How to Group Market Participants?

Heterogeneity in Hedging Behavior

Joost M.E. Pennings[♣], Philip Garcia, Scott H. Irwin and Darrel L. Good

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[♣] Correspondence should be addressed to: Joost M.E. Pennings, Office for Futures & Options Research, University of Illinois at Urbana-Champaign, 326 Mumford Hall, MC-710, 1301 W. Gregory Drive, Urbana, IL 61801.

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Abstract

Using a generalized mixture model, we model individual heterogeneity by identifying groups of participants that respond in a similar manner to the determinants of economic behavior. The procedure emphasizes the role of theory as the determinants of behavior are used to simultaneously explain market activities *and* to discriminate among groups of market participants. We show the appealing properties of this modeling approach by comparing it with two often used grouping methods in an empirical study in which we estimate the factors affecting market participants' hedging behavior.

Introduction

Economists are becoming more aware of the effect of heterogeneity in understanding economic phenomena. Recent studies suggest that heterogeneity is an omitted variable that needs to be taken into account to develop an appropriate understanding of individual consumption, asset allocation, and productivity activities (e.g., Heckman; Caselli and Ventura; Herrendorf, Valentinyi and Waldmann). Various empirical methods have been employed to address heterogeneous behavior in economic analysis, including *a priori* classification of the decision units and cluster analysis. In this paper, we propose the use of a generalized mixture model to investigate the hedging behavior of market participants. The generalized mixture model classifies decision makers into groups based on whether participants *respond* in a similar manner to the determinants of behavior (Wedel and Kamakura; Wedel and DeSarbo). Within a group, the *influence* of these determinants on behavior is the same while the actual behavior is dependent on the *level* of these determinants. In effect, each group has a different econometric structure which is estimated with the observations that have the highest probability of conforming to that structure. In the context of an economic situation, the mixture method is attractive because it groups decision makers into groups so that within each group the responses of its members to the economic determinants of behavior are similar. Because classification is based on the determinants of behavior, the method emphasizes the role of economic theory in grouping decision makers rather than a simple reliance on arbitrary decisions or statistical analysis of the behavior considered.

Previous studies have associated heterogeneity with differences in observable variables, often using characteristics such as age or firm size to separate decision makers into groups. We implicitly propose to segment decision-makers into groups based on their decision-making behavior as revealed in the relationship between economic behavior and its determinants.

Heterogeneity in this context implies that individual decision making may be driven by factors that are not the same for all decision makers or that the effects of the factors across individuals may differ.

We investigate the properties of the grouping procedure for a sample of hog producers, wholesalers, and processors in a hedging context. Specifically, we compare and discuss the results of the generalized regression mixture model with two other grouping procedures often used in (agricultural) economics. The first procedure groups the population based on an arbitrary classification, e.g., company type, which translates into grouping the decision-makers based on whether they are a producer, wholesaler or processor. The second procedure is cluster analysis (CA) which groups participants based on the similarities they have regarding a set of variables (e.g., characteristics). While these grouping procedures are intuitive appealing, their attractiveness declines when we realize that they do not capture the idea that heterogeneity of economic behavior can be driven by differences in the decision-making process.

The remainder of the paper is organized in a straightforward manner. First we provide a brief overview of grouping methods. Then we present the generalized mixture modeling procedure, showing how it emphasizes economic theory and discussing its advantages and limitations compared to the other grouping procedures. The merits of the mixture model are then illustrated in our empirical study, comparing its results with the two other procedures used. Finally we discuss the results and offer suggestions for future research.

Grouping Methods

Classification of statistical grouping methods

Grouping methods are classified based on whether the groups are determined in advance by the researcher, *a-priori* methods, or are determined on the basis of data analysis, *post-hoc* methods. Grouping methods can also be classified based on whether they are *descriptive* or *predictive.* Descriptive methods examine heterogeneity without making a distinction between dependent or independent variables while predictive methods do make the distinction.

Based on this general taxonomy, we select two widely used grouping methods and compare their empirical findings with those from the proposed generalized mixture regression grouping method. The first method is an *a-priori* procedure that segments the population based on company type. The second method is a form of cluster analysis that can be classified as a *post-hoc descriptive* method. The generalized mixture regression grouping method can be classified as a *post-hoc predictive* method.

Single-variable grouping: Company-type grouping

To understand the factors that drive agents' behavior (e.g., contract behavior), agricultural economists often group these participants based on *a priori* hypotheses about how decision makers behave. For example, when trying to understand the factors that drive contract behavior of producers, wholesalers and processors, one might group the sample based on whether the agricultural market participant is a processor, wholesaler or producer. The next step would be to run a regression analysis for each group separately where behavior is explained by a set of explanatory variables. We refer to this method as the *company-type* grouping (CTG). CTG simply means that we split our sample along the lines of company type (e.g. producer, wholesaler and processor) and estimate within each group the relationship between hedging behavior and a set of explanatory variables identified in the literature. This two-step procedure assumes that all participants within a group behave in a similar manner, and that this differs from how participants in other groups behave.

Cluster analysis grouping

Another procedure often used is cluster analysis (CA). CA is a grouping method in which there is no formal distinction between dependent and independent variables. CA's identifies market participants based on the "average values" of the characteristics they possess, and classifies them so that each market participant is similar to other agents in its cluster. In our analysis these characteristics refer to the extent of hedging, and the set of explanatory variables associated with hedging. In the empirical study we use a hierarchical agglomerative average linkage cluster procedure in which the Euclidean distance is used as a measure of similarity (e.g., Hair et al.). Hierarchical refers to the fact that classification has an increasing number of nested classes, resembling a phylogenetic classification. This bottom-up strategy starts by placing each market participant in its own cluster and then merges these clusters based on the Euclidean distance between the clusters. The number of groups is determined by the dendogram and magnitude of change in the fusion coefficient, the latter being the level of similarity at fusion versus the number of clusters (Everitt). Subsequently we estimate within each identified cluster (e.g., group) the relationship between hedging behavior and a set of explanatory variables (The hierarchical agglomerative average linkage cluster procedure is described in detail in the Appendix). While this grouping method is useful in identifying groups, the results are often hampered by the limited theoretical rationale for the classifications. Hence, grouping is often a statistical exercise and the interpretation can sometimes be very difficult.

Decision-making process as a grouping criteria

When economists model behavior they identify the theoretical factors that influence decision makers' activities. Empirical estimates of the coefficients of the underlying model reveal the importance of these factors in the decision-making process. Differences in the coefficients across participants may arise as decision makers place different weights on the factors influencing their behavior, resulting in an econometric structure that is not homogeneous. If differences occur in a systematic way across participants, it would be attractive to classify observations such that participants within a group respond in a similar way to the determinants of behavior. This logic leads to the use of the generalized mixture framework for grouping participants such that the decision-making process as revealed in the estimated coefficients is similar within but different across groups. For economists, this idea is a natural and useful way of thinking about heterogeneity and the classification of participants. The mixture method segments market participants based on their underlying decision-making process as reflected in a relation between economic behavior and the determinants of that behavior. For developing a better understanding of behavior and policy purposes, it is of value to classify participants so that they reflect similar decision-making characteristics.

To this point, we have referred to groups as if they were directly observable. However, this may not be the case, particularly if what influences participants' response are differences in the underlying decision-making process. In this case, differences in the way that participants respond to the determinants of their behavior - the heterogeneity in the decision-making process - are unobserved prior to estimation, but drive heterogeneity of observed economic behavior. Differences in the decision-making process are only revealed through the estimated coefficients of the relationship between the behavior which are developed in the statistical procedure.

Generalized Mixture Regression Grouping

To address unobservable (e.g., latent) groups based on the decision-making process we need a modeling procedure that groups participants together so that the members of each group have a similar relationship between behavior and the set of independent variables driving it as reflected by the estimated regression coefficients which will differ across groups. In an econometric sense, each group will have a different structure (i.e., different coefficients that reflect the relationship between the dependent and the independent variables) that is estimated with the observations that have the highest probability of conforming to that structure. From a conceptual perspective, such a procedure permits the determinants of behavior to have a different influence on actual hedging practices for each group identified. The generalized mixture regression framework based on work by Wedel and Desarbo and others allows us to simultaneously investigate the relationship between economic behavior and a set of explanatory variables for each unobserved group in the population and at the same time identify these groups.

Model specification

Mixture models assume that a sample of observations arises from a number of underlying populations of unknown proportions. A specific form of the density function is specified, and the mixture approach decomposes the sample into its components. Conditional mixture models have been developed that allow for the simultaneous probabilistic classification of observations and the estimation of regression models relating covariates to the expectations of the dependent variable within unobserved (latent) groups (DeSarbo and Cron). We use a generalized linear regression mixture model first formulated by Wedel and DeSarbo. This approach allows us to simultaneously estimate the probabilistic classification of agricultural market participants by their behavior, and to explain behavior by a set of explanatory variables in each group. In our empirical analysis, behavior refers the extent to which market participants hedge.

Assume that the measures on derivative usage are indexed by $k = 1,....K$ for $j = 1,....J$ market participants. The measurements are denoted by y_{jk}. We assume that the market participants come from a population that is composed of a mixture of G unobserved groups, with relative sizes $p_1, \ldots p_G$ and that $p_G > 0$ and $\sum_{g=1}^{G} p = 1$. The distribution of y_{jk}, given that the market participant j comes from group g, is from the exponential family of distributions and is denoted as $f_{jk\backslash g}(y_{jk})$.[1] Given group g the expectation of the y_{jk} is denoted as J_{gjk}. Within groups, these expectations are modeled as a function of our set of P (p = 1,…P) explanatory variables and the parameter vector b_{pg} in group g:

$$L(J_{gjk}) = \sum_{p=1}^{P} x_{jkp} b_{pg} \tag{1}$$

where $L(.)$ is the link function which links the expectations of the measurements to the explanatory variables. Within each identified group the b_{pg} are the same; however across groups they differ. The linear predictor is thus the linear combination of the explanatory variables, and the set of betas that are to be estimated. The linear predictor is in turn related to the mean of the distribution, m_{gk}, through a link function $L(.)$ such that in group g:

$$L(J_{gjk}) = L(m_{gjk}) \quad . \tag{2}$$

Thus, for each group, a linear model is formulated with a specification of the distribution of the variable (within the exponential family), a linear predictor J_{gjk} and a function $L(.)$ that links the linear predictor to the expectation of the distribution. Since we assume that the dependent variable, the underlying value of the hedge position, is normally distributed, the canonical link is the identity, $J_{gjk} = m_{gjk}$. By combining Equations (2) and (3), the standard linear regression model within groups arises. Because we use a single measure in our empirical study to measure hedging behavior, $K = 1$.

Then, the unconditional probability density function of an observation y_{jk} is:

$$f_j(y_{jk} \mid \Phi) = \sum_{g=1}^{G} p_g f_{j\mid g}(y_{jk} \mid b_g), \tag{3}$$

and the likelihood for F is:

$$L(F; y) = \prod_{j=1}^{J} f_j(y_j \mid F) \tag{4}$$

where y_j is the observation vector y of market participant j and p_g is the relative group size.

An estimate of F, the set of parameters that identifies the groups to which the market participants belong, and the regression functions within groups, is obtained by maximizing the likelihood of (4) with respect to F subject to $p_g > 0$ and $\sum_{g=1}^{G} p_g = 1$.

The parameters of the mixture model can be estimated using the method of moments or maximum likelihood (Basford and McLachlan; Hasselblad; Quandt and Ramsey). Since maximum likelihood has been shown to be superior for the estimation of the mixture, we use this method to estimate the parameters of the model in (4) (cf., Fryer and Robertson; Wedel and DeSarbo). The likelihood function is maximized using the iterative EM algorithm (Redner and Walker; Titterington).

The EM algorithm is based on the notion that the likelihood function contains missing observations, i.e., the 0/1 membership of subjects in the g groups. If these were known, maximization of the likelihood would be straightforward. Based on a multinomial distribution for group membership, the expectation of the likelihood can be formulated. This involves calculating the posterior membership probabilities according to Bayes rule and the current parameter estimates of F and substituting them into the likelihood. Once this is accomplished, the likelihood can be maximized. See Wedel and Kamakura and Pennings and Garcia (2003) for the derivation of the EM algorithm.

The actual number of groups is unknown and must be inferred from the model. We use Bozdogan's Consistent Akaike's Information Criteria (CAIC) to determine the number of groups. The CAIC is defined as:

$$CAIC = -2\ln L + (P \cdot G + G - 1)(\ln(J) + 1) . \tag{5}$$

The number of groups that best represents the data is determined when the CAIC reaches a minimum.

For any set of groups, an Entropy statistic, $E_{g,}$ can be calculated to assess whether the groups are well separated or defined. E_g is defined as:

$$E_g = 1 - \sum_{j=1}^{J} \sum_{g=1}^{G} - a_{jg} \ln a_{jg} / J \qquad (6)$$

where a_{gj} is the posterior probability that market participant j comes from latent group g. The posterior probability can be calculated for each observation vector y_j with an estimate of F (e.g. Equation (4)) by means of Bayes' Theorem and is given by:

$$a_{gj}(y_j, \Phi) = \frac{p_g \prod_{k=1}^{K} f_{jk|g}(y_{jk} \mid b_g)}{\sum_{g=1}^{G} p_g \prod_{k=1}^{K} f_{jk|g}(y_{jk} \mid b_g)} \quad . \qquad (7)$$

The entropy statistic E_g in (6) is a relative measure, bounded between 0 and 1, and describes the degree of separation in the estimated posterior probabilities. E_g values close to 1 indicate that the posterior probabilities of the respondents belonging to specific groups are close to either 0 or 1; the groups are well defined. E_g values close to 0 indicate that the groups are not well defined.

The proposed grouping procedure emphasizes the role of theory in the empirical analysis as the determinants of behavior are used both to explain behavior and to discriminate among groups of individual decision makers. This differs fundamentally from previous studies dealing with heterogeneity, where groups were determined *a priori*, based on a single observable variable or by clustering groups based on observable variables. The proposed grouping procedure permits the determinants of behavior to have a different influence on actual behavior for each group identified. A challenging dimension of using this procedure is to assess why decision makers in a particular group might respond differently from participants in other groups.

Research Design

Sample

To examine heterogeneity in behavior and to illustrate the properties of the generalized mixture regression model we use a dataset that reflects hedging activity of producers, wholesalers and processors developed by Pennings and Garcia (2003). The sample consists of 335 producers, 50 wholesalers and 30 processors. A personal computer-guided interview was conducted in the first half of 1998 that took place at the market participant's company. The market participants worked through several assignments and questions, and the interviews lasted about 35 minutes. We also obtained accounting data from these 415 firms for the fiscal year 1997 which included information on: company size, leverage, ownership structure, risk exposure, number of contracts, corresponding notional value, and education level of decision maker.

Determinants of hedging behaviour

To explain the extent to which market participants hedge we selected variables that have been identified in the agricultural economics and finance literature. We hypothesize that factors that have been associated with affecting hedging also influence the extent to which market participants hedge. Here, we do not review the factors that have been identified to influence hedging behavior. The combined work of Froot, Scharfstein and Stein, Nance, Smith and Smithson, Mian, Tufano (1996), Géczy, Minton and Schrand, Lee and Hoyt, Koski and Pontiff, Pennings and Garcia (2003), and Graham and Rogers provide a discussion of these factors in the financial literature. In the agricultural economics literature Asplund, Foster, and Stout, Goodwin and Schroeder, Makus et al., Musser, Patrick, and Eckman, Pennings and Leuthold, Shapiro and

Brorsen, and Turvey and Baker, provide a discussion of the factors. Based on this literature the following variables, with their hypothesized sign in brackets, are: decision-maker's risk attitude - e.g., risk aversion (+), decision-maker's risk perception (+), the interaction between risk attitude and risk perception (+), education level of decision maker (+), the extent to which the decision-maker's decision-making unit (DMU) favors hedging (+), firm's risk exposure (+), firm's debt-to-asset ratio (+), and firm size (+).

Measurement of dependent and independent variables

The dependent variable describing the economic behavior is the extent of hedging. The extent of hedging is measured as the sum of the underlying value of hedged positions in relation to annual sales (e.g., Chorafas and Steinmann; Gunther and Siems) which relates closely to the hedge ratio. Risk attitude was measured in a set of unique experiments in which we elicited the respondents utility function. Our experimental design and procedures follow Pennings and Smidts, and Pennings and Garcia (2001). We measure the utility functions of managers in a way consistent with the decision-makers' daily decision-making behavior (e.g., trading in the hog and pork markets). The utility function $u(x)$ is assessed by means of the certainty equivalence method (cf. Keeney and Raiffa; Smidts). In the certainty equivalence method, the respondent compares a certain outcome with the lottery $(x_l,p;x_h)$, whereby $(x_l,p;x_h)$ is the two-outcome lottery that assigns probability p to outcome x_l and probability 1-p to outcome x_h, with $x_l<x_h$. The certain outcome is varied until the respondent reveals indifference, which is denoted by CE(p). By applying the Von Neumann-Morgenstern utility u we obtain: $u(\mathrm{CE}(p)) = pu(x_l) + (1-p)u(x_h)$. Based on the assessed utility curve, the Pratt-Arrow coefficient of absolute risk aversion was derived as a measure of risk attitude (cf. Smidts). An exponential function was fit to each

manager’s outcomes; after scaling the boundaries of the functions, the estimation of just one parameter suffices to characterize a decision-maker's risk attitude. Since it is the certainty equivalents and not the utility levels that are measured with error, the inverse function is estimated (see Pennings and Garcia ,2001). Following Pennings and Smidts, risk perception is measured by a scale consisting of a number of statements (multi-indicator measurement). The scale measures the extent to which decision makers perceive the market in which they operate as risky. Confirmatory factor analysis was used to assess the (psychometric) measurement quality of our constructs (Hair et al.). The overall fit of the confirmatory factor model provides sufficient information to determine whether the set of indicators (items) describes the construct. The composite reliability is 0.72, indicating a reliable construct measurement (Hair et al.). The level of education is measured on a 5-point scale using the five education levels in the Dutch school system. This 5-level system ranges from a high school to a University level. The influence of the DMU is measured by asking managers to indicate the extent to which significant persons surrounding them thought that they should hedge. The manager was asked to distribute 100 points between using or not using derivatives as a hedging mechanism to reflect the influence of the DMU. Risk exposure is measured by the firms’ annual number of market transactions in the cash market to sell (buy) its output (input) (Tufano, 1998). Risk exposure decreases (increases) as the number of market transactions increases (decreases). The leverage is measured by the firm’s debt-to-asset ratio and the size of the firm is measured by the firm’s annual sales.

Empirical Results

Assuming homogeneity

Table 1 shows the OLS results when we assume a homogeneous decision-making process and hence homogeneity in market participants hedging behavior. The regression has a modest fit with a R^2 of 0.172. Risk perception and the influence of the DMU are significantly related to the extent of hedging which is consistent with Géczy, Minton and Schrand and Pennings and Leuthold.

Table 1. Factors Influencing Hedging Behavior: Homogeneous Behavior.

	Regression Coefficients (ß)
Risk Exposure[a]	0.160
Leverage	0.029
Size of firm	-0.08
Risk Attitude (RA)	0.158
Risk Perception (RP)	0.122**
Interaction (RP*RA)[b]	-0.121
Level of Education	0.440
DMU	0.382**
Fit Statistics	R^2 = 0.172 F=10.557; df 8 (p=0.000)

[a]Risk exposure decreases as the number of market transactions increases, hence we hypothesize a negative sign.
[b]The risk perception and risk attitude variables were centered prior to forming the multiplicative term (Cronbach; Jaccard, Turrisi and Wan).
* denotes p< 0.05; ** denotes p< 0.01.

The fundamental drivers of risk management, risk attitude and the interaction between risk attitude and risk perception are not significantly related to the extent of hedging, a finding that has been found in some empirical studies in both agricultural economics and finance (Géczy, Minton, and Schrand; Haushalter; Makus et al.; Shapiro and Brorsen). The firm's leverage is not significantly related to the extent of hedging, a finding consistent with Mian, nor is the level of education and firm size significantly related to derivative usage.

Company-type grouping

Recall that using the CTG method we group the sample based on whether the market participant is a processor, wholesaler or producer. For each group we estimate the relationship between the extent of hedging and the independent variables. Seemingly unrelated regression (SUR) is used to account for contemporaneous correlation in the errors across equations (Zellner; Srivastava and Giles). Table 2 shows the results when we take the heterogeneity in hedging behavior into account using the CTG-grouping method.

Table 2. Factors Influencing Hedging Behavior: Grouping Based on Company Type.

	Processors	Wholesalers	Producers
		Regression coefficients (ß)	
Risk Exposure[a]	-0.215	-0.059	-0.007
Size of firm	0.234	0.000	-0.037
Leverage	0.200	0.071	0.056
Risk Attitude (RA)	-0.396	0.113	0.085
Risk Perception (RP)	0.131	-0.153	0.093*
Interaction (RP*RA)[b]	-0.031	-0.148	0.089
Level of Education	0.203	0.017	0.000
DMU	0.088	0.172	0.219**
Relative Group Size	7.2% (n = 30)	12.0% (n = 50)	80.7% (n = 335)
Fit Statistic	R^2=0.335	R^2=0.09	R^2= 0.094
	F=1.934; df 8 (p=0.108)	F=0.591; df 8 (p=0.779)	F=4.467 df 8 (p=0.000)
	?^{2}= 15.468; df 8 (p= 0.051)	?^{2}= 4.731; df 8 (p= 0.789)	?^{2}= 35.734; df 8 (p= 0.000)

[a]Risk exposure decreases as the number of market transactions increases, hence we hypothesize a negative sign.
[b]The risk perception and risk attitude variables were centered prior to forming the multiplicative term (Cronbach; Jaccard, Turrisi and Wan).
* denotes p< 0.05; ** denotes p< 0.01.

For processors and wholesalers, none of the explanatory variables are significantly related to hedging behavior. For producers, risk perception and the influence of decision making unit are significantly related to hedging behavior, a similar result to the homogeneous case. The strong influence of the decision making unit on producers hedging behavior confirms the empirical results found in organizational behavior literature and decision sciences where it has been shown that the manager's decision making unit has a significant impact on decisions (e.g., Moriarty and Bateson). The fact that the model fits are low and that almost none of the hypothesized relationships between hedging behavior and the set of explanatory variables are significant indicates that this *a priori* grouping method is not able to identify heterogeneity in market participants' hedging behavior. In part, this may be explained by the fact that the classification in the CTG method is not based on the determinants of hedging behavior but rather on an arbitrary grouping criterion.

Cluster analysis grouping

Based on the hierarchical agglomerative average linkage cluster procedure, the market participants were segmented in three groups. Recall that in this procedure clusters (e.g., groups) are formed based on the similarities of market participants with respect to variables in our analysis (e.g., firm size, risk attitude, risk perception, etc). To gain insight in whether these clusters differ significantly regarding the means of the variables we used ANOVA. All three clusters were significantly different, and based on the extent of hedging can be described as "low users", "medium users," and "high users".

Table 3. Factors Influencing Hedging Behavior: Grouping Based on Cluster Analysis.

	Group 1 ("low users")	Group 2 ("medium users")	Group 3 ("high users")
		Regression coefficients (ß)	
Risk Exposure[a]	-0.080	0.069	-0.163
Size of firm	-0.052	0.031	0.096
Leverage	-0.083	-0.199**	0.243*
Risk Attitude (RA)	0.168	0.390*	-0.303
Risk Perception (RP)	0.019	0.102	0.206*
Interaction (RP*RA)[b]	-0.067	-0.309	-0.059
Level of Education	0.048	-0.041	0.276**
DMU	0.167**	-0.034	0.226*
Relative Group	57.11% (n = 237)	29.15% (n=121)	13.73% (n = 57)
Fit Statistic	R^2= 0.07 F=2.039; df 8 (p=0.042) ?^{2}= 16.319; df 8 (p= 0.004)	R^2=0.08 F=1.426; df 8 (p=0.193) ?^{2}= 11.407; df 8 (p= 0.179)	R^2=0.327 F=3.400; df 8 (p=0.004) ?^{2}= 27.203; df 8 (p= 0.000)

[a]Risk exposure decreases as the number of market transactions increases, hence we hypothesize a negative sign.
[b]The risk perception and risk attitude variables were centered prior to forming the multiplicative term (Cronbach; Jaccard, Turrisi and Wan).
* denotes p< 0.05; ** denotes p< 0.01.

Table 3 presents the SUR results for the three groups. For group 1 ("low users" that represent 57.1% of the sample), only the decision making unit significantly impacts hedging behavior. For group 2 ("medium users" that represent 29.2% of the sample), hedging behavior is driven by the financial structure (e.g., leverage) and risk attitude, however the sign of the leverage variable differs from expectations. In contrast, for group 3 ("heavy users" that represent 13.7% of the sample), numerous factors appear to affect hedging behavior. The influence of the financial structure, risk perception, the level of education, and the decision-making unit which seem to drive hedging behavior confirm recent findings in the financial and agricultural economic literature (e.g. Goodwin and Schroeder; Makus et al.; Musser, Patrick and Eckman; Nance, Smith and Smithson, Géczy, Minton and Schrand). When comparing the results of the CA method with those obtained by CTG method, the CA method appears superior; the empirical results are more in line with hedging theory, and the statistical findings are more attractive. This finding is not surprising when we realize that the CA method does not arbitrarily group market participants, but rather is driven by similarities among the market participants.

Generalized mixture regression grouping

We applied the mixture regression model (Equations 1 to 4) to the data for $G = 1$ to $G = 6$. Based on the minimum CAIC statistic (Equation 5), we selected $G = 3$ as the appropriate number of groups. The results of the 3 group solution are presented in Table 4. The solution has a log likelihood of -934 and an R^2 of 0.54. The entropy value of 0.79 indicates that the mixture groups are well separated or defined, i.e., the posteriors are close to 1 or 0. The R^2 has significantly improved from 0.173 for the aggregate regression model ($G = 1$) to 0.54 for the three-group solution ($G = 3$).

Table 4. Factors Influencing Hedging Behavior: Mixture Regression Results

	Regression coefficients(ß)		
	g = 1	g = 2	g = 3
Risk Exposure[a]	-0.136*	-0.103*	-0.096
Size of firm	0.237**	0.207*	0.186
Influence DMU	0.396**	0.004	0.246*
Leverage	0.067	0.045	0.291*
Risk Attitude (RA)	0.009	0.067	0.644*
Risk Perception (RP)	0.074*	0.031	0.359*
Interaction (RP*RA)[b]	0.305*	0.087	0.506*
Level of Education	0.029	0.128*	0.629**
Relative Group Size p	0.44	0.30	0.26
	Comparison with Company Type Grouping: Percentage of company type in group		
Producers	48.9% (n =164)	28.9% (n = 97)	22.2% (n = 74)
Wholesalers	36.0% (n = 18)	42.0% (n = 21)	22.0% (n = 11)
Processors	3.3% (n = 1)	20.0% (n = 6)	76.6% (n =23)
	Comparison with Company Type Grouping: Percentage of company type in group		
Group 1	64.1% (n = 152)	19.8% (n = 47)	16.1% (n = 38)
Group 2	21.5% (n = 26)	51.2% (n = 62)	27.3% (n = 33)
Group 3	8.8% (n = 5)	26.3% (n =15)	64.9% (n =37)

[a]Risk exposure decreases as the number of market transactions increases, hence the negative sign.
[b]The risk perception and risk attitude variables were centered prior to forming the multiplicative term (Cronbach, 1987; Jaccard, Turrisi and Wan, 1990).
* denotes p< 0.05; ** denotes p< 0.01.

Group 1 (g = 1) constitutes 44.1% of the sample. For this segment risk exposure, size of firm, the influence of the DMU, the manager's risk perception and the interaction between risk attitude and risk perception are significantly related to the extent of hedging which confirms previous findings in the agricultural economics and finance literature (e.g., Nance, Smith and Smithson; Géczy, Minton and Schrand; Carter and Sinkey). Compared to the other two segments developed using the mixture model, this group reflects a low level of derivative use. Group 2 (g = 2) constitutes 29.8% of the sample, and shows that risk exposure, size of firm, and level of education significantly affect hedging behavior. However, risk attitude, risk perception, and their interaction are not significantly related to hedging. For this group the use of derivatives is modest, higher than in Group 1 but lower than in Group 3. For Group 3, which contains 26.1% of the sample, numerous factors influence hedging behavior. Risk perception, risk attitude, and their interaction, and leverage, the level of education, and the influence of the DMU are all significantly related to hedging behavior.

Table 4 also presents the CTG and the CA groupings in relation to the mixture segments. A perfect correspondence between groupings would result in diagonal matrix such that for example Group 1 (*g=1*) from the mixture results would consist of all the producers in the sample. Clearly, membership in the groups based on the mixture model does not perfectly coincide with either the *a-priori* or cluster analysis classifications. The highest degree of correspondence is found between the CA and the mixture segments, which is consistent with the fact that the classifications from both procedures rank the extent of derivative use in a similar manner. It should be evident that the mixture procedure places producers, wholesalers and processors in groups based on similar hedging behavior rather than on arbitrary classifications.

Overall, our findings identify the superiority of mixture procedure for identifying the effect of heterogeneity on the hedging process. The findings from the mixture model resulted in a large number of statistically significant factors influencing hedging in a manner consistent with theory and expectations. The improved performance of the mixture model over the other procedures is also supported by statistical measures of fit. Furthermore, these results, as shown in Pennings and Garcia (2003) have clear economic interpretations. Group 1 is characterized by companies whose decision regarding derivative use depends on their risk exposure and the opinions of members of the decision-making unit regarding futures usage. This group is dominated by relatively small firms that do not use derivatives extensively. Group 2 used derivatives more extensively, and has the highest proportion of wholesalers. Use of derivatives seems to be less motivated by risk perceptions and risk attitudes, but more by risk exposure, a behavior consistent with ‘natural hedges’ that may be occurring for participants with frequent buying and selling opportunities. In contrast, the hedging behavior of the firms in Group 3 is driven by the fundamental drivers, risk attitude, risk perception and their interaction, and is consistent with Pratt and Arrow’s models and economic theory that suggest that risk attitude and risk perception are important concepts in determining optimal hedging positions (Holthausen; Rolfo). Further, other financial determinants such as leverage are significant in these managers’ decisions.

Discussion

The empirical results show that accounting for heterogeneity increases our understanding of economic behavior (e.g., hedging behavior), confirming the recent findings of Heckman that heterogeneity is an omitted variable. Furthermore the empirical results reveal that different grouping techniques lead to significantly different findings regarding the relationship between the hedging behavior and its determinants. When evaluating the three grouping methods in terms of the consistency of the empirical results with economic theory we observe a clear hierarchy. The grouping technique based on company type (CTG method) performed poorly as hardly any variable that has been identified as influencing hedging was significantly related to behavior in the groups identified. The cluster analysis (CA) grouping method performed better that the CTG method. The improvement in performance can be explained by the fact that prior to the regression analysis the CA method grouped participants with respect to the variables in the analysis such that members within a group were similar but differed between groups. The generalized mixture regression grouping method outperformed both the CA and CTG method as the empirical results were most consistent with economic theory, and the statistical findings were stronger. Furthermore, the mixture method has an appealing economic interpretation. That is, the generalized method recognizes that heterogeneity in economic behavior can be driven by the heterogeneity of the decision-making process. The mixture method classifies market participants based on their decision-making process as measured by whether participants respond to the determinants of behavior in a similar manner. These results suggest that the mixture method may be a response to the recent search for procedures that account for heterogeneity in a theoretical consistent way (Heckman; Caselli and Ventura; Herrendorf, Valentinyi and Waldmann).

The results of the mixture grouping method show that its groups are not homogeneous with respect to the type of market participants, and that its groups differ from those developed through more conventional cluster analysis. The performance of the mixture method suggests that heterogeneity emerges from differences in the influence of the determinants of derivative use on behavior rather than from a single observable variable (e.g., company type), or a statistical classification of variables based on differences in their 'means'. To ignore the heterogeneity driven by the decision-making process can lead to a misunderstanding of the factors influencing economic behavior, and may result in economic costs from classifying market participants incorrectly.

What do the results imply for agricultural economists when grouping participants to gain insight into economic behavior? Should we always use the mixture method? In our view, economic theory should drive the grouping method used, and in this paper we demonstrate that the mixture method is a procedure that can be used successfully to group market participants based on theory. However, the improved performance of the mixture method comes at a cost. The grouping criteria are unobservable and hence the groups are latent. In terms of our empirical work, this means that we can not observe the beta coefficients in the regressions for market participants (e.g., reflecting market participants' decision-making process) that are the basis for grouping without performing the analysis. For extension economists and marketers who are primarily interested in reaching the groups identified in the mixture method analysis, this may be an important limitation. This contrasts with the CA and the CTG methods which provide criteria, although not necessarily the most useful for classifying participants into groups with similar behavior, that are readily observable, and can result in more straightforward classifications. Hence, while the mixture method may be more useful for developing an understanding of economic phenomena in the presence of heterogeneity, it may be limited in a practical sense. One way to cope with this practical dilemma is to profile the groups and to find observable profile variables that can be used as a proxy to group the sample and/or identity to which group a market participant belongs. For example, in our data, we performed this procedure on the groups from the mixture analysis, and found that the ownership structure differed significantly across the three groups. Group 3 ($g=3$), for which the fundamental risk variables are most important, is dominated by limited and public companies, i.e., companies that have third-party (outside) shareholders. These companies are inclined to optimize their risk-return trade off in order to maximize shareholder value, and hence it seems logical that the fundamental risk variables play a role for this group. This contrasts with Groups 1 and 2 from the mixture analysis which are dominated by private companies and where derivative use is less extensive. Since one can observe the ownership structure, extension economist and marketers could use this variable as a tool to reach the different groups. Clearly, future research should try to identify a more formal procedure to make the mixture method attractive from a practical as well as conceptual perspective. However, in light of the fact that the underlying decision-making process of participants is not directly observable, this will be a challenge. In the end, trade offs may exist between consistency with theory, the costs of misclassifying participants, and practically. In the near future, these trade offs may be less problematic as we collect more information about market participants and their behavior.

FOOTNOTES

1. The exponential family includes the normal, binomial, poisson, and gamma distributions.

Appendix: Cluster Analysis

In the appendix we discuss the hierarchical agglomerative average linkage cluster procedure.

Assume we have k measurements on each of the n market participants. The $n \times k$ matrix of the raw data is then transformed into a $n \times n$ matrix of distance measures (e.g., similarities), where the distances are computed between pairs of market participants across the k variables. The goal of cluster analysis now is to arrive at groups of market participants that display small within-group variation relative to the between-groups variation. Consider the market participants in a k dimensional space, with each of the k variables represented by one of the axes of the space, we can than think of the groups as continuous regions appearing in this space with a relatively large mass.

To measure the distance between market participants we use a Euclidean distance measure. Each market participant can be represented by a vector of observations $X' = (x_1, x_2 ... x_p)$ on the k variables. Denote $X'_i = (x_{i1,} x_{i,2} ..., x_{ip})$ as the measurements collected on the ith market participant. The Euclidean distance measure can now be defined as: $d_{ij} = (\sum_{k=1}^{K} \left| x_{ik} - x_{jk} \right|^2)^{1/2}$

where d_{ij} denotes the distance between two market participants i and j.

The hierarchical agglomerative cluster analysis procedure performs successive fusions of the data. Each market participant starts out in its own group. At the next level, the two closest market participants are fused. At the third level, a new market participant joins the group containing the two market participants, or another group is formed. This process continues until eventually a single group contains all n market participants. The distance between groups then is defined as the average distance between all pairs of points, using $\frac{1}{n_I n_J} \sum_i \sum_j d_{ij}$ where n_I and n_J are the numbers of market participants in the two groups. The optimal number of groups can be determined inspecting the dendogram and the fusion coefficient. The dendogram shows which groups are joined together and at what distance, and at latter stages which groups are joined together into larger groups. Srivastava suggests that the optimal number of groups arises when the "foothills" become "mountain peaks" in plots of the dendogram. Another criterion to establish the number of groups is the change in the fusion coefficient, where the fusion coefficient is defined as the squared Euclidean distance over which two groups are joined. Because larger fusion coefficients indicate more distance between groups, a large jump in the magnitude of fusion coefficients indicates the optimal number of groups (Hair. et al).

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