

# Heterogeneity in Economic Behavior<sup>☆</sup>

Joost M.E. Pennings<sup>\*</sup>, Philip Garcia and Scott H. Irwin

Copyright 2005 by Joost M.E. Pennings, Philip Garcia and Scott H. Irwin. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

---

<sup>☆</sup> The authors are grateful for the generous participation of the 335 producers, 50 wholesalers and 30 processors in the personal computer-assisted interviews. The authors thank seminar participants at Brown University, INSEAD, London Business School, Rotterdam School of Management, Erasmus Graduate School of Business, Syracuse University, Tilburg University, UC Berkeley, UC Los Angeles, University of Illinois at Urbana-Champaign and the Wageningen University, for their comments. The authors express special thanks to Erno Kuiper, Raymond Leuthold, Matthew Meulenberg, Ale Smidts and Michel Wedel, who provided helpful comments on the research project and preliminary versions of the manuscript. This paper has been screened to ensure that no confidential data are revealed.

<sup>\*</sup> Correspondence should be addressed to: Joost M.E. Pennings, Department of Agriculture & Consumer Economics, Marketing & Decision Sciences Group, University of Illinois at Urbana-Champaign, 326 Mumford Hall, MC-710, 1301 W. Gregory Drive, Urbana, IL 61801.

# Heterogeneity in Economic Behavior<sup>☆</sup>

---

## **Abstract**

Heterogeneity, i.e., the notion that individuals respond differently to economic stimuli, can have profound consequences for the interpretation of empirical evidence and the formulation of economic policy. This paper compares and evaluates three grouping techniques that can be used to account for heterogeneity in economic 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 economic behavior.

*Keywords:* Economic Behavior; Heterogeneity; Hedging; Methods

*JEL Classification:* A10; B40; C1; D0; G0; L2; Q13

---

<sup>☆</sup> The authors are grateful for the generous participation of the 335 producers, 50 wholesalers and 30 processors in the personal computer-assisted interviews. The authors thank seminar participants at Brown University, INSEAD, London Business School, Rotterdam School of Management, Erasmus Graduate School of Business, Syracuse University, Tilburg University, UC Berkeley, UC Los Angeles, University of Illinois at Urbana-Champaign and the Wageningen University, for their comments. The authors express special thanks to Erno Kuiper, Raymond Leuthold, Matthew Meulenberg, Ale Smidts and Michel Wedel, who provided helpful comments on the research project and preliminary versions of the manuscript. This paper has been screened to ensure that no confidential data are revealed.

## 1. Introduction

Economists are becoming more aware of the role of heterogeneity in explaining economic phenomena. Heterogeneity, the notion that individuals respond differently to economic stimuli, can have profound consequences for the interpretation of empirical evidence and the formulation of economic policy. Heckman (2001) states in his Nobel Lecture that “The most important discovery was the evidence on the pervasiveness of heterogeneity and diversity in economic life. When a full analysis was made of heterogeneity in response, a variety of candidate averages emerged to describe the “average” person, and the long-standing edifice of the representative consumer was shown to lack empirical support” (Heckman, 2001, p. 674). Heckman’s observation and other recent studies suggest that heterogeneity is an omitted factor that should be considered when developing an understanding of economic behavior in consumption, asset allocation, and production (e.g., Caselli and Ventura, 2000; Heckman, 2001; Herrendorf et al., 2000). In the presence of heterogeneous behavior, modeling of a “representative agent” can lead to counterintuitive or theoretically controversial results in applied economics. In the extreme, to eliminate the bias, one can model behavior for each agent separately or allow coefficients to behave randomly. While appealing conceptually, as it permits each agent to respond differently to a set of economic stimuli, this strategy is highly demanding of the data. It may require a time series of individual observations and may provide decision makers interested in agent behavior with information of only limited value. Decision makers such as policy makers may be more interested in the existence and identification of groups of agents that behave similarly so that their products, advice, or policy measures can be directed to affecting activities and well-being in a more efficient manner. The procedure one uses for grouping may influence the results, thereby biasing interpretation, and our understanding of market participants’ behavior.

The purpose of this paper is to compare and evaluate three grouping techniques that have been used to deal with heterogeneity in economic behavior. Two of the methods are well established in the economics 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 economic 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 theory. In the empirical study we focus on hedging behavior for which a well-defined theoretical framework exists. Statistically we compare the overall explanatory power of the three grouping methods and investigate whether the estimated (hedging) behavior based on method A significantly contributes to the relationship between (hedging) behavior 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 and on their statistical performance (i.e., performing a *J*-test) provides a balanced and objective evaluation yardstick.

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*

Grouping methods are classified based on whether the groups are determined in advance by the researcher, *a-priori* methods, or 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 this distinction.

Based on this general taxonomy, 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. In the review of the grouping methods we pay special attention to the mixture model grouping method, as this is a relatively new grouping method.

## 2.2. *Single-variable grouping: Company-type grouping*

To understand the factors that drive market participants' behavior (e.g., contract behavior), 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 dendrogram, 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](#)). The entire procedure is described in detail in the Appendix. 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 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 economic behavior and the determinants of that behavior.

To this point, we have referred to groups as if they were directly observable. However, direct observation is not always possible, particularly if market participants’ responses are influenced by differences in the relationship between behavior and its determinants. In this case, the differences in how market participants respond to the determinants of their behavior – i.e., the heterogeneity in the decision-making process - remain unobserved prior to estimation, yet drive the heterogeneity of observed economic behavior. Differences in the relationship between behavior and its determinants are only revealed through the estimated coefficients which are developed in the statistical procedure.

### **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 specification*

Mixture models assume that a sample of observations arises from a number of underlying populations of unknown proportions.<sup>1</sup> 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 dependent variable within unobserved (latent) groups (DeSarbo and Cron, 1988). We use a generalized linear regression mixture model first formulated by Wedel and DeSarbo (1995) and further elaborated on by among others Arcidiacono and Jones (2003). 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.

Assume that the measures on behavior are indexed by  $k = 1, \dots, K$  for  $j = 1, \dots, J$  market participants (in the empirical study hedging behavior is measured by a single variable and hence  $K=1$ ). 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

---

<sup>1</sup> The development of mixture models has a rich tradition beginning with Newcomb (1886) in the late 1800s.

$\pi_1, \dots, \pi_G$  and that  $\pi_G > 0$  and  $\sum_{g=1}^G \pi = 1$ . 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  $f_{jk|g}(y_{jk})$ .<sup>2</sup> Given group  $g$ , the expectation of the  $y_{jk}$  is denoted as  $\mathcal{G}_{gjk}$ . Within groups, these expectations are modeled as a function of the set of  $P$  ( $p = 1, \dots, P$ ) explanatory variables and the parameter vector  $\beta_{pg}$  in group  $g$ :

$$L(\mathcal{G}_{gjk}) = \sum_{p=1}^P x_{jkp} \beta_{pg} \quad (1)$$

where  $L(\cdot)$  is the link function which links the expectations of the measurements to the explanatory variables. Within each identified group the  $\beta_{pg}$  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,  $\mu_{gk}$ , through a link function  $L(\cdot)$  such that in group  $g$ :

$$L(\mathcal{G}_{gjk}) = L(\mu_{gjk}) \quad (2)$$

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  $\mathcal{G}_{gjk}$  and a function  $L(\cdot)$  that links the linear predictor to the expectation of the distribution. Since we assume that the dependent variable, the employed hedge ratio (measured as the sum of the underlying value of hedged positions in relation to annual sales), is normally distributed, the canonical link is the identity,

---

<sup>2</sup> The exponential family includes the normal, binomial, poisson, and gamma distributions.

$\vartheta_{gjk} = \mu_{gjk}$ .<sup>3</sup> By combining Equations (2) and (3), the standard linear regression model within groups arises.

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

$$f_j(y_{jk} | \Phi) = \sum_{g=1}^G \pi_g f_{j|g}(y_{jk} | \beta_g), \quad (3)$$

and the likelihood for  $\Phi$  is:

$$L(\Phi; y) = \prod_{j=1}^J f_j(y_j | \Phi) \quad (4)$$

where  $y_j$  is the observation vector  $y$  of market participant  $j$  and  $\pi_g$  is the relative group size. An estimate of  $\Phi$ , 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  $\Phi$  subject to  $\pi_g > 0$  and  $\sum_{g=1}^G \pi_g = 1$ .

The parameters of the mixture model can be estimated using the method of moments, or maximum likelihood (Hasselblad, 1969; Quandt and Ramsey, 1978; Basford and McLachlan, 1985). 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, 1972; Wedel and DeSarbo, 1995). The likelihood function is maximized using the iterative EM algorithm (Redner and Walker, 1984; Titterton, 1990).

---

<sup>3</sup> We tested the dependent variable for normality in the empirical study, using the Jarque-Bera test. The test indicates that we cannot reject the hypothesis of normality at the 10% level.

This involves calculating the posterior membership probabilities according to Bayes rule and the current parameter estimates of  $\Phi$  and substituting them into the likelihood. Once this is accomplished, the likelihood can be maximized. See [Wedel and Kamakura \(1998\)](#) 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:

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

where  $P$  is the number of explanatory variables,  $G$  is the number of groups and  $J$  is the number of market participants. 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:

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

where  $\alpha_{gj}$  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  $\Phi$  (e.g. Equation (4)) by means of Bayes' Theorem and is given by:

$$\alpha_{gj}(y_j, \Phi) = \frac{\pi_g \prod_{k=1}^K f_{jk|g}(y_{jk} | \beta_g)}{\sum_{g=1}^G \pi_g \prod_{k=1}^K f_{jk|g}(y_{jk} | \beta_g)} . \quad (7)$$

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 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*

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, Working (1953), Johnson (1960), Telser (1981), Williams (1986), and Collins (1997), and empirical work by, among-others, Froot et al. (1993), Tufano (1996), 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. The sample consists of 335 producers, 50 wholesalers and 30 processors in the Netherlands. A personal computer-guided interview was conducted at the market participant's company in the first half of 1998. 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 for the fiscal year 1997, including information on: firm size, leverage, ownership structure, and risk exposure. Table 1 provides insight into the size of the firms, leverage, ownership structure and risk exposure.

[TABLE 1 ABOUT HERE]

#### 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.<sup>4</sup>

Risk attitude is measured in a set of experiments in which we elicited the respondents' utility function. The utility function  $u(x)$  is assessed by means of the certainty equivalence method (cf., [Keeney and Raiffa, 1976](#); [Smidts, 1997](#)). In the certainty equivalence method, the respondent compares a certain outcome (fixed price) with the lottery  $(x_l, p; x_h)$  (selling in the spot market), 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  $CE(p)$ . The experimental design and procedures follow [Pennings and Smidts \(2000\)](#) and [Pennings and Garcia \(2001\)](#). The utility functions of market participants were measured in a context that reflected daily decision-making behavior (e.g., trading in the hog and pork markets). By applying the Von Neumann-Morgenstern utility  $u$  we

---

<sup>4</sup> 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.

obtained:  $u(CE(p)) = pu(x_i) + (1-p)u(x_n)$ . Based on the assessed utility curve, the Pratt-Arrow coefficient of absolute risk aversion was derived as a measure of risk attitude (cf., [Smidts, 1997](#)). An exponential function was fit to each market-participant's outcomes; after scaling the boundaries of the functions, the estimation of just one parameter suffices to characterize a market-participant's risk attitude (see [Pennings and Garcia, 2001](#)). Following [Pennings and Smidts \(2000\)](#), risk perception was measured by a scale consisting of a number of statements (multi-indicator measurement). The scale measures the extent to which market participants perceive the market in which they operate as risky. Confirmatory factor analysis was used to assess the (psychometric) measurement quality of the constructs ([Hair et al., 1995](#)). 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., 1995](#)). 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. Applying the Grouping Methods

The variables described above are used differently in the three grouping methods. These differences are explained below and provide additional insight about theoretical differences between the grouping methods.

### 5.1. *Single-variable grouping: Company-type grouping*

In CTG, the sample is classified based on company type. In the empirical study, three company types are distinguished: producers, wholesalers, and processors. Hence, CTG does not use the variables identified to drive hedging behavior to group the market participants. After identifying the groups in CTG, we use the aforementioned variables to relate them with hedging behavior within each group identified (producers, wholesalers, and processors). CTG, by grouping market participants based on company type, assumes that producers as a group (as well as wholesalers and processors) behave similarly, as expressed by the estimated relationship between the independent variables (the determinants of hedging behavior) and hedging behavior (e.g., regression coefficients). CTG assumes moreover that producers as a group behave differently from wholesalers and processors, while wholesalers as a group behave differently from processors.

### 5.2. *Cluster analysis*

In CA, market participants are grouped using all the variables (dependent and independent) that are available for the market participants. In CA, market participants are grouped on the basis of the values of these variables, such that each market participant is similar to other market participants in its cluster. In the Appendix, the mechanics of the CA procedure are detailed.

Since CA uses all variables in developing the groups, it should be more informative than the CTG criterion which is based on a single variable. After identifying the groups, a relationship between the determinants of hedging behavior and hedging behavior is estimated. CA may include producers, wholesalers, and processors in the same group.

### 5.3. *Mixture model grouping*

Like CA, the mixture grouping method includes all variables for group participants. Where cluster analysis groups market participants based on the average *values* of these variables, the mixture model groups market participants based on the *influence* of these variables on (hedging) behavior, as reflected in the regression coefficients that relate the explanatory variables to economic behavior. The mixture model approach allows us to investigate the relationship between hedging behavior and the independent variables for each latent group in the sample, and at the same time identify these groups. Such a grouping method is consistent with the notion that heterogeneity in economic behavior is driven by heterogeneity in the decision-making process of the market participant. The latter is reflected in the regression relation between hedging behavior and the independent variables.

## **6. Comparing & 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) and on their statistical performance (i.e., performing a *J*-test) provides a balanced and objective evaluation yardstick.

### *6.1. Economic significance*

From a theoretical perspective it is appealing to evaluate the grouping methods on the basis of their nomological validity. Nomological validity refers to the notion that, if valid, the grouping methods should yield groups consistent with theory (Campbell and Fiske, 1959; Cook and Campbell, 1979; Peter, 1981; Nunnally and Bernstein, 1994). Here, we use nomological validity and hence recognize the importance of considering economic and statistical significance (McCloskey and Ziliak, 1996). In our context, this translates into whether the variables identified to drive hedging actually drive hedging behavior in the identified groups in a significant manner. Evaluating the grouping methods on their nomological validity is equivalent to evaluating their ability to reflect the notion that behavior is an outcome of the decision-making process and that heterogeneity in behavior is driven by heterogeneity in the decision-making process (Heckman, 2001). Whether or not a variable is driving hedging behavior within identified groups is examined by estimating the relationship between the extent of hedging and the independent variables.

## 6.2. Statistical Significance

From a statistical perspective we first compare the overall explanatory power of the three grouping methods. In order to do so we estimate a full model for each method, where the full model for each grouping method is defined as:

$$HR_i = \alpha_0 + \delta_1 D_1 + \delta_2 D_2 + \sum_{p=1}^P VAR_{ip} \beta_{ip} + \sum_{p=1}^P D_1 * VAR_{ip} \omega_{ip} + \sum_{p=1}^P D_2 * VAR_{ip} \lambda_{ip} \quad (8)$$

and  $HR_i$  is the hedge ratio for market participant  $i$ ,  $D_1$  and  $D_2$  are dummy variables to indicate to which group a market participant belongs to as identified by the grouping method, and  $VAR_{ip}$  is the explanatory variable  $p$  for market participant  $i$ . We are particularly interested in comparing and evaluating the R-squareds, the AIC and BIC obtained for each grouping method.

While comparing the R-squareds, the AIC and BIC provide us with a relative ranking of the explanatory power of the different grouping methods, they do not permit us to statistically test whether alternative grouping methods yield an improvement in the explanatory power. Therefore we also evaluate CTG and CA relative to the mixture model (MM) using a pair-wise  $J$ -test proposed by [Davidson and Mackinnon \(1981, 2002\)](#). In our context the  $J$ -test translates into first running Equation (8) for each grouping method, and generating the predicted hedge ratios based on the estimated coefficients. Then specifying a particular method (CTG) as the appropriate procedure (i.e., the null hypothesis), Equation (8) is rerun for CTG with the predicted hedge ratios from the mixture model included as an additional explanatory variable (i.e., the alternative hypothesis). If the coefficient of the predicted hedge ratio from the mixture model is significant, the null hypothesis is rejected in favor of the alternative, indicating that the mixture model provides additional information beyond that found in the CTG method. The roles of the

null and alternative hypotheses are then reversed and the test is performed again. The test between the mixture model and the CTG as the null hypothesis is expressed as:

$$HR_{iCTG} = \alpha_0 + \delta_1 D_1 + \delta_2 D_2 + \sum_{p=1}^P VAR_{ip} \beta_{ip} + \sum_{p=1}^P D_1 * VAR_{ip} \omega_{ip} + \sum_{p=1}^P D_2 * VAR_{ip} \lambda_{ip} + \gamma_{MM} \hat{HR}_{iMM} \quad (9)$$

where  $HR_{iCTG}$  is the hedge ratio of market participant  $i$  explained by the CTG groupings as reflected in the first six terms on the right hand side, and  $\hat{HR}_{iMM}$  is the predicated hedge ratio for the  $i$  market participant from the mixture model. If  $\gamma_{MM}$  is significant, then the mixture model provides additional information to explain hedging behavior beyond the CTG grouping method. Various authors have shown that the  $J$ -test is not exact in finite samples (Godfrey, 1998). In our case the sample is relatively large ( $N = 415$ ) compared to the samples sizes used in studies that discuss the shortcomings of the  $J$ -test for small samples (e.g., Davidson and MacKinnon, 2002), and hence we may expect the size distortion to be limited.

## 7. Empirical Results

### 7.1. Assuming homogeneity

Table 2 shows the OLS results when we assume a homogeneous decision-making process, i.e., the relationship between hedging behavior and its determinants is the same for all market participants. The regression has a modest fit with an  $R^2$  of 0.172. Risk perception and the influence of the DMU are significantly related to the extent of hedging, consistent with Géczy et al. (1997) and Pennings and Leuthold (2000), and their signs are consistent with expectations.

[TABLE 2 ABOUT HERE]

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 empirical studies in both the economics and finance literature (Géczy et al., 1997; Haushalter, 2000). The firm's leverage is not related to the extent of hedging, a finding consistent with Mian (1996), nor is the level of education and firm size related to the extent of hedging.

## 7.2. *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.

[TABLE 3 ABOUT HERE]

For processors and wholesalers, none of the explanatory variables are driving hedging behavior.<sup>5</sup> 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

---

<sup>5</sup> The relative high R-squared and limited number of statistically significant coefficient are attributed to multicollinearity and the small number of observations.

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).

### 7.3. *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”.

[TABLE 4 ABOUT HERE]

After having identified the clusters, we estimated the relationship between hedging behavior and its determinants for each cluster. Table 4 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 nomological 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).

#### 7.4. *Mixture model grouping*

We applied the mixture model (Equations 1 to 4) to the data for  $G = 1$  to  $G = 5$ . Based on the minimum CAIC statistic (Equation 5), we selected  $G = 3$  as the appropriate number of groups. The log-likelihoods, corresponding CAIC, and the Entropy  $E_g$  and  $R^2$  statistics are listed in Table 5. The solution has a log likelihood of -458 and an  $R^2$  of 0.54.<sup>6</sup> 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.

[TABLE 5 ABOUT HERE]

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 6.

---

<sup>6</sup> 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.

[TABLE 6 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.

[TABLE 7 ABOUT HERE]

Table 7 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 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.

To further analyze the performances of the three grouping methods we estimated the R-squareds, AIC and BIC for each grouping method in a full regression model as given in Equation (8), and performed the *J*-test based on Equation (9). Clearly some care must be taken in interpreting the size of the R-squared as a measure of the goodness of fit of the economic model (McGuirk and Driscoll, 1995). Also, it should be noted that direct comparison using the AIC, BIC, and the *J*-tests are complicated because the CA and Mixture procedures use additional information to develop the groups that can not be included in the framework of the evaluation measures. Specifically, the CA method uses the hierarchical agglomerative average linkage procedure to identify the groups, and the Mixture method uses the EM algorithm which iterates between a multinomial classification of group membership, and estimation of the relationship between the explanatory variables in each group. Regardless, large differences in the values of the measures and tests should be highly suggestive that the procedures do in fact capture differences in the underlying structure of the data related to the change in the mean of the dependent variable among the three groups and their slope coefficients which is their purpose.

[TABLE 8 ABOUT HERE]

The results in Table 8 show a clear hierarchy that was also observed when comparing the grouping technique based on their nomological validity: the mixture model grouping method has the highest overall R-squared and corresponding lowest AIC and BIC values, followed by the

CA method and the CTG method. The pair-wise *J*-test results also support the notion that mixture group method is more informative. The last column of Table 8 shows that the estimated hedge ratio based on the mixture grouping method was a significant variable in the CTG and CA the full regression models. The estimated hedge ratios based on the CA and CTG however were not significant in the full mixture regression models. These results indicate that the mixture grouping method provides additional information that can explain hedging behavior beyond the other two grouping methods, but that CTG and CA group methods are not informative in the presence of the mixture method.

## **8. 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 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. Similar results were found when comparing

the overall fit of the three grouping methods (Equation (8)) and when evaluating the three grouping methods using a non-nested  $J$ -test (Equation (9)).

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 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).

Some caveats and challenges of the analysis should be mentioned. In this study, we evaluate the grouping methods on the basis of their nomological validity and their statistical performance. The nomological validity was investigated by examining whether the variables identified to affect hedging actually drive hedging behavior in the identified groups. Whether or not they did was determined in a OLS framework examining the significance of the variables. However, the number of observations in each identified group can influence these significance levels. Therefore, the fact that the groups identified by the three grouping methods were not equal in size may have influenced the evaluation of the grouping methods on their nomological validity. Statistical fit measures along with the pair-wise  $J$ -tests however were supportive of the nomological validity findings.

Grouping market participants with the mixture model has the appealing conceptual property that individuals within a group respond in a similar manner, but across groups individuals behave

differently. For policy makers the mixture model grouping technique provides valuable information. Policy makers need to know the existence of the groups, their proportion of the population, and how likely they are to respond to changes in policy measures. The situation described above for policy makers may also apply for companies who are developing new products and are interested to find out how consumers may respond to different product attributes. In such situation it is crucial to know how consumer respond to these product attributes and how large the group of consumers is that respond in a favorable to these attributes before the company invests in the development, production and marketing of the product.

Overall, what do these results imply for grouping market participants to gain insight into economic behavior? Should we always use the mixture model grouping method? Not necessarily, as it depends on the goal of the research question. If we are interesting in understanding the differences in (hedging) behavior between producers, wholesalers and processors, clearly one should group the sample based on company type. However, if we are interested in grouping market participants to deal with heterogeneity in economic behavior such that their responses are similar within groups but dissimilar among groups, the mixture model grouping method is worth considering. It groups market participants based on the influence of the determinants of economic behavior (as established in economic theory) on actual behavior. Another way of looking at the mixture model grouping method is that it can signal misspecifications of other grouping procedures, as its grouping is based on the influence of economic determinants on economic behavior.

## Appendix A. 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 is to arrive at groups of market participants that display small within-group variation, relative to 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 then 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  $X' = (x_1, x_2 \dots x_p)$  on the  $k$  variables. Denote  $X'_i = (x_{i1}, x_{i2} \dots, x_{ip})$  as the measurements collected on the  $i$ th market

participant. The Euclidean distance measure can now be defined as:  $d_{ij} = \left( \sum_{k=1}^K |x_{ik} - x_{jk}|^2 \right)^{1/2}$

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 is then 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 by inspecting the dendrogram and the fusion coefficient. The dendrogram shows which groups are joined together and at what distance and at latter stages which groups are joined together into larger groups. [Srivastava \(2002\)](#) suggests that the optimal number of groups lies where the "foothills" become "mountain peaks" in plots of the dendrogram. 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., 1995](#)).

## References

- Arcidiacono, P., Jones, J.B., 2003. Finite Mixture Distributions, Sequential Likelihood and the EM Algorithm. *Econometrica* 71, 933-946.
- Basford, K.E., McLachlan, G.J., 1985. The Mixture Method of Clustering Applied to Three-way Data. *Journal of Classification* 2, 109-125.
- Bozdogan, H., 1994. Mixture Model Cluster Analysis Using Model Selection Criteria and a New Informational Measure of Complexity. In: Bozdogan, H. (Ed.), *Multivariate Statistical Modeling*. Kluwer Academic Publishers, Dordrecht, pp. 69-113.
- Cameron, A.C., Windmeijer, F.A.G., 1997. An R-squared Measure of Goodness of Fit for Some Common Nonlinear Regression Models. *Journal of Econometrics* 77, 329-342.
- Campbell, D.T., Fiske, D.W., 1959. Convergent and Discriminant Validation by the Multitrait-multimethod Matrix. *Psychological Bulletin* 56, 81-105.
- Caselli, F., Ventura, J., 2000. A Representative Consumer Theory of Distribution. *American Economic Review* 90, 909-926.
- Chorafas, D.N., Steinmann, H., 1994. *Off-balance Sheet Financial Instruments: Maximizing Profitability and Managing Risk in Financial Services*. Probus, Chicago.
- Collins, R.A., 1997. Towards A Positive Economic Theory of Hedging. *American Journal of Agricultural Economics* 79, 488-499.
- Cook, Th.D., Campbell, D.T., 1979. *Quasi-experimentation. Design and Analysis Issues for the Field Settings*. Rand McNally, Chicago.
- Cronbach, L.J., 1987. Statistical Tests for Moderate Variables: Flaws in Analysis Recently Proposed. *Psychological Bulletin* 102, 414-417.

- Davidson, R., MacKinnon, J.G., 1981. Several Tests for Model Specification in the Presence of Alternative Hypotheses. *Econometrica* 49, 781-793.
- Davidson, R., MacKinnon, J.G., 2002. Bootstrap *J* Tests of Nonnested Linear Regression Models. *Journal of Econometrics* 109, 167-193.
- DeSarbo, W.S., Cron, W.L., 1988. A Maximum Likelihood Methodology for Clusterwise Linear Regression. *Journal of Classification* 5, 249-282.
- Dholakia, R.R., Johnson, J.L., Della Bitta, A.J., Dholakia, N., 1993. Decision-making Time in Organizational Buying Behavior: An Investigation of its Antecedents. *Journal of the Academy of Marketing Science* 21, 281-292.
- Everitt, B.S., 1993. *Cluster Analysis*. Edward Arnold, London.
- Froot, K.A., Scharfstein, D.S., Stein, J.C., 1993. Risk Management: Coordinating Corporate Investment and Financing Policies. *Journal of Finance* 48, 1629-1658.
- Fryer, I.G., Robertson, C.A., 1972. A Comparison of Some Methods for Estimating Mixed Normal Distributions. *Biometrika* 59, 639-648.
- Géczy, C., Minton, B.A., Schrand, C., 1997. Why Firms Use Currency Derivatives. *Journal of Finance* 52, 1323-1354.
- Godfrey, L.G., 1998. Tests of Non-nested Regression Models: some Results on Small Sample Behaviour and the Bootstrap. *Journal of Econometrics* 84, 59-74.
- Gunther, J.W., Siems, Th.F., 1995. The Likelihood and Extent of Bank Participation in Derivatives Activities. *Financial Industry Studies Working paper No. 195*, Federal Reserve Bank of Dallas, Dallas.
- Hair, J.F., Anderson, R.E., Tanham, R.L., Black, W.C., 1995. *Multivariate Data Analysis*. Prentice Hall, Inc., Englewood Cliffs, NJ.

- Hasselblad, V., 1969. Estimation of Finite Mixtures of Distributions from the Exponential Family. *Journal of the American Statistical Association* 64, 1459-1471.
- Haushalter, G.D., 2000. Financing Policy, Basis Risk, and Corporate Hedging: Evidence from Oil and Gas Producers. *Journal of Finance* 55, 107-152.
- Heckman, J.J., 2001. Micro Data, Heterogeneity, and the Evaluation of Public Policy: Nobel Lecture. *Journal of Political Economy* 109, 673-748.
- Herrendorf, B., Valentinyi, A., Waldmann, R., 2000. Ruling Out Multiplicity and Indeterminacy: The Role of Heterogeneity. *Review of Economic Studies* 67, 295-307.
- Jaccard, J., Turrisi, R., Wan, C.K., 1990. *Interaction Effects in Multiple Regression*. Sage Publications, New York.
- Johnson, L.L., 1960. The Theory of Hedging and Speculation in Commodity Futures Markets. *Review of Economic Studies* 27, 139-151.
- Keeney, R.L., Raiffa, H., 1976. *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. Wiley, New York.
- McCloskey, D.N., Ziliak, S.T., 1996. The Standard Error of Regressions. *Journal of Economic Literature* 34, 97-114.
- McGuirk, A.M., Driscoll, P.J., 1995. The Hot Air in R<sup>2</sup> and Consistent Measures of Explained Variation. *American Journal of Agricultural Economics* 77, 319-328.
- Mian, S.L., 1996. Evidence on Corporate Hedging Policy. *Journal of Financial and Quantitative Analysis* 31, 419-439.
- Moriarty, R.T., Bateson, J.E.G., 1982. Exploring Complex Decision Making Units: A New Approach. *Journal of Marketing Research* 19, 182-191.

- Nance, D.R., Smith, Jr., C.W., Smithson, C.W., 1993. On the Determinants of Corporate Hedging. *Journal of Finance* 48, 267-284.
- Newcomb, S., 1886. A Generalized Theory of the Combination of Observation so as to Obtain the Best Result. *American Journal of Mathematics* 8, 343-366.
- Nunnally, J.C., Bernstein, I.H., 1994. *Psychometric Theory* (3rd. ed.). McGraw-Hill, New York.
- Pennings, J.M.E., Leuthold, R.M., 2000. The Role of Farmers' Behavioral Attitudes and Heterogeneity in Futures Contracts Usage. *American Journal of Agricultural Economics* 82, 908-919.
- Pennings, J.M.E., Smidts, A., 2000. Assessing the construct validity of risk attitude. *Management Science* 46, 1337-1348.
- Pennings, J.M.E., Garcia, P., 2001. Measuring Producers' Risk Preferences: A Global Risk Attitude Construct. *American Journal of Agricultural Economics* 83, 993-1009.
- Pennings, J.M.E., Garcia, P., 2004. Hedging Behavior in Small and Medium-sized Enterprises: The Role of Unobserved Heterogeneity. *Journal of Banking and Finance* 28, 951-978.
- Peter, J.P., 1981. Construct Validity: A Review of Basic Issues and Marketing Practices. *Journal of Marketing Research* 18, 133-145.
- Quandt, R.E., Ramsey, J.B., 1978. Estimating Mixtures of Normal Distributions and Switching Regressions. *Journal of the American Statistical Association* 73, 730-738.
- Redner, R.A., Walker, H.F., 1984. Mixture Densities, Maximum Likelihood and the EM Algorithm. *SIAM Review* 26, 195-239.
- Smidts, A., 1997. The Relationship Between Risk Attitude and Strength of Preference: A Test of Intrinsic Risk Attitude. *Management Science* 43, 357-370.
- Srivastava, M.S., 2002. *Methods in Multivariate Statistics*. Wiley, New York.

- Telser, L.G., 1981. Why There Are Organized Futures Markets. *Journal of Law and Economics* 24, 1-22.
- Titterton, D.M., 1990. Some Recent Research in the Analysis of Mixture Distributions. *Statistics* 21, 619-641.
- Tufano, P., 1996. Who Manages Risk? An Empirical Examination of Risk Management Practices in the Gold Mining Industry. *Journal of Finance* 51, 1097-1137.
- Tufano, P., 1998. The Determinants of Stock Price Exposure: Financial Engineering and the Gold Mining Industry. *Journal of Finance* 35, 1015-1052.
- Wedel, M., DeSarbo, W.S., 1995. A Mixture Likelihood Approach for Generalized Linear Models. *Journal of Classification* 12, 21-55.
- Wedel, M., Kamakura, W.A., 1998. *Market Segmentation: Conceptual and Methodological Foundations*. International Series in Quantitative Marketing. Kluwer Academic Publishers, Boston.
- Williams, J.C., 1986. *The Economic Function of Futures Markets*. Cambridge University Press, Cambridge.
- Working, H., 1953. Hedging reconsidered. *Journal of Farm Economics* 35, 544-561.

Table 1

Sample Descriptive Statistics of Market participants in Sample ( $N=415$ )

	Processors ( $n = 30$ )	Wholesalers ( $n = 50$ )	Producers ( $n = 335$ )
Average number of employees <sup>a</sup>	60	7	3
Average sales <sup>b</sup>	\$8,100,000	\$925,000	\$185,000
Ownership structure <sup>c</sup>			
Private	0.0%	10.0%	89.9%
Private limited	23.3%	88.0%	10.1%
Public traded	76.7%	2.0%	0.0%
Leverage <sup>d</sup>	60.8%	45.6%	40.5%
Risk exposure <sup>e</sup>	50.1	80.8	30.2

<sup>a</sup> Measured in full-time equivalents.

<sup>b</sup> Average sales based on 1997 fiscal year.

<sup>c</sup> In the Netherlands, three broad ownership structures can be distinguished: private companies in which the owner carries personally the risk of the company; private-limited companies in which there are shareholders but the shares are not traded publicly; and publicly-traded companies whose shares are publicly traded.

<sup>d</sup> debt-to-asset ratio.

<sup>e</sup> Risk exposure is measured by the market participant's annual number of market transactions in the cash market to sell (buy) its output (input).

Table 2

Factors Influencing Hedging Behavior: Assuming Homogeneous Behavior ( $N = 415$ )

	Standardized Regression Coefficients ( $\beta$ 's)
Risk Exposure <sup>a</sup>	0.160
Size of firm	-0.080
Leverage	0.029
Risk Attitude (RA)	0.158
Risk Perception (RP)	0.122**
Interaction (RP*RA) <sup>b</sup>	-0.121
Level of Education	0.440
DMU	0.382**
Fit Statistics	$R^2 = 0.172$ $F=10.557$ ; $df\ 8$ ( $p=0.000$ )
Average hedge ratio	0.17

<sup>a</sup>Risk exposure decreases as the number of market transactions increases, hence we hypothesize a negative sign.

<sup>b</sup>The risk perception and risk attitude variables were centered prior to forming the multiplicative term (Cronbach, 1987; Jaccard et al., 1990).

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

Table 3

## Factors Influencing Hedging Behavior: Grouping Based on Company Type

	Processors ( <i>n</i> = 30)	Wholesalers ( <i>n</i> = 50)	Producers ( <i>n</i> = 335)
Standardized regression coefficients ( $\beta$ 's)			
Risk Exposure <sup>a</sup>	-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) <sup>b</sup>	-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 <sup>2</sup> =0.335 <i>F</i> =1.934; <i>df</i> 7 ( <i>p</i> =0.108)	R <sup>2</sup> =0.091 <i>F</i> =0.591; <i>df</i> 7 ( <i>p</i> =0.779)	R <sup>2</sup> = 0.094 <i>F</i> =4.467 <i>df</i> 7 ( <i>p</i> =0.000)
Average hedge ratio	0.59	0.37	0.10

<sup>a</sup>Risk exposure decreases as the number of market transactions increases, hence we hypothesize a negative sign.

<sup>b</sup>The risk perception and risk attitude variables were centered prior to forming the multiplicative term (Cronbach, 1987; Jaccard et al., 1990).

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

Table 4

## Factors Influencing Hedging Behavior: Grouping Based on Cluster Analysis

	Cluster 1 ("low users") ( <i>n</i> = 237)	Cluster 2 ("medium users") ( <i>n</i> = 121)	Cluster 3 ("high users") ( <i>n</i> = 57)
	Standardized regression coefficients ( $\beta$ 's)		
Risk Exposure <sup>a</sup>	-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) <sup>b</sup>	-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% ( <i>n</i> = 237)	29.15% ( <i>n</i> =121)	13.73% ( <i>n</i> = 57)
Fit Statistics	$R^2=0.07$ $F=2.039$ ; $df\ 7$ ( $p=0.042$ )	$R^2=0.08$ $F=1.426$ ; $df\ 7$ ( $p=0.193$ )	$R^2=0.327$ $F=3.400$ ; $df\ 7$ ( $p=0.004$ )
Average hedge ratio	0.11	0.22	0.30

<sup>a</sup>Risk exposure decreases as the number of market transactions increases, hence we hypothesize a negative sign.

<sup>b</sup>The risk perception and risk attitude variables were centered prior to forming the multiplicative term (Cronbach, 1987; Jaccard et al., 1990).

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

Table 5

Statistics of the Mixture Models for the Groups,  $G = 1$  to  $G = 5$ 

Segment $G$	Log Likelihood	CAIC*	$E_s$	$R^2$
1	-549	1161	1.00	0.172
2	-498	1131	0.47	0.438
3	-458	1121	0.78	0.541
4	-472	1218	0.43	0.473
5	-446	1237	0.54	0.529

\*CAIC is the Consistent Akaike's Information Criterion and is used to determine the optimal number of groups. This criterion imposes a penalty on the likelihood that is related to the number of parameters estimated.  $E_g$  is the entropy statistic which is 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 posteriors probabilities of the market participants belonging to specific groups are close to either 0 or 1; the segments are well defined. The CAIC was minimized for three groups, indicating that the sample consisted of three groups.

Table 6

## Factors Influencing Hedging Behavior: Mixture Model Results

	Standardized regression coefficients ( $\beta$ 's)		
	$g = 1$ ( $n = 183$ )	$g = 2$ ( $n = 124$ )	$g = 3$ ( $n = 108$ )
Risk Exposure <sup>a</sup>	-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) <sup>b</sup>	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 $\pi$	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

<sup>a</sup>Risk exposure decreases as the number of market transactions increases, hence the negative sign.

<sup>b</sup>The risk perception and risk attitude variables were centered prior to forming the multiplicative term (Cronbach, 1987; Jaccard et al., 1990).

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

Table 7

Relating the Mixture Model Groups, with the Groups Obtained in the CTG and CA

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

Table 8

Overall Fit of the Three Grouping Methods (Equation (8)) and Results of  $J$ -test (Equation (9))

Grouping Methods	$R^2$	AIC	BIC	Standardized Regression Coefficient $\gamma$ (Equation (9)) from the Pair-Wise $J$ -Test		
				$\hat{H}R$ CTG	$\hat{H}R$ CA	$\hat{H}R$ Mixture
CTG	0.20	10.26	10.53		0.041 ( $p = 0.306$ )	0.791 ( $p = 0.00$ )
CA	0.74	9.16	9.42	0.061 ( $p = 0.37$ )		0.288 ( $p = 0.00$ )
Mixture	0.91	8.05	8.31	0.060 ( $p = 0.37$ )	0.040 ( $p = 0.311$ )	