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Modeling Farmers' Use of Market Advisory Services

Practioner's Abstract

In an effort to improve marketing of their products, many farmers use market advisory services (MAS). To date, there is only fragmented anecdotal information about how farmers actually use the recommendations of market advisory services in their marketing plans, and how they choose among these services. Based on the literature on consulting services usage, a conceptual framework is developed in which perceived performance of the MAS regarding realized crop price and risk reduction, and the match between the MAS and the farmer's marketing philosophy drive MAS usage. To account for possible heterogeneity among farmers regarding to the use of MAS, we introduce a mixture-modeling framework that is able to identify unobserved heterogeneity. With this modeling framework we are able to simultaneously investigate the relationship between market advisory usage and the key components of our conceptual model for each unobservable segment in the population. A large scale interview of US farmers that contained several experiments revealed that farmers' use of MAS not only depends on the outcome of their services (price and risk reduction performance) but also on the way these services are delivered, i.e., the match of marketing philosophy between farmers and MAS. The influence of the factors in our conceptual model did not influenced farmers MAS usage equally across the whole sample. Using the generalized mixture model framework we found 5 segments that differed regarding the influence that these factors have on farmers MAS usage. The heterogeneity of the farmers appeared to be unobserved, in that it could not be traced back to observable variables such as age and region. It is the decision-making process itself, as reflected in our conceptual model, that caused the heterogeneity.

Key words : *Market advisory services, survey, farmers, selection, mixture model, unobserved heterogeneity*

Modeling Farmers' Use of Market Advisory Services

Farmers in the US continue to identify price and income risk as one of their greatest management challenges. Using a survey of midwestern grain farmers, Patrick and Ullerich (1996) report that price variability is the highest rated source of risk by crop farmers. Coble et al. (1999) survey farmers in Indiana, Mississippi, Nebraska and Texas and find that crop price variability, by a wide margin, is rated as having the most potential to affect farm income. Norvell and Lattz (1999) survey a random sample of Illinois farmers and show that price and income risk management rank second (following computer education and training) among ten business categories in which farmers identify needs for additional consulting services.

Farmers have a variety of price and income risk management tools at their disposal. These include numerous public and private sources of market information; futures and options contracts; an increasing number of yield and revenue insurance instruments and a new generation of cash indexing contracts. While farmers value and use these tools, they place an even higher 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 Ullerich (1996) report MAS are outranked only by farm records. Schroeder et al. (1998) find that a sample of Kansas farmers rank MAS as the number one source of information for developing price expectations. Norvell and Lattz (1999) find that marketing consultants tie for first (with accountants), in a list of seven, as likely to be most important to Illinois farmers in the future. These survey results mirror the finding by Chavas and Pope and Taylor and Chavas that external information plays an important role in farmer decision-making.

The pricing performance of MAS in corn, soybeans and wheat has been examined in a series of reports from the Agricultural Market Advisory Service (AgMAS) Project (e.g., Martines-Filho, Good, and Irwin 2000; Martines-Filho, Good, and Irwin 2001). A key assumption in these evaluations is that a representative farmer follows the recommendations exactly as provided by the advisory services. In reality, there is only fragmented anecdotal information about how farmers actually use the marketing recommendations provided by advisory services. More generally, there is literally no evidence about how they choose among these services. It is important to better understand the way farmers use and select among advisory services in order to improve performance evaluations. Analysis in this regard will also provide valuable evidence on the way external information affects farmer decision-making. Hence, the purpose of this study is to determine the nature of farmers' use of advisory service recommendations and what factors drive farmers' selection of such services.

The first step in the analysis is the development of a conceptual framework in which perceived performance of a MAS regarding realized crop price and risk reduction and the match between the advisory service and farmer's marketing philosophy drive advisory service use. In this model, the use of a MAS is driven not only by the main effect of these three attributes, but also by the interaction among them.

The second step in the analysis is to test the conceptual model and gain empirical evidence regarding actual MAS usage. The data for this step was collected in a large-scale survey of farmers across the US in January/February 2000. The survey measures farmers' stated

and revealed behavior, along with some key constructs, hypothesized to be related to MAS usage. The survey included an experiment in which farmers were exposed to different scenarios, described in terms of three attributes: the MAS pricing performance, the MAS risk reduction performance and the match between farmer's and MAS marketing philosophy. Farmers had to indicate on a nine-point semantic scale the extent to which they would use the MAS in a particular scenario.

The experiment allows us to investigate the influence of the MAS performance (in our experiment reflected by the dimensions of realized crop price and risk reduction) and the match between farmer's and MAS market philosophy. Traditionally, the influences of such attributes would be investigated by a multiple regression in which farmers' responses to a nine-point scale is the dependent variable and the three attributes are the independent variables (e.g., Géczy, Minton, and Schrand). When the response variable is binary, Probit and Tobit models typically are used (e.g. Goodwin and Schroeder). In addition, when such models are estimated, the data are treated as if they were collected from a single population, which is equivalent to assuming farmers are homogeneous regarding their responses. This assumption of homogeneity might be unrealistic.

Pennings and Leuthold, in their study on farmers' futures contract usage, showed that heterogeneity at the segment level masked important effects on the aggregate. To test for heterogeneity Pennings and Leuthold use the traditional cluster analysis method, extensively used in marketing research (Punj and Stewart). There are two drawbacks of clustering analysis that could trouble our insight into how farmers behave (e.g., farmers' MAS usage). First, in cluster analysis, segments (clusters) are identified by forming groups of farmers that are homogeneous along a set of observable characteristics, such as farm size, age etc. This property of cluster analysis excludes heterogeneity caused by the fact that the decision-making process of farmers itself (which can not be directly observed, and in this paper is referred to as unobserved) might differ across segments. Second, the number of segments is a priori, arbitrarily, determined by the researcher, not by the data. To address these two drawbacks, we use a mixture regression-modeling framework, first introduced by Wedel and DeSarbo, that is able to identify unobserved heterogeneity and at the same time infers from the data the number of segments. This modeling framework allows us to simultaneously investigate the relationship between farmers' MAS usage and the explanatory variables of our conceptual model for each unobservable segment in the population. That is, our modeling framework will identify segments of farmers that behave according to the same regression equation. So, within a segment, each farmer's responses can be adequately reflected by the regression equation, while this regression equation differs for each segment. The proposed mixture regression modeling framework can be very helpful for agricultural economists when investigating farmers' behavior and when they expect farmers behavior will not be homogeneous, and the heterogeneity might be unobserved, e.g., can not be traced back to observable variables such as age and farm size.

The challenge in the third step of the analysis is to interpret the knowledge we obtain from the unobserved segments in a managerial way and try to characterize these segments. The latter is a difficult challenge since the heterogeneity is not based on observable variables.

Our empirical results show that only eleven percent of farmers closely follow the recommendations given by MAS. However, a large number of farmers use advisory recommendations as background information and compare it with other sources of information. Pricing performance (average price and risk) is not the only important factor driving a farmer's decision to use a particular MAS. In addition, the extent to which the perceived marketing philosophy of the advisory service matches a farmer's marketing philosophy is an important factor. Both criteria, advisory service pricing performance and the match between marketing philosophies, differ in importance across segments of farmers. Furthermore, the influence of the interaction between these components on MAS usage differs across segments.

The remainder of this paper is structured as follows. First, we introduce a conceptual framework in which the characteristics that might be associated with MAS usage are discussed and hypotheses are formulated. Then we describe the experimental design to illustrate our framework. After discussing the operationalization of the unobserved constructs risk attitude and risk perception, the survey design and data gathering procedure are discussed. Next, empirical results based on data gathered from 1,399 farmers across the US are reported. We conclude with an evaluation of the study and make suggestions for further research.

Conceptual Model

An important motivation for farmers to adopt MAS is their expectation that such services will directly or indirectly improve the financial performance of their operations. Direct evidence on the relationship between MAS usage and improved farm financial performance is not available. However, studies that investigate the relationship between the financial performance of small businesses and the usage of management advisory services have found a positive relationship (Kent). In these studies, management advisory services are companies that advise clients in any aspect of business management whether the client is engaged in commerce, industry or government.

Prior research has shown the importance of distinguishing between the result of the advice (e.g., performance of the management advisory service) and the satisfaction with the consultant's performance in arriving at these results (Ginzberg). Zeithaml, Parasuraman, and Berry argued that customers do not evaluate service quality solely on the outcome of a service, but also on the process of service delivery. Therefore, we propose to make a distinction between the performance of agricultural MAS and the delivery process.

We assume that the pricing performance of MAS in the context of crop farming has two dimensions: realized price and realized risk reduction.¹ For a given risk reduction, it is hypothesized that services that have shown strong performance regarding the realized crop price have a higher chance to be chosen by a farmer than services that have shown weak crop price performance. Likewise, for a given realized price, it is hypothesized that services that have shown strong risk reduction regarding the realized crop price have a higher chance to be chosen by a farmer than services that have shown weak risk reduction performance.

The process of delivering the marketing recommendations can be described in terms of the advisory services' marketing philosophy. More specifically, marketing philosophy refers to

the tools that a service recommends to farmers for marketing their crops and to the complexity of the recommended marketing strategies involving these tools. For example, a service which recommends initiating futures and options positions and at times recommends selling more of a certain crop in the futures market than the farmer actually possesses has what may be considered an “aggressive” marketing philosophy. A service that sticks to selling a crop proportionally in the cash market has a more “conservative” marketing philosophy. Farmers too have marketing philosophies that can be described in terms of the tools they use to market their crops and the complexity of their marketing strategies. For example, Sartwelle et al. distinguished cash market-oriented marketing practices, forward contract-oriented marketing practices and futures/options-oriented marketing practices. We hypothesize that there is a positive relationship between the extent to which the marketing philosophy of a particular MAS and the farmer match and the farmer’s decision to use a particular advisory service. That is, a farmer will not only look at the advisory service’s pricing performance, but will also take the nature of the recommendations into account. Furthermore, we hypothesize an interactive effect between the match of marketing philosophy and the advisory service’s performance regarding the realized crop price. That is, the effect of the advisory service’s pricing performance on farmers’ usage will be larger the more the marketing philosophy of the advisory service matches the marketing philosophy of the farmer. So, the effect of the advisory service performance regarding realized crop price on a farmer’s use of a service is reinforced when there is a marketing philosophy match between the service and farmer. Similar we expect an interaction effect between the match of marketing philosophy and advisory service performance regarding risk reduction.

Experimental Design

To test the conceptual model, an experiment was designed in which farmers had to indicate the chance of using a MAS for several scenarios. When designing the experiment we had to acknowledge that decision-makers find it difficult to evaluate scenarios that contain many attributes. Attributes in this context refer to strong or weak realized price performance, strong or weak realized risk performance and match of market philosophy. In marketing research, in particular conjoint analysis, it has been shown that too many attributes introduces response error (often referred to as “level effects”), because respondents are unable to process all the information to which a scenario exposes them (Green and Srinivasan; Wittink, Krishnamurthi, and Nutter). In the scenarios, farmers have to make a trade-off between different attributes. Pre-tests indicated that farmers indeed found it very difficult to evaluate scenarios with three or more attributes. Therefore, we formulated scenarios that consisted of two attributes. We had the following pairs of components: MAS matches your marketing philosophy (or not) and strong (weak) performance regarding the realized crop price, and MAS matches your marketing philosophy (or not) and strong (weak) performance regarding risk reduction. A total of eight scenarios could be developed on the basis of this $2*2 + 2*2$ design, as displayed in Figure 1.

Farmers indicated the extent that they will use the MAS in the context of a particular scenario on a semantic differential nine-point rating scale (1= not use at all, 9 = certainly use) (e.g., Churchill 1995). This research design allows us to measure the influence of the main effects of advisory service pricing performance and match of marketing philosophy, as well as the interactions between them. Each scenario can be decomposed into its underlying components by means of introducing dummy variables. These dummy variables indicate whether or not a

specific characteristic of a MAS is present in the scenario (similar to conjoint analysis in which products are described in terms of a bundle of product attributes). For example, the dummy variable for MAS realized crop price is zero when the service has weak performance regarding realized crop price and one when the service has strong performance regarding realized crop price. These dummy variables are the explanatory variables. The Appendix Table A1 provides the dummy variable scheme. Based on farmers' responses to our scenarios and the dummy variable scheme, we are able to investigate the influence of marketing philosophy match, MAS price performance, MAS risk performance and their interaction with the following regression model:

$$(1) \quad y_{nk} = \mathbf{b}_0 + \mathbf{b}_1 MP_{nk} + \mathbf{b}_2 PP_{nk} + \mathbf{b}_3 PRG_{nk} + \mathbf{b}_4 PRB_{nk} + \mathbf{b}_5 MPPP_{nk} + \mathbf{b}_6 MPPRG_{nk} + \mathbf{b}_7 MPPRB_{nk} + \mathbf{e}_{nk}$$

where y_{nk} is the rating on the nine-point semantic scale by the n^{th} farmer of the k^{th} scenario, MP_{nk} is the marketing philosophy (match 0 = no match, 1 = match), PP_{nk} is the advisory service price performance (0 = weak performance and 1 = strong performance), PRG_{nk} is strong risk reduction performance (1 = yes, no = 0), PRB_{nk} is weak risk reduction performance (yes = 1, no = 0), $MPPP_{nk}$ is the interaction between market philosophy and price performance (yes 1, no = 0), $MPPRG_{nk}$ is the interaction between market philosophy and good risk reduction performance (yes = 1, no = 0), $MPPRB_{nk}$ is the interaction between market philosophy and bad risk reduction performance (yes = 1 and no = 0) and \mathbf{e}_{nk} is an *iid* normal error term.² Note that this dummy scheme is orthogonal, similar to a conjoint experiment in which the attributes have only two levels. The intercept captures the situation in which the advisory service has a weak performance regarding crop price and does not match the farmers' marketing philosophy. The regression coefficients indicate the change in the farmers response on the nine-point semantic MAS usage scale 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.

Finally, marketing researchers have long known that respondents use rating scales in different ways (Greenleaf). 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 farmer on the nine-point scale can be thought of as consisting of the true score plus their response bias. Hence, the reported score has no absolute meaning. Correcting rating scales for the response bias by standardizing respondents' scores has proven to be a powerful tool (Churchill 1995). Therefore, the regression model uses the farmers' standardized scores as the dependent variable. The absolute scores for a given farmer are standardized based on that farmer'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 farmers for the case of no market 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 farmers' response due to a particular variable, with the change measured in number of standard deviations.

Modeling Unobserved Heterogeneity

Since we do not *a priori* assume farmers to be homogeneous regarding the usage of MAS and the attributes that drive their usage, we propose a generalized mixture regression model. In the mixture model it is assumed that our sample of farmers on which the measurement is taken (farmers' responses to the scenarios (e.g., Figure 1), the so-called observations), is composed of a number of underlying segments of farmers. In order to describe the process generating farmers' responses, a certain statistical distribution is assumed for them. Such a distribution function describes the probabilities that the farmers' responses (e.g. observations) take certain values. Such a statistical distribution is characterized by its expectation (for example the expectation of the normal distribution is equal to the mean of the observations). Given the distributional form, the purpose of the mixture model is to decompose the farmers' population into the underlying segments. Based on the work of Wedel and DeSarbo, we propose a mixture regression methodology that enables the estimation of the relation of the farmers' responses (e.g. the observations) in each underlying segment with the set of explanatory variables. That is our methodology estimates the relation between farmers' MAS usage and our explanatory variables as defined in the conceptual model (e.g., Equation (1)) within each of the segments and at the same time derive the segments. The mixture regression framework provides the probability that each farmer belongs to the derived segments, and the regression coefficients in each respective segment which relates the expectation of the farmers' response to our explanatory variables. What is particularly powerful about this method is the fact that the segmentation criterion is the regression equation (e.g., Equation (1)). Hence, we are able to find segments, such that members of that segment are behaving according to the beta coefficients as estimated for that particular segment. Formally, we can define our mixture regression model as follows.

Assume the vector of farmers responses, y_n (e.g., the observations), arises from a population that is a mixture of S segments in proportions $\mathbf{p}_1, \dots, \mathbf{p}_S$, where we do not know in advance the segment from which a particular vector of observations arises. The probabilities \mathbf{p}_S are positive and sum to one. We assume that the distribution of y_n , given that y_n comes from segment s , $f_s(y_{nk}|\mathbf{q}_s)$, is one of the distributions in the exponential family or the multivariate exponential family, where \mathbf{q}_s is the vector of regression coefficients for each segment. Conditional on segment s , the y_n are independent. The distribution $f_s(y_{nk}|\mathbf{q}_s)$ is characterized by parameters \mathbf{q}_{sk} . The means of the distribution in segment s (or expectations) are denoted by \mathbf{m}_{sk} .

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

$$(2) \quad \mathbf{h}_{nks} = \sum_{p=1}^p X_{nkp} \mathbf{b}_{sp}.$$

The linear predictor is thus the linear combination of our explanatory variables, and the set of betas that are to be estimated. The beta coefficients can be interpreted as the amount of change in the farmers extent to use the MAS compared to the base situation as captured by the constant (e.g., \mathbf{b}_{s0}). 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, \mathbf{m}_{sk} , through a link function $g(\cdot)$ such that in segment s :

$$(3) \quad \mathbf{h}_{nsk} = g(\mathbf{m}_{nsk}).$$

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 \mathbf{h}_{nsk} and a function $g(\cdot)$ that links the linear predictor to the expectation of the distribution. Since our dependent variable, a nine point scale in which farmers indicate their extent of MAS usage, is normally distributed, the canonical link is the identity, i.e., $\mathbf{h}_{nsk} = \mathbf{m}_{sk}$, 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:

$$(4) \quad f(y_n | \mathbf{f}) = \sum_{s=1}^s \mathbf{p}_s f_s(y_n | \mathbf{q}_s),$$

where the parameter vector $\mathbf{f} = (\mathbf{p}, \mathbf{q}_s)$, and $\mathbf{q}_s = \mathbf{b}_s$. The parameter vector \mathbf{f} is estimated via maximum likelihood using the EM algorithm. 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, and Rubin) that sequentially improves upon some sets of starting values of the parameters, and permits simultaneous estimation of all model parameters (cf. Wedel and Kamakura). The idea behind the EM algorithm is that the likelihood function contains missing observations, i.e. the 0/1 membership of subjects in the S segments. If these were known, maximization of the likelihood would be straightforward. 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 \mathbf{f} and substituting those into the likelihood. Once this is accomplished, the likelihood can be maximized. Given the

new estimates of \mathbf{f} , new posteriors can be calculated in the next E (expectation)-step, followed by a new M-(maximization) step to find new \mathbf{f} . The E- and M- steps are thus alternated until convergence (see Appendix A for the statistical details). Estimates of the posterior probability, p_{ns} , that observations of farmer n come from segment s can be calculated for each observation vector y_n , as shown in Equation (5):

$$(5) \quad p_{ns} = \frac{\mathbf{p}_s f_s(y_n | \mathbf{q}_s)}{\sum_{s=1}^S \mathbf{p}_s f_s(y_n | \mathbf{q}_s)}.$$

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

Survey Design and Data Gathering Procedure

First, a survey developed from in-person interviews with 15 farmers was sent to a different sample of 100 farmers. Second, farmers 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 sent to 3,990 US farmers.³ The sample of addresses was drawn from directories kept by a US firm that delivers agricultural market information and advisory services via satellite. The final sample of 3,990 farmers consisted of 3,500 farmers that subscribed (“subscribers”) to at least one of the ten most popular market advisory services offered by the satellite network. The remaining 490 farmers served as a control group, in that they did not subscribe (“non-subscribers”) to any of the advisory services offered by the network.

Because we wish to test that heterogeneity is truly unobserved and wish to characterize segments of farmers, we gathered data that might be associated with the attributes in our conceptual model. For example, farmers who are in a segment that is characterized by farmers attaching a high value on the risk reduction performance of MAS, as reflected by a high regression coefficient for advisory service risk reduction performance, might be characterized by farmers that are relative more risk averse and perceive more risk than farmers that are in a segment that attach a relatively low value on the risk reduction performance of MAS. We measured risk attitude and risk perception in our survey 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. We used similar items as Pennings and Leuthold and Pennings and Smidts. Confirmatory factor analysis was used to assess the (psychometric) measurement quality of our constructs (Hair et al.). For a detailed description of a factor analytical model the reader is referred to Pennings and Leuthold. Furthermore, segments may be different regarding other farmers’ characteristics. In the survey we measured a variety of

demographic variables, such as age, farm size, crop grown etc. These background variables can possibly be used to profile the segments.

The survey questionnaire consisted of 31 questions and could easily be completed within 10 minutes. The questions were formulated such that farmers could easily check the answers. The cover letter mentioned the importance of this survey for farmers, by communicating the benefits for farmers (i.e. gaining insight in the performance of MAS). It was indicated that completing the survey would take 10 minutes and that it was part of a university research program. In addition, it was indicated that they would be eligible to win one of ten \$200 cash prizes, if they returned the questionnaire. In the cover letter, the names and phone numbers of the researchers were given, so that farmers with questions about the mail survey might contact them. Following Dillman's Total Design Method, farmers who had not responded were contacted twice by means of a postcard reminder and an extra copy of the questionnaire (Dillman). The questionnaires were sent on January 21, 2000 and the cut-off date for returning questionnaires was March 10, 2001.

A total of 1,399 usable questionnaires were sent back, resulting in a response rate of 35%, which is high compared to previous surveys among small- and medium-sized enterprises (Jobber; Karimabay, and Brunn). It turns out that "non-subscribing" farmers among the sample respondents nearly all use market advisory services, just not the ones offered by the satellite network. Consequently, the statistical results presented below are based on the combined sample of "subscriber" and "non-subscriber" respondents.

Sample Statistics and Farmers' Opinions of Advisory Services

Table 1 provides some background information on the sample responses. Our sample of farmers can be classified as relatively large commercial farms. A large part of the farmers monitor the cash prices of their crops several times a day, showing their involvement in the crop pricing decisions. Farmers indicated that they generally use the recommendations of MAS as background information. Only 11 percent of the farmers followed the specific pricing recommendation of MAS closely.

Table 2 shows that farmers are highly involved in pricing the crop. Most corn, cotton, soybean, and wheat farmers price part of the crops 2 to 5 times during the marketing year. Compared to cotton and wheat farmers, corn farmers market their crops relatively often during the market year.

The responses shown in Table 3 indicate that MAS are used particularly for market information and market analyses. Furthermore, Table 3 shows that MAS are more often used in an attempt to receive an above average price than to reduce price fluctuations. Furthermore, it appears that the recommendations of advisory services do make a moderate impact on the pricing decision of farmers.

Table 4 shows that farmers highly value good quality information provided by MAS. Farmers do not seem to care whether the analysis is based on the knowledge of one person or a group, nor do they care about the way the information is presented (text versus charts). The MAS

method used to arrive at the recommendation, technical versus fundamental analysis, is an important aspect of an advisory service for farmers. Frequent updates of analysis and consistency of recommendations is also valued. In sum, these results supports the hypothesis that farmers do not evaluate service quality solely on the pricing outcome of the service, but also on the process of service delivery.

Modeling Results

Figure 1 shows the mean and standard deviation of farmers' responses to the eight scenarios. To illustrate the usefulness of our generalized linear mixture modeling framework, we estimated Equation (1) across the whole sample. This resulted in an extremely low R^2 of 0.009, indicating that ignoring unobserved heterogeneity results in a model that is able to explain only about one percent of the variance of farmers' responses to the scenarios. However, a dramatic change in results is found when we account for unobserved heterogeneity, using our model as expressed in Equations (2) through (4). We estimated our 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 our sample consisted of five unobserved segments.

The results for the five-segment model are shown in Table 5. The R^2 of the 5-segment model, 0.789, is dramatically higher than the R^2 of the one-segment model. This indicates that our mixture model can explain 79 percent of the variance of farmers' responses to the scenarios. 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 (6):

$$(6) E_S = 1 - \frac{\sum_{n=1}^N \sum_{s=1}^S p_{ns} \ln p_{ns}}{N \ln S}$$

The entropy value of 0.827 indicates that the mixture components are well-separated, i.e. the posteriors (cf. Equation (5)) are close to 1 or 0.

As hypothesized, Table 5 shows that in all segments the base case, which is the situation where the MAS has a poor price performance and does not match the farmer's market philosophy, has a strong negative influence on advisory service usage. However, this influence is not equal for all segments. For example, the intercept for segment 2 is -0.889 , indicating that farmers in this segment rate the 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 farmers 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 does hold across segments. To demonstrate this point, it is helpful to "add up" the score for the most beneficial scenario: market philosophy match, good pricing performance, and good risk reduction performance. This score is computed by summing the intercept coefficient and the coefficients for MP, PP, PRG, and their interactions MPPP and MPPRG in Table 5 for each segment. The score ranges from $+0.149$ for segment 5 to $+0.589$ for segment 1. The clear

implication is that farmers more heavily penalize the mismatch of market philosophies and weak pricing performance than they reward positive performance in the same dimensions.

As can be seen from Table 5, the influence on MAS usage of the different components differs across the segments. That is, farmers in different segments attach different values to match of market philosophy, advisory service price performance, and risk performance. MAS price performance is an important driver of farmers' advisory service usage in all segments. However, the influence of advisory service price performance on farmer usage is different for each segment. It is more than twice as large in segment 4 as in segment 2. A good price risk reduction performance is important for all segments, except for segment 4. In segment 4 good price risk performance does not have a direct effect on advisory service usage, but an indirect effect by means of the interaction between match of market philosophy and price risk performance (good as well as bad price risk performance). Market philosophy is indeed an important driver behind advisory service usage, as we proposed in our conceptual model. This confirms the argument of Ginzberg, and Zeithaml, Parasuraman, and Berry that customers not only value the outcome of a service but also the process of service delivery. Only 10 percent of the farmers, as represented by segment 4 and 5, do not take the marketing philosophy match into account. The influence of the match of market philosophy is introduced in these two segments indirectly by the interaction with MAS price performance (segment 5) or through advisory service risk reduction performance (segment 4). All segments show that the influence of price performance is larger than the influence of the match of market 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 MAS usage, excepting segment 5. Table 5 shows that our hypothesis regarding the interaction between marketing philosophy match and advisory service performance regarding realized crop price and risk production performance are not confirmed, as only in the relative small segments 4 and 5 are these interactions significant related to farmers' use of MAS. That is, the main effect of philosophy match and MAS performance (price and risk performance) drives farmers' behaviors.

In our experiment, farmers did had to make a direct trade-off between MAS price performance and MAS risk performance. However, we can indirectly investigate the weight that farmers attach to risk and return by comparing the beta coefficients for risk and price performance in our regression results for each segment. From Table 5, it becomes clear that a large part of the farmers attach a higher value to the MAS price performance than the risk reduction performance, although the differences are fairly small for segments 1, 2 and 3. Only farmers in segment 5 put more value on the MAS risk reduction performance than price performance.

A question that may arise from a managerial perspective is "how can these segments be characterized?" This question is not easy to answer since the heterogeneity is not based on observable variables. We tested whether farmers in the different segments significantly differed on the questions in the survey using ANOVA analysis and Chi-Square tests. Our analysis showed that the farmers in the five segments do not significantly differ regarding demographic characteristics, nor do they differ regarding their risk perceptions, but they do differ in their attitudes towards risk (The hypothesis that the means of these variables of the 5 segments is equal was rejected at the 5% level using an ANOVA analysis). The farmers from segment 1 and

5 are significantly more risk-averse than the farmers in segments 2, 3, and 4 (4.02 and 3.82 versus 3.38, 3.72, and 3.62 risk attitude score), as measured by the indicators of our risk attitude scale (see Appendix B). These findings correspond to the relatively high regression coefficient for the influence of MAS risk reduction performance in segments 1 and 5, compared to the other three segments. Furthermore we found that farmers in the 5 segments differed regarding the value they attach to some aspects of MAS (see Table 6).

Farmers in segments 1,2 and 3 value consistent recommendations of MAS higher than farmers in segments 4 and 5. This is in accordance with the regression coefficients displayed in Table 5 for the match of market 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. Also here the farmers in segments with relatively high regression coefficient for match of marketing philosophy, segments 1, 2 and 3, value high quality information of MAS relatively higher. Farmers in the 5 segments also significantly differ regarding how they value the fact that the recommendations of MAS include futures and options.

The farmers in the different segments also showed differences in the MAS they use(d). Table 7 displays three well-known services. It appears that the segments significantly differ regarding their usage, substantiating the usefulness of our conceptual model in trying to understand farmers MAS usage and choice.

Conclusions

Farmers' use of market advisory services and consulting services in general not only depends on the outcome of these services but also on the way these services are delivered. The great influence of the match of marketing philosophy in our empirical study shows that farmers consider the whole service delivery process as well as the final outcome. Had we treated the sample of farmers as homogenous, we would have concluded that our three attributes, marketing philosophy match, advisory service price performance, and advisory service risk performance, were unable to explain farmers' use of services. However, accounting for the heterogeneity of farmers – and thereby recognizing the fact that these attributes may have different influence on farmers' advisory service usage for each segment – revealed that farmers' advisory service usage can indeed be explained by these three attributes and their interaction. The heterogeneity of the farmers appeared to be unobserved, in that it could not be traced back to observable variables such as age and region. The segments of farmers could not be profiled (characterized) along observable variables. It is the decision-making process itself that caused the heterogeneity. By introducing a generalized mixture model framework we found 5 segments that differed in their decision-making process. This framework not only revealed these segments but also estimated the decision-making process for each segment. This confirms that sometimes heterogeneity can be “unobserved” because it is caused by the farmers decision-making process itself, or more statistically said, it is the regression equation itself that differs across the segments. If we had used traditional, observable segment criteria, such as age and farm size, we would have concluded that the farmers were homogeneous regarding advisory service usage. Estimating a multiple regression, using the explanatory variables of the conceptual model, across the whole sample, would have led us to conclude that the conceptual model is not able to explain farmers advisory service usage, since such a model has an extremely low R^2 . That is, the assumption of

homogeneity would have masked important driver of advisory service usage. Furthermore, our statistical method allowed us to test for heterogeneity on the basis of farmers' decision-making process as described in our conceptual model, in contrast to traditional segmentation methods. Methodological research is needed that combines the convenient properties of the generalized mixture model and the properties of regression frameworks that take measurement error of psychological constructs into account (cf. Pennings and Leuthold).

To gain more insight into farmers' choices regarding advisory services, the marketing philosophies of both farmers and advisory services need defining and accurate measurement. This paper has not disentangled the construct of market philosophy. Doing so might reveal a powerful concept, able to explain farmers' choices for a particular service. Our finding that the marketing philosophy match is such an important driver of farmers' usage suggests that research that investigates the risk-return profile of the different services and relating that to farmers' choice for a particular service might be valuable, since such a research design could test the hypothesis that a farmer's choice for a particular advisory service is driven by the match between the risk return profile of a particular service and the risk-return profile of a farmer. Furthermore, Chevalier and Ellison showed that the performance of mutual fund managers could be traced back to their education level. It would be very interesting to investigate the factors that drive the performance of advisory services and whether these factors are recognized by farmers.

The segments differed regarding the use of particular market advisory service. The challenge is now to characterize these services in terms of their performance and market philosophy such that they can be linked to the farmers in these segments. We may hypothesize that farmers choose a particular service that matches their market philosophy and that they perceive as performing well. Research on these topics is underway.

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Endnotes

- 1 Implicitly we assume that the mean and variance of price is sufficient to describe the performance of a MAS. This EV model type of approach is proven to be valid when investigating the direction of change in relevant variables (cf. Meyer and Rasche; Garcia, Adam, and Hauser).
- 2 If we had been able to construct scenarios that consisted of all three attributes (i.e. price performance, risk performance and match of market philosophy simultaneously), Equation (1) would have been less complex: instead of two variables for risk reduction performance one would have been sufficient and the interpretation of regression coefficients would have been easier. As explained above, we chose the two-attribute scenario, since a three-attribute scenario design proved to be too complex for the farmers to handle.
- 3 Detailed information about this method to improve farmers' response to mail questionnaires can be found in Pennings, Irwin and Good.

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).

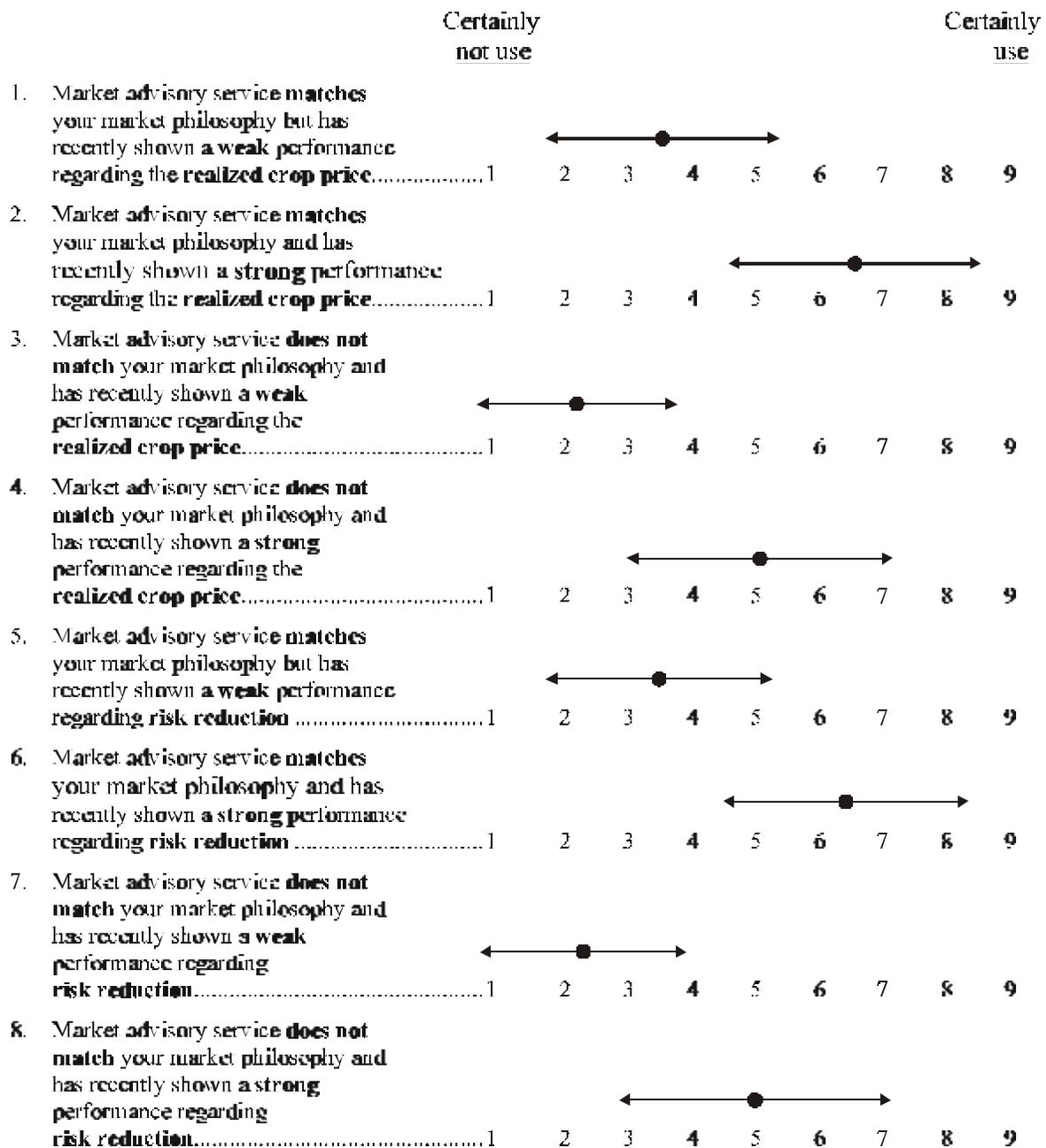


Figure 1. Farmers' responses to the scenarios (mean)

The length of the arrows reflect the standard deviation.

Table 1. Descriptive Statistics of the Sample: Percentage of Farmers that Fall into a Particular Category (N = 1,395)

Age			
<25	0.8	45 – 49	17.6
25 – 29	4.2	50 – 59	19.6
30 – 34	12.4	60 – 64	3.5
35 – 39	20.3	> 65	1.9
40 – 44	19.7		
Total acres (owned and rented)			
Over 2000	5.36	500 – 999	9.40
1500 – 1999	19.40	300 – 499	8.21
1000 – 1499	50.34	Less than 300	3.45
Approximate gross annual farm sales			
Over \$ 1,000,000	17.3	\$ 200,000 - \$ 299,999	16.9
\$ 500,000 - \$ 999,999	26.0	\$ 100,000 - \$ 199,999	10.0
\$ 400,000 - \$ 499,999	13.3	\$ 50,000 - \$ 99,999	1.3
\$ 300,000 - \$ 399,999	15.0	Less than \$ 50,000	0.2
US Regions			
Midwest	52.2		
Great Plains	29.9		
Southeast	17.9		
How often do you follow cash or futures market prices?			
Several times a day	74.7	Once to several times a month	0.6
Once a day	18.8	Never	0.3
Once to several times a week	5.6		
Do you use the specific pricing recommendations that the market advisory services provide you as background information?			
Yes	58.7	No	41.3
Do you follow the specific pricing recommendations that the market advisory services provide you loosely			
Yes	68.8	No	31.2
Do you follow the specific pricing recommendations that the market advisory services provide you closely?			
Yes	11.4	No	88.6

Table 2. Frequency of Crop Pricing per Marketing Year

	Corn	Cotton	Soybeans	Wheat
Once	6.6 %	30.5 %	7.2 %	20.2 %
2 – 5 times	51.3 %	58.8 %	59.6 %	61.7 %
6 – 10 times	30.5 %	9.2 %	25.9 %	30.5 %
> 10 times	11.5 %	1.5 %	7.3 %	4.7 %

Table 3. Ways of Using Market Advisory Services

	Mean
To what extent do you use market advisory services (1 = never use, 9 = use extremely often)	
• Marketing Information (facts)	7.17
• Market Analyses	7.10
• To receive a higher price than average	6.68
• Keeping up with markets	6.61
• Price Information	6.30
• To reduce fluctuations in the prices I receive	6.19
How great is the impact of Market Advisory Services' recommendations on your pricing decisions? (1 = no impact at all, 9 = great impact)	5.96

Table 4. Farmers' Valuation of Specific Aspects of Marketing Advisory Services (1= do not value at all, 9 = value extremely)?

	Mean		Mean
• High quality information	7.29	• Analysis based on group consensus	5.76
• Daily updates of recommendations	6.52	• Presentation mainly with text	5.18
• Use of fundamental analysis	6.36	• Presentation mainly with charts	4.98
• Consistent recommendations	6.35	• Recommendations use only cash	4.94
• Specialist regarding particular crops	6.15	• High frequency of use of futures and options strategies	4.82
• Recommendations focused on your farm operation circumstances	6.05	• Low frequency of use of futures and options	4.78
• Use of technical analysis	6.03	• Analysis based on the knowledge of one person	4.32
• Recommendations include futures and options	5.98	• Market advisory service is also broker	4.04
• The fact that the market advisory service tries to establish a relationship with you	5.83		

Table 5. Mixture Regression Results

Explanatory variables	Regression coefficient estimates for segments (<i>s</i>)				
	<i>s</i> = 1	<i>s</i> = 2	<i>s</i> = 3	<i>s</i> = 4	<i>s</i> = 5
MP	0.365*	0.207*	0.380*	-0.234	0.324
PP	0.807*	0.463*	0.707*	1.131*	0.619*
PRG	0.783*	0.449*	0.693*	0.385	0.770*
PRB	0.010	0.009	0.038	-0.209	0.065
MPPP	0.039	0.122	-0.066	0.279	0.371*
MPPRG	0.018	0.092	-0.125	1.103*	-0.221
MPPRB	0.030	-0.019	-0.064	-0.619*	-0.082
Intercept (reflecting base situation of a market advisory service that has weak price performance and does not match farmers' market philosophy)	-1.423*	-0.889*	-1.235*	-2.031*	-1.935*
Proportion of farmers that are in a particular segment (e.g., <i>p</i>)	15 %	40 %	35 %	3 %	7 %
$R^2 = 0.798$					
$Es = 0.827$					

Note: The regression model uses standardized rating scores as the dependent variable. The absolute scores for a given farmer are standardized based on that farmer's average score and standard deviation of scores across scenarios. The definitions of the independent dummy variables are: *MP* is the marketing philosophy (match 0 = no match, 1 = match), *PP* is the advisory service price performance (0 = weak performance and 1 = strong performance), *PRG* is strong risk reduction performance (1 = yes, no = 0), *PRB* is weak risk reduction performance (yes = 1, no = 0), *MPPP* is the interaction between market philosophy and price performance (yes 1, no = 0), *MPPRG* is the interaction between market philosophy and good risk reduction performance (yes = 1, no = 0), and *MPPRB* is the interaction between market philosophy and bad risk reduction performance (yes = 1 and no = 0). *Es* is the entropy value and * denotes $p < 0.01$.

Table 6. MAS' Aspects that Farmers Value that Differ Across Segments

Segment	How much do you value the following aspects (1 = do not value at all and 9 = value extremely)?*		
	<i>Consistent recommendations</i>	<i>High quality information</i>	<i>Recommendations include futures and options</i>
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

*The hypothesis that the means of these variables of the 5 segments is equal was rejected at the 5% level using an ANOVA analysis.

Table 7. Different Segments, Different MAS Choice

Segment	Have you ever used one of the following MAS?*		
	<i>Agline by Doane</i>	<i>Ag Resource</i>	<i>Harris-Elliot</i>
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%

*Chi-square test on the independence between segments and MAS usage resulted for Agline by Doane in a χ^2 of 9.57 (df. 4) ($p < 0.05$), for Ag Resource in a χ^2 of 13.866 (df. 4) ($p < 0.001$), and for Harris-Elliot in a χ^2 of 9.73 (df. 4) ($p < 0.05$).

Appendix A: The EM Algorithm

Following closely the work of Wedel and Kamakura, we introduce unobserved data, z_{ns} , indicating whether observation vector $y_n = (y_{nk})$ from subject n belongs to segment s : $z_{ns} = 1$ if n comes from segment s and $z_{ns} = 0$ otherwise, to derive the EM algorithm. The z_{ns} are assumed to be i.i.d. multinomial:

$$(A.1) \quad f(z_n | \mathbf{p}) = \prod_{n=1}^N \mathbf{p}_n^{z_{ns}},$$

where the vector $z_n = (z_{n1}, \dots, z_{nS})'$. We denote the matrix (z_1, \dots, z_n) by \mathbf{Z} . With z_{ns} considered as missing data, the complete log-likelihood function can be formed:

$$(A.2) \quad \ln L_c(\mathbf{f} | y, \mathbf{Z}) = \sum_{n=1}^N \sum_{s=1}^S z_{ns} \ln f_{n|s}(y_n | \mathbf{b}_s) + \sum_{n=1}^N \sum_{s=1}^S z_{ns} \ln \mathbf{p}_s.$$

The complete log-likelihood is maximized by using the iterative EM algorithm. Dempster, Laird, and Rubin prove that the EM algorithm provides monotone increasing values of $\ln L_c$ (cf. Titterington, Smith, and Makov).

In the E-step, the expectation of $\ln L_c$ is calculated with respect to the conditional distribution of the unobserved data \mathbf{Z} , given the observed data y and provisional estimates of \mathbf{f} .

The conditional distribution of y_n given z_{ns} , is:

$$(A.3) \quad f(y_n | \mathbf{Z}, \mathbf{f}) = \prod_{s=1}^S f_s(y_n | \mathbf{b}_s)^{z_{ns}}.$$

Using Bayes' rule, we can now derive the conditional distribution of z_{ns} given y_n from Equations A.3 and A.1, which is in turn used to calculate the required conditional expectation:

$$(A.4) \quad E(z_{ns} | y_n, \mathbf{f}) = \frac{\mathbf{p}_s f_s(y_n | \mathbf{b}_s, \mathbf{I}_s)}{\sum_{s'=1}^S \mathbf{p}_{s'} f_{s'}(y_n | \mathbf{b}_{s'}, \mathbf{I}_{s'})}.$$

To maximize the expectation of $\ln L_c$ with respect to \mathbf{f} , in the M-step, the unobserved data \mathbf{Z} in Equation A.2 are replaced by their current expectations:

$$(A.5) \quad E(\ln L_c(\mathbf{f} | y, \mathbf{Z})) = \sum_{s=1}^S \sum_{n=1}^N p_{ns} \ln f_s(y_n | \mathbf{b}_s) + \sum_{s=1}^S \sum_{n=1}^N p_{ns} \ln \mathbf{p}_s.$$

Maximizing Equation A.3 with respect to \mathbf{b} is equivalent to independently maximizing each of the S expressions:

$$(A.6) \quad L_s^* = \sum_{n=1}^N p_{ns} \ln f_s(y_n | \mathbf{b}_s).$$

The maximization of L_s^* is equivalent to the maximization problem of the generalized linear model for the complete data, except that each observation y_n contributes to the log-likelihood for each segments with a known weight p_{ns} , which is obtained in the preceding E-step. The stationary equations are obtained by equating the first-order partial derivatives of Equation A.6 to zero:

$$(A.7) \quad \frac{\partial L_s^*}{\partial \mathbf{b}_{sp}} = \sum_{n=1}^N p_{ns}^{(0)} r_{nsk} (y_{nk} - \mathbf{m}_{nsk}) x_{nkp} \frac{d\mathbf{h}_{nsk}}{d\mathbf{m}_{nsk}} = 0.$$

Equation A.7 is the ordinary stationary equation of the generalized linear model fitted across all observations, where observation n contributes to the estimating equations with fixed weight p_{ns} . Therefore, for each segment L_s^* can be maximized by the iterative re-weighted least squares procedure, with each observation y_n weighted additionally with p_{ns} .

Appendix B: Risk attitude and Risk Perception Scale: results of Confirmatory Factor Analysis

Farmers 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

1. Selling my crops is....
2. Crop prices are.....
3. The fluctuation in my farm income are....

Model is saturated resulting in a perfect fit

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

Risk attitude

Construct reliability = 0.85

1. I am willing to take higher financial risks when selling my crops, in order to realize higher average returns.
2. I like taking big financial risks.
3. I like taking risks when selling crops
4. I accept more risk in my farm business than other farmers.

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

* The likelihood-ratio Chi-square statistic (χ^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), which represents 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 suggested that a value below 0.08 indicates a close fit.

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

Scenario	MP	PP	PRG	PRB	MPPP	MPPRG	MPPRB
1. MAS matches your market philosophy but has recently shown a weak performance regarding the realized crop price	1	0	0	0	0	0	0
2. MAS matches your market philosophy but has recently shown a strong performance regarding the realized crop price	1	1	0	0	1	0	0
3. MAS does not match your market philosophy but has recently shown a weak performance regarding the realized crop price	0	0	0	0	0	0	0
4. MAS does not match your market philosophy but has recently shown a strong performance regarding the realized crop price	0	1	0	0	0	0	0
5. MAS matches your market philosophy but has recently shown a weak performance regarding the risk reduction	1	0	0	1	0	0	1
6. MAS matches your market philosophy but has recently shown a strong performance regarding the risk reduction	1	0	1	0	0	1	0
7. MAS does not match your market philosophy but has recently shown a weak performance regarding the risk reduction	0	0	0	1	0	0	0
8. MAS does not match your market philosophy but has recently shown a strong performance regarding the risk reduction	0	0	1	0	0	0	0

Note: The regression model uses standardized rating scores as the dependent variable. The absolute scores for a given farmer are standardized based on that farmer's average score and standard deviation of scores across scenarios. The definitions of the independent dummy variables are: *MP* is the marketing philosophy (match 0 = no match, 1 = match), *PP* is the advisory service price performance (0 = weak performance and 1 = strong performance), *PRG* is strong risk reduction performance (1 = yes, no = 0), *PRB* is weak risk reduction performance (yes = 1, no = 0), *MPPP* is the interaction between market philosophy and price performance (yes 1, no = 0), *MPPRG* is the interaction between market philosophy and good risk reduction performance (yes = 1, no = 0), and *MPPRB* is the interaction between market philosophy and bad risk reduction performance (yes = 1 and no = 0).