adoption, are common methods for overcoming adverse perceptions. These types of incentives are costly, especially if adoption depends primarily upon producer perceptions. An alternative is to implement programs that educate producers. These programs are essentially informational incentives because they encourage adoption by revising producer perceptions about the cost effectiveness of new farming practices. Although fixed start-up costs are incurred, informational incentives may be less costly than financial incentives in the long run as information spreads throughout the farm community.

* Corresponding author.
The views expressed are those of the authors and not necessarily their respective institutions. The authors wish to thank Arun Malik and two anonymous reviewers for comments which improved the paper. We also wish to thank Peter Nowak and Garret O'Keefe for supplying survey data.

SSDI 0169-5150(94)00013-R

The United States Department of Agriculture (USDA) has recently implemented a program based on this premise. The program relies on several demonstration projects (DPs) located across the country. Each DP is a geographic area containing farms practicing one or more BMPs. The purpose of the program is to encourage adoption through the demonstration of BMPs to local producers. The DP program can only be successful if producers' perceptions are affected by the presence of DPs, and if these perception changes lead to increased adoption.

This paper investigates the empirical significance of informational incentives in BMP adoption. The empirical model utilizes data from a recent adoption survey commissioned by the USDA to evaluate the DP approach. The first phase of the survey was conducted in 1991, one year after the program was initiated (see Nowak and O'Keefe, 1992). The empirical model allows for an assessment of how producer perceptions of risk, profitability, and improvements in environmental quality influence adoption. Additionally, the sampling design of the survey allows for a direct comparison of producers under different levels of influence from the DP, yet sharing similar cropping and livestock characteristics. Differences in behavior across states and geographic regions are also examined.

In the next section, a model of BMP adoption is discussed. Instead of categorizing the adoption process as a single dichotomous choice, the model treats the decisions of adopting and then employing BMPs as a two-stage process. This allows BMPs to be utilized in varying intensity levels once the initial decision to adopt has been made. Examination of the intensity decision allows for a more realistic and informative assessment of the adoption process. Feder et al. (1985, p. 286) point out that such a two-stage approach is particularly desirable when dealing with problems such as fertilizer applications where intensity may vary widely over individuals who adopt. The following sections contain a description of the survey data and empirical model, the estimation results, and the conclusions of the study.

2. A model of BMP adoption

BMPs are at least as profitable as existing practices and improve water quality. Given this, their adoption should depend primarily upon the producer's perceptions of the BMP's benefits. Better informed producers are assumed to adopt BMPs because they are more aware of the benefits. The adoption model can be formalized with the producer's problem. Consider a firm that must decide which farming practice to employ. For simplicity, assume each farming practice is associated an input, X_i. Let the producer's strictly concave utility function be given by [1]:

$$U[\pi_i(X_i;\gamma), Q_i(X_i;\delta);\Omega] = \alpha_j\, U[\pi_i(X_i;\gamma);\Omega] + (1-\alpha_j)\, V[Q_i(X_i;\delta);\Omega] \tag{1}$$

where γ and δ are independent random parameters with distributions f_γ and f_δ, so that $\pi_i(\cdot)$ is uncertain farm profit and $Q_i(\cdot)$ is uncertain on-farm environmental quality from adopting the ith BMP; Ω represents the producer's socioeconomic characteristics that can affect adoption, and $\alpha_j \in [0, 1]$ is a producer-specific weight attached to profits and environmental quality. Utilizing the ith practice involves allocating X_i, the input associated with the practice. Because BMPs considered in the empirical portion of the paper utilize different inputs (e.g. labor, fertilizer, or consultant fees), X_i is not specifically defined. The intensity of input usage represents the extent that the practice is used on the farm. X_i is a joint input in both production and environmental quality [2]. Separability of the utility function accommodates the fact that, for improved farming practices, abatement and crop production are often

[1] It is assumed $\partial U(\cdot)/\partial\pi_i > 0$, $\partial U^2(\cdot)/\partial\pi_i^2 < 0$, $\partial V(\cdot)/\partial Q_i > 0$, and $\partial V^2(\cdot)/\partial Q_i^2 < 0$.

[2] For example, consider a BMP which involves allocating fertilization labor in stages as corn emerges. Here, the single labor input jointly produces both water quality benefits and profits, because nitrate infiltration is reduced and productivity is increased through more timely fertilizer applications.

separate events, yet are the result of employing the same input (see Malik and Shoemaker, 1993) [3]

Given the benefits associated with the BMPs, the most important way to encourage adoption is to reduce the uncertainty surrounding use of the practice. Accordingly, the purpose of the DPs is to use information to reduce uncertainties producers have about BMPs. The effect of improved information is reflected in (1). The random parameters in the utility function represent the producer's uncertainty concerning the adoption of the ith practice. It is assumed that better informed producers are more confident of a practice's effects on profits and environmental quality, thus reducing their perceived variance of γ and δ. The effect of better information raises confidence in the benefits of the BMPs and increases adoption.

The profit function in (1) for the ith practice can be defined further as:

$$\pi_i(X_i; \gamma) = P f_i(X_i; \gamma) - wX_i - C_i \tag{2}$$

where P is the output price, w is the input cost, $f_i(\cdot)$ and X_i are the uncertain output and input requirements resulting from adoption of the ith practice, C_i is a known initial investment cost, and $\partial f(\cdot)/\partial X_i \geq 0$ and $\partial^2 f(\cdot)/\ \partial X_i^2 \leq 0$. Fixed costs appear in (2) to reflect the possibility that some practices require initial capital investment costs that are unique to the adoption decision.

If the expected utility of using the ith practice exceeds that of the currently used practice (U_0), then it is adopted:

$$\alpha_j E_\gamma\ U[\pi_i(X_i; \gamma); \Omega] \\ + (1 - \alpha_j) E_\delta\ V[Q_i(X_i; \delta); \Omega] \geq U_0 \tag{3}$$

where E_γ (E_δ) is the expectations operator taken over γ (δ). From (3), adoption of a BMP is more likely whenever initial investment costs are low, expected increases in environmental quality are high, or costs and production are such that expected profits increase. If condition (3) holds, then the producer maximizes (1) subject to (2) to determine at what intensity the practice is used:

$$PE_\gamma\ U'(\cdot)\ [\partial f(X_i; \gamma)/\partial X_i - w] \\ + [(1 - \alpha_j)/(\alpha_j)] E_\delta\ V'(\cdot)\ [\partial Q(X_i; \delta)/\partial X_i] \\ = 0 \tag{4}$$

If the ith practice is adopted, then the producer determines optimal input use from (4). It is determined so that the expectation of the product of marginal utility and marginal profit from using the practice are equal to the expectation of the product of marginal utility and marginal benefits in water quality. As X_i increases, input intensity (either per acre or per farm) increases because the producer uses the practice more extensively. Intensity depends positively on price, expected marginal input productivity, and expected improvement of environmental quality, but negatively on input cost and the variance of γ. The effects of cost and price variables on the adoption and intensity decisions appear in the Appendix.

3. Estimation and data

To specify the adoption decision, (3) is restated in a random utility framework formalized by Manski (1973). Individuals are assumed to always select the alternative with greatest utility, but since the true function is unknown, it must be treated as random by the analyst [4]. Restating the decision to adopt the ith practice given by (3) under the random utility framework results in:

$$\alpha_j E_\gamma\ U[\pi_i(X_i; \gamma); \Omega] \\ + (1 - \alpha_j) E_\delta\ V[Q_i(X_i; \delta); \Omega] + \varepsilon_j \\ \geq U_0 + \varepsilon_0$$

[3] These assumptions are not restrictive. Although the same input affects both abatement and production, its ultimate effect is different through the random parameters, because an input such as labor can cause different expost effects on profits and environmental quality. While the case $\gamma = \delta$ can exist, the effects of two types of uncertainty will not in general be equal. To illustrate a case where $\gamma = \delta$, consider some practice that incurs far greater labor requirements than the producer was expecting. Here, use of the practice decreases both environmental quality and profits.

[4] Manski (1973) discusses four sources of randomness: unobserved attributes, unobserved taste variations, measurement errors, and instrumental variables. These concepts are also discussed in Ben-Akiva and Lerman (1985, pp. 55–57).

where ε_j and ε_0 are independently and identically distributed random variables with mean zero and variance one for all producers. This distributional assumption allows (7) to be estimated using a bivariate probit model (see Ben-Akiva and Lerman, 1985):

$$P_i = \Phi(\beta' Y_i) \quad (6)$$

where P_i is the probability that the ith BMP is adopted, $\Phi(\cdot)$ denotes the cumulative normal distribution function, Y_i is a vector of variables that are arguments of (5), and β is a vector of parameters to be estimated.

The intensity decision is estimated as a linear function to approximate condition (3) while accounting for censoring of the data set to include only producers who have adopted the practice:

$$I_i = \boldsymbol{\Theta} Z_i + \eta_i \quad (7)$$

where I_i is the intensity of adoption for the ith practice, Z is a vector of variables that are arguments in the utility function, $\boldsymbol{\Theta}$ is a vector of parameters to be estimated and η_i is an error term capturing the investigator's uncertainty regarding the producer's expectations of γ and δ. The correction for censoring consists of calculating a correction term from the probit model and including it as an independent variable in the intensity model (see Maddala, 1983).

Data used to estimate the model are taken from a survey of producer BMP adoption behavior conducted by Nowak and O'Keefe (1992) under partial funding from a USDA cooperative agreement; 957 completed questionnaires were obtained from agricultural producers in eight states (Nebraska, Minnesota, Wisconsin, North Carolina, Maryland, Texas, California and Florida). Enough survey information exists to form testable hypotheses for the adoption patterns of five practices:

Manure crediting. The producer estimates the amount of nutrients available for crops from applying livestock or poultry manure. The amount of commercial fertilizer applied is then adjusted by the amount provided by the manure.

Table 1
Description independent variables

Survey question [a]	Variable name [b]	Response = 1 [c]	Response = 0 [d]
Have you heard about or were you aware of the DP?	Demo Aware	Yes	No Can't recall
Prior to now, were you aware of the practice?	Prac Aware	Yes	No
How risky is it to use the practice?	Risk	High risk, Medium risk	Low risk, No risk
How much current farm labor is required?	Labor	More work for existing labor, Hire more labor	No change in labor, Less labor
Number of acres used to produce corn in 1991		Corn [e]	
How does the practice influence farm profitability?	Profits	Increase profits	No change in profits, Decrease profits
How can the practice affect water quality on your farm?	Quality	Prevent but not improve problems Improve water quality	Not hurt or help, Cause more pollution
Number of dairy cattle	Dairy [f]		
Number of beef cattle	Beef [f]		

[a] Paraphrased survey question from Nowack and O'Keefe.
[b] Name of the variable as it appears in the results tables.
[c] Survey response(s) where the variable is assigned a value of one.
[d] Survey response(s) where the variable is assigned a value of zero.
[e] This variable has a continuous response.
[f] These variables have a continuous response and only appear in the manure crediting models.

Legume crediting. The producer estimates amount of nitrogen available for crops from previous legumes. The amount of commercial fertilizer applied is then adjusted by the amount of nitrogen provided by the legumes.

Split application of nitrogen. The producer applies one-half or less of the required amount of nitrogen for corn production at or before planting. The remainder is applied after the corn emerges.

Irrigation scheduling. The producer establishes a set of practices and techniques to determine when and how much water to apply for the most profitable crop production while still protecting groundwater.

Deep soil nitrate nesting. The producer measures the amount of residual nitrogen in the soil profile. The amount of commercial fertilizer is then adjusted by the amount of nitrogen in the soil available for crops.

Although specific cost and return information was not ascertained, a series of questions eliciting the respondent's subjective assessments of the

Table 2
Manure crediting adoption models [a]

Variable	Demo/Comp [b]	State [c]	Constant [d]	% Adopt [e]
Constant	N/A	N/A	−2.1316 **	
Demo	−0.2453 *	N/A	N/A	45.62 (274)
Comp	−2.0162 **	N/A	N/A	43.57 (140)
MD	N/A	−2.3089 **	N/A	37.17 (113)
MN	N/A	−2.2464 **	N/A	25.51 (98)
NC	N/A	−1.8326 **	N/A	24.14 (29)
WI	N/A	−1.9266 **	N/A	64.37 (174)
Demo Aware	0.2663 *	0.2381	0.1889	
Prac Aware	0.5351 **	0.5380 **	0.5461 **	
Risk	0.1049	0.0701	0.1028	
Labor	0.2834	0.2966	0.2893	
Corn	0.0006 *	0.0006 *	0.0005	
Dairy	1.1144 **	1.0916 **	1.1754 **	
Beef	0.1366	0.2078	0.1423	
Profits	0.4457 **	0.4116 **	0.4318 **	
Quality	0.4033 **	0.3876 **	0.3995 **	

[a] Probit models. The dependent variable equals one if the respondent practiced the BMP in 1991; zero otherwise.
[b] Adoption model accounting for demonstration and comparison area effects.
[c] Adoption model accounting for state effects.
[d] Adoption model with a constant term.
[e] Percentage adoption in each type of model. Total observations in parentheses.
** (*) denotes significance at the 5% (10%) level.
Constant is a constant term.
Demo equals one if the respondent farms in a demonstration area; zero otherwise.
Comp equals one if the respondent farms in a comparison area; zero otherwise.
MD/MN/NC/WI equals one if the respondent farms in Maryland/Minnesota/North Carolina/Wisconsin; zero otherwise.
Demo Aware equals one if the respondent is aware of the demonstration project; zero otherwise.
Prac Aware equals one if the respondent is aware of the BMP; zero otherwise.
Risk equals one if the respondent is feels that the BMP is risky; zero otherwise.
Labor equals one if the respondent is feels that the BMP requires increased labor; zero otherwise.
Corn is the number of acres of corn grown on the respondent's farm.
Dairy equals one if the respondent owns dairy cattle; zero otherwise.
Beef equals one if the respondent owns beef cattle; zero otherwise.
Profits equals one if the respondent feels that the BMP will increase profits; zero otherwise.
Quality equals one if the respondent feels that the BMP will improve/prevent water quality problems on the farm; zero otherwise.

expected cost, profit, risk and environmental impacts associated with each BMP on an ordered scale was available. These were converted to dummy variables in order to divide the responses into high or low expectations for each variable. Since (3) and (4) rely on the magnitude of producer expectations, these questions serve as suitable proxies for the elements in the theoretical model.

Table 1 contains a description of the variables used to estimate the adoption models. Knowledge of the BMP and the DP measures the producer's information regarding the practice. Perceptions of risk measure the producer's confidence in the benefits of adopting the BMP. Opinions regarding the profitability and labor requirements of each BMP approximate variables appearing in (2); anticipated quality changes serve as an indicator of Q_i in (1). The importance of these variables in the adoption decision can be determined using simple t-tests of the parameter estimates. The corn acreage variable (Corn) describes the size of the operation. This variable was selected because a majority of the respondents grow corn, and the majority of the BMPs involve row cropping practices. Finally, the presence of livestock is assumed to influence manure crediting.

In each state, two types of areas were sampled: the first is the DP area itself, while the other ('comparison' area) lies outside the DP and is essentially a control. Differences in adoption rates between DP areas and comparison areas, or between states, can be determined using likelihood ratio (LR) tests (see Judge et al., 1985). Using the former as an example, define:

$$d_c \begin{cases} 1 \text{ if the individual farms} \\ \text{in a comparison area} \\ 0 \text{ otherwise} \end{cases} \tag{9}$$

$$d_d \begin{cases} 1 \text{ if the individual farms} \\ \text{in a DP area} \\ 0 \text{ otherwise} \end{cases} \tag{10}$$

$\boldsymbol{Z} = \{\text{a vector of explanatory variables}\}$

Testing the null hypothesis that adoption rates (or intensity rates) are equal between DP areas and comparison areas reduces to an LR test between an 'unrestricted' model using $\boldsymbol{Z}$, d_c and d_d versus a 'restricted' model using $\boldsymbol{Z}$ and a constant term. If the null hypothesis is true, then the estimated parameters on (9) and (10) (β_c and β_d, respectively) are equal meaning that the 'restricted' and 'unrestricted' models are equivalent. Testing differences between states can be accomplished in a similar manner.

Table 3
Legume crediting adoption models [a]

Variable	Demo/Comp [b]	State [c]	Constant [d]	% Adopt [e]
Constant	N/A	N/A	−1.6292 **	
Demo	−1.7979 **	N/A	N/A	43.77 (329)
Comp	−1.5350 **	N/A	N/A	33.86 (254)
MD	N/A	−2.0258 **	N/A	29.92 (127)
MN	N/A	−1.9788 **	N/A	31.13 (106)
NE	N/A	−1.6968 **	N/A	52.67 (139)
WI	N/A	−1.3265 **	N/A	54.03 (211)
Demo	Aware	0.4012 **	0.3627 **	0.3268 **
Prac Aware	0.6300 **	0.6657 **	0.6252 **	
Risk	−0.0592	−0.1356	0.0826	
Labor	−0.1669	−0.1784	−0.1563	
Corn	0.0010 **	0.0010 **	0.0009 **	
Profits	0.6394 **	0.6165 **	0.6535 **	
Quality	0.2706 **	0.2708 **	0.2622 **	

NE equals one if the respondent farms in Nebraska; zero otherwise.
Other notes as listed in Table 2.

Table 4
Irrigation scheduling adoption models [a]

Variable	Demo/Comp [b]	State [c]	Constant [d]	%Adopt [e]
Constant	N/A	N/A	−2.0147 **	
Demo	−2.0183 **	N/A	N/A	52.11 (142)
Comp	−2.0055 **	N/A	N/A	56.67 (30)
MN	N/A	−1.5862 **	N/A	64.52 (82)
NE	N/A	−2.1582 **	N/A	50.35 (141)
Demo Aware	−0.0381	−0.0724	−0.0397	
Prac Aware	1.2567 **	1.2531 **	1.2547 **	
Risk	0.0128	−0.0077	0.0123	
Labor	−0.1697	−0.1540	−0.1699	
Corn	0.0006 **	0.0008 **	0.0006 **	
Profits	0.7466 **	0.7426 **	0.7471 **	
Quality	0.3020	0.2907	0.3028	

Notes as listed in Tables 2 and 3.

Table 5
Deep soil nitrate testing adoption models [a]

Variable	Demo/Comp [b]	Constant [d]	% Adopt [e]
Constant	N/A	−1.6664 **	33.80 (148)
Demo	−1.7039 **	N/A	31.09 (119)
Comp	−1.3185 *	N/A	44.85 (29)
Demo Aware	0.4696 *	0.4052 *	
Prac Aware	0.2963	0.3212	
Risk	−0.2101	−0.1813	
Labor	−0.4713	−0.1699	
Corn	0.0005 *	0.0005 *	
Profits	0.7577 **	0.7529 **	
Quality	0.2808	0.3239	

Table 6
Split application adoption models [a]

Variable	Demo/Comp [b]	State [c]	Constant [d]	% Adopt [e]
Constant	N/A	N/A	−1.6544 **	
Demo	−1.4318 **	N/A	N/A	35.63 (334)
Comp	−1.8038 **	N/A	N/A	22.04 (245)
MD	N/A	−2.6083 **	N/A	13.33 (105)
MN	N/A	−1.3253 **	N/A	58.54 (82)
NC	N/A	−2.4771 **	N/A	80.39 (51)
NE	N/A	−0.3959	N/A	20.16 (131)
TX	N/A	−1.4120 **	N/A	44.44 (9)
WI	N/A	−2.2210 **	N/A	19.40 (201)
Demo Aware	−0.3078 **	0.0225	0.2161 *	
Prac Aware	1.0519 **	0.9899 **	1.0589 **	
Risk	−0.4045 **	−0.1137	−0.4012 **	
Labor	−0.1933	−0.1351	−0.2023	
Corn	0.0003 *	0.0006 **	0.0004 **	
Profits	0.5951 **	0.6458 **	0.5988 **	
Quality	−0.0118	0.1736	−0.0085	

TX equals one if the respondent farms in Texas; zero otherwise.
Other symbols as listed in Tables 2 and 3.

Table 7
Split application intensity models [a]

Variable	Demo/Comp [b]	State [c]	Constant [d]	Intensity [e]
Constant	N/A	N/A	0.9705	
Demo	0.9578 **	N/A	N/A	84.68 (119)
Comp	0.8578 **	N/A	N/A	74.27 (54)
MD	N/A	1.0481 **	N/A	85.87 (14)
MN	N/A	0.9965 **	N/A	89.48 (48)
NC	N/A	0.7861 **	N/A	97.95 (41)
NE	N/A	1.0361 **	N/A	62.44 (27)
TX	N/A	1.0217 **	N/A	90.00 (4)
WI	N/A	0.8122 **	N/A	64.85 (39)
Demo Aware	−0.0606	−0.0173	−0.0380	
Risk	−0.0842	0.0281	−0.0839	
Labor	−0.1310 **	−0.0736 *	−0.1394 **	
Corn	−0.00002 **	−0.00002 **	−0.00002 **	
Profits	0.0289	0.0270	0.0087	
Quality	−0.0586	−0.0260	−0.0578	
Lambda	0.0276	−0.0849	−0.0068	

Lambda is the parameter on the correction term.
Other symbols as listed in Tables 2 and 3.

4. Estimation results and discussion

The first stage of the two-stage model is solely used to evaluate the adoption of each BMP, with the exception of split application of nitrogen which is the only BMP that varies significantly in intensity [5]. Probit estimates of the first stage of the adoption models appear in Tables 2–6. Two 'unrestricted' probit models are included for each practice. The first ('state' model) is used to test for differences in adoption between states; the second ('Demo/Comp' model) is used to test for differences in adoption between the DP areas and the comparison areas. The Demo/Comp models contain dummy variables for observations in comparison areas or DP areas; the state models contain dummy variables for each state. These models will be compared to a model containing a constant term ('Constant' model) to test for differences in adoption rates. Each Table also contains a column showing the observed adoption rate in each state and in the DP and comparison areas.

[5] All other practices are usually used at full intensity once adopted.

Two variables are used to measure producer informational states: knowledge of the practice (Prac Aware) and of the demonstration project (Demo Aware). Both parameters usually have an anticipated positive sign and are often significant. This result was expected because information is assumed to effect the mean and variance of γ and δ. By definition, BMPs are at least as profitable as existing practices and improve water quality. As the producer becomes more informed, the uncertainty regarding the use of the BMP decreases and the expectations of γ and δ may increase, since the better informed producer views the practice as more profitable and less polluting. In contrast, the dummy variable associated with the assessed riskiness of each practice (Risk) performed poorly in the adoption models. This parameter was expected to be negative because producers who perceive a practice to be risky have a higher variance associated with γ and will tend not to adopt.

The anticipated change in profits (Profits) variable is consistently significant and positive in all of the adoption models. This result reflects condition (3) where adoption occurs if profits are anticipated to increase. Another component in (3), environmental quality, is positive in four of the five adoption models, but significant in only two of the models. Comparing the two parameters across all models reveals that the Profits parameter is larger than the environmental quality (Quality) parameter in the majority of the adoption models. This may indicate that the adoption decision is driven more by anticipated increases in profits than by environmental quality. In the theoretical model, expectations regarding the input requirements of a BMP directly effect intensity at which it is practiced, but only indirectly effect the adoption decision via the profit function. Adoption decisions are influenced by perceived profits and environmental quality. Intensity decisions are influenced by the allocation of an input according to (4). The survey contains information about changes in a single input, labor, associated with the adoption of each BMP. Although the labor variable is more appropriate in the intensity model than the adoption model, it appears in the adoption models mainly because most of the BMPs are practiced at full intensity once adopted. The parameter associated with this variable is negative, as anticipated, in four of the five models. However, the parameter is never significantly different from zero. This suggests that anticipated labor requirements are less important in the adoption decision than profits and environmental quality.

The number of acres used in corn production is positive and significant in all of the adoption models. The manure crediting adoption model contains two additional variables to account for the presence of beef cattle (Beef) and dairy cattle (Dairy). Both positively effect adoption rates of this practice, but only Dairy is significantly different from zero.

Estimation results for the split application of nitrogen intensity model appear in Table 7. The dependent variable is the percentage of total corn acres receiving split applications of nitrogen. To test for differences in intensity, this model is also estimated in the 'State' and 'Demo/Comp' versions. The input variable (Labor) is negative and significant indicating that producers who find the practice more labor intensive tend to practice it at lower intensity. The theoretical model also predicts that increases in output price (reflected in the Profits variable) should increase intensity while increases in the variance of γ (reflected in the Risk variable) should decrease intensity. Although both of these variables were insignificant in the estimated model, the parameter signs concur with the theoretical model. Finally, the number of acres of corn produced on the farm (Corn) is highly significant in explaining intensity. As corn acreage increases, intensity diminishes.

Table 8
Likelihood ratio test statistics: Differences between states and between DP areas and comparison areas

Management practice statistics [b]	State test statistics [a]	Demo/Comp test
Manure crediting [c]	6.302 **	2.590
Irrigation scheduling [c]	4.142 **	0.0002
Legume crediting [c]	26.370 **	4.666 **
Nitrogen testing [c]	N/A	1.664
Split application [c]	105.600 **	8.730 **
Split application [d]	18.215 **	4.794 **

[a] Test: H_0: State has no effect on adoption rates.
[b] Test: H_0: DP areas or Comparison areas have no effect on adoption rates.
[c] Test of adoption rates (probit models).
[d] Test of adoption intensity (intensity models).
** Indicates rejection of H_0 at the 5% error rate (critical value is 3.841).
* Indicates rejection of H_0 at the 10% error rate (critical value is 2.706).

Likelihood ratio statistics for tests of significance between DP and comparison areas appear in Table 8. The results indicate that significant differences exist for the adoption and intensity of split application of nitrogen and the adoption of legume crediting across DP and comparison areas. No differences are found for the remaining three BMPs [6]. Inspection of Tables 2–7 reveals that adoption levels are almost equal across DP areas and comparison areas for all but these two BMPs (where adoption levels are higher in the DP areas).

Test statistics for differences in adoption levels across states also appear in Table 8. Adoption

[6] It should be noted that the null hypothesis of equal adoption rates between Demonstration Areas and Comparison Areas would be rejected at approximately the 13.5% error level for manure crediting.

rates were found to significantly differ across states for every practice. The test results, magnitude of differences in state dummy variable parameters, and adoption percentages shown in Tables 2–6 indicate that adoption rates vary much more across states than across DP and comparison areas. Factors such as the quality of extension services, output price variations and soil fertility that vary from state to state, but are not included in the model, are likely to account for this result. Differences in the models then arise because these factors are captured in the state dummy variables. In order to control for variation between states when testing DP areas versus comparison areas, two models were estimated for each practice in each state. The first contains a constant term; the second contains dummy variables for DP areas and comparison areas. Likelihood ratio tests, appearing in Table 9, were then carried out to determine if the two models differ (individual models are not reported). The results show that few significant differences in adoption rates exist between DP and comparison areas across states and practices. A pessimistic explanation for the lack of difference in adoption levels between the DP and comparison areas would be that the DP program is not working. However, given the overwhelming significance of the 'Demo Aware' variable in the adoption models, a more plausible explanation is that the comparison area is not completely isolated from the DP area. This seems more likely given that some producers in the comparison area have knowledge of the DP program.

5. Concluding remarks

This paper has examined the adoption of management practices which improve water quality and maintain or improve farm profitability. The USDA Demonstration Project program is based on the premise that information regarding the benefits of the practices will provide sufficient adoption incentives. Fostering adoption through education is a reasonable, and possibly more cost-effective, alternative to direct regulation or financial incentives. To assess the DP program, a theoretical adoption model which allows information to influence the adoption decision by decreasing uncertainties associated with each practice was specified. This model was estimated using the results of a producer survey containing information about the adoption patterns for five BMPs across different states, and across DP and comparison areas.

The estimation results are cautiously in favor of the DP program. Formal tests of the models

Table 9
Likelihood ratio test statistics: Differences between DP areas and comparison areas by practice and state [a]

Management practice [c]	State				
	MD	MN	NC	WI	NE
Manure crediting	0.116 (37.2)	0.275 (25.5)	1.023 (24.1)	4.680 ** (64.4)	N/A
Split application	5.466 ** (13.3)	2.320 (58.5)	0.139 (80.4)	0.006 (19.4)	2.858 * (20.6)
Legume crediting	0.312 (29.9)	0.0006 (31.1)	N/A (54.0)	1.867 (52.7)	0.020
Irrigation scheduling	N/A	1.185 (64.5)	N/A	N/A	0.020 (50.4)
Nitrate testing	N/A	N/A	N/A	N/A	1.664 (33.8)

[a] Test H_0: DP area and Comparison area has no effect on adoption rates for the state (column) and practice (row) percentage of producers that the practice appears in parenthesis.
[b] MD is Maryland, MN is Minnesota, NC is North Carolina, WI is Wisconsin, NE is Nebraska.
[c] N/A means the BMP is not practiced in the state.
** Indicates rejection of H_0 at the 5% error rate (critical value is 3.841).
* Indicates rejection of H_0 at the 5% error rate (critical value is 2.706).

revealed that adoption patterns are significantly different for two of the five practices, and marginally different for a third. More importantly, the models demonstrated that knowledge of the DP program has a significantly positive influence on adoption rates. Because producer assessments of each BMPs impact on farm profitability was important, this suggests that the success of information programs depends on improved practices being *economically* appealing as well as environmentally sound. Only then will voluntarily adoption occur.

Given the objectives of an informational incentive program, the results also suggest that producers in different regions respond differently to information about the benefits of BMPs. Care must be taken in designing an efficient incentive program that accounts for these regional differences in water quality problems and crop production particulars. In implementing such a program, the results in this paper show that the effect of a DP site is not confined to small, localized areas near the DP. If BMPs are economically attractive, this information should spread through the farming community and increase adoption.

6. Appendix of qualitative results

If a BMP is adopted, its level of use is defined from condition (4) in the text. The endogenous parameter is X; the exogenous parameters are p, α, C_i, and w. The change in the endogenous parameters with respect to the exogenous parameters is found through application of the implicit function theorem to condition (4) (Silberberg, 1989). If g is any exogenous parameter, the form of this expression is $-V_{Xg}/V_{XX}$, where the denominator (i.e., the second-order condition for (4)) is negative and the numerator is defined for each parameter as follows:

$$V_{\mathrm{LP}} = E\ U'(\cdot)\left[\frac{\partial f(X;\gamma)}{\partial X}\right] + E\ U''(\cdot)\ f(X;\gamma)\left[P\frac{\partial f(X;\gamma)}{\partial X} - w\right] \geq 0 \qquad \text{(A1)}$$

$$V_{Xw} = -E\ U'(\cdot) - E\ U''(\cdot)\ X\left[p\frac{\partial f(X;\gamma)}{\partial X} - w\right] \leq 0 \qquad \text{(A2)}$$

$$V_{XCi} = 0$$

$$V_{X\alpha j} = 0$$

For (A1), the first term is positive given the utility function (see footnote 1); the second term is positive because $U'' < 0$, and the term in brackets is negative from (4): $V' > 0$, $U' > 0$, so $p\,\partial f(\cdot)/\partial X - w < 0$ to satisfy (4). Identical reasoning applies in determining the sign of (A2).

In the text, we explained the association between increases in the variance of γ_i with increases in uncertainty surrounding adoption of practice i. For simplicity we can parameterize an increase in the variance of γ_i as a mean-preserving spread:

$$\hat{\gamma}_i = \gamma_i + (\gamma_i - \bar{\gamma}_i)\eta$$

where $\bar{\gamma}$ is the mean of γ_i in (1). Note that $E[\hat{\gamma}_i] = \bar{\gamma}_i$, and $\mathrm{var}(\hat{\gamma}_i) = (\gamma_i - \bar{\gamma}_i)^2\eta^2$. Inserting $\hat{\gamma}_i$ for γ_i in condition (4) and dropping the i subscript for notational simplicity, it can be shown:

$$V_{X\eta} = E\ U''(\cdot)\frac{\partial\pi(\cdot)}{\partial\hat{\gamma}}[\gamma - \bar{\gamma}]\left[P\frac{\partial f(X;\hat{\gamma})}{\partial X} - w\right] + E\ U'(\cdot)\frac{P\,\partial^2 f(X;\hat{\gamma})}{\partial X\,\partial\hat{\gamma}}[\gamma - \bar{\gamma}]$$

The first term is positive if $\gamma > \bar{\gamma}$ (see discussion of (A1)). If the cross partial, $\partial^2 f(X;\gamma)/\partial X\,\partial\gamma$, is large and negative, the expression above is therefore nonpositive; the producer practices the BMP less intensively as the variance of γ increases.

To investigate how decreasing absolute risk aversion (DARA) affects the results of the comparative statics, consider the expressions for $\partial X/\partial\pi$ and $\partial X/\partial\eta$. As the producer's income increases, his attitudes toward risk will determine whether $\partial X/\partial\pi$ and $\partial X/\partial\eta$ become more positive or negative. Because P is a component of π, we can further expect that any parameter change that makes π increase will have the same effect as the price. We investigate these propositions here.

The importance of risk aversion to the input use/intensity decision is determined from the expression $-V_{X\pi}/V_{XX}$, where:

$$V_{X\pi} = E_\gamma\, U''(\cdot)\ [P\ \partial f(X;\gamma)/\partial X - w] \geq 0$$

Dividing the numerator and the denominator of this expression by $U'(\cdot) \neq 0$, and using the Arrow–Pratt measure of risk aversion (Varian, 1984) gives the following result:

$$\frac{\partial X}{\partial \pi} = -E\ \rho(\pi)\ [B]$$

$$\left[-E\ \rho(\pi)\ [B^2] + PE\frac{\partial^2 f(X;\gamma)}{\partial X^2} + ED\frac{\partial^2 Q(X;\delta)}{\partial X^2}(1-\alpha)/\alpha + ED'\left(\frac{\partial Q(X;\delta)}{\partial X}\right)^2 \right]^{-1}$$

where $\rho(\pi) = -U''(\cdot)/U'(\cdot)$ is the Arrow–Pratt measure of absolute risk aversion, $D = [V'(\cdot)/U'(\cdot)]$, $D' = V''(\cdot)/U'(\cdot)$, and $B = P\ \partial f(X;\gamma)/\partial X - w = \leq 0$ from condition (4) (see discussion of (A1) and A2)) and strict concavity of $U(\cdot)$. For increases in profits, both D and D' decrease in absolute value (assuming separable utility). Therefore, under DARA, $\rho'(\pi)\ \leq 0$, so that $\partial L/\partial \pi$ becomes more positive as profits increase if the producer becomes less risk-averse with increasing income.

Similarly, we can investigate how changes in risk aversion effects the decision to accept practices with greater uncertainty (i.e., greater variances). Proceeding as above, but this time dividing $\partial X/\partial \eta$ through by $U'(\cdot) \neq 0$:

$$\frac{\partial L}{\partial \eta} = -\left[E\ \rho(\pi)\frac{\partial \pi(\cdot)}{\partial \eta}[\gamma - \bar{\gamma}] \cdot \left[P\frac{\partial f(L;\hat{\gamma})}{\partial L} - w \right] + E\frac{\partial^2 f(L;\hat{\gamma})}{\partial L \partial \eta}[\gamma - \bar{\gamma}] \right] N^{-1}$$

where the denominator N is equivalent to that of $\partial X/\partial \pi$. The condition above generally has an indeterminant sign. Under DARA and for relatively small changes in η, $\partial X/\partial \eta$ becomes more positive (intensity of use increases) as farm income increases. For a practice that has a very large variance in its effect on profits, the effect of risk aversion on intensity is unclear.

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