

# Heterogeneity in the Likelihood of Market Advisory Service Use by U.S. Crop Producers

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## **ABSTRACT**

Analysis of a unique data set of 1,400 U.S. crop producers using a mixture-modeling framework shows that the likelihood of Marketing Advisory Services (MAS) use is, among others, driven by the perceived performance of MAS in terms of return and risk reduction, the match between the MAS and the crop producer's marketing philosophy, and the interaction between them. The influence of these factors on crop producers' MAS usage is not homogeneous across crop producers. The heterogeneity is played out in different MAS choices and appears to be driven by crop producers' risk attitudes. [EconLit citations: D210, D400, L100, L200, M310, Q120, Q130.]  
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## **1. INTRODUCTION**

Several researchers have identified a trend towards outsourcing and have indicated increased firm reliance on external consultants in operational capacities (e.g., Henderson, 1990; Venkatesan, 1992). Some of the most commonly used external consultants in agriculture

are Marketing Advisory Services (MAS) (Ortmann et al., 1993). These MAS are specialized companies that provide crop producers with recommendations regarding selling their crops. Their recommendations include when to sell and how to sell (for instance, selling crops forward by means of futures and options or in the spot market). Farmers place a high value on market advisory services (MAS) as a source of price risk management information and advice. For example, in a rating of seventeen risk management information sources, Patrick and Ullrich (1996) report that MAS are outranked only by farm records and computerized information services. Schroeder et al. (1998) find that a sample of Kansas farmers rank MAS as the number one source of information for developing price expectations. Davis and Patrick (2000) report that marketing consultants have the largest impact on the use of forward pricing by soybean producers. Norvell and Lantz (1999) find that marketing consultants tie for first place (with accountants), in a list of seven, as likely to be most important to Illinois farmers in the future. The importance rating of MAS among participants of Purdue Top Farmer Workshops has steadily increased from fifth in 1997 to fourth in 1999 to third in 2001.

Surveys also report that a growing number of farmers subscribe to marketing advisory services. Among the participants of Purdue's Top Farmer Workshop, the share of subscribers grew from 53% in 1997 to 62% in 2001. Davis and Patrick (2000) report that 39% of producers in Mississippi and 49% of producers in Indiana used marketing consultants or subscribed to market information services in 1999. Pennings et al. (2001) report that 85% of large-scale U.S. crop producers use, or have used, MAS. Along with the increase in value of market advisory services for marketing decisions, producers are willing to spend increasing amounts of money to receive this advice. Annual expenses on marketing advice moved from the fourth highest expense for consultants to the second highest from 1991 to 2001 among Purdue's Top Farmer Workshop participants, growing in absolute terms from \$755 to \$3,455. The majority of respondents to Coble et al.'s (1999) survey that used marketing consultants indicated that they spent \$1,000 or more on marketing advice in 1998.

Despite their importance, limited research has been devoted to marketing advisory services. Previous studies focused primarily on the pricing performance of MAS in corn, soybeans, and wheat (e.g., Irwin, Martines-Filho, & Good, 2003). These studies revealed that the use of MAS results in mixed marketing performance across commodities. Other studies evaluated MAS as sources of consulting advice and information (e.g., Ortmann, et al., 1993; Jones, Batte, & Schnitkey, 1990). These studies found that the use of consulting advice may be affected by the operator's age, farm size, farm ownership, education and risk aversion, among other factors. Ortmann et al. (1993) revealed that producers rate their marketing management skills lower than their other management skills. They also found that marketing sources of information were ranked lower than other sources of information, which may indicate that producers' needs are not being met in this area. These findings emphasize the need to investigate the nature of MAS use.

The use of management consulting services has been extensively investigated in the behavioral economics and management sciences literature (e.g., Ginzberg, 1978; Zeithaml, Parasuraman, & Berry, 1990). These studies suggest that the use of consulting services is based on both the outcome of the service (such as performance) and the process of service delivery. Ginzberg (1978, 1981) argued that it is important to identify the criteria by which the service's efforts are judged, as these criteria impact the effectiveness of the advisory service's effort and the relationship with the client. Increasing the value of a firm requires firms to make optimal risk-return trade-offs (e.g., Smith & Stulz, 1985; Froot, Scharfstein, & Stein, 1993). Therefore, it can be hypothesized that both price-

enhancing and risk-reducing aspects of services are critical in making decisions about their use.

In this paper, the insights about the use of management consulting services are applied to the decision to use MAS (viewed as a special case of management consulting services) by U.S. crop producers. We are particularly interested in examining the main factors that drive MAS usage and whether the influence of these factors on MAS usage are the same for all crop producers. Recently, various economists, including Heckman (2001) have argued that the notion that individuals respond differently to economic stimuli can have profound consequences for the interpretation of empirical evidence and understanding behavior. Heterogeneity in economic behavior is driven by the heterogeneity in individual decision-making behavior that is reflected in the relationship between economic behavior, in our context crop producers MAS usage, and its determinants (i.e., the beta-regression vector that relates behavior to the explanatory variables). To model potential heterogeneous behavior we use a generalized mixture regression approach that has recently been developed in the statistical and biometric literature (Wedel & DeSarbo, 1995; Pennings & Garcia, 2004). The generalized mixture model framework allows us to simultaneously investigate the relationship between MAS usage and the set of factors that are hypothesized to drive MAS usage for each latent segment in the population of crop producers, and at the same time identify these segments.

Data for this study were collected in a large scale survey of U.S. crop producers in January/February 2000. The sample of crop producers utilized in this study presents a unique opportunity to study MAS usage by Small and Medium-sized Enterprises (SMEs), as opposed to the large firms examined in previous studies. U.S. crop producers are of particular interest because of the highly uncertain and dynamic nature of the markets in which they operate and the fact that these producers heavily use MAS in their farming operations. Furthermore, MAS use by crop producers has a direct impact on their financial performance, as they receive specific advice regarding marketing their crops.

The remainder of this paper is organized as follows. First, we introduce a conceptual framework based on the organizational behavior literature in which we identify and discuss three factors that are hypothesized to influence crop producers' MAS use. Then, we describe the experimental design to illustrate the conceptual framework, followed by the formulation of the mixture regression model. After discussing the operationalization of risk attitude and risk perception measures, the survey design and data-gathering procedures are discussed. Next, the empirical results are reported, based on data gathered from 1,399 producers across the U.S. We conclude with an evaluation of the study and make suggestions for further research.

## 2. CONCEPTUAL FRAMEWORK

Inspired by the findings of Ginzberg (1978) and Zeithaml, Parasuraman, and Berry (1990), we hypothesize that producers' propensity to use MAS is based on both the outcome of the service (e.g., MAS performance) *and* the process of service delivery. The perceived performance of MAS in the context of crop farming has two dimensions: realized crop price and realized risk reduction.<sup>1</sup> For a given risk reduction, it is hypothesized that MAS that have shown strong performance regarding realized crop price are more likely to be chosen by a producer than services that have shown weak crop price performance. Likewise, for a given realized price, it is hypothesized that MAS that have shown strong risk

<sup>1</sup>See Irwin, Martines-Filho, and Good (2001) for a thorough analysis of market advisory service performance.

reduction regarding realized crop price are more likely to be chosen by a producer than services that have shown weak risk reduction performance.

The process of delivering the service by the MAS can be described in terms of the MAS' marketing philosophy or style (Henderson & Nutt, 1980). In-depth interviews with 35 Midwest producers at a DTN workshop held in Omaha and 20 producers in Illinois in 1999 revealed that producers interpret marketing philosophy as the tools that MAS recommend to producers for marketing their crops and the complexity of the recommended marketing strategies involving these tools. For example, a MAS that recommends initiating futures and options positions, and at times recommends selling more of a certain crop in the futures market than the producer actually possesses, may be considered a MAS with an "aggressive" marketing philosophy. A MAS that recommends selling a crop proportionally in the cash market has a more "conservative" marketing philosophy. Producers also have marketing philosophies that can be described in terms of the tools they (are willing to) use to market their crops and the complexity of their marketing strategies. For example, Sartwelle et al. (2000) distinguished cash-market-oriented marketing practices, forward-contract-oriented marketing practices and futures/options-oriented marketing practices. We hypothesize a positive relationship between the extent to which the marketing philosophies of a particular MAS and a particular producer match and the producer's decision to use that particular MAS. That is, a producer will not only consider MAS performance, but will also take into account the nature of the recommendations.

Furthermore, we hypothesize an interaction between the match of marketing philosophy and MAS performance regarding the realized crop price. That is, the effect of the MAS' pricing performance on producers' use of that MAS will be larger as the MAS' marketing philosophy matches that of the producer more closely. Therefore, the effect of the MAS' performance regarding realized crop price on a producer's use of a service is reinforced when there is a marketing philosophy match between the service and producer. Similarly, we expect an interaction effect between the match of marketing philosophy and MAS' performance regarding risk reduction.

This conceptual framework was tested in a survey "experiment" in which producers were asked to indicate the likelihood of using MAS for several scenarios. The limitation of an experimental setup is that subjects find it difficult to evaluate scenarios that contain many attributes. In marketing research, in particular conjoint analysis, it has been shown that too many attributes introduce response error (often referred to as the "level effect"), because respondents are unable to process all the information to which a scenario exposes them (Green & Srinivasan, 1990; Wittink, Krishnamurthi, & Nutter, 1982). Pre-tests indicated that producers found it very difficult to evaluate scenarios with three or more attributes. Therefore, we formulated scenarios consisted of two attributes only. A total of eight scenarios were developed on the basis of this  $2 \times 2 + 2 \times 2$  design, as displayed in Figure 1.

Based on the outlined conceptual model, the likelihood of MAS use is investigated in terms of the following attributes: MAS' price performance, MAS' risk-reduction performance, marketing philosophy match, and their interaction within the following regression model:

$$y_{nk} = \beta_0 + \beta_1 MP_{nk} + \beta_2 PP_{nk} + \beta_3 PRG_{nk} + \beta_4 PRB_{nk} \\ + \beta_5 MPPP_{nk} + \beta_6 MPPRG_{nk} + \beta_7 MPPRB_{nk} + \varepsilon_{nk} \quad (1)$$

What is the probability (or chance) of your using a market advisory service in the situations listed below? Please circle a number from 1 (certainly not use) to 9 (certainly use).

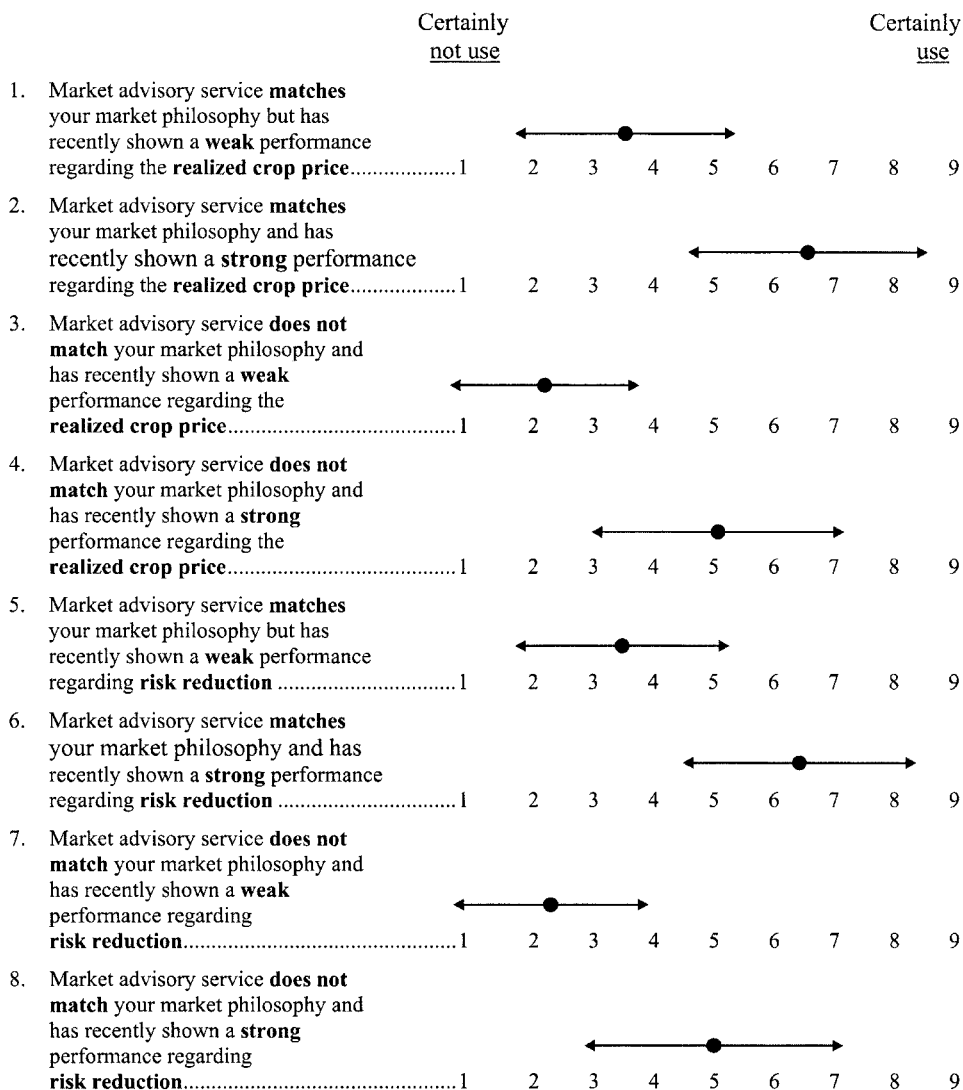


Figure 1 Producers' responses to the scenarios (the length of the arrow reflects one standard deviation from the mean response illustrated by a dot).

where  $y_{nk}$  is the likelihood of MAS use by the  $n$ th producer for the  $k$ th scenario, and scenarios are described as following:  $MP_{nk}$  is marketing philosophy (0 = no match, 1 = match),  $PP_{nk}$  is the MAS' price performance (0 = weak performance, 1 = strong performance),  $PRG_{nk}$  is strong risk reduction performance (1 = yes, 0 = no),  $PRB_{nk}$  is weak risk reduction performance (1 = yes, 0 = no),  $MPPP_{nk}$  is the interaction between marketing philosophy and price performance (1 = yes, 0 = no),  $MPPRG_{nk}$  is the interaction between marketing philosophy and strong risk reduction performance (1 = yes, no = 0),  $MPPRB_{nk}$

is the interaction between marketing philosophy and weak risk reduction performance (1 = yes, 0 = no), and  $\varepsilon_{nk}$  is an *iid* normal error term. The dummy variable schemes for each scenario are described in the Appendix Table A1 and the scenarios are described in Figure 1. The intercept captures the situation in which the MAS has weak performance regarding crop price and does not match a producer's marketing philosophy. The regression coefficients indicate the change in the likelihood of producers' use of MAS when the variable changes by one unit, which in our context means when MAS changes from not having a particular feature to having that feature, for example, from having a weak price performance to a strong price performance.

The dependent variable in the above model is measured on a semantic differential nine-point rating scale, where 1 = certainly not use, and 9 = certainly use. Marketing researchers have long known that respondents use rating scales in different ways (Greenleaf, 1992). Some tend to choose extreme answers, thus using the entire scale, while others use only a small part of the scale. This means that the scores of a producer on the nine-point scale can be thought of as consisting of the true score plus their response bias. Correcting rating scales for the response bias by standardizing respondents' scores has proven to be a useful procedure (Churchill, 1995). Therefore, the regression model uses the producers' standardized scores as the dependent variable. The absolute scores for a given producer are standardized based on that producer's average score and standard deviation of scores across the eight scenarios. As a result, the intercept is interpreted as the number of standard deviations above or below the average score of producers for the case of no marketing philosophy match and poor pricing performance. We expect the sign of the intercept in this context to be negative. The remaining coefficients then indicate the change in producers' response due to a particular variable, with the change measured in number of standard deviations.

### 3. MODELING HETEROGENEITY

Since we do not *a priori* assume producers to be homogeneous regarding the usage of MAS and the attributes that drive their usage, we need a grouping method that classifies producers based on the influence that these attributes have on their behavior (e.g., use of MAS). Recently Pennings, Garcia, and Irwin (2004) have argued that researchers interested in identifying segments of the population in which participants behave in a similar manner should consider using a mixture model framework as the mixture model groups participants such that the marginal economic effects (i.e., the regression coefficients) are similar within each group. In the context of this study this means that the mixture model groups crop producers such that the influence of the perceived performance regarding return and risk reduction, the match between the MAS and the crop producer's marketing philosophy on MAS use is similar within each group, but dissimilar across groups. In the mixture model, the sample of producers, based on which the measurement is taken (producers' responses to the scenarios (e.g., Figure 1), the so-called observations), is assumed to be composed of a number of underlying segments. In order to describe the process generating producers' responses, a certain statistical distribution is assumed for them. Such a distribution function describes the probabilities that the producers' responses (e.g., observations) take certain values. Such a statistical distribution is characterized by its expectation. Given the distributional form, the purpose of the mixture model is to decompose the producers' population into the underlying segments. Based on the work of Wedel and DeSarbo (1995) and Arcidiacono and Jones (2003) we use a mixture regression meth-

odology that enables the estimation of the relation of the producers' responses (e.g., the observations) in each underlying segment with the set of explanatory variables. That is, the methodology estimates the relation between producers' MAS usage and the explanatory variables as defined in the conceptual model (e.g., Equation (1)) within each of the segments, and at the same time derives the segments. The mixture-regression framework provides the probability that each producer belongs to the derived segment and gives the regression coefficients for each respective segment that relate the expectation of the producers' response to the explanatory variables. That is, the modeling framework will identify segments of producers that behave according to the same regression equation (e.g., Equation (1)), so that, within a segment, each producer's responses are adequately reflected by the regression equation, while this regression equation differs for each segment. What makes this method particularly powerful is the fact that the criterion for segmentation is the regression equation (e.g., Equation (1)).

Formally, we can define the mixture regression model as follows. First, assume the vector of producers' responses to the  $k$  scenarios,  $y_n = (y_{nk})$  (e.g., the observations), arises from a population that is a mixture of  $S$  segments in proportions  $\pi_1, \dots, \pi_s$ , where we do not know in advance the segment from which a particular vector of observations arises. The probabilities  $\pi_s$  are positive and sum to one. We assume that the distribution of  $y_n$ , given that  $y_n$  comes from segment  $s$ ,  $f_s(y_{nk}|\theta_s)$ , is one of the distributions in the exponential family or the multivariate exponential family, where  $\theta_s$  is the vector of regression coefficients for each segment. Conditional on segment  $s$ , the  $y_n$  are independent. The distribution  $f_s(y_{nk}|\theta_s)$  is characterized by parameters  $\theta_{sk}$ . The means of the distribution in segment  $s$  (or expectations) are denoted by  $\mu_{sk}$ .

Since we want to predict the means of the observations in each segment by using the set of explanatory variables ( $MP, PP \dots MPPRB$ ), we specify a linear predictor  $\eta_{nsk}$ , which is produced by the explanatory variables denoted by  $X_1, \dots, X_P$  ( $X_P = (X_{nkp}); p = 1, \dots, P$ ), and parameter vectors  $\beta_s = (\beta_{sp})$  in segment  $s$ :

$$\eta_{nks} = \sum_{p=1}^P X_{nkp} \beta_{sp}. \quad (2)$$

Equation (2) is similar to Equation (1) but in matrix notation. The linear predictor is thus the linear combination of the explanatory variables, and the set of betas that are to be estimated. The beta coefficients can be interpreted as the amount of change in producer use of the MAS compared to the base situation as captured by the constant. As such, the regression coefficients do not have an absolute meaning; they should be interpreted against the base situation.

The linear predictor is in turn related to the mean of the distribution,  $\mu_{sk}$ , through a link function  $g(\cdot)$  such that in segment  $s$ :

$$\eta_{nsk} = g(\mu_{nsk}) \quad (3)$$

Thus, for each segment, a linear model is formulated with a specification of the distribution of the variable (within the exponential family), a linear predictor  $\eta_{nsk}$ , and a function  $g(\cdot)$  that links the linear predictor to the expectation of the distribution. Since the dependent variable, a nine point scale in which producers indicate their extent of MAS usage, is normally distributed, the canonical link is the identity, that is  $\eta_{nsk} = \mu_{sk}$ , so that, by

combining Equations (2) and (3), the standard linear regression model within segments arises.

The unconditional probability-density function of an observation vector  $y_{nk}$ , can now be expressed in the finite mixture form:

$$f(y_n | \phi) = \sum_{s=1}^s \pi_s f_s(y_n | \theta_s), \quad (4)$$

where the parameter vector  $\phi = (\pi, \theta_s)$  and  $\theta_s = \beta_s$ . The parameter vector  $\phi$  is estimated via maximum likelihood using the expectation-maximization (EM) algorithm (Redner & Walker, 1984; Titterton, 1990). To accomplish this, the likelihood function is maximized. The likelihood function describes the probability that the data were generated, given the specific set of model parameters (e.g., equation (4)). By maximizing the likelihood, that set of parameters is obtained that most likely has given rise to the data at hand. The estimation algorithm is an iterative algorithm (Dempster, Laird, & Rubin, 1977) that sequentially improves upon some sets of starting values of the parameters, and permits simultaneous estimation of all model parameters (cf. Wedel & Kamakura, 1998). The EM algorithm is based on a multinomial distribution for the memberships, the expectation of the likelihood can be formulated over the missing observations. This involves calculating the posterior membership probabilities according to Bayes' rule and the current parameter estimates of  $\phi$  and substituting those into the likelihood. Once this is accomplished, the likelihood can be maximized. Given the new estimates of  $\phi$ , new posteriors can be calculated in the next E (expectation)-step, followed by a new M-(maximization) step to find the new  $\phi$ . The E- and M-steps are thus alternated until convergence occurs.<sup>2</sup> Estimates of the posterior probability,  $p_{ns}$ , that observations of producer  $n$  come from segment  $s$  can be calculated for each observation vector  $y_n$ , as shown in equation (5):

$$p_{ns} = \frac{\pi_s f_s(y_n | \theta_s)}{\sum_{s=1}^s \pi_s f_s(y_n | \theta_s)}. \quad (5)$$

We will use equation (5) to classify producers in a particular segment. In order to determine the optimal number of segments, Akaike (1974) and Bozdogan (1994) developed information criteria tools. These criteria impose a penalty on the likelihood that is related to the number of parameters estimated. Studies by Bozdogan (1994) indicate that the consistent Akaike (1974) information criterion, CAIC, is generally preferable for mixture models.

#### 4. SURVEY DESIGN AND DATA-GATHERING PROCEDURE

First, an initial survey, developed from in-person interviews with 20 producers, was sent to 100 producers. Second, producers who did not respond to this mail survey were contacted by phone to investigate the reasons for not responding. Third, based on the information from these non-respondents, the survey instrument was revised and mailed to 3,990 U.S. producers.

<sup>2</sup>The EM algorithm is available on request.



Because we wish to test whether the heterogeneity is caused by the decision-making process of producers, reflected by the influence of the three attributes on MAS usage, and wish to characterize segments of producers, we gathered data that might be associated with the attributes in the conceptual model. For example, a segment where producers attach high value to the risk-reduction performance of MAS, as reflected by a relatively high regression coefficient for MAS risk-reduction performance, might be populated by producers that are relatively more risk averse and perceive more risk than producers in other segments. Because characteristics like risk aversion and risk perception are latent, they were measured with a set of observable variables (so-called indicators). We adhered to the iterative procedure recommended by Churchill (1979) to obtain reliable and valid constructs. First, a large pool of questions (i.e., indicators) was generated. The indicators were based on the literature available (e.g., Pennings & Garcia, 2001). Next, the indicators were tested for clarity and appropriateness in personally administered pre-tests. The producers were asked to complete a questionnaire and indicate any ambiguity or other difficulty they experienced in responding to the indicators, and to make any suggestions they deemed appropriate. Based on the feedback received from the producers, some indicators were eliminated, others were modified, and additional indicators were developed. The resulting set of indicators was administered to the producers in the large-scale survey. Confirmatory factor analysis was used to assess the (psychometric) measurement quality of our constructs risk attitude and risk perception (Hair et al., 1995). The factor analytical model assumes that the observed variables are generated by a smaller number of latent variables (called factors). The relationship between the observed and latent variables can be represented by the following matrix equation:

$$x = \Lambda\kappa + \delta \quad (6)$$

where  $x$  is the  $q \times 1$  vector of the  $n$  sets of observed variables (i.e., indicators),  $\kappa$  is the  $n \times 1$  vector of underlying factors,  $\Lambda$  is the  $q \times n$  matrix of regression coefficients relating the indicators to the underlying factors, and  $\delta$  is the  $q \times 1$  vector of error terms of the indicators. Because we wish to develop unidimensional constructs, a construct is hypothesized to consist of a single factor. The overall fit of the model provides the necessary and sufficient information to determine whether a set of indicators describes a construct. Hence, equation (6) describes a measurement model. In the Appendix, the results for the confirmatory factor analysis are given. All factor loadings (i.e., the regression coefficients in  $\Lambda$  in equation (6)) were significant (minimum  $t$  value was 4.60,  $p < 0.001$ ) and greater than 0.4. These findings support the convergent validity of the indicators (Anderson & Gerbing, 1988). The composite reliabilities for the constructs ranged from 0.83 for the risk perception construct to 0.85 for the risk attitude construct, indicating good reliabilities for the construct measurements (see Appendix). Therefore, these scales may be presumed to accurately reflect producers' attitudes and perceptions toward price risk. Furthermore, segments of producers may be different regarding other characteristics. Producers were asked to indicate the value they attach to some aspects of MAS. In the survey, we measured a variety of demographic variables, such as age, firm size, crop grown, etc. Producers' use of several specific MAS was elicited. These background variables can possibly be used to profile the segments.

Following Dillman's Total Design Method, producers who had not responded were contacted twice by means of a postcard reminder and an extra copy of the questionnaire (Dillman, 1978). The questionnaires were sent on January 21, 2000 and the cut-off date

for returning them was March 10, 2000. A total of 1,399 usable questionnaires were sent back, amounting to a response rate of 35%, which is high compared to previous surveys among small and medium-sized enterprises (Jobber, 1986; Karimabay & Brunn, 1991). Accounting data for these 1,399 crop producers complemented the experimental data. Complete details about the survey producers can be found in Pennings, Irwin, and Good (2002) and Pennings et al (2004).

## 5. RESULTS

Table 1 provides some background information on the sample. The sample of producers can be classified as relatively large commercial farm operations. Figure 1 shows the mean and standard deviation of producers' responses to the eight scenarios. To illustrate the usefulness of the generalized linear mixture-modeling framework we estimated equation (1) across the whole sample. This resulted in a relative low  $R^2$  of 0.09, indicating that ignoring heterogeneity results in a model that can explain only 9% of the variance of producers' responses to the scenarios. However, a dramatic change in results is found as soon as we account for heterogeneity, using the model as given in equations (2) through (4). We estimated the model for several segments and, as noted earlier, chose the optimal number of segments based on the CAIC. The CAIC was minimized for five segments, indicating that the sample consisted of five segments. Note, that these segments are defined by the mixture model based on statistical differences in the estimated regression coefficients for each segment. That is, the segments reveal different behavior with respect to the likelihood of MAS use. The regression coefficients across the segments are significantly different from each other at  $p = 0.05$ .

The results for the five-segment model are shown in Table 2. The  $R^2$  of the five-segment model, 0.79, indicates that the mixture model can explain 79% of the variance of

TABLE 1. Descriptive Statistics of the Sample ( $N = 1,399$ )

Age:		Approximate Gross Annual Sales:	
<25	0.8	Over \$ 1,000,000	17.3
25–29	4.2	\$ 500,000–\$ 999,999	26.0
30–34	12.4	\$ 400,000–\$ 499,999	13.3
35–39	20.3	\$ 300,000–\$ 399,999	15.0
40–44	19.7	\$ 200,000–\$ 299,999	16.9
45–49	17.6	\$ 100,000–\$ 199,999	10.0
50–59	19.6	\$ 50,000–\$ 99,999	1.3
60–64	3.5	Less than \$ 50,000	0.2
> 65	1.9		
U.S. Regions:		Total Acres (owned and rented):	
Midwest	52.2	Less than 499	0.7
Great Plains	29.9	500 to 999	4.9
Southeast	17.9	1,000 to 1,499	24.8
		1,500 to 1,999	18.8
		Over 2,000	49.4

TABLE 2. Mixture Regression Results ( $N = 1,399$ )

Explanatory Variables	Regression Coefficient Estimates for the Identified Segments ( $s$ ) (standard errors in brackets)				
	$s = 1$	$s = 2$	$s = 3$	$s = 4$	$s = 5$
<i>MP</i>	0.365* (0.080)	0.207* (0.046)	0.380* (0.050)	-0.234 (0.197)	0.324 (0.117)
<i>PP</i>	0.807* (0.807)	0.463* (0.047)	0.707* (0.050)	1.131* (0.181)	0.619* (0.106)
<i>PRG</i>	0.783* (0.081)	0.449* (0.042)	0.693* (0.051)	0.385 (0.211)	0.770* (0.123)
<i>PRB</i>	0.010 (0.091)	0.009 (0.051)	0.038 (0.048)	-0.209 (0.197)	0.065 (0.141)
<i>MPPP</i>	0.039 (0.114)	0.122 (0.065)	-0.066 (0.071)	0.278 (0.279)	0.371* (0.164)
<i>MPPRG</i>	0.018 (0.114)	0.092 (0.067)	-0.125 (0.073)	1.103* (0.261)	-0.221 (0.174)
<i>MPPRB</i>	0.030 (0.114)	-0.019 (0.065)	-0.064 (0.081)	-0.619* (0.241)	-0.082 (0.138)
Intercept	-1.423* (0.057)	-0.889* (0.022)	-1.235* (0.035)	-2.031* (0.139)	-1.935* (0.082)
Proportion of producers in segment ( $\pi$ )	15%	40%	35%	3%	7%
	$R^2 = 0.798$				
	$E_s = 0.827$				

Note: The regression model uses standardized rating scores as the dependent variable. The absolute scores for a given producer are standardized based on that producer’s average score and standard deviation of scores across scenarios. The definitions of the independent dummy variables are: *MP* is the marketing philosophy (0 = no match, 1 = match), *PP* is the advisory service price performance (0 = weak performance, 1 = strong performance), *PRG* is strong risk-reduction performance (1 = yes, no = 0), *PRB* is weak risk reduction performance (1 = yes, 0 = no), *MPPP* is the interaction between marketing philosophy and price performance (1 = yes, 0 = no), *MPPRG* is the interaction between marketing philosophy and strong risk-reduction performance (1 = yes, 0 = no), and *MPPRB* is the interaction between marketing philosophy and weak risk-reduction performance (1 = yes, no = 0). The intercept reflects the base situation of a MAS that has weak price performance and does not match producer’s marketing philosophy.  $E_s$  is the entropy value and \* denotes  $p < 0.01$ .

producers’ responses to the scenarios.<sup>3</sup> To assess the separation of the segments, an entropy statistic can be used to investigate the degree of separation in the estimated posterior probabilities as defined in equation (7):

$$E_s = 1 - \frac{\sum_{n=1}^N \sum_{s=1}^S p_{ns} \ln p_{ns}}{N \ln S} \tag{7}$$

<sup>3</sup>This  $R$ -square is defined as the proportionate reduction in uncertainty, measured by Kullback-Leibler divergence, due to the inclusion of regressors (e.g., Cameron & Windmeijer, 1997). It can also be interpreted as the fraction of uncertainty explained by the fitted model.

where  $p_{ns}$  is the posterior probability that crop producer  $n$  comes from latent group  $s$ . The entropy value of 0.827 indicates that the mixture components are well separated, that is, the posteriors (cf. equation (6)) are close to 1 or 0.

As hypothesized, Table 2 shows that in all segments the base case, i.e., the situation where the MAS has a poor price performance and does not match the producer's marketing philosophy, has a strong negative influence on the likelihood of MAS usage. The mixture model reveals that this influence is statistically different across segments. For example, the intercept for segment 2 is  $-0.889$ , indicating that producers in this segment rate the base situation of poor pricing performance and no match of philosophies about one standard deviation below the average score for all scenarios. By comparison, the intercept for segment 4 is  $-2.031$ , indicating that producers in this segment rate the base scenario about two standard deviations below the average score for all scenarios.

While the magnitude of the intercept does vary, the fundamental asymmetry of responses holds across segments. To demonstrate this point, it is helpful to "add up" the scores for the most beneficial scenario: strong pricing performance, strong risk reduction performance and marketing philosophy match. This aggregate score is computed by summing the intercept coefficient and the coefficients for *MP*, *PP*, *PRG*, and their interactions *MPPP* and *MPPRG*. Aggregate scores range from  $+0.149$  for segment 5 to  $+0.589$  for segment 1. The clear implication is that producers penalize the mismatch of marketing philosophies and weak pricing performance more heavily than they reward positive performance in those same areas.

The mixture model shows that the influence of the various components on the likelihood of MAS use differs across the segments (e.g., Table 2). That is, producers in different segments attach different values to match of marketing philosophy, MAS price performance, and risk performance. MAS price performance is an important driver in producers' decisions to use MAS in all segments. However, the influence of MAS' price performance on the likelihood of producers' use of MAS is different for each segment. It is more than twice as large in segment 4 as in segment 2. A strong price-risk reduction performance is important for all segments, except for segment 4. In segment 4, strong price-risk performance does not have a direct effect on the likelihood of MAS use, but an indirect effect, by means of the interaction between match of marketing philosophy and price-risk performance (both strong and weak price-risk performance).

Marketing philosophy match is an important driver behind the decision to use MAS, as we hypothesized in the conceptual model. This confirms the argument of Ginzberg (1978) and Zeithaml, Parasuraman, and Berry (1990) that customers not only value the outcome of a service but also the process of service delivery. Only 10% of the producers, as represented by segment 4 and 5, do not take the marketing philosophy match into account. The influence of the match of marketing philosophy is introduced in these two segments indirectly by the interaction with MAS' price performance (segment 5) or MAS' risk-reduction performance (segment 4). All segments show that the influence of price performance is larger than the influence of the match of marketing philosophy. This is also the case when we compare the influence of price performance with MAS' risk-reduction performance. Here too, we find that the price performance is the most important driver for the likelihood of MAS use, except for segment 2. Table 2 shows that the hypotheses regarding the interaction between marketing philosophy match and MAS' performance regarding realized crop price and risk-reduction are not confirmed, as these interactions are significantly related to the likelihood of producers' use of MAS only in the relatively

small segments 4 and 5. That is, the direct effects of marketing philosophy match and MAS' performance (price and risk) are the main drivers of producers' behavior.

In this study, producers did not have to make a direct trade-off between MAS' price performance and MAS' risk performance. However, we can indirectly investigate the weights that producers attach to risk and return by comparing the beta coefficients for risk and price performance in the regression results for each segment. From Table 2 it becomes clear that a large portion of producers attach a higher value to MAS' price performance than risk reduction performance, although the differences are fairly small for segments 1, 2 and 3. Only producers in segment 5 put more value on the MAS' risk reduction performance than on price performance.

From a managerial perspective, it may be interesting to find out how these segments can be characterized. Using ANOVA analysis and chi-square tests, we tested whether the producers in the various segments differed significantly as to their answers to the survey questions. The analyses showed that producers in the five segments do not differ significantly regarding demographic characteristics. Nor do they differ regarding their risk *perceptions*, in that they all feel that the markets in which they operate are risky. However, interestingly, producers in the different segments do differ in their *attitudes* towards risk (e.g., Table 3).

Table 3 shows that producers from segment 1 and 5 are significantly more risk averse than the producers in segments 2, 3, and 4 (respective risk-attitude scores of 4.02 and 3.82 versus 3.38, 3.72, and 3.62), as measured by the indicators of the risk-attitude scale (see Appendix). The hypothesis that the means of these variables across the 5 segments are equal was rejected at the 5% level, using an ANOVA analysis. These findings correspond to the relatively high regression coefficients for the influence of MAS' risk-reduction performance in segments 1 and 5, compared to the other three segments. This finding shows the important role of risk attitude when understanding producers' heterogeneity. These results indicate that the influence of MAS' performance (return and risk) and match between MAS' and crop producer's marketing philosophy are conditioned by the crop producer's risk attitudes. That is, the attitude toward risk does not have a direct effect on the likelihood to use MAS, but rather an indirect effect as it drives the

TABLE 3. Producers' Risk Attitudes and Risk Perceptions Across Segments

Segment	<i>Risk Attitude</i> <sup>a</sup> (1 = risk seeking, 9 = risk averse)	<i>Risk Perception</i> <sup>a</sup> (1 = not at all risky, 9 = very risky)
1	4.02*	7.59
2	3.38*	7.87
3	3.72*	7.72
4	3.62*	7.57
5	3.82*	7.64

<sup>a</sup>Risk attitude and risk perception are measured using the average sum score of the producer (e.g., Appendix).

\*The hypothesis that the mean of the producers' risk attitudes of the five segments is equal was rejected at the 5% level in an ANOVA analysis.

TABLE 4. Aspects of MAS Valued by Producers: Differences Across Segments

Segment	How Much Do You Value the Following Aspects (1 = do not value at all and 9 = value extremely)? <sup>a</sup>		
	Consistent Recommendations	High-Quality Information	Recommendations Include Futures and Options
1	6.14	7.24	5.80
2	6.59	7.56	6.05
3	6.62	7.55	6.29
4	5.77	6.05	5.68
5	5.93	6.95	6.16

<sup>a</sup>The hypothesis that the mean of these variables of the five segments is equal was rejected at the 5% level using an ANOVA analysis.

heterogeneity.<sup>4</sup> Furthermore, we found that producers in the 5 segments differed regarding the value they attach to some aspects of MAS (see Table 4).

Producers in segments 1, 2, and 3 value consistent recommendations of MAS higher than producers in segments 4 and 5. This is in accordance with the regression coefficients displayed in Table 2 for the match of marketing philosophy, which are higher for segments 1, 2, and 3 compared to segments 4 and 5. The same pattern is found for the high-quality information aspect of MAS. Here too, the producers in the segments with relatively high regression coefficients for match of marketing philosophy (i.e., segments 1, 2, and 3) value high-quality information of MAS relatively higher. Producers in the five segments also differ significantly as to how they value the fact that MAS' recommendations include futures and options.

The producers in the different segments also showed differences regarding MAS they used. Table 5 displays three well-known MAS and their use by producers in the five segments. The results show that producers in the different segments differed significantly, substantiating the usefulness of the conceptual model in trying to understand the likelihood of MAS use.

## 6. SUMMARY AND CONCLUSIONS

The purpose of this study has been to determine the factors that drive producers' selection of MAS and to examine whether the influence of these factors on producers' behavior is homogeneous. That is we examined whether heterogeneity in crop produces MAS use is driven by the heterogeneity in crop producers decision-making behavior which is reflected in the relationship between MAS usage and its determinants. The first step in the analysis was the development of a conceptual framework explaining how the likelihood of MAS use is driven by the perceived performance of a MAS regarding realized crop price and risk reduction and the match between the MAS' and the producer's marketing philosophy. The second step in the analysis was to test the conceptual model and gain empirical evidence regarding actual MAS usage. The data were collected in a large-scale survey of

<sup>4</sup>Note that a producer's risk attitude does not vary across the scenarios to which they were exposed. Hence, risk attitude cannot explain producers' responses to the different scenarios. Risk attitude does explain, however, why a producer is in a particular segment.

TABLE 5. Different Segments, Different Choice of MAS

Segment	Have You Ever Used One of the Following MAS? <sup>a</sup>		
	Agline by Doane	Ag Resource	Harris-Elliot
1	47.7%	34.6%	14.7%
2	34.1%	22.0%	9.9%
3	38.4%	27.0%	9.8%
4	36.0%	37.5%	25.0%
5	35.4%	17.2%	7.7%

<sup>a</sup>Chi-square tests on the independence between segments and MAS usage resulted in a  $\chi^2$  of 9.57 (df 4) ( $p < 0.05$ ) for Agline by Doane; in a  $\chi^2$  of 13.866 (df 4) ( $p < 0.001$ ) for Ag Resource; and in a  $\chi^2$  of 9.73 (df 4) ( $p < 0.05$ ) for Harris-Elliot.

producers across the U.S. in January/February 2000. In these surveys, respondents had to indicate the likelihood of using a MAS for several scenarios. The scenarios consisted of three attributes with two levels: realized price performance (strong versus weak), realized risk-reduction performance (strong versus weak), and correspondence of marketing philosophy between MAS and crop producer (match versus mismatch). A mixture regression-modeling framework was employed that allows identification of heterogeneity in crop producers’ responses and at the same time infers from the data the number of distinct segments of respondents.

Estimation results for the mixture regression model revealed 5 distinct segments of producers that differ regarding the influence of the determinants of MAS use. This framework not only identified the segments but also modeled the process of MAS selection based on the influence that these determinants have in each segment. The mixture regression modeling results show that producers’ selection of MAS depends on all three of the attributes specified in the conceptual model: MAS’ price performance, risk performance and marketing philosophy match. Hence, the choice of MAS not only depends on the outcomes that these services provide, but also on the way these services are delivered. However, the magnitude of the influence of these different components on MAS usage differs across the segments. That is, producers in different segments attach different values to match of marketing philosophy, MAS’ price performance, and risk performance. For example, the influence of MAS’ price performance on producer usage is twice as large in segment 4 as in segment 2, a difference that was played out in different MAS choices. Finally, the estimation results revealed a fundamental asymmetry, in that producers penalize a mismatch of market philosophies and weak pricing performance more heavily than they would reward a positive performance in those same dimensions.

Analyzing different characteristics of producers across the segments revealed that only risk attitude differs significantly across the segments. Depending on risk attitude, the influence of MAS’ performance (risk and return), match between the MAS’ and the crop producer’s marketing philosophy and their interaction on crop producers’ MAS usage varies. Therefore, risk attitude may be seen as an important characteristic that (partly) generates the heterogeneity. This result confirms the importance of the concept of risk attitude in understanding choice behavior (Pennings & Smidts, 2000; Pennings & Wansink, 2004). The observed heterogeneity is played out in producers’ use of a particular MAS: the producers in the different segments appeared to differ significantly regarding the MAS they used. The present challenge is to characterize the MAS in terms of their

performance and marketing philosophy, such that they can be linked to the producers in these segments. We may hypothesize that producers choose a MAS that matches their marketing philosophy and that they perceive as performing well.

Some caveats and challenges of the analysis should be mentioned. First, theoretical models link producer's risk attitude and wealth. The level of wealth effects producers' willingness to assume risk which in turn effects their decision making process. In this study, due to lack of data, producers' gross annual sales are used in this study as a proxy for wealth. Second, we measure risk attitude in a scaling framework. Pennings and Smidts (2000) have shown that measuring risk attitude using the certainty-equivalent technique may yield more valid risk attitude measures. However, the certainty-equivalent technique requires face-to-face experiments, which can hardly be done with 1,400 crop producers. Third the conceptual model did not contain all possible variables that affect producers' use of MAS. In this paper we focus on three important determinants that we manipulated in our survey-based experiments. It was clear from the depth-in interviews that this was the maximum numbers of attributes that farmers could manage in a scenario framework. Further research that combines these three attributes with other farm characteristics and characteristics of particular MAS is clearly called for.

## APPENDIX

### **Risk-Attitude and Risk-Perception Scale: Results of Confirmatory Factor Analysis**

Producers were asked to indicate their agreement with each item through a nine-point scale, ranging from "not at all risky" to "very risky" for risk perception, and "strongly disagree" to "strongly agree" for risk attitude.

#### *Risk perception*

Construct reliability = 0.83

Selling my crops is . . .

Crop prices are . . .

The fluctuations in my farm income are . . .

The model is saturated resulting in a perfect fit

( $\chi^2 = 0$ ;  $df = 0$ ;  $p = 1$ ).

#### *Risk attitude*

Construct reliability = 0.85

I am willing to take higher financial risks when selling my crops, in order to realize higher average returns.

I like taking big financial risks.

I like taking risks when selling crops

I accept more risk in my farm business than other producers.

$\chi^2/df = 1.0$  ( $p = 0.37$ ); GFI = 0.99; RMSEA = 0.0.

The likelihood-ratio chi-square statistic ( $\chi^2$ ) tests whether the matrices observed and those estimated differ. Statistical significance levels indicate the probability that these differences are due solely to sampling variations. The goodness-of-fit index (GFI) rep-



TABLE A1. Experimental Design: Dummy Variable Scheme for the Scenarios

Scenario	<i>MP</i>	<i>PP</i>	<i>PRG</i>	<i>PRB</i>	<i>MPPP</i>	<i>MPPRG</i>	<i>MPPRB</i>
MAS <b>matches</b> your marketing philosophy but has recently shown a <b>weak</b> performance regarding the <b>realized crop price</b>	1	0	0	0	0	0	0
MAS <b>matches</b> your marketing philosophy but has recently shown a <b>strong</b> performance regarding the <b>realized crop price</b>	1	1	0	0	1	0	0
MAS <b>does not</b> match your marketing philosophy but has recently shown a <b>weak</b> performance regarding the <b>realized crop price</b>	0	0	0	0	0	0	0
MAS <b>does not</b> match your marketing philosophy but has recently shown a <b>strong</b> performance regarding the <b>realized crop price</b>	0	1	0	0	0	0	0
MAS <b>matches</b> your marketing philosophy but has recently shown a <b>weak</b> performance regarding the <b>risk reduction</b>	1	0	0	1	0	0	1
MAS <b>matches</b> your marketing philosophy but has recently shown a <b>strong</b> performance regarding the <b>risk reduction</b>	1	0	1	0	0	1	0
MAS <b>does not</b> match your marketing philosophy but has recently shown a <b>weak</b> performance regarding the <b>risk reduction</b>	0	0	0	1	0	0	0
MAS <b>does not</b> match your marketing philosophy but has recently shown a <b>strong</b> performance regarding the <b>risk reduction</b>	0	0	1	0	0	0	0

The definitions of the independent dummy variables are: *MP* is the marketing philosophy (0 = no match, 1 = match), *PP* is the advisory service price performance (0 = weak performance, 1 = strong performance), *PRG* is strong risk-reduction performance (1 = yes, no = 0), *PRB* is weak risk-reduction performance (1 = yes, 0 = no), *MPPP* is the interaction between marketing philosophy and price performance (1 = yes, 0 = no), *MPPRG* is the interaction between marketing philosophy and strong risk-reduction performance (1 = yes, 0 = 1), and *MPPRB* is the interaction between marketing philosophy and weak risk-reduction performance (1 = yes, 0 = 1).

resents the overall degree of fit, that is, the squared residuals from prediction compared with the actual data. The measure ranges from 0 (poor fit) to 1.0 (perfect fit). The root mean squared error of approximation (RMSEA) estimates how well the fitted model approximates the population covariance matrix per degree of freedom. Browne and Cudeck (1986) suggested that a value below 0.08 indicates a close fit.

## ACKNOWLEDGMENTS

The authors are grateful for the generous participation of the 55 crop producers in the in-depth interviews and the 1,399 crop producers in the survey. Financial support provided by the Algemene Stichting Termijnhandel (AST), the Niels Stensen Foundation, Risk Management Agency, U.S. Department of Agriculture and the Illinois Council for Food and Agricultural Research is gratefully acknowledged. The authors express special thanks to W. Erno Kuiper, Ronald W. Cotterill (Editor), and two anonymous reviewers who provided helpful comments on the research project and preliminary versions of the manuscript.

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