Accounting for Heterogeneity in Hedging Behavior:
Comparing & Evaluating Grouping Methods

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Abstract

Heterogeneity, i.e., the notion that individuals respond differently to economic stimuli, can have profound consequences for the interpretation of behavior and the formulation of agricultural policy. This paper compares and evaluates three grouping techniques that can be used to account for heterogeneity in financial behavior. Two are well established: company-type grouping and cluster analysis. A third, the generalized mixture regression model, has recently been developed and is worth considering as market participants are grouped such that their response to the determinants of economic behavior is similar. We evaluate the grouping methods in a hedging framework by assessing their ability to reflect relationships consistent with theory. The empirical findings show that the economic relationships are more consistent with theory within the groups identified by the mixture model, and suggest that researchers interested in identifying segments of the population in which participants behave in a similar manner may consider using of mixture model in the presence of heterogeneity in financial behavior.

1. Introduction

The purpose of this paper is to compare and evaluate three grouping techniques that have been used to deal with heterogeneity in agricultural financial behavior. Two of the methods are well established in the literature e.g., company-type grouping and cluster analysis. A third method, the generalized mixture regression approach, has recently been developed in the statistical and biometric literature. The mixture model method has appealing properties that make it worth considering as market participants are grouped such that the response to the determinants of financial behavior within each group is similar. This notion is consistent with heterogeneity in the economic decision-making process (e.g., Herrendorf et al., 2000; Heckman, 2001), and the search for a ''variety of candidate averages'' that can improve our understanding of behavior and at the same time provide useful information to decision makers interested in identifying groups of agents that behave similarly. Conceptually, we posit that the decision-making process is reflected in the estimated relationships between actual behavior and its explanatory determinants. The mixture model groups participants such that the marginal economic effects (i.e., the regression coefficients) are similar within each group.

  We compare and evaluate the grouping methods from a theoretical perspective and statistical perspective. Theoretically we compare and evaluate the grouping methods based on how the grouping methods show relationships between behavior and the determinants that are consistent with financial theory. In the empirical study we focus on hedging behavior for which a well-defined theoretical framework exists. In the next section, we provide a brief overview of the three

grouping methods and elaborate on the mixture model grouping method. Subsequently we discuss how the three grouping methods are applied, and how we compare and evaluate them. We then introduce the empirical context in which the analysis is performed. Finally we discuss the results and offer suggestions for future research.

2. Grouping methods

2.1. Classification of statistical grouping methods

We select two widely-used grouping methods and compare them empirically with the mixture model 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 mixture model grouping method can be classified as a *post-hoc predictive* method.

2.2. Single-variable grouping: Company-type grouping

To understand the factors that drive financial behavior, financial economists often group participants based on *a priori* hypotheses about how market participants behave. For example, in understanding the factors that drive contract behavior of market participants, one might classify participants into processors, wholesalers or producers. The next step would be to run a regression analysis for each group separately, where behavior is explained by a set of variables. We refer to this method as the *company-type* grouping method (CTG). CTG simply means that we split the 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. When using the CTG method, one implicitly assumes that all market participants of a single company type respond (e.g., behave) similarly to economic stimuli, and differently from market participants in other groups. Thus, market participants of the same company type are assumed to be homogeneous with regards to the relationship between economic behavior and its determinants.

2.3. 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 identifies market participants based simply on the "average values" of the characteristics they possess, and classifies them so that each market participant is similar to other market participants in its cluster. In the empirical 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., 1995). 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, which is a visual representation of the steps in a hierarchical clustering solution that shows the clusters being combined and the values of the distance coefficients at each step, and magnitude of change in the relative distance between market participants that were linked in each

step (e.g., fusion coefficient) (Everitt, 1993). Subsequently, we estimate the relationship between hedging behavior and a set of explanatory variables within each identified cluster (i.e., group). While this 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 difficult.

2.4. The relationship between behavior and its determinants as a grouping criterion

When agricultural and financial economists model behavior, they identify the theoretical factors that influence market participants' activities. Empirical estimates of the coefficients of the underlying model reveal the importance of these factors in determining behavior. The coefficients may differ across market participants, as they place different weights on the factors influencing their behavior. This results in an econometric structure that is not homogeneous. If differences across market participants occur in a systematic way, it is possible to classify observations such that market participants within a group respond similarly to the determinants of behavior. This logic leads to the use of the mixture model framework for grouping market participants, such that the relationship between behavior and its determinants, as revealed in the estimated coefficients, is similar within each group but different across groups. For economists, this idea is a natural and useful way of thinking about heterogeneity and the classification of market participants. The mixture model grouping method segments market participants based on their underlying "decision-making process" as reflected in a relation between financial behavior and the determinants of that behavior.

3. Mixture model grouping method

To address unobservable (i.e., latent) groups based on the relationship between behavior and its determinants, we need a modeling procedure that groups market participants together based on a similar relationship between behavior and the factors driving it (i.e., the estimated regression coefficients). 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. This structure 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 behavior for each group identified. The generalized mixture model framework allows us to simultaneously investigate the relationship between economic behavior and a set of variables for each unobserved group in the population, and at the same time identify these groups.

3.1. Model

Mixture models assume that a sample of observations arises from a number of underlying populations of unknown proportions.[1] A specific form of the density function is specified, and the mixture model 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

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[1] The development of mixture models has a rich tradition beginning with Newcomb (1886) in the late 1800s.

dependent variable within unobserved (latent) groups (DeSarbo and Cron, 1988). We use a generalized linear regression mixture model formulated by Wedel and DeSarbo (1995). This approach allows us to simultaneously estimate the probabilistic classification of market participants by their behavior, and to explain behavior by a set of explanatory variables in each group. In the empirical analysis, behavior refers to the extent to which market participants hedge. A detailed model specification can be obtained in Pennings and Leuthold (2010). The mixture model 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 market participants such that the response of the participants in each group to economic stimuli is similar. This differs from the CTG and CA methods discussed above, where groups were determined *a priori*, based on a single observable variable or by clustering groups based "average values" of observable variables. The mixture model grouping procedure permits the determinants of behavior to have a different influence on actual behavior for each group identified.

4. Research design

4.1. Empirical context: Hedging in the agricultural & food sector

To compare and evaluate the three grouping methods, and to examine whether the theoretical relationships between behavior and its determinants hold for the identified groups, we need a context with a well-defined theoretical framework in which these relationships have been established. The hedging context meets this requirement. There is a massive body of literature in economics and finance that identifies variables that drive the extent to which market participants hedge. Here, we do not review these variables. Both theoretical work by, among others, Johnson (1960), Williams (1986), and Collins (1997), and empirical work by, among–others, Froot et al. (1993), Géczy et al. (1997), and Pennings and Leuthold (2000), provide a discussion of these variables. Based on the theoretical and empirical work reviewed, the following variables, with their hypothesized sign in brackets, can be discerned: market-participant's risk attitude - e.g., risk aversion (+), market-participant's risk perception (+), the interaction between risk attitude and risk perception (+), education level of the market participant (+), firm's risk exposure (+), firm's debt-to-asset ratio (+), firm size (+) and the extent to which the market-participant's decision-making unit (DMU) favors hedging (+). The DMU has been identified as having a significant effect on firms' major decisions, particularly in the case of small and medium-sized enterprises (Dholakia et al., 1993). The DMU are individuals external to the firm such as advisors, consultants or bank account managers, who are involved in firm decisions. Pennings and Garcia (2004) show that these individuals influence the hedging behavior of firms.

4.2. Sample

We use a dataset developed by Pennings and Garcia (2004) that reflects hedging activity of producers, wholesalers and processors in the pork industry. The sample consists of 335 producers, 50 wholesalers and 30 processors. A personal computer-guided interview was conducted at the market participant's company. In about 35 minutes, the market participants worked through several assignments and questions. An important part of the interview dealt with eliciting market participants' risk attitude through an experimental design that made market

participants choose between selling/buying in the cash market or using fixed price contracts. Furthermore, each participant's level of education was obtained during the interview. We also received accounting data from these 415 firms, including information on: firm size, leverage, ownership structure, and risk exposure.

4.3. 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 relative to annual sales (e.g., Chorafas and Steinmann, 1994; Gunther and Siems, 1995), which closely relates to the hedge ratio. The number of observation near the limits (0 and 1) was relatively small. The Jarque-Bera test indicated that the distribution of the dependent variable in our sample could be approximated by a normal distribution.[2]

Risk attitude is measured in a set of experiments in which we elicited the respondents' utility function closely following Pennings and Garcia (2001) and Pennings and Smidts (2000). Risk perception was measured by a scale consisting of a number of statements (multi-indicator measurement). 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 market participants to indicate the extent to which significant persons surrounding them (e.g., advisors) thought they should hedge. The market participant was asked to distribute 100 points between hedging or not hedging, to reflect the influence of the DMU. Risk exposure was 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). Leverage was measured by the firm's debt-to-asset ratio and firm size by annual sales.

5. Comparing and evaluating grouping methods

We compare and evaluate the grouping methods from a theoretical perspective and statistical perspective. Theoretically we can compare and evaluate the grouping methods based on how the grouping methods show relationships between hedging behavior and the determinants of hedging behavior that are consistent with theory. Statistically we can compare the overall explanatory power of the three grouping methods and investigate whether the estimated hedge ratio based on method A significantly contributes to the relationship between hedging and its determinants for method B. Comparing and evaluating the three grouping methods based on how well the grouping methods yield results that are consistent with economic theory (i.e., nomological validity).

6. Empirical results

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[2] The subsequent analysis was also performed with the number of contracts as the dependent variable in a poisson distribution framework. The robustness of the results was reassuring. The estimates of the coefficients differ only modestly, and the qualitative implications are identical to those reported in the text.

6.1. Company-type grouping

Recall that in 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 in an OLS framework. Table 3 shows the results of the CTG-grouping method, when we take the heterogeneity in hedging behavior into account.

(Insert Table 2 about here)

For processors and wholesalers, none of the explanatory variables are driving hedging behavior.[3] 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, decision sciences and more recently the economics literature (e.g., Moriarty and Bateson, 1982). The nomological validity of the grouping method seems low, as many of the variables identified by theory to drive hedging behavior are not found to drive hedging behavior in the identified groups. 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 a single variable grouping criterion (e.g., company-type).

6.2. Cluster analysis grouping

Based on the hierarchical agglomerative average linkage cluster procedure, the market participants were segmented in three clusters. Recall that in this procedure, clusters (e.g., groups) are formed based on the similarities of market participants with respect to all variables in the 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".

(Insert Table 2 about here)

After having identified the clusters, we estimated the relationship between hedging behavior and its determinants for each cluster. Table 2 presents the OLS results for the three clusters. For cluster 1 ("low users" who represent 57.1% of the sample) only the decision-making unit impacts hedging behavior. For cluster 2 ("medium users", who represent 29.2% of the sample), hedging behavior is driven by the financial structure (e.g., leverage) and risk attitude. In contrast, for cluster 3 ("heavy users", who represent 13.7% of the sample), numerous factors appear to affect hedging behavior. The financial structure, risk perception, level of education, and the decision-making unit seem to drive hedging behavior, confirming recent findings in the financial and economic literature (Nance et al., 1993; Géczy et al., 1997). When comparing the results of the CA method with those of the CTG method, the CA method appears to have higher nomoligical

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[3] The relative high R-squared and limited number of statistically significant coefficient are attributed to

multicollinearity and the small number of observations.

validity. Also, the empirical results from CA are more consistent with hedging theory, and the statistical findings are stronger. This finding is not surprising when we realize that the CA method does not group market participants based on a single variable, but is driven instead by similarities among the market participants on a set of variables that seem to be relevant for the empirical context (e.g., hedging behavior).

6.3. Mixture model grouping

We applied the mixture model to the data for G = 1 to G = 5. Based on the minimum CAIC statistic, we selected G = 3 as the appropriate number of groups. The solution has a log likelihood of -458 and an R^2 of 0.54.[4] The entropy value of 0.78 indicates that the mixture model groups are well separated or defined, i.e., the posteriors are close to 1 or 0. The mixture procedure identifies the groups, its participants, and estimates the parameters of the variables simultaneously. For purposes of comparison with the CTG and CA results, after having identified the mixture groups we estimated for each group the relationship between hedging behavior and its determinants using OLS. The results of the three-group solution, which differ only slightly from the mixture model's findings, are presented in Table 3.

(Insert Table 3 about here)

Mixture group 1 ($g = 1$) constitutes 44.1% of the sample. For this segment, risk exposure, size of firm, the influence of the DMU, the market-participant's risk perception, and the interaction between risk attitude and risk perception are related to the extent of hedging. This confirms previous findings in the literature (e.g., Nance et al., 1993; Géczy et al., 1997). Mixture group 2 ($g = 2$) constitutes 29.8% of the sample, and shows that risk exposure, size of firm, and level of education affect hedging behavior. However, risk attitude, risk perception, and their interaction are not (significantly) related to hedging. For Mixture group 3, which contains 26.1% of the sample, numerous factors influence hedging behavior, including: risk perception, risk attitude, and their interaction, leverage, the level of education, and the influence of the DMU. These results show that many of the variables identified by theory to drive hedging behavior do actually drive hedging behavior in the identified groups. It is clear that the mixture model grouping method has a relatively higher nomological validity compared to the other two grouping methods.

(Insert Table 4 about here)

Table 4 presents the CTG and the CA groupings in relation to the groups obtained from the mixture model. A perfect correspondence between groupings would result in a diagonal matrix, such that, for example, mixture group 1 ($g=1$) from the mixture results would consist of all the producers in the sample. Membership of the groups based on the mixture model does not perfectly coincide with either the CTG or CA classifications. The highest degree of correspondence is found between the CA and the mixture model groups, which is consistent with

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[4] This R-squared is defined as the proportionate reduction in uncertainty, measured by Kullback-Leibler divergence, due to the inclusion of regressors (Cameron and Windmeijer, 1997). Under further conditions concerning the conditional mean function, it can also be interpreted as the fraction of uncertainty explained by the fitted model.

the fact that both grouping techniques use information from all variables (be it in a different manner) to determine the groupings. It should be evident that the mixture model procedure places producers, wholesalers and processors in groups based on whether market participants respond similarly to the determinants of behavior rather than on company type. The findings show the attractiveness of the mixture model procedure for identifying the effect of heterogeneity on the hedging process. The mixture model yielded a large number of variables that influence hedging in a manner consistent with theory and expectations.

7. Discussion

The empirical results show that accounting for heterogeneity increases our understanding of financial behavior (e.g., hedging behavior), confirming the recent findings of Heckman that heterogeneity is an omitted factor. Further, the empirical results reveal that different grouping techniques lead to significantly different findings regarding the relationship between hedging behavior and its determinants. When evaluating the three grouping methods in terms of the consistency of the empirical results with economic theory (i.e. nomological validity), we observe a hierarchy. The grouping technique based on company type (the CTG method) did not perform satisfactorily, as hardly any variable identified to influence hedging was related to behavior in the groups identified. The cluster analysis (CA) grouping method performed better than the CTG method. The improvement can be explained by the fact that, prior to the regression analysis, the CA method grouped market participants with respect to the variables in the analysis, such that members were similar within a group, but different between groups. The mixture model grouping results were most consistent with theory.

The mixture model grouping method suggests that heterogeneity emerges from differences in the influence of the determinants of hedging behavior, rather than from a single observable variable (e.g., company type), or a statistical classification of variables based on differences in their 'means' (e.g., cluster analysis). To ignore the heterogeneity driven by the relationship between financial behavior and its determinants may lead to a misunderstanding of the factors influencing economic behavior and may result in economic costs from classifying market participants incorrectly. The findings also suggest that the mixture model method may be part of an effective response to the recent search for procedures that account for heterogeneity in a theoretically consistent way (Caselli and Ventura, 2000; Herrendorf et al., 2000; Heckman, 2001).

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Table 1. Factors influencing hedging behavior: grouping based on company type

	Processors (n= 30)		Wholesalers (n = 50)		Producers (n = 335)		
	Standardized regression coefficients (β's)						
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%		12.1%		80.7%		
Fit Statistics	R^2=0.335		R^2=0.091		R^2= 0.094		
	F=1.934;	df 7	F=0.591;	df 7	F=4.467	df	7
	(p=0.108)		(p=0.779)		(p=0.000)		
Average hedge ratio	0.59		0.37		0.10		

[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 (Jaccard et al., 1990).

* denotes $p < 0.05$; ** denotes $p < 0.01$.

Table 2. Factors influencing hedging behavior: grouping based on cluster analysis

	Cluster 1 ("low users") ($n = 237$)	Cluster 2 ("medium users") ($n = 121$)	Cluster 3 ("high users") ($n = 57$)
Standardized regression coefficients (β's)			
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 Statistics	R^2= 0.07	R^2=0.08	R^2=0.327
	F=2.039; df 7 (p=0.042)	F=1.426; df 7 (p=0.193)	F=3.400; df 7 (p=0.004)
Average hedge ratio	0.11	0.22	0.30

[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 (Jaccard et al., 1990).

* denotes $p< 0.05$; ** denotes $p< 0.01$.

Table 3. Factors influencing hedging behavior: mixture model results

	Standardized regression coefficients (β's)		
	$g = 1$ ($n = 183$)	$g = 2$ ($n = 124$)	$g = 3$ ($n = 108$)
Risk Exposure[a]	-0.136*	-0.103*	-0.096
Size of firm	0.237**	0.207*	0.186
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**
DMU	0.396**	0.004	0.246*
Relative Group Size π	0.44	0.30	0.26
Fit Statistics	R^2= 0.243	R^2=0.293	R^2=0.118
	F=5.953;　df　7 (p=0.000)	F=5.823　df　7 (p=0.000)	F=3.444;　df　7 (p=0.006)
Average hedge ratio	0.16	0.17	0.17

[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 (Jaccard et al., 1990).
* denotes $p< 0.05$; ** denotes $p< 0.01$.

Table 4. Relating the mixture model groups, with the groups obtained in the CTG and CA

	Mixture Group 1 ($g=1$)	Mixture Group 2 ($g=2$)	Mixture Group 3 ($g=3$)	
Company Type Grouping (CTG):	Percentage of company type in mixture model groups			
Producers	48.9% ($n =164$)	28.9% ($n = 97$)	22.2% ($n = 74$)	100%
Wholesalers	36.0% ($n = 18$)	42.0% ($n = 21$)	22.0% ($n = 11$)	100%
Processors	3.3% ($n = 1$)	20.0% ($n = 6$)	76.6% ($n = 23$)	100%
Cluster Analysis (CA):	Percentage of cluster members in mixture model groups			
Cluster 1	64.1% ($n = 152$)	19.8% ($n = 47$)	16.1% ($n = 38$)	100%
Cluster 2	21.5% ($n = 26$)	51.2% ($n = 62$)	27.3% ($n = 33$)	100%
Cluster 3	8.8% ($n = 5$)	26.3% ($n =15$)	64.9% ($n =37$)	100%