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Factors Affecting Farmers' Utilization of Agricultural Risk Management Tools: The Case of Crop Insurance, Forward Contracting, and Spreading Sales

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Factors affecting the adoption of crop insurance, forward contracting, and spreading sales are analyzed using multivariate and multinomial probit approaches that account for simultaneous adoption and/or correlation among the three risk management adoption decisions. Our empirical results suggest that the decision to adopt crop insurance, forward contracting, and/or spreading sales are correlated. Richer insights can be drawn from our multivariate and multinomial probit analysis than from separate, single-equation probit estimation that assumes independence of adoption decisions. Some factors significantly affecting the adoption of the risk management tools analyzed are proportion of owned acres, off-farm income, education, age, and level of business risks.

Key Words: adoption decisions, crop insurance, forward contracting, multinomial probit, multivariate probit, risk management, spreading sales

JEL Classifications: G22, Q12, Q18

A key characteristic of agriculture is the high level of production, market, and financial risks confronted by producers. The presence of these risks has given impetus to the development of a number of agricultural risk management tools and strategies. To reduce production or yield risk, for example, a producer has the option of using several risk reducing instruments or strategies such as yield-based crop insurance and enterprise diversification. Producers can also use futures hedging, forward contracting, and spreading sales to manage market or price risks.

Among the most fundamental and complex decisions that an agricultural producer has to make is the choice of a combination or portfolio of risk management instruments to provide the best income safety net for his or her particular situation (Ke and Wang; Coble, Heifner, and Zuniga). It is not uncommon for a producer to utilize several risk management tools, rather than just a single tool, to manage

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risks. Yet studies of factors affecting the adoption of agricultural risk management tools usually do not analyze this issue in this context. That is, most previous studies only analyze factors influencing the adoption of a single risk management tool (i.e., crop insurance or hedging), rather than analyzing these factors while recognizing the possibility of simultaneous adoption and the potential correlation of adoption decisions. Examples of studies that analyze adoption of a single risk management tool are: Shapiro and Brorsen and Makus et al. for hedging with futures and options; Goodwin and Schroeder and Davis et al. for forward contracting/pricing; and Calvin, Sherrick et al., and Makki and Somwaru for crop insurance.

One exception is the study of Mishra and El-Osta, which analyzed the factors that determine the adoption of both hedging strategies and crop insurance. Knight et al. is another exception that examined the determinants of adopting crop insurance and forward contracting. However, the estimation procedures and analysis in these studies implicitly assume that the adoption decisions for the two risk management options considered are independent of each other, even though they conduct the analysis with the knowledge that these two risk management instruments can be utilized at the same time. In these two studies, two discrete choice models (e.g., logit models) were estimated separately to model the factors influencing hedging/forward contracting and crop insurance adoption decisions. By construction, this procedure ignores the potential relationship between the adoption decisions of the two risk management instruments. Ignoring the possibility of simultaneous utilization of these instruments and the potential relationship between the two adoption decisions may cause invalid inferences and incorrect conclusions to be made (Kiefer).

The objective of this study is to examine the factors that influence producers' risk management adoption decisions while taking into account the possibility of simultaneous utilization of multiple risk reducing instruments and the potential correlations among these adoption decisions. In particular, we examine factors influencing farmers' use of the following risk management instruments: crop insurance, forward contracting, and spreading sales. Data from farmers in the states of Illinois, Indiana, and Iowa are used to support multivariate probit and multinomial probit models, to achieve the study objectives. The study results provide a better understanding of which farmer/farm characteristics influence the use of different risk management strategies. This information should be valuable to policy makers, government agencies (i.e., the Risk Management Agency, RMA), crop insurance companies, and extension agents/educators. For example, an awareness of which type of producer is more likely to adopt crop insurance would help insurance companies to better identify potential clientele. This information should also help extension educators target producers that need crop insurance or risk management education the most.

The remainder of this article proceeds as follows. The theoretical framework is presented in the next section. The estimation procedure, data used, and the empirical specification are then described. This is followed by a presentation and discussion of the empirical results. Conclusions are presented in the final section.

Conceptual Framework

In this article, we model the farmer's choice of agricultural risk management tools in an expected utility framework (Ke and Wang; Coble, Heifner, and Zuniga; Sherrick et al.). This framework assumes that different farmers assess their end-of-period expected utilities for their own specific risk environments (i.e., production and marketing risks) and risk preferences. This approach further assumes that the presence of risk management tools fundamentally affects the net return distribution of each producer. The farmer then examines his or her net return distribution by considering the certainty equivalent for each risk management tool and calculating its associated reservation cost. The reservation cost is the amount that would make the farmer indifferent to the use of an agricultural risk management tool (i.e., for crop insurance, it is the reservation premium). The farmer then compares the reservation cost with the actual cost of adoption and adopts an agricultural risk management tool if the reservation cost is larger than the actual cost. This is equivalent to having a larger certainty equivalent net return with the risk management tool relative to without the risk management tool.

More formally, consider a producer making the decision of whether or not to adopt any, some, or all of the agricultural risk management tools, j, available to him or her ($j = 1, \ldots, m$). This producer evaluates each of these m risk management tools by considering its effect on the returns distribution to a set of assets, A, used in production. These assets have a stochastic rate of return $\tilde{r}_A$, with mean $\bar{r}_A$, and variance σ_A^2, reflecting overall business risks. Financial risk is introduced through the use of debt capital. Utilizing the accounting identity that assets are equal to debt plus equity ($A = D + E$) and assuming a fixed cost of debt, c_D, the expected rate of return to equity ($\bar{r}_E$) and the variance of the return to equity (σ_E^2) can, respectively, be expressed as:

$$\bar{r}_E = \bar{r}_A\left(\frac{A}{E}\right) - c_D\left(\frac{D}{E}\right), \quad \text{and} \tag{1}$$

$$\sigma_E^2 = \left(\frac{A}{E}\right)^2 \sigma_A^2. \tag{2}$$

Given the stochastic environment above, the producer's certainty equivalent end-of-period wealth can be approximated as follows (under known sufficient conditions):

$$W_{CE} = \overline{W} - \rho\sigma_W^2, \tag{3}$$

where W_{CE} is the farmer's certainty equivalent of end-of-period wealth (W), $\overline{W}$ is the mean of W, σ_W^2 is the variance of W, and ρ is the parameter reflective of risk preferences. Note that maximizing W_{CE} is equivalent to maximizing the certainty equivalent rate of return on equity (r_{CE}), which can be defined as:

$$r_{\text{CE}} = \bar{r}_E - \rho\sigma_E^2. \tag{4}$$

From Equations (1) and (2), the expression in Equation (4) can be rewritten as:

$$r_{\text{CE}} = \bar{r}_A\left(\frac{A}{E}\right) - c_D\left(\frac{D}{E}\right) - \rho\left(\frac{A}{E}\right)^2 \sigma_A^2. \tag{5}$$

The effects of using agricultural risk management tools are then assumed to be embodied in the changes in the mean and variance of the asset return distribution, and in the costs (C) of using these types of tools for managing risks (i.e., the cost for crop insurance use is the premium paid). Given this cost, the effect of using a particular agricultural risk management tool is to reduce the rate of return to equity by C/E. Taking this reduction into account, for every risk management tool j available to the producer, the certainty equivalent rate of return to equity can then be redefined as:

$$r_{\text{CE},j} = \bar{r}_{A,j}\left(\frac{A}{E}\right) - c_D\left(\frac{D}{E}\right) - \left(\frac{C_j}{E}\right) - \rho\left(\frac{A}{E}\right)^2 \sigma_{A,j}^2. \tag{6}$$

In theory, the highest cost that a producer is willing to incur for the use of an agricultural risk management tool (i.e., the reservation cost C_j^*) is the amount that implicitly equates the expected utilities from using and not using the risk management tool. Hence, by Equations (5) and (6) the reservation cost can be calculated based on:

$$\left[\bar{r}_A\left(\frac{A}{E}\right) - c_D\left(\frac{D}{E}\right) - \rho\left(\frac{A}{E}\right)^2 \sigma_A^2\right] = \left[\bar{r}_{A,j}\left(\frac{A}{E}\right) - c_D\left(\frac{D}{E}\right) - \left(\frac{C_j^*}{E}\right) - \rho\left(\frac{A}{E}\right)^2 \sigma_{A,j}^2\right]. \tag{7}$$

Solving for C_j^*, we then get the following expression:

$$C_j^* = A(\bar{r}_{A,j} - \bar{r}_A) - \rho A\left(\frac{A}{E}\right)(\sigma_{A,j}^2 - \sigma_A^2). \tag{8}$$

Using Equation (8), the producer will then decide to use a particular risk management tool if the difference between the reservation cost and the actual cost of using j is greater than zero ($\hat{C}^D > 0$); where $\hat{C}^D = (C_j^* - C_j^{\text{Actual}})$. Note that the difference $\hat{C}^D$ is an unobserved latent variable, but the adoption decision (Y_j) is observable such that:

$$Y_j = \begin{cases} 1 \text{ if } \hat{C}^D > 0 \\ 0 \text{ if } \hat{C}^D \leq 0 \end{cases}, \tag{9}$$

where $Y_j = 1$ if the producer adopts the risk management tool j and $Y_j = 0$, otherwise.

The formulation in Equation (9) makes it empirically tractable to estimate the factors influencing the simultaneous utilization of risk management tools. In this regard, the expression in Equation (8) suggests that variables related to asset size (A), risk attitudes (ρ), leverage (A/E), as well as variables that determine how the risk management tool affects the mean and variance of the return to assets $((\bar{r}_{A,j} - \bar{r}_A)$ and $(\sigma^2_{A,j} - \sigma^2_A))$, all help determine the producer's reservation cost for j. Consequently, these factors directly affect the value of the unobserved latent variable $\hat{C}^D$ and the decision of whether or not to utilize a particular risk management tool.

From a different perspective, the framework above also suggests that the farmer's decision to adopt a particular risk management tool depends on: (1) factors affecting the return distribution even *without* the use of risk management tools (i.e., asset size, leverage, and risk attitudes), and (2) the factors that determine the degree to which the return distribution is altered *with* the use of risk management tool j. Moreover, the framework above allows for simultaneous utilization of several risk management tools through its effect on $(\bar{r}_{A,j} - \bar{r}_A)$ and $(\sigma^2_{A,j} - \sigma^2_A)$. That is, the effect of a particular risk management tool, say $j = 1$, on the mean and variance of the return distribution depends on whether or not the producer uses other available risk management tools $j = 2, \ldots, n$; and vice versa. This implicitly assumes that the decision to adopt one risk management tool is correlated with whether or not other risk management tools will be used. Hence, it may be important to take this into account when conducting an empirical analysis of factors affecting the adoption of several risk management tools.

Empirical Approach and Data

Estimation Procedures: Multivariate Probit Model

The conceptual framework above can be empirically implemented using a multivariate probit estimation procedure. This approach allows for the possible contemporaneous correlation in the decisions to adopt the three risk management tools we are considering: crop insurance, forward contracting, and spreading sales.[1] In line with Equations (8) and (9) above, a general multivariate probit model can be specified as follows:

$$(10) \qquad Y_{ij} = x'_{ij}\beta_j + \varepsilon_{ij},$$

where Y_{ij} ($j = 1,.., m$) represent the risk management alternatives (in our case $m = 3$) faced by the ith producer ($i = 1,..,n$),[2] x'_{ij} is a $1 \times k$ vector of observed variables that affect the risk management adoption decision (i.e., as discussed above, the observed variables related to A, ρ, etc.), β_j is a $k \times 1$ vector of unknown parameters (to be estimated), and ε_{ij} is the unobserved error term.

The model specified in Equation (10) can be empirically implemented using a series of independent probit or logit models for each risk management alternative j. However, as we noted above, it is possible to adopt risk management tools simultaneously and thus it is likely that these decisions are correlated. In this case, the unobserved error terms for the probit or logit models would not be independent. Ignoring this correlation in analyzing the simultaneous adoption of risk management tools

[1] Note that multivariate probit estimation has already been used in a number of studies that evaluate factors that affect adoption of agricultural technologies (see Gillespie, Davis, and Rahelizatovo; Fernandez-Cornejo, Hendricks, and Mishra). For example, Gillespie, Davis, and Rahelizatovo use this approach to estimate factors that affect adoption of four breeding technologies in hog production. They argue that modeling adoption decisions using a multivariate probit framework "allows for increased efficiency in estimation in the case of simultaneity of adoption." However, they admit the limitation of a multivariate probit procedure, relative to a multinomial probit model, that "Such a model does not allow for the computation of the probability of adoption of more than one technology at a time . . . ". At the same time, Gillespie, Davis, and Rahelizatovo eventually defend the use of a multivariate probit in their estimation since it "does account for contemporaneous correlation and reduce bias" and using the multinomial probit for analyzing three or more alternatives is computationally difficult (See Gillespie, Davis, and Rahelizatovo, pp. 38 and 39).

[2] In this specification, each Y_j is a binary variable and, thus, Equation (10) is actually a system of m equations ($m = 3$ in this case).

may lead to biased estimates of the choice probabilities and incorrect estimates of the standard errors of the parameters (Kiefer). Hence, in the multivariate probit approach to estimate the unknown parameters in Equation (10), the error terms (across $j = 1,.., m$ alternatives) are assumed to have multivariate normal distributions with mean vector equal to zero and a covariance matrix **R** with diagonal elements equal to one.

With the assumption of multivariate normality, the unknown parameters in Equation (10) can be estimated using maximum likelihood (ML) procedures. The probabilities that enter the likelihood function (as well as the derivatives needed for the ML procedure) are computed using the Geweke-Hajivassiliou-Keane (GHK) simulation procedure (see Geweke; Hajivassiliou; Keane), which produces approximations to the m-fold multivariate normal integrals:

$$\int_{-\infty_m}^{x_m} \cdots \int_{-\infty}^{x_1} \rho(\mathbf{x}_1, \ldots, \mathbf{x}_m) d\mathbf{x}_1 \ldots d\mathbf{x}_m, \tag{11}$$

where $\rho(\cdot)$ is the m-variate normal density of x with mean vector equal to zero and $m \times m$ positive definite covariance matrix **W**. The log-likelihood for the model is then calculated as the sum of the logs of the probabilities of the observed outcomes defined as:

$$\begin{aligned} &\text{Prob}(,(y_1, \ldots, y_m | \mathbf{x}_1, \ldots, \mathbf{x}_m) \\ &\quad = \text{MVN}(\mathbf{Tz}, \mathbf{TRT}'), \end{aligned} \tag{12}$$

where $\mathbf{z}$ is a vector defined from $\mathbf{z}_m = \beta'_m \mathbf{x}_m$, **R** is the correlation matrix, and **T** is a diagonal matrix with $t_{mm} = 2y_m - 1$, and MVN refers to the density being multivariate normal (see Greene 2007). In this study, pairwise correlation of the error terms associated with each risk management adoption decision is computed and its significance is tested.

Note that there are a number of different marginal effects that can be computed given the multivariate nature of the model (see Greene 2003). The approach taken here is to first obtain the expected value of a positive adoption decision for a particular risk management tool (say, $Y_1 = 1$), *conditional* on all other risk management tools also being adopted ($Y_2, \ldots, Y_m = 1$):

$$\begin{aligned} &E(Y_1 | Y_2, \ldots, Y_m). \\ &= \frac{\text{Prob}(Y_1 = 1, \ldots, Y_m = 1)}{\text{Prob}(Y_2 = 1, \ldots, Y_m = 1)} = \frac{P_{1\ldots m}}{P_{2\ldots m}} = E_1. \end{aligned} \tag{13}$$

Then, to get the marginal effects, the derivative of Equation (13) is taken with respect to the explanatory variables of interest:

$$\begin{aligned} \frac{\partial E_1}{\partial \mathbf{x}} &= \sum\nolimits_{j=1}^{m} \left[\frac{1}{P_{2\ldots m}} \frac{\partial P_{1\ldots m}}{\partial \mathbf{z}_m} \right] \gamma_m - E_1 \\ &\quad \times \sum\nolimits_{j=2}^{m} \left[\frac{1}{P_{2\ldots m}} \frac{\partial P_{2\ldots m}}{\partial \mathbf{z}_m} \right] \gamma_m, \end{aligned} \tag{14}$$

where $\mathbf{x}$ is the union of all the regressors that appear in the model and γ_m is defined such that $\mathbf{z}_m = \mathbf{x}'\gamma_m = \beta'_m \mathbf{x}_m$. Hence, the marginal effect in Equation (14) shows how an explanatory variable affects the probability of adopting the first risk management tool, conditional on the other tools being adopted. Standard errors for these marginal effects are obtained using the delta method and a bootstrapping procedure (see Greene 2007 for more details).

Estimation Procedures: Multinomial Probit Model

An alternative estimation approach to the multivariate probit model presented above is the multinomial probit procedure.[3] In a multinomial (rather than multivariate) probit model,

[3] The multinomial probit has been recognized as an alternative to multivariate probit (and vice versa) in a number of previous agricultural economics studies. In the technology adoption literature (as discussed in footnote 1), Gillespie, Davis, and Rahelizatovo recognize that both approaches are equally valid and discussed the advantages/disadvantages of each. But they eventually decided to use the multivariate probit approach for their analysis (see Anton; Nhemachena and Hassan for studies that used similar arguments to defend the use of a multivariate probit approach). On the other hand, Seo and Mendelsohn (p. 7) suggests that both approaches to analyzing adoption decisions are "theoretically sound" and that it really depends on the particular context of the study on which one to use. Hence, there are studies that have used both approaches since each approach provides slightly different inferences that can be useful for further understanding the adoption decisions of interest (see Roucan-Kane and Keeney; Seo and Mendelsohn). In this study, we opted to use the two approaches precisely because of this reason.

the choice set is made up of all possible *combinations* of risk management tools instead of just the risk management alternatives by themselves. With three risk management alternatives in this study, we have eight possible combinations (2^3) that a producer can choose to adopt: (1) use no risk management tool considered in this study (i.e., the producer did not adopt any of the following: crop insurance, forward contracts, and spreading sales), (2) use crop insurance only, (3) use forward contracting only, (4) use spreading sales only, (5) use crop insurance and forward contracting, (6) use crop insurance and spreading sales, (7) use forward contracting and spreading sales, and (8) use all three risk management tools simultaneously. Given this choice set, a multinomial probit model can be specified as follows:

$$(15) \qquad Y_i = x_i'\beta + \varepsilon_i, \quad \varepsilon_i \simeq MVN(0,\Sigma),$$

where Y_i in this case represent the risk management tool combination ($Y_i = 1, .., m$) that the ith producer ($i = 1,.., n$) chooses,[4] x'_i is a $1 \times k$ vector of observed variables that affect the risk management combination chosen, β is a $k \times 1$ vector of unknown parameters (to be estimated), and ε_i is the unobserved error term. The unobserved error term in this case is assumed to be multivariate normal with mean zero and variance-covariance matrix Σ.[5] A maximum likelihood (ML) procedure is used to estimate the unknown parameters in Equation (15).

Using the multinomial probit estimation procedure allows one to calculate the marginal effects of the explanatory variables with respect to the probability of adopting one of the risk management combinations discussed above. For example, one can calculate the marginal effect of a particular explanatory variable on the probability of adopting all three risk management tools (i.e., how does farm size, for example, affect the probability of adopting combination 8?). Note that this is different from the marginal effect calculated using the multivariate probit approach (see Equations (13) and (14)) where one calculates the marginal effect for one particular risk management tool, conditional on adoption of the other tools (i.e., how does farm size, for example, affect the probability of adopting crop insurance conditional on the producer also adopting forward contracting and spreading sales?). Hence, the marginal effects from the multinomial probit estimation provide additional information that can also be helpful to various stakeholders interested in risk management tool adoption (i.e., policymakers, crop insurance companies, RMA, extension educators).[6]

Data Description

The data used in this study are from a 2001 mail survey of corn and soybean farmers in Illinois, Iowa, and Indiana that was sent prior to the start of the planting season. This survey was structured to provide a relatively broad geographic base, a sizeable farm population, and a cost-effective data collection approach. Three thousand farmers, each of whom operates at least 160 acres, were randomly chosen to receive the survey from a mailing list maintained by *Progressive Farmer*, a company that communicates extensively with farmers

[4] The variable Y is coded from $1,..,m$ (where $m = 8$ in our case), so that Equation (15) is only one equation to be estimated. In practice, only $m - 1$ choices (instead of m) are included in the choice set (i.e., one choice serves as the "base" category) for identification purposes. This restriction is required because in practice only data on the actual choices are available so that identification comes from comparisons of utilities and not from levels of utilities (see Greene 2003). Hence, interpretations of parameters and marginal effects are always relative to the "base" category.

[5] The covariance structure (Σ) allows the multinomial probit to *not* have the independence of irrelevant alternatives (IIA) assumption, which is the limitation of another popular discrete multiple choice model—the multinomial logit.

[6] One reviewer pointed out that some stakeholders may be more interested in how explanatory variables affect the risk management tool *combination* chosen by producers, rather than how explanatory variables affect adoption of *one particular* risk management tool, conditional on the other tools being adopted. Using the multinomial probit approach allows us to easily calculate how different variables affect the probability of choosing a certain *combination* of risk management tools, which is the primary reason why we also use this estimation procedure in this study.

through farm magazines, surveys, and personal interviews.

Survey development was aided by discussions with two focus groups of farmers, extensive pretesting, and input from USDA-ERS and Risk Management Agency (RMA) reviewers. Included in the survey were questions related to demographic and business information, risk management, risk attributes and perceptions, and other related information (a copy of the survey is available from the authors upon request). A total of 926 surveys were returned and 871 were considered sufficiently complete to be usable (that is an effective response rate of 29%).

Empirical Specification

As mentioned above, the three risk management adoption decisions that serve as the dependent variable for the multivariate probit estimation procedure are *crop insurance*, *forward contracting*, and *spreading sales*. These three risk management practices were chosen because they are the production and/or marketing risk management tools most frequently adopted by producers in our sample. Moreover, with these three risk management tools under consideration, eight possible combinations of these tools are used as the basis for the dependent variable in the multinomial probit estimation.

Consistent with the conceptual framework above, the independent variables (x_i) included in our empirical specification are observable factors related to asset size (A), risk attitudes (ρ), and/or leverage (A/E). Note that we do not explicitly observe how the risk management tools interact to affect the net return distribution (mean and variance) of the producer, which means that this factor would be subsumed in the error terms of the system of equations in the multivariate probit model. Importantly, we account for this unobserved interaction among the adoption decisions by allowing for simultaneous adoption and correlation of the error terms in the multivariate probit approach.

The factors related to asset size included in the empirical specification are proportion of total acres owned and total farm size. A larger proportion of owned acres is related to greater wealth, greater stability of land control, and a larger asset base. Consequently, a higher proportion of owned aces and/or greater farm size signals a larger capacity for bearing risk (i.e., it also affects risk attitudes ρ) and a lesser need for risk management instruments. Hence, we expect that owned acres is negatively related to risk management tool adoption. Larger farm size is also suggestive of a larger asset base from which to draw resources. A larger farm size necessarily reflects at least some degree of increased spatial dispersion, perhaps including multiple farm locations, that tends to reduce production risk. Larger operations also benefit from economies of scale and better managerial capacities that fundamentally affect asset base and risk attitudes. In light of these characteristics, the relationship between farm size and adoption of different risk management tools appears ambiguous (and depends on the particular tool).

A farmer's perception about his or her level of business risk is one variable that empirically represents risk attitudes. In particular, farmers' risk perceptions are measured by their perceived probability of receiving a multiperil or actual production history (APH) crop insurance indemnity payment at the 85% coverage level (for both corn and soybeans). A higher probability of receiving an APH payment reflects higher perceived business risks. Producers with higher business risks may have more incentives to adopt risk management tools. We also posit that socioeconomic and demographic factors, such as age, education, and off-farm income, signal differences in risk attitudes and are included in the empirical specification as well (Smith and Baquet; Sherrick et al.). Previous studies have found mixed results in terms of the effect of age and education on risk management tool adoption (Mishra and El-Osta). But, in general, it is typically hypothesized that producers with more experience and more education tend to adopt more sophisticated risk management tools. Experience and education are also perceived to contribute to more precise risk assessments and reflect differing risk attitudes (Sherrick et al.). Off-farm income, on the other hand, represents a form of diversification that would have an impact on the risk attitudes of producers. Higher off-farm incomes may indicate a greater capacity to bear risks (i.e., because of stability of income, the possibility of "self-insurance") and may reduce incentives to adopt risk management tools.

The financial leverage variable used in the empirical analysis is the debt-to-asset ratio. In general, higher debts (reflected by higher debt-to-asset ratios) are indicative of greater financial risks. Producers with higher financial risk are expected to have more incentive to use risk management instruments and, thus, a positive relationship between debt-to-asset ratio and risk management decisions is anticipated. Note that state dummy variables are also included in the specification as control variables.

Results and Discussion

Descriptive Statistics and Correlation Coefficient

Table 1 provides definitions and descriptive statistics for the variables included in the empirical specification of the multivariate probit model. The percentage of producers in the sample using some form of crop insurance is 46%. Producers who utilize forward contracts and are spreading sales comprise 38% and 49% of the sample, respectively. The detailed proportions of producers using different combinations of risk management tools are presented in Table 2. Note that there is no producer in our sample that used crop insurance by itself. Hence, this category is omitted in our multinomial probit analysis below.

Pairwise correlation coefficients across the three risk management adoption equations are presented in Table 3. These coefficients measure the correlation between the risk management decisions considered, after the influence of the observed factors has been accounted for (Greene 2003). These coefficients are essentially the pairwise correlation between the error terms in the system of equations in the multivariate probit model. All of the correlation coefficients are positive and statistically significant at the 1% level. This supports our hypothesis that the error terms in the risk management adoption equations are correlated, and a multivariate probit approach would be appropriate in this case. The perceived interaction between risk management tools (which is unobserved) and its potential effects on the producer's net return distribution is accounted for in the multivariate probit approach.

Moreover, the positive signs of the correlation coefficients suggest that the decision to adopt one particular risk management tool may make it more likely that another tool is adopted. For example, a producer who uses crop insurance may also tend to spread sales (once the observable factors are controlled for), and vice versa (see Sartwelle et al. for a similar result). The positive correlation between crop insurance and spreading sales/forward contracting is consistent with the notion that, in general, these types of instruments are needed to cover both production and price risks. As an alternative explanation, it could be argued that producers who adopt one kind of risk management instrument (say, crop insurance) tend to be highly risk-averse such that, behaviorally, they are also more likely to adopt other risk management tools (say spreading sales and/or forward contracting).

Parameter Estimates: Multivariate Probit Model

The parameter estimates from the multivariate probit and (for comparison) the individual probit models are presented in Table 4. Based on the multivariate model, the observed factors that tend to significantly affect adoption of crop insurance are the proportion of owned acres, and off-farm income levels. As expected, producers who farm more owned acres do not tend to use crop insurance. Farmers with off-farm income greater than $50,000 also do not tend to use crop insurance. On the other hand, our results do suggest that producers with low levels of off-farm income still tend to use crop insurance as a risk-reducing instrument. The positive and significant parameter estimate on the Iowa state dummy reflects a higher likelihood of adopting crop insurance in this state relative to the omitted state (Indiana).

For the forward contracting adoption equation, the significant variables in the multivariate probit approach are education, total farm

Table 1. Descriptive Statistics of Variables (n = 871)

Variable	Description	Mean	St. Dev.
A. Dependent variables:			
Crop insurance	= 1 if the producer is using any kind of crop insurance (yield or revenue insurance), zero otherwise	0.4592	0.4986
Forward contracting	= 1 if the producer is using forward contracting, zero otherwise	0.3823	0.4862
Spreading sales	= 1 if the producer is spreading sales over the year, zero otherwise	0.4879	0.5001
B. Independent variables:			
Proportion of acres owned	Proportion of own acres	0.4805	0.3769
Age	Age of respondent as of February 2001	53.8037	12.0879
Off-farm income \$0–\$5,000	= 1 if farmer has off-farm income between \$0–\$5,000/year, zero otherwise	0.0873	0.2824
Off-farm income \$5–\$50,000	= 1 if farmer has off-farm income between \$5,000–\$50,000/year, zero otherwise	0.2870	0.4562
Off-farm income > \$50,000	= 1 if farmer has off-farm income > \$50,000/year, zero otherwise	0.0723	0.2592
Education	Years of education (no. of years)	13.7910	1.7856
Debt/asset ratio	= 1 if farm has a debt-to-asset ratio > 40%, zero otherwise	0.1469	0.3543
Farm size	Total farm size (acres)	844.758	1395.576
Probability of APH/corn	Perceived probability of getting an insurance payment under APH plan at 85% coverage level for corn (%)	25.7210	20.9016
Probability of APH/soybeans	Perceived probability of getting an insurance payment under APH plan at 85% coverage level for soybeans (%)	23.6383	20.2901
Illinois	= 1 if farm is located in Illinois, zero otherwise	0.3949	0.4891
Iowa	= 1 if farm is located is Iowa, zero otherwise	0.4707	0.4994
Indiana	= 1 if farm is located is Indiana, zero otherwise	0.1332	0.3399

size, proportion of acres owned, and off-farm income levels. As with the crop insurance results above, producers with higher proportions of owned acres do not tend to use forward contracting. On the other hand, producers with low levels of off-farm income (between 0 and \$5,000) tend to use forward contracting as a risk-reducing instrument. Our results also suggest that older farmers do not use forward contracting, which is consistent with the notion that farmers with more experience tend to not use risk management instruments such as forward contracting. In contrast, farmers with more education and larger farms tend to use forward contracting. This is consistent with the notion that well-educated producers have the human capital to more fully comprehend and utilize the nuances of effectively utilizing risk management tools, especially the more complex ones (Goodwin and Schroeder; Smith and Baquet; Mishra and El-Osta). The positive effect of larger farm size suggests that there may be economies of size and increased managerial efficiencies in the utilization of forward contracting instruments (Sherrick et al.).

Significant variables in the spreading sales equation are off-farm income levels, education, and age. Farmers with off-farm income greater than \$50,000 do not tend to spread sales over time. Younger producers and producers with higher levels of education are more likely to spread sales. The significant parameter estimate on the Iowa state dummy variable suggests that producers in this state are more likely to spread sales than producers in the omitted state (Indiana).

Table 2. Proportion of Producers Adopting Different Combinations of Risk Management Tools

Possible Risk Management Tool Combinations[a]	Number of Farmers	Proportion (%)
(1) Use no risk management tool	393	45.12
(2) Use crop insurance only	0	0.00
(3) Use forward contracting only	19	2.18
(4) Use spreading sales only	52	5.97
(5) Use crop insurance and forward contracting	34	3.90
(6) Use crop insurance and spreading sales	93	10.68
(7) Use forward contracting and spreading sales	65	7.46
(8) Use all three risk management tools	215	24.68
Total	871	100.00

[a] The different combinations of risk management tools above serve as the basis for coding the dependent variable in the multinomial probit model. The dependent variable is coded such that $Y_i = 1, \ldots, 8$ and only one combination (among the eight) is chosen by the producer. Note that combinatin 2 is dropped in the analysis since no producer used this particular combination.

The results discussed above are for the parameter estimates from the multivariate probit approach. For comparison, we also report the parameter estimates from an equation-by-equation individual probit approach. In general, the signs and significant variables in both approaches are fairly similar (except for the following variables in the spreading sales equation: *Off-Farm Income $0–$5,000* and *Farm Size*). However, note that the multivariate probit approach allows for calculating a "conditional" marginal effect (i.e., marginal effects conditional on the adoption of the other risk management tools), while the individual probit models do not allow for this calculation. The next section discusses this issue in more detail.

Marginal Effects: Multivariate Probit Model

The marginal effects for both the multivariate probit and individual probit approaches are presented in Table 5. The significant variables in Table 4 also have significant marginal effects in Table 5. In addition, the marginal effect for education in the crop insurance equation, the debt-to-asset ratio, and levels of business risk (as reflected by the perceived probability of getting an insurance payment under the APH plan at 85% coverage level for both corn and soybeans) in all equations are significant as well. Producers with higher perceived probability of getting APH payments on corn (*Probability of APH/Corn*) are more likely to adopt crop insurance and spread sales. On the other hand, producers with higher levels of business risk associated with soybeans production (higher perceived probability of APH payments for soybeans, *Probability of APH/Soybeans*) tend to use forward contracting. Furthermore, the negative signs on the *Probability of APH/Corn* variable in the forward contracting equation, and *Probability of APH/Soybeans* variable in the spread sales equations, suggest that producers with higher levels of business risk in corn do not tend to use forward contracting, while producers with higher levels of business risk in soybeans are less likely to adopt spread sales.

Table 3. Multivariate Probit Model Results: Correlation Coefficients of Risk Management Adoption Decisions

Risk Management Decisions	Correlation Coefficient	Standard Deviation
Crop Insurance and Forward Contracting	0.7282***	0.0332
Crop Insurance and Spreading Sales	0.6892***	0.0378
Forward Contracting and Spreading Sales	0.7759***	0.0300

Note: *** indicates statistical significance at the 1% level.

Table 4. Parameter Estimates from the Multivariate Probit and Individual Probit Approach for Estimating the Factors Affecting Adoption of Agricultural Risk Management Tools

	Parameter Estimates from the Multivariate Probit Approach			Parameter Estimates from the Individual Probit Approach		
	Adoption Equations			Adoption Equations		
Independent Variables	Crop Insurance	Forward Contracting	Spreading Sales	Crop Insurance	Forward Contracting	Spreading Sales
Proportion of acres owned	−0.3333**	−0.2896**	−0.1819	−0.3163**	−0.2885**	−0.1917
	(0.1321)	(0.1346)	(0.1299)	(0.1281)	(0.1308)	(0.1262)
Age	−0.0047	−0.0156***	−0.0119***	0.0049	−0.0167***	−0.0117***
	(0.0034)	(0.0036)	(0.0034)	(0.0034)	(0.0035)	(0.0034)
Off-farm income $0–$5,000	0.4926***	0.4727***	0.2607	0.4912***	0.4904***	0.2664*
	(0.1656)	(0.1676)	(0.1649)	(0.1625)	(0.1606)	(0.1589)
Off-farm income $5–$50,000	0.1754*	0.1046	0.0927	0.1764*	0.0989	0.0952
	(0.1052)	(0.1047)	(0.1036)	(0.1020)	(0.1037)	(0.1012)
Off-farm income > $50,000	−0.4629**	−0.2518	−0.3561*	−0.4402**	−0.2459	−0.3574**
	(0.1935)	(0.1926)	(0.1905)	(0.1883)	(0.1859)	(0.1801)
Education	−0.0135	0.0492***	0.0313**	−0.0129	0.0540***	0.0318**
	(0.0152)	(0.0152)	(0.0149)	(0.0144)	(0.0149)	(0.0144)
Debt/asset ratio	0.0980	0.1222	0.0225	0.1157	0.1099	0.0339
	(0.1280)	(0.1293)	(0.1293)	(0.1267)	(0.1276)	(0.1259)
Farm size	0.0043	0.0091***	0.0065	0.0045	0.0083**	0.0056*
	(0.0053)	(0.0032)	(0.0058)	(0.0032)	(0.0033)	(0.0033)
Probability of APH/corn	0.0085	−0.0070	0.0003	0.0083*	−0.0049	0.0005
	(0.0056)	(0.0063)	(0.0056)	(0.0049)	(0.0053)	(0.0049)
Probability of APH/soybeans	0.0004	0.0023	−0.0011	0.0004	0.0006	−0.0016
	(0.0057)	(0.0064)	(0.0057)	(0.0051)	(0.0054)	(0.0051)
Illinois	0.0434	−0.0032	0.1680	0.0427	−0.0039	0.1712
	(0.1413)	(0.1437)	(0.1375)	(0.1383)	(0.1391)	(0.1364)
Iowa	0.2784**	−0.1083	0.2664**	0.2832**	−0.1225	0.2722**
	(0.1357)	(0.1381)	(0.1324)	(0.1318)	(0.1333)	(0.1302)
Log-likelihood value		−1418.7750		−567.5860	−541.3639	583.4922
Akaike I.C.				1.3309	1.2706	1.3674
Schwarz I.C.				1216.4077	1163.9635	1248.2202

Notes: Figures in parenthesis are standard errors. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively.

The negative marginal effect for education in the crop insurance equation is consistent with the hypothesis of Shapiro and Brorsen that farmers become less risk-averse as they gain more education, thus decreasing the likelihood of using crop insurance as a risk reducing strategy. In contrast, the education variable is positive and significant in the forward contracting and spreading sales equations. As we mentioned above, these mixed results are consistent with the results from the empirical literature in general. Investigating the reasons for these mixed results may be a fruitful direction for future research.

It is important to reiterate here that the calculated marginal effects for the multivariate probit approach are conditional on the adoption of the other risk management instruments [see Equations (13) and (14) above]. This means that we are measuring the effects of an observed factor on the probability of adoption of one risk management tool given that the other risk management tools are adopted. This is different from the calculated marginal effects

Table 5. Marginal Effects from the Multivariate Probit Versus Individual Probit Approach to Estimating the Factors Affecting Adoption of Agricultural Risk Management Tools

	Marginal Effects from the Multivariate Probit Approach			Marginal Effects from the Individual Probit Approach		
	Adoption Equations			Adoption Equations		
Independent Variables	Crop Insurance	Forward Contracting	Spreading Sales	Crop Insurance	Forward Contracting	Spreading Sales
Proportion of acres owned	−0.0787***	−0.0746***	0.0096	−0.1255**	−0.1092**	−0.0764
	(0.0119)	(0.0115)	(0.0160)	(0.0508)	(0.0495)	(0.0503)
Age	0.0011	−0.0051***	−0.0012**	−0.0019	−0.0063***	−0.0047***
	(0.0008)	(0.0003)	(0.0006)	(0.0013)	(0.0013)	(0.0013)
Off-farm income $0–$5,000	0.1157***	0.1301***	−0.0218	0.1931**	0.1923**	0.1057*
	(0.0184)	(0.0169)	(0.0.0247)	(0.0613)	(0.0633)	(0.0621)
Off-farm income $5–$50,000	0.0464***	0.0157**	0.0013	0.0701*	0.0377	0.0379
	(0.0045)	(0.0068)	(0.0069)	(0.0406)	(0.0397)	(0.0403)
Off-farm income > $50,000	−0.1098***	−0.0137	−0.0481***	−0.1669*	−0.0893	−0.1393**
	(0.0140)	(0.0213)	(0.0164)	(0.0665)	(0.0642)	(0.0674)
Education	−0.0138***	0.0208***	0.0038***	0.0051	0.0205***	0.0127**
	(0.0026)	(0.0004)	(0.0012)	(0.0057)	(0.0057)	(0.0057)
Debt/asset ratio	0.0232***	0.0408***	−0.0154**	0.0460	0.0421	0.0135
	(0.0041)	(0.0028)	(0.0052)	(0.0505)	(0.0494)	(0.0502)
Farm size	−0.0001	0.0028***	0.0004	0.0018	0.0031**	0.0022*
	(0.0005)	(0.0002)	(0.0004)	(0.0013)	(0.0013)	(0.0013)
Probability of APH/corn	0.0039***	−0.0043***	0.0006***	0.0033*	−0.0019	0.0002
	(0.0003)	(0.0004)	(0.0001)	(0.0019)	(0.0019)	(0.0019)
Probability of APH/soybeans	0.0002	0.0012***	−0.0008***	0.0002	0.0002	−0.0006
	(0.0001)	(0.0001)	(0.0001)	(0.0020)	(0.0020)	(0.0020)
Illinois	−0.0007	−0.0342***	0.0521***	0.0169	−0.0015	0.0682
	(0.0027)	(0.0067)	(0.0016)	(0.0549)	(0.0526)	(0.0542)
Iowa	0.0885**	−0.1252***	0.0838***	0.1121**	−0.0463	0.1082**
	(0.0019)	(0.0179)	(0.0030)	(0.0519)	(0.0502)	(0.0515)

Notes: Figures in parenthesis are bootstrapped standard errors. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. Marginal effects are calculated at the means of explanatory variables.

for the individual probit approach where each adoption decision is assumed exogenous to the other risk management decision.

In general, we find that marginal effects from the multivariate probit approach tend to be lower than the marginal effects from the individual probit approach. This suggests that the effect of an observed factor on the likelihood of adopting a risk management tool tends to be tempered when another risk management tool is already being used. For example, the marginal effect of the proportion of owned acres on crop insurance use is −0.13 for the individual probit while it is −0.08 for the multivariate probit. The magnitude of the effect of owned acres on crop insurance adoption is lower when forward contracting and spreading sales are already being used. Another general observation from Table 5 is that the number of significant variables and the level of significance using the multivariate probit approach are higher compared to the individual probit model approach. Thus, even though the magnitudes of the effects of the observable factors are lower in the multivariate approach, the significance tends to be higher when the marginal effects are calculated conditional on the adoption of the other risk management tools. Also, some marginal effects are insignificant in the individual probit case, but are significant in the multivariate probit

Table 6. Parameter Estimates and Marginal Effects from the Multinomial Probit Model

	Parameter Estimate		Marginal Effect	
Combination/Independent Variables	Estimate	St. Error	Estimate	St. Error
Combination 3: Forward contracting only				
Proportion of acres owned	−0.6545*	0.3607	−0.0063	0.1077
Age	−0.0065	0.0120	0.0001	0.0010
Off-farm income $0–$5,000	−3.7817	91.7813	−0.0148*	0.0057
Off-farm income$5–$50,000	−0.1013	0.2955	−0.0025	0.0425
Off-farm income > $50,000	−0.2865	0.4730	0.0001	0.0073
Education	0.0205	0.0772	0.0002	0.0048
Debt/asset ratio	0.2156	0.3756	0.0036	0.0592
Farm size	−0.0784**	0.0347	−0.0012	0.0202
Probability of APH/corn	−0.0319	0.0196	−0.0004	0.0083
Probability of APH/soybeans	0.0176	0.0193	0.0003	0.0052
Illinois	−0.1389	0.3671	−0.0037	0.0633
Iowa	−0.3557	0.3642	−0.0079	0.1322
Combination 4: Spreading sales only				
Proportion of acres owned	−0.3381	0.2617	−0.0072	0.0226
Age	−0.0134	0.0086	−0.0002	0.0006
Off-farm income $0–$5,000	−0.7104	0.5272	−0.0483***	0.0130
Off-farm income$5–$50,000	−0.0588	0.2168	−0.0107	0.0165
Off-farm income > $50,000	−0.4605	0.3943	−0.0146	0.0248
Education	−0.0981*	0.0587	−0.0094**	0.0047
Debt/asset ratio	−0.2764	0.3119	−0.0238	0.0182
Farm size	−0.0480**	0.0199	−0.0040	0.0026
Probability of APH/corn	−0.0034	0.0114	−0.0001	0.0011
Probability of APH/soybeans	−0.0061	0.0117	−0.0004	0.0010
Illinois	0.1531	0.3001	0.0050	0.0248
Iowa	0.1812	0.2916	0.0042	0.0249
Combination 5: Crop insurance and forward contracting				
Proportion of acres owned	−0.8842***	0.3141	−0.0472*	0.0249
Age	−0.0070	0.0094	0.0002	0.0006
Off-farm income $0–$5,000	0.4777	0.3391	0.0235	0.0297
Off-farm income$5–$50,000	0.1131	0.2426	0.0039	0.0168
Off-farm income > $50,000	−0.6429	0.5340	−0.0211	0.0219
Education	−0.0469	0.0614	−0.0038	0.0040
Debt/asset ratio	0.0289	0.2997	0.0001	0.0203
Farm size	−0.0070	0.0159	−0.0001	0.0017
Probability of APH/corn	−0.0006	0.0124	0.0001	0.0010
Probability of APH/soybeans	−0.0055	0.0126	−0.0003	0.0009
Illinois	−0.0431	0.3100	−0.0105	0.0205
Iowa	−0.0846	0.3051	−0.0162	0.0227
Combination 6: Crop insurance and spreading sales				
Proportion of acres owned	−0.4048*	0.2303	−0.0253	0.0350
Age	0.0007	0.0074	0.0018*	0.0010
Off-farm income $0–$5,000	−0.0229	0.3133	−0.0349	0.0323
Off-farm income$5–$50,000	0.0839	0.1858	0.0036	0.0256
Off-farm income > $50,000	−0.6806*	0.3809	−0.0541	0.0340
Education	−0.0042	0.0468	−0.0014	0.0062
Debt/asset ratio	0.0473	0.2307	0.0034	0.0324
Farm Size	−0.0224	0.0140	−0.0030	0.0036
Probability of APH/Corn	0.0082	0.0089	0.0016	0.0015

Table 6. Continued.

Combination/Independent Variables	Parameter Estimate		Marginal Effect	
	Estimate	St. Error	Estimate	St. Error
Probability of APH/Soybeans	−0.0033	0.0090	−0.0003	0.0013
Illinois	0.4302	0.3029	0.0592	0.0455
Iowa	0.8265***	0.2933	0.1217***	0.0427
Combination 7: Forward contracting and spreading sales				
Proportion of acres owned	−0.0135	0.2590	0.0279	0.0254
Age	−0.0267***	0.0083	−0.0018**	0.0008
Off-farm income $0–$5,000	0.4055	0.3132	0.0239	0.0353
Off-farm income$5–$50,000	-0.0091	0.2082	−0.0079	0.0196
Off-farm income > $50,000	-0.2982	0.3540	−0.0022	0.0327
Education	0.0255	0.0511	0.0024	0.0049
Debt/asset ratio	0.0730	0.2585	0.0053	0.0264
Farm size	0.0055	0.0072	0.0011	0.0018
Probability of APH/corn	-0.0261**	0.0124	−0.0028*	0.0016
Probability of APH/soybeans	-0.0004	0.0126	0.0001	0.0013
Illinois	0.0919	0.2672	−0.0007	0.0261
Iowa	-0.1702	0.2640	−0.0007	0.0301
Combination 8: Use all three risk management tools				
Proportion of acres owned	−0.4895**	0.2006	−0.0817	0.0557
Age	−0.0268***	0.0064	−0.0057***	0.0014
Off-farm income $0–$5,000	0.6298***	0.2382	0.1656***	0.0623
Off-farm income$5–$50,000	0.2020	0.1574	0.0490	0.0376
Off-farm income > $50,000	−0.4878*	0.2867	−0.0677	0.0564
Education	0.0494	0.0395	0.0151	0.0092
Debt/asset ratio	0.1030	0.1909	0.0266	0.0476
Farm Size	0.0113**	0.0047	0.0052	0.0046
Probability of APH/corn	0.0020	0.0076	0.0011	0.0026
Probability of APH/soybeans	−0.0013	0.0078	−0.00001	0.0022
Illinois	0.1083	0.2141	0.0041	0.0517
Iowa	0.1497	0.2097	0.0057	0.0576
Log-likelihood value	−1225.23			

Notes: *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively. Omitted combination is the case where no risk management tool is used.Marginal effects are calculated at the means of explanatory variables.

approach. For example, marginal effects for debt-to-asset ratio and levels of business risk are significant in the multivariate model approach, while they are insignificant in the individual probit model approach.

Paramater Estimates and Marginal Effects: Multinomial Probit Model

Parameter estimates and marginal effects from the multinomial probit model are presented in Table 6. As mentioned above, the multinomial probit results provide information/inference that is different from the multivariate probit model because it focuses on factors affecting the *combination* of risk management tools that a producer chooses. But note that most of the significant variables found in the multivariate probit analysis are also significant in the multinomial probit analysis, which is indicative of the robustness of the results. For example, the proportion of owned acres is significant for combinations that include either crop insurance or forward contracting (e.g., forward contracting only, crop insurance and forward contracting, crop insurance and spreading sales, and the use of all three risk management tools). Recall that the proportion of owned acres also strongly influences the decision to adopt crop insurance and forward contracting in the multivariate probit analysis above. Other observable covariates in the multinomial probit specification that substantially influence the different combinations of risk management tools chosen are: farm size, age, off-farm income, education, and perceived probability of receiving APH payment (corn). The marginal effects for these variables (evaluated at the mean) also tend to be significant and have modest magnitudes (see Table 6).

The results from the analysis of factors affecting the use of *all* three risk management tools (i.e., combination 8) merits further discussion here since this is the combination most frequently adopted by the producers in our sample (i.e., aside from the "use no risk management tool considered in this study" combination). The parameter estimates associated with proportion of owned acres, age, and higher off-farm incomes (*Off-Farm Income > $50,000*) tend to reduce the probability of simultaneously adopting all three risk management tools considered in this study (crop insurance, forward contracting, and spreading sales). In contrast, having low off-farm income (*Off-Farm Income $0–$5,000*) and larger farm sizes tend to increase the probability of using all three risk management tools (crop insurance, forward contracting, and spreading sales) at the same time. The signs of these significant variables are consistent with the multivariate probit analysis results in the previous section and coincide with *a priori* expectations. Note, however, that only *Age* and *Off-Farm Income $0–$5,000* have statistically significant marginal effects evaluated at the means.

Concluding Comments

Farmers have a number of options in managing agricultural risks and many of them utilize these risk management tools simultaneously. However, the literature on factors affecting adoption of two or more risk management tools has not analyzed the issue in this context. It is often implicitly assumed that the decision to adopt one risk management tool is independent of the decision to adopt other risk management tools. In this study, we specifically investigate the factors that affect farmers' adoption of crop insurance, forward contracting, and spreading sales, while taking into account the potential for simultaneous adoption and/or correlation among the adoption decisions using multivariate probit and multinomial probit approaches.

Using a multivariate probit approach, we find that risk management adoption decisions are indeed correlated (even after controlling for observable factors). Furthermore, our analysis suggests that the decision to adopt one risk management tool positively influences the decision to adopt the other tools. These results suggest that producers consider how the different risk management tools interact to affect their net return distributions and they consequently take this correlation into account in their decision process. Given the correlation of risk management adoption decisions, it appears more appropriate to investigate factors that affect risk management decisions in a multivariate context rather than estimating each adoption equation individually. Future studies need to take the correlation among adoption decisions into account to provide more accurate parameter estimates and inferences. Although estimated parameters are fairly similar under the multivariate probit estimation and individual probit estimation, there are differences in terms of the magnitude, significance levels, and interpretation of the marginal effects calculation under both procedures.

Our empirical results from the multivariate probit approach point to the importance of the proportion of owned acres, off-farm income levels, education, age, and level of business risks as factors that determine adoption of crop insurance, forward contracting, and spreading sales. Furthermore, we note that the conditional marginal effects of these factors with respect to the likelihood of adopting a particular risk management tool tend to be lower than the marginal effects from the individual equation-by-equation probit model. Again, this emphasizes the importance of accounting for potential correlation among the risk management adoption decisions by using a multivariate approach because an equation-by-equation probit analysis would not be able to capture marginal effects that are conditional on the simultaneous adoption of other risk management tools.

The multinomial probit estimation procedure points to the same variables that the multivariate probit analysis reveals as the ones substantially influencing the risk management tools that producers adopt (i.e., proportion of owned acres, age, off-farm income levels, and farm size). But the multinomial probit provides additional information that the multivariate probit does not provide because the former looks at factors affecting the *combination* of tools utilized by the farmers in our sample. Hence, using both multivariate and multinomial probit approaches to analyze risk management choices provides richer interpretations, better inferences, and more information that may further enhance understanding of the risk management decisions of producers. Extension educators and other risk management information providers may be able to tailor their programs better, based on the information gleaned from the multivariate and multinomial probit procedures. For example, since older farmers with larger farms tend to use all three tools, risk management educators can tailor a more comprehensive training/outreach program for this target population that covers the fundamentals of all three risk management tools considered in this study. Policy makers can also better anticipate which types of farmers would adopt crop insurance or other government supported risk management tools in the presence of other risk management tools based on the multivariate probit analysis.

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