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Hedging behavior in small and medium-sized enterprises: The role of unobserved heterogeneity

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Abstract

We investigate factors that drive derivative usage in small and medium-sized enterprises (SMEs). The influence of these factors on hedging behavior cannot a priori be assumed equal for all SMEs. To address this heterogeneity, a generalized mixture regression model is used which classifies firms into segments, so that the hedging response to the determinants of derivative usage is the same within each segment. Using a unique data set of 415 SMEs, containing both accounting and experimental data, we find that factors like risk exposure, risk perception, risk attitude, and the decision-making unit, among others are useful in explaining hedging behavior. However, the effects of these factors are not homogeneous across all managers, and the roots of the heterogeneity can partially be traced to differences in attitudes, perceptions, and to differences in ownership structure.

JEL classification: C1; G0
Keywords: Derivatives usage; Hedging behavior; Unobserved heterogeneity

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1. Introduction

Financial derivatives, such as futures and options, provide managers with tools to manage price risk. Derivative exchanges and financial institutions facilitate the exchange of these instruments through over-the-counter trading. Recently, the competition among financial institutions that provide these services has increased, leading to customized financial products which fulfill user needs better. Accordingly, the interest of financial institutions in identifying the motivation behind the derivative usage of different groups of (potential) users has increased (e.g., Fridson, 1992; Angel et al., 1997; Nesbitt and Reynolds, 1997).

Froot et al. (1993), Nance et al. (1993), Mian (1996), Tufano (1996), Géczy et al. (1997), Lee and Hoyt (1997), and Koski and Pontiff (1999) among others have conducted research on the determinants of derivative use. In these studies, large, often publicly traded companies have been examined. Here, we expand the literature by studying the derivative usage of managers of small and medium-sized enterprises (SMEs). SMEs do not have different departments, nor do they have separate organizational structures to administer functions such as research and development, quality control, sales, and accounting. The management of these functions rests on one single manager. Moreover, the ownership of SMEs is often concentrated. In such a structure, a manager's risk aversion can provide an important motivation to manage risk (Mayers and Smith, 1982; Smith, 1995). The wealth of the manager often is directly affected by the variance of the SME's expected profit, constituting an (extra) motivation to consider hedging (Smith and Stulz, 1985). [1] SMEs also differ from large corporations in their capital structure, as bondholders are relatively scarce. Avery and Bostic (1998) and Berger and Udell (1998) show that private equity, bank loans, and personal commitments dominate the capital structure of SMEs. These differences motivate the importance of considering the manager's, along with the firm's, characteristics in the investigation of the determinants of derivative usage.

We also build on previous work, by incorporating the notion that the motivations of enterprises to use derivatives as a hedging tool may not be homogenous. Firms from different regions or of different organizational structures may face dissimilar economic constraints and conditions that might lead to a different choice of derivatives. Similarly, managers may possess dissimilar objectives and motivations that can also result in different derivative decisions. This could be particularly relevant for SMEs, as they show a wide variety of organizational structures. Furthermore, managers of SMEs may have different risk attitudes and risk perceptions, suggesting that these firms may behave differently (e.g., Pennings and Smidts, 2000). Consequently, we may expect the factors that influence a firm's choice of financial instrument to vary across segments of an industry, and common factors to influence firms differ-

[1] This is consistent with the notion that firms whose portfolios are poorly diversified have a stronger incentive to hedge (Smith, 1995).

ently. Clearly, this heterogeneity impacts the efforts of financial institutions in developing appropriate derivatives, particularly for customized products.

Here, we model the effects of "unobserved heterogeneity" on the determinants of firms' derivative usage. The term unobserved heterogeneity posits two interrelated ideas that are central to the empirical procedure we employ. The first notion is that not all managers respond similarly to a given change in the determinants of derivative use, but instead that segments of managers who behave in a similar manner may exist. The second notion is that these segments are not directly observable prior to the analysis. Rather, they are determined by grouping together managers who reveal a similar relationship between the determinants of derivative use and their hedging behavior. In this context, we present a generalized linear mixture model that simultaneously investigates the relationship between managers' derivative usage and a set of explanatory variables for each identified segment in the sample. We demonstrate how managers behave differently regarding derivative usage, and show the importance for financial institutions to develop an understanding of their customers.

We focus exclusively on derivative usage for reducing price risk when buying inputs and selling outputs, and thus do not consider hedging motivated by risky investment projects. Our empirical investigation is in the raw food industry, and, as such, derivative use refers to *commodity* derivative usage. We pay special attention to the fundamental motivation behind derivative usage as a hedging tool: risk attitude, risk perception and their interaction. Although these factors are recognized in theory as being crucial in motivating and explaining derivative usage, to date risk attitudes and risk perceptions rarely appear in empirical studies of derivative usage. Their absence can primarily be explained by two reasons. First, most studies focus on large corporations, rather than on their managers, thus concentrating on firm characteristics. Second, risk attitudes and risk perceptions are not directly observable and cannot be obtained from accounting data. Measuring these concepts in a realistic and accurate manner is a difficult task. Here, we measure risk attitudes of 415 SMEs in a relevant economic business setting using computer-guided interviews and an experimental design based on the expected utility model.

This paper is organized as follows: Section 2 provides an overview of the determinants that are hypothesized to influence the derivative usage of SMEs. Section 3 discusses the heterogeneity in the relationship between the determinants of derivative usage and hedging behavior, followed in Section 4 by the statistical specification of the generalized-mixture model that is able to empirically identify this type of heterogeneity. Section 5 describes the sample and the measurements, in particular the elicitation of the manager's global risk attitude. Section 6 presents the empirical results. A discussion of the findings follows in Section 7.

2. The determinants of SMEs derivative hedging usage

First, we provide background information on the decision context of SMEs operating in a commodity marketing channel. In particular, we elaborate on the Dutch pork industry, our empirical domain. Subsequently, we discuss the factors that drive derivative usage in this decision context.

2.1. Decision context

Previous studies have focused on the derivative usage of large corporations (e.g., Tufano, 1996; Géczy et al., 1997; Koski and Pontiff, 1999; Rogers, 2002). In these studies the risk-management behavior of CEOs is explained by various factors, among others firm size, CEO risk-taking incentives, tax schedules, and financial distress costs. Here we study hedging behavior of SMEs operating in the same commodity marketing channel. This decision context differs from that of large companies, and factors not considered for large companies, such as education level of the manager(s) of the SME, and the influence of the SME's decision-making unit, might be relevant for SMEs. In addition, the psychological concepts of manager's risk attitudes and risk perceptions may be particularly relevant for SMEs. In this paper, we study derivative usage for companies in the Dutch pork marketing channel. This marketing channel consists of producers (hog farmers), wholesalers (companies that trade live hogs), and processors (slaughterhouses and meat packers). This type of marketing channel exists for a wide variety of commodities, such as soybeans, wheat, beef and cotton. The companies in commodity marketing channels, especially the producers and wholesalers, are relatively small. For example, the average sales of the Dutch hog producers in our sample was $185,000 in fiscal year 1997 (see Table 1). Most producers and wholesalers are family owned, with the manager often the owner. Processors are more diverse, but are generally larger than producers and wholesalers, and consist of private-limited companies, as well as sometimes publicly traded com-

Table 1
Sample descriptive statistics of SMEs ($N = 415$)

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

[a] Measured in full-time equivalents.

[b] Average sales based on 1997 fiscal year.

[c] 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.

[d] Debt-to-asset ratio.

[e] Risk exposure is measured by the SME's annual number of market transactions in the cash market to sell (buy) its output (input).

panies (see Table 1). The production process is relatively straightforward in these commodity channels. In the Dutch pork marketing channel, producers raise piglets to hogs which are sold to the wholesalers, who then sell them to the processor. The majority of these transactions are spot market transactions; cash-forward contracts are rare. This commodity marketing channel reflects the decision context of the early work done on hedging behavior (e.g., Blau, 1944; Johnson, 1960; Working, 1962).

Companies in a commodity marketing channel are exposed to the spot price risk of the commodity. With a coefficient of variation (CV) of 0.19, the Dutch hog prices fluctuate widely (based on daily observations over the period 1990–1997), even compared to the prices of US soybeans (CV 0.14), which is generally considered to be a risky commodity. The ex ante risk exposure of these firms is determined by hog price fluctuations and the number of times that they enter the spot market. Wholesalers and processors enter the hog spot market on a weekly or sometimes daily basis, in contrast to hog producers, who, depending on the production system employed, may enter the spot market as few as four times a year (since piglets are raised to slaughter hogs in three to four months) (see Table 1). At present, there is only one risk management tool available: the hog futures contract traded at Euronext (the result of a merger of the exchanges in Amsterdam, Brussels, London, and Paris) and the pork belly futures contract traded at the Chicago Mercantile Exchange.

Several factors have been identified to explain why firms use derivatives as a hedging tool. The combined work of Froot et al. (1993), Nance et al. (1993), Mian (1996), Tufano (1996, 1998), Géczy et al. (1997), Lee and Hoyt (1997), Koski and Pontiff (1999) and recently Graham and Rogers (2002), and Rogers (2002) among others provide a discussion of these factors. This paper provides a brief overview of the primary determinants of derivative usage relevant for the empirical decision context (commodity marketing channel of SMEs), concentrating on the use of (commodity) derivatives as a means to reduce SMEs' input and output price risk. Particular attention is given to the "fundamental determinants" behind risk management and the use of derivatives: risk attitude and risk perception. While previous studies have accounted for managerial risk aversion indirectly, by measuring risk aversion through proxies like officers' and director share ownership (Tufano, 1996), we focus on managers' risk attitudes, explicitly recognizing that risk attitude is a psychological concept. We hypothesize that the risk-attitude concept is particularly important for managers of SMEs (e.g., Pennings and Smidts, 2000). We first discuss the influence of the manager's risk attitude and risk perception on derivative use, as well as the manager's education level, followed by the characteristics of the firm.

2.2. *Managers' characteristics influencing derivative usage*

Risk aversion has been a key element in understanding hedging behavior. Marshall (1919), Keynes (1930), Hicks (1939), and Kaldor (1939) in the first part of the previous century, argued that hedging was motivated by risk aversion. Using normative models, various authors have shown that the hedge ratio is determined by the decision-maker's risk attitude (Ederington, 1979). The well-known mean–variance models illustrate this relation between risk attitude and hedging behavior (Levy and Markowitz, 1979). Hence, we expect *risk attitude* (RA) to be an important determinant of an SME's hedging behavior. Risk aversion refers to a preference for a guaranteed outcome over a probabilistic one of equal value; risk-taking implies the opposite. Risk-averse managers are willing to take risks, but must be compensated for assuming the risk. Risk-seeking managers will engage in risky (speculative) behavior or seek out ways to increase their risk. When managers are risk-neutral they will not engage in any risk management. Recently Tufano (1996) has found that managerial risk aversion affects corporate risk management policy in the North American gold-mining industry. We hypothesize a positive relationship between risk aversion and the use of derivatives.

Risk must first be perceived, before a manager is able to respond. *Risk perception* (RP) may be defined as a manager's assessment of the risk inherent in a situation. While a market might be considered turbulent by economic standards, the level of risk it presents depends on the manager's risk perception. A manager who can predict the market price will perceive the market as less risky, and take fewer steps to reduce risk. We hypothesize a positive relationship between risk perception and the use of derivatives.

Only when managers of SMEs perceive risk and are risk averse will they show risk management behavior. In a hedging context, risk-seeking managers who perceive risk, and risk-neutral managers will not engage in derivative usage. Moreover, when managers perceive no risk, risk attitude will have no influence on behavior. Thus risk perception is linked to actual behavior by means of the manager's risk attitude. The effect of risk attitude on derivative usage will be larger the more (less) risk the risk-averse (risk-seeking) manager perceives. Consequently, we hypothesize the *interaction between risk perception and risk attitude* ($RP * RA$) to be a primary determinant of derivative use (Pennings and Wansink, in press).

Managers of SMEs often perceive derivatives as providing a complex financial service, which restricts participation in derivative trading (Glaum and Belk, 1992). Costs associated with using derivatives include information gathering and the efficiency of their adoption. The level of *education* (EDU) is related inversely to the cost of information gathering and efficiency of using derivatives, as it increases the ability of the manager to assimilate new ideas and analyze changing situations. We hypothesize the level of education to be positively related to the manager's use of derivatives.

2.3. Firm characteristics influencing derivative usage

Related to risk perception but conceptually different is the notion of ex ante risk exposure. When a firm trades daily in a risky market its ex ante *risk exposure* (RE) will be smaller than that of a firm that enters the market on a monthly basis, although both firms might perceive the market as equally risky. Several researchers have empirically identified the relationship between the degree of risk exposure and use of derivatives. Géczy et al. (1997) in a study of currency derivatives find that firms with extensive foreign exchange-rate exposure are more likely to use currency derivatives. Carter and Sinkey (1998), in a study of interest-rate derivatives by US commercial banks, find that the use of derivatives is positively related to interest-rate risk exposure, as measured by the absolute value of the 12-month maturity gap. [2] We hypothesize a positive relationship between risk exposure and the use of derivatives.

The expected costs of a *firm's financial distress* increase with an increased probability of the firm's insolvency. A firm with a higher probability of insolvency would benefit from a decrease in the variance of the firm's value. Therefore highly leveraged (LEV) firms with a high debt-to-asset ratio are more likely to use derivatives to reduce risk than less leveraged firms. Turvey and Baker (1990) and Nance et al. (1993) identified this relationship between leverage and derivative usage. Hentschel and Kothari (2001), and more recently Graham and Rogers (2002), show strong evidence of the association between leverage and derivative use. We hypothesize a positive relationship between leverage and the use of derivatives.

Another important factor that influences derivative use is the *size of the firm* (SF). Larger firms are believed to participate in derivatives more actively because of informational economies and economies of scale. Moreover, larger firms are more likely to have the necessary resources and potential trading volume to warrant the use of derivatives (Nance et al., 1993). Géczy et al. (1997) argue that firms with the greatest economies of scale in implementing and maintaining a risk-management program are more likely to use (currency) derivatives. Mian (1996) and Carter and Sinkey (1998) find evidence for a positive relationship between a firm's decision to participate in derivative contracts and its size. Furthermore, Block and Gallagher (1986) determine for general corporations that informational economies or economies of scale are positively related to derivative use. [3] We hypothesize a positive relationship between firm size and the use of derivatives.

Finance theory identifies that *taxes* may provide an incentive to hedge, when firms are faced with a convex tax function, as hedging lowers expected tax liabilities (Graham and Smith, 1999). However, empirical evidence is mixed: while Nance et al. (1993) found that hedging firms face more convex tax functions, Shanker (2000) found no relationship between hedging behavior and tax schedules. While we may expect tax schedules to influence derivatives usage, our empirical study does not include taxes, because the managers in the sample face a flat tax schedule.

The literature in organizational behavior and decision sciences has shown a significant impact of the people surrounding the decision-maker on the decisions made (e.g., Moriarty and Bateson, 1982). This is particularly true for SMEs. While the manager is the primary decision-maker, the decision to use derivatives is often influenced by advisors, employees, and other important people (e.g., bankers). These people form the *SME's decision-making unit* (DMU). Recent findings suggest that the DMU has a significant effect on firms making major decisions (Dholakia et al.,

[2] In a related context, Schrand and Unal (1998) provide an explanation for hedging as a means of allocating rather than reducing risk. They argue that firms optimally allocate risk when increases in total risk are costly, by reducing (increasing) exposure to risks that provide zero (positive) economic rents.

[3] Arguments also have been formulated for a negative relationship between firm size and hedging activity (Nance et al., 1993). However, the weight of the evidence is most consistent with the discussion in the text.

1993). Various members of the SME may be involved in the SMEs' decisions. The SMEs' employees, particularly those responsible for financial decisions, and those who experience directly or indirectly the consequences of using derivatives, may be motivated to become involved in the decision about the extent of derivative usage. [4] Individuals external to the SME may also influence the decision to use derivatives. SMEs use advisors, such as consultants or bank account managers, to optimize their decisions regarding the use of derivatives. We hypothesize that the opinion of these individuals influences the SME's use of derivatives.

3. Heterogeneity of derivative users

When analyzing behavior, the assumption of homogeneity of decision makers has often been rejected. The assumption that all observations can be characterized by a single model is convenient, but may mask critical relationships. Recently Pennings and Leuthold (2000) have found that heterogeneity may mask important effects at the aggregate level, when studying farmers' hedging behavior. Factors that play an important role in derivative usage for some managers may be inconsequential for others. This may especially be relevant in the case of SMEs which show a wide variety in organizational structures. The role of risk attitudes and risk perceptions may also vary widely among SMEs. While economic theory suggests that risk attitude and risk perception are important concepts in understanding hedging behavior (Holthausen, 1979; Rolfo, 1980), recent empirical work has raised questions about the relationship between managerial risk aversion and hedging behavior (Haushalter, 2000). One might hypothesize that risk attitudes and risk perceptions are not equally important factors in managers' hedging behavior.

Previous research has accounted for heterogeneity by using observable variables like firm size or company type to segment the total population. This procedure implicitly assumes that firms of, for instance, the same company type will respond similarly to changes in the determinants of derivative use. However, this may not be the case, particularly for SMEs, where many of the factors reflect the managers' attitudes and perceptions, and where a priori classifications may not account for the wide variability in management activities and the mix of organizational structures. We use a generalized mixture model to reflect the heterogeneity in the sample. The generalized mixture model simultaneously classifies firms in the sample into segments on the basis of the relationship between hedging behavior and the determinants of derivative usage, and estimates the influence of the determinants on hedging practices for each segment identified. The classification of the firms is based on whether firms *respond to* the determinants of derivative use in a similar manner. For firms within a segment, the *influence* of these determinants on hedging behavior is the same, and the actual derivative use of a firm is dependent on the

[4] We do not study the decision-making process within a DMU, rather we are interested in the effect that members of the DMU have on the manager's decision to use derivatives.

level of the determinants. For example, ceteris paribus, firms with a similar relationship between their debt-to-asset ratio and hedging practices are classified together, regardless of their size or whether they are a processor, wholesaler, or producer. In a predictive sense the exact effect of the firm's debt-to-asset ratio on hedging practices will then be determined by the leverage of the firm. The procedure emphasizes the role of theory in the empirical analysis, as the determinants of derivative usage are used both to explain hedging practices and to discriminate among groups of firms. This is a fundamentally different approach from previous studies dealing with heterogeneity, where segments were determined a priori, based on a single observable variable.

From a conceptual perspective, the procedure permits the determinants of derivative usage to have a different influence on actual hedging practices for each segment identified. A challenging dimension of using this procedure is to assess why managers in a particular segment might respond differently to managers in other segments. For factors such as risk attitude and risk perception, which are the underlying drivers of hedging practices, managers with similar predispositions and perceptions may be grouped together as they respond ceteris paribus in a similar manner to hedging opportunities. The heterogeneity across the segments may also be influenced by the manager's perception of the effectiveness of the hedging instrument, its ease of use, and hence its implicit costs. Other economic factors, marketing practices, and organizational structure as well may influence why managers respond differently across groups and must be determined using knowledge of marketing practices and the structure of the industry.

4. Statistical model

Our procedure is a generalized mixture model. In mixture models it is assumed that a sample of observations arises from a specified number of underlying populations of unknown proportions. A specific form of the density of the observations in each of the underlying populations is specified, and the mixture approach decomposes the sample into its components. [5] Recently, 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) segments. DeSarbo and Cron (1988) propose a conditional mixture model that enables the estimation of separate regression functions and corresponding membership in a number of segments using maximum likelihood. We use a generalized linear regression mixture model, first formulated by Wedel and DeSarbo (1995). This approach allows us to simultaneously estimate the probabilistic classification of the SMEs by their

[5] The development of mixture models dates back to Newcomb (1886) and Pearson (1894). For a detailed review on mixture models, see Everitt and Hand (1981), Titterington et al. (1985), Langeheine and Rost (1988), McLachlan and Basford (1988), and Wedel and Kamakura (1998).

derivative use, and to explain derivative use by a set of explanatory variables in each segment. [6]

Assume that the measures on derivative usage are indexed by $k = 1, \ldots, K$ for $j = 1, \ldots, J$ SMEs. The measurements are denoted by y_{jk}. We assume that the SMEs come from a population that is composed of a mixture of S unobserved segments, with relative sizes $\pi_1, \ldots, \pi_S$ and that $\pi_s > 0$ and $\sum_{s=1}^{S} \pi = 1$. The distribution of y_{jk}, given that the SME j comes from segment s, is from the exponential family of distributions and is denoted as $f_{jk\backslash s}(y_{jk})$. [7] Given segment s the expectation of the y_{jk} is denoted as ϑ_{sjk}. Within segments, these expectations are modeled as a function of our set of P ($p = 1, \ldots, P$) explanatory variables and the parameter vector β_{ps} in segment s:

$$g(\vartheta_{sjk}) = \sum_{p=1}^{P} x_{jkp}\beta_{ps}, \tag{1}$$

where $g(\cdot)$ is the link function, which links the expectations of the measurements to the explanatory variables. Within each identified segment the β_{ps} are the same. However across segments they are dissimilar. Since our dependent variable consists of counts of the number of derivatives used, we use a Poisson mixture regression model (e.g., Böckenholt, 1999; Gurmu et al., 1999). For the Poisson mixture, the conditional probability function of y_{jk}, given that y_{jk} comes from segment s, is

$$f_{jk|s}(y_{sk}|\vartheta_{sjk}) = \exp[y_{jk}\vartheta_{sjk} - \exp(\vartheta_{sjk}) - \log(y_{sk})] \tag{2}$$

with the link function $g(\cdot) = \log(\cdot)$. Because we use a single measure in our empirical study to measure derivative usage, $K = 1$.

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

$$f_j(y_{jk}|\Phi) = \sum_{s=1}^{S} \pi_s f_{j|s}(y_{jk}|\beta_s), \tag{3}$$

and the likelihood for Φ is

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

where y_j is the observation vector y of SME j and π_s is the relative segment size.

An estimate of Φ, the set of parameters that identifies the segments to which the SMEs belong, and the regression functions within segments, is obtained by maximizing the likelihood of (4) with respect to Φ subject to $\pi_s > 0$ and $\sum_{s=1}^{S} \pi_s = 1$.

The parameters of the mixture model can be estimated using the method of moments or maximum likelihood (Basford and Mclachlan, 1985; Hasselblad, 1969;

[6] In an econometric sense, each segment has a different structure (i.e., a different set of coefficients that reflects the relationship between the dependent and the independent variables) which is estimated with the observations that have the highest probability of conforming to that structure.

[7] The exponential family includes the Normal, Binomial, Poisson, and Gamma distributions.

Quandt and Ramsey, 1978). 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; Titterington, 1990).

The EM algorithm is based on the notion that the likelihood function contains missing observations, i.e., the 0/1 membership of subjects in the s segments. If these were known, maximization of the likelihood would be straightforward. Based on a multinomial distribution for segment membership, the expectation of the likelihood can be formulated. This involves calculating the posterior membership probabilities according to Bayes rule and the current parameter estimates of Φ and substituting them into the likelihood. Once this is accomplished, the likelihood can be maximized.

To derive the EM algorithm, we introduce non-observed data, z_{sj}, indicating if SME j belongs to latent segment s: $z_{sj} = 1$ if j comes from segment s, and $z_{sj} = 0$ otherwise. It assumed that z_{sj} are i.i.d. multinomial:

$$f(z_j|\pi) = \sum_{s=1}^{S} \pi_s^{\pi_{sj}}, \tag{5}$$

where the vector $z_j = (z_{sj}, \ldots, z_{Sj})'$. We denote the matrix $(z_1, \ldots, z_j)'$ by $\mathbf{Z}$ and the matrix of explanatory variables $(X_1, \ldots, X_p)$ by $\mathbf{X}$. We assume that y_{jk} given z_j are conditionally independent, and that y_{jk} given z_j has the density

$$f(y_{jk}|z_j) = \sum_{s=1}^{S} f_{jk|s}(y_{jk}|\beta_s)^{z_{sj}}. \tag{6}$$

With z_{sj} considered as missing data, the log-likelihood function for the complete $\mathbf{X}$ and $\mathbf{Z}$ can be formulated now as

$$\ln L_c(\Phi; y, Z) = \sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{s=1}^{S} z_{sj} \ln f_{jk|s}(y_{jk}|\beta_s) + \sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{s=1}^{S} z_{sj} \ln \pi_s. \tag{7}$$

This complete log-likelihood is maximized using the iterative EM algorithm. In the E step the log-likelihood is replaced by its expectation, calculated on the basis of provisional estimates of Φ. In the M step, the expectation of $\ln L_c$ is maximized with respect to Φ to obtain new provisional estimates. The E and M steps are alternated until convergence (a detailed description of this procedure is given by Wedel and Kamakura, 1998).

The actual number of segments is unknown and must be inferred from the model. We use Bozdogan's (1987) consistent Akaike's information criteria (CAIC) to determine the number of segments. The CAIC is defined as

$$\mathrm{CAIC} = -2 \ln L + (P \cdot S + S - 1)(\ln(J) + 1). \tag{8}$$

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

For any set of segments, an Entropy statistic, E_s, can be calculated to assess whether the segments are well separated or defined. E_s is defined as

$$E_s = 1 - \sum_{j=1}^{J} \sum_{s=1}^{S} -\alpha_{js} \ln \alpha_{js}/J, \tag{9}$$

where α_{sj} is the posterior probability that SME j comes from latent segment s. The posterior probability can be calculated for each observation vector y_j with an estimate of Φ (e.g., Eq. (4)) by means of Bayes' Theorem and is given by

$$\alpha_{sj}(y_j, \Phi) = \frac{\pi_s \prod_{k=1}^{K} f_{jk|s}(y_{jk}|\beta_s)}{\sum_{s=1}^{S} \pi_s \prod_{k=1}^{K} f_{jk|s}(y_{jk}|\beta_s)}. \tag{10}$$

The entropy statistic E_s in (9) is a relative measure, bounded between 0 and 1, and describes the degree of separation in the estimated posterior probabilities. E_s values close to 1 indicate that the posterior probabilities of the respondents belonging to specific segments are close to either 0 or 1; the segments are well defined. [8] E_s values close to 0 indicate that the segments are not well defined.

The estimated parameters in our model are distributed asymptotically normal (DeSarbo and Cron, 1988), and Φ is identifiable. Titterington et al. (1985) have shown that mixtures of distributions in the exponential family are generally identified. An exception occurs when there is a high degree of collinearity in the **X** matrix of the explanatory variables. In this study, we assessed collinearity by investigating the squared multiple correlations coefficient, R_x^2 between x_x and the other set of P explanatory variables. Using Klein's rule, we found that $R_y^2 > R_x^2$ where R_y^2 is the squared multiple correlation between y and the explanatory variables (Klein, 1962), thereby indicating that the assumption of limited collinearity is tenable. Another potential problem associated with the application of the EM algorithm to mixture models is its convergence to local maximum. To overcome this problem we started the algorithm from a wide range of starting values, as suggested by McLachlan and Basford (1988).

We apply the mixture model outlined above to experimental and accounting data gathered from the Dutch hog industry to identify the determinants of hedging behavior for our SME sample.

5. Methods

5.1. Sample and data collection procedure

The Dutch pork industry is among the largest exporters in the European Union and accounts for an important part of Dutch exports. Wholesalers assemble hogs

[8] In the case where only one segment is used, E_s is trivially 1.

from hog farms and then sell them to meat processors, slaughterhouses that prepare and pack the meat. In contrast to markets for other food products, the pork market in the European Union is free from government intervention. The Dutch hog industry consists of about 20,000 producers, 150 hog wholesalers and 65 processors. A sample was randomly drawn from directories kept by the Dutch Agricultural Association of hog farms, the Dutch Union of Livestock Wholesalers, and the Dutch Pork Association of processors.

A total of 335 producers, 50 wholesalers and 30 processors were interviewed. A personal computer-guided interview was developed and 30 test interviews were conducted to ensure that the questions were interpreted correctly. The interviews took place at the manager's enterprises and were conducted during the first half of 1998. The managers worked through several assignments and questions, and the interviews lasted about 35 minutes. We also obtained accounting data from these 415 firms for the fiscal year 1997, and hence were in a position to combine accounting data with survey data. Table 1 provides some insight into the size of the companies, leverage, ownership structure, risk exposure, number of contracts, corresponding notional value, and education level of the managers.

5.2. Measures

5.2.1. Dependent variable

The use of derivatives. Because we have accounting and survey data, we are able to distinguish between derivative use for speculative and for risk management reasons. Our measure exclusively reflects derivative usage in a hedging context. [9] The use of derivatives was based on past market activity, and reflects the number of contracts traded in the period 1995–1997. The number of contracts was determined by dividing the underlying value of a firm's traded contracts by an average hog contract value from Euronext for the three-year period. [10] The use of the number of contracts traded to reflect involvement in derivative markets differs from Chorafas and Steinmann (1994) and Gunther and Siems (1995) who use the underlying value of the derivatives. Our decision to use the number of contracts is based on a desire to reflect the structure of our SME sample, where a considerable portion of our firms do not participate in derivative activities. [11] The use of count data with the Poisson distribution more clearly reflects this discrete notion of the probability distribution. [12]

[9] We only took positions into account that could be characterized as a hedging activity. For example, a producer who is long in pork belly futures is not hedging. These positions were not included in our measure.

[10] While some export firms may trade pork belly futures on the Chicago Mercantile Exchange, the Euronext hog contract is the predominant derivative used in the Dutch hog industry.

[11] Risk can be managed by various instruments or marketing strategies. Because of data limitations we were unable to consider non-derivative hedges and natural hedges (e.g., Pennings and Leuthold, 2001).

[12] The subsequent analysis was also performed with the underlying value of the derivatives as the dependent variable. The robustness of the results was reassuring. While the measures of goodness of fit are somewhat smaller using the underlying value of the contracts, the estimates of the coefficients differ only modestly, and the qualitative implications are identical to those reported in the text.

5.2.2. Independent variables

Risk attitude. Individual risk attitude is a psychological construct that is not easily measured directly in a reliable and valid way. Individuals may have different incentives, and risk aversion may lead to different outcomes, depending upon the characteristics of the decision maker and the environment. Here, we develop a risk-attitude measure (based on the volatility in spot prices that is common to all managers in the industry) that is an input in the risk-management process (i.e., the hedging decision).

Various authors using indirect measures of risk attitude have found that risk-taking behavior is influenced by a manager's compensation structure (e.g., Lypny, 1993; Rogers, 2002). In this study, consistent with the literature for developing direct measures of risk attitude, the effect of the compensation structure is reflected in our risk-attitude measure. As shown by March and Shapira (1987), a key aspect of direct risk-attitude measurement is that it is context specific, and influenced by significant factors in an environment. In terms of SMEs' derivative use, the compensation structure is an important factor influencing a manager's willingness to accept certain levels of risk and return. Since we measure the manager's risk in experiments that closely reflect their daily work environment, our risk-attitude measures incorporate the effect of compensation structure and the manager's own risk attitude. We call this concept *global risk attitude*, as opposed to manager's own intrinsic risk attitudes, because it is a composite of the manager's intrinsic risk attitudes and risk-taking incentives.

Following Pennings and Smidts (2000), we measure the utility functions of managers in a way consistent with the decision-makers' daily decision-making behavior (e.g., trading in meat markets). Below, we describe in detail the experiments from which the global risk attitude construct was obtained.

Recently Pennings and Smidts (2000) showed that the elicitation certainty equivalence method, based on the expected utility paradigm, had higher predictive validity in explaining managerial decision making under risk than psychometric techniques. Therefore, we use the expected utility model in order to derive the global risk attitude. Decision making under risk is modeled as a choice between alternatives, in which each alternative is represented by a probability distribution. Decision makers are assumed to have a preference ordering defined over the probability distributions. In the presence of several preference-ordering axioms (Fishburn, 1988), risky alternatives can be ordered using the utility function, $u(x)$. In this model, the curvature of the utility function $u(x)$ reflects risk attitude (Keeney and Raiffa, 1976; Smidts, 1997; Pennings and Smidts, 2000), and the well-known Pratt–Arrow coefficient of risk aversion, defined on $u(x)$, provides a quantitative measure of risk attitude.

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 with the lottery $(x_l, p; x_h)$, whereby $(x_l, p; x_h)$ is the two-outcome lottery that assigns probability p to outcome x_l and probability $1 - p$ to outcome x_h, with $x_l < x_h$. The certain outcome is varied until the respondent reveals indifference, which is denoted by $\mathrm{CE}(p)$. By applying the von Neumann and Morgenstern (1947) utility u we obtain $u(\mathrm{CE}(p)) = pu(x_l) + (1 - p)u(x_h)$. Based on the assessed utility curve, the Pratt–Arrow coefficient of absolute risk aversion was derived as a measure of risk attitude (cf. Smidts, 1997). The widely used exponential function was fit to each manager's outcomes; after scaling the boundaries of the functions, the estimation of just one parameter suffices to characterize a decision-maker's risk attitude. [13] Since it is the certainty equivalents and not the utility levels that are measured with error, the inverse function is estimated (see Pennings and Smidts, 2000 for the estimation procedure).

When designing the risk-attitude elicitation task for the managers, we used the findings of previous research regarding the sources of bias in utility assessment procedures (Tversky et al., 1988). In line with Hershey et al. (1982) and Hershey and Schoemaker (1985), we believe that the main sources of bias are due to the fact that the experiment often does not match the subject's real decision situation. We describe the procedure conducted for the producers and the wholesalers. Our subjects have two choices in selling hogs: take a fixed-price contract or sell the hogs in the volatile spot market, for which they have well-articulated preferences (Payne, 1997; Shapira, 1997). This decision context closely resembles the certainty equivalence method (Smidts, 1997; Pennings and Smidts, 2000). An important research design issue involves the dimensions of the lottery. Specifically, what probability and outcome levels should one use in eliciting risk preferences? Since it has been argued that prices follow a random walk path, we chose a probability of 0.5 expressing this random walk where prices can go up or down with equal probability (Working, 1934; Kendall, 1953; Cargill and Rausser, 1975). The lottery technique was computerized. The first lottery presented to the respondents was a 50/50 lottery with outcomes of 2.34 and 4.29 Dutch Guilders per kilogram live weight of hogs chosen as boundaries. The minimum and maximum boundaries for the price of hogs were based on historical data. For each lottery, managers had to assess the fixed price (i.e., the certainty equivalent) by choosing A (a relatively high price or a relatively low price with a 50/50 chance) or B (a fixed price) over and over until they were indifferent between the alternatives, at which time a new lottery would start. The assessment of the certainty equivalent was an iterative process. The same procedure was adopted with the processors to elicit their risk attitudes, with the exception that we now focused on buying hogs, thus closely matching their daily purchasing decisions. [14]

Risk perception. Following Pennings and Smidts (2000), risk perception is measured by a scale consisting of a number of statements (multi-indicator measurement). The scale measures the extent to which industry members perceive the market in which they operate as risky (see Appendix A for a detailed description of the scale). Confirmatory factor analysis was used to assess the (psychometric) measurement quality of our constructs (Hair et al., 1998). The overall fit of the confirmatory factor model provides the necessary and sufficient information to determine whether the set

[13] The power function and the exponential function were fit to the data because of their theoretical properties regarding absolute and proportional risk aversion (Tsiang, 1972). Since the exponential function fit the data slightly better than the power function, we use the risk-attitude measures obtained from the exponential function.

[14] The experimental risk-attitude elicitation design closely follows the work of Pennings and Smidts (2000).

of indicators (items) describes the construct. The composite reliability is 0.72, indicating a reliable construct measurement (Hair et al., 1998). [15]

Risk exposure. Risk exposure is measured by the SME's 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. The leverage is measured by the firm's debt-to-asset ratio.

Size of the firm. The size of the firm is measured by the firm's annual sales.

Decision-making unit. The influence of the DMU is measured by asking managers to indicate the extent to which significant persons surrounding them thought that they should use derivatives. The manager was asked to distribute 100 points between using or not using derivatives as a hedging mechanism to reflect the influence of the DMU.

Level of education. 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.

6. Results

We investigate whether it is appropriate to treat all managers in a similar way or whether segments of managers exist that exhibit different derivative use behavior. To clarify the benefits of considering various segments, the effect of manager and firm characteristics on derivative usage were first estimated treating all managers as one segment (i.e., $s = 1$). The results are presented in Table 2.

The solution has a log likelihood of −1198 and an R^2 of 0.06. From Table 2 it appears that the level of risk exposure, size of the firm and the influence of the decision-making unit are significantly positively related to derivative usage, which is consistent with Géczy et al. (1997) and Carter and Sinkey (1998). Interestingly, the decision-making unit, often neglected in research, has a significant influence on the use of derivatives. Although managers of SMEs ultimately make decisions regarding derivative usage on their own, they are influenced by people in their DMU. Consequently, it would seem valuable for financial institutions to target their marketing efforts not only at the managers, but also at their consultants and bank account managers. Surprisingly, the fundamental determinants behind risk management, risk attitude, risk perception, are not significantly related to derivative usage, but the interaction between the two is. This supports the notion that the interaction between risk attitude and risks perception is the important driving force behind risk management behavior, and that risk attitude links risk perception to behavior, as reflected in the interaction (e.g., Pennings et al., 2002). The firm's leverage is not significantly

[15] Reliability refers to the extent to which a variable or set of variables is consistent with what it is intended to measure. The value of the construct reliability ranges between 0 and 1, with higher values indicating higher reliability (see Hair et al., 1998, for the calculation of this measure).

Table 2
Aggregate mixture regression parameter estimates

	Regression coefficient
Risk exposure[a]	−0.107*
Size of firm	0.015*
Influence of DMU	0.100*
Leverage	0.038
Risk attitude (RA)	0.025
Risk perception (RP)	0.017
Interaction[b] (RP * RA)	0.210*
Level of education	0.048
Intercept	0.581
Log-likelihood	−1198.0
CAIC	2451.0
R^2	0.06

Table 2 presents the results of the mixture regression model in which managers' derivative usage is the dependent variable, and risk exposure, size of firm, influence of SMU, leverage, risk attitude, risk perception, their interaction, and level of education are the independent variables. The one-segment solution assumes that the influence the determinants of derivative usage is equal for all managers in the sample.
$^*p < 0.05$.

[a] Risk exposure declines as the number of market transactions increases. Hence the negative sign.

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

related to derivative usage, a finding that is confirmed by Mian (1996), nor is the level of education significantly related to derivative usage.

Because we expected latent segments in our sample, the mixture regression model was applied to the data for $S = 1$ to 6. The log-likelihoods, corresponding CAIC, and the Entropy E_s and R^2 statistics are listed in Table 3.

Table 3
Fit statistics of the mixture models for the segments, $S = 1$ to 6

Segments S	Log likelihood	CAIC[a]	E_s	R^2
1	−1198	2451	1.00	0.057
2	−864	1843	0.81	0.454
3	−845	1820	0.78	0.477
4	−837	1909	0.52	0.480
5	−831	1957	0.39	0.481
6	−830	2021	0.38	0.490

[a] CAIC is the consistent Akaike's information criteria and is used to determine the optimal number of segments. This criterion imposes a penalty on the likelihood that is related to the number of parameters estimated. E_s is the entropy statistic which is bounded between 0 and 1, and describes the degree of separation in the estimated posterior probabilities. E_s values close to 1 indicate that the posteriors probabilities of the managers belonging to specific segments are close to either 0 or 1; the segments are well defined. The CAIC was minimized for three segments, indicating that the sample consisted of three segments.

Based on the minimum CAIC statistic, we selected $S = 3$ as the appropriate number of segments. The solution has a log likelihood of −845 and an R^2 of 0.48. Table 4 presents the estimated coefficient for this three-segment solution.

The entropy value of 0.78 indicates that the mixture components are well separated or defined, i.e., the posteriors are close to 1 or 0. The R^2 has significantly improved from 0.06 for the aggregate regression model ($S = 1$) to 0.48 for the three-segment solution ($S = 3$).

The results of the three-segment solution demonstrate the existence of multiple industry segments with different relationships between manager and firm characteristics and derivative use. In segment 1 ($s = 1$), which contains 48.9% of the producers, 36.0% of the wholesalers and 3.3% of the processors, and constitutes 44.1% of the sample, risk exposure, size of firm, the influence of the DMU, and the manager's risk perception show a significant association with the use of derivatives. These findings confirm the previous findings of Nance et al. (1993), Géczy et al.

Table 4
Mixture regression results for the three-segment solution in which the manager's derivative usage is the dependent variable

	$s = 1$	$s = 2$	$s = 3$
Regression coefficients			
Risk exposure[a]	−0.167*	−0.093*	−0.161
Size of firm	0.440**	0.196*	0.287
Influence DMU	0.478**	0.015	0.231*
Leverage	0.021	0.028	0.221*
Risk attitude (RA)	0.012	0.047	0.701*
Risk perception (RP)	0.064*	0.026	0.414*
Interaction (RP∗RA)[b]	0.226*	0.048	0.443*
Level of education	0.038	0.122*	0.789**
Relative segment size π	0.441	0.298	0.261
Percentage of channel member type in segment			
Producers	48.9% ($n = 164$)	28.9% ($n = 97$)	22.2% ($n = 74$)
Wholesalers	36.0% ($n = 18$)	42.0% ($n = 21$)	22.0% ($n = 11$)
Processors	3.3% ($n = 1$)	20.0% ($n = 6$)	76.6% ($n = 23$)
Descriptive statistics for identified segments			
Average sales	286,038	693,306	1,971,388
Percentage using derivatives	28.9%	62.1%	92.8%
Average number of contracts	3.9	9.2	21.5
Average notional value[c]	58,500	138,000	322,500
Highest educational degree			
High school	39.9%	20.9%	15.7%
College (BS degree)	59.5%	68.5%	62.0%
University (MS/MA degree)	0.6%	11.0%	22.3%
Other	0.0%	0.02%	0.0%

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

[a] Risk exposure decreases as the number of market transactions increases, hence the negative sign.

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

[c] Based on the hog contract value from Euronext for the three-year period 1995–1997.

(1997), and Carter and Sinkey (1998). Moreover, the interaction between risk attitude and risk perception is significantly associated with derivative usage. Compared to the other two segments, this segment uses the least derivatives (e.g., Table 4). Segment 2 ($s = 2$) contains 28.9% of the producers, 42.0% of the wholesalers and 20.0% of the processors, constitutes 29.8% of the sample, and shows significant effects of risk exposure, size of firm, and level of education on hedging behavior. In this segment the use of derivatives is modest, higher than in segment 1 but lower than in segment 3 ($s = 3$). Interestingly, the fundamental determinants, risk attitude, risk perception, and their interaction, are not significantly related to derivative usage in this segment. In contrast, risk perception, risk attitude, and their interaction are significantly related to derivative usage in segment 3. In this segment the terms can be clearly interpreted. A risk-averse manager will use relatively more derivatives in order to reduce price risk. When a manager perceives a large price risk (i.e., high-risk perception), the use of derivatives will be more prominent. A risk-averse manager, with high-risk perception will rely on derivatives more heavily. Moreover, other financial determinants, such as leverage, are also significantly related to derivative use in this segment. The level of education, and the influence of the DMU are significantly related to derivative use as well. [16] Segment 3 is the smallest segment, containing 26.1% of the sample, and 22.2% of the producers, 22.0% of the wholesalers, and 76.6% of the processors.

The results from the mixture model have a clear economic interpretation. Segment 1 is characterized by companies whose decision regarding derivative use depends on their risk exposure and the opinions of members of the decision-making unit regarding futures usage. This segment is dominated by relatively small firms that do not use derivatives extensively. In contrast, the hedging behavior of the firms in segment 3 is driven by the fundamental drivers, risk attitude, risk perception and their interaction, and is consistent with Pratt and Arrow's models and economic theory that suggest that risk attitude and risk perception are important concepts in determining optimal hedging positions (Holthausen, 1979; Rolfo, 1980). Furthermore, other financial determinants, such as leverage, are significant in these managers' decisions.

The fact that the three segments are not homogeneous with respect to the type of firm (producers, wholesalers or processors) further substantiates the usefulness of the generalized mixture regression model. Heterogeneity emerges from the influence of the determinants of derivative use (as measured in the estimated coefficients of the separate relationships for each segment) rather than from a single observable variable (e.g., company type). If we were to ignore *latent* heterogeneity, but instead use company type, for instance, as a classifying criterion, we would explicitly restrict the relationship between the factors and hedging behavior to be the same for all producers, wholesalers, or processors, but dissimilar across these groups which is not consistent with our findings.

[16] A reviewer suggested the use of the number of years of experience as another important determinant of derivative use. We concur, but unfortunately do not have this information.

6.1. What sets these segments apart?

To put the question in a different way: why do these managers respond differently across segments? As indicated, generating the answer to this question is challenging, and we have used survey information and knowledge of the industry to develop our analysis. First, to examine the manager's market experiences and perceptions of derivative use, we posed several questions in the form of 7-point Likert statements. We asked managers to identify the extent to which: (a) they use risk-spreading techniques, e.g., sell to more than one buyer (1 = no use of techniques and 7 = extensive use of techniques); (b) derivatives yield good prices (1 = yield very bad prices and 7 = yield very good prices); (c) they follow market prices (1 = do not follow and 7 = follow very closely); (d) derivatives are able to reduce price risk (1 = not at all and 7 = able to eliminate price risk); and (e) derivatives are easy to use (1 = not easy at all and 7 = very easy to use). Next, we classified the managers into our three segments, the membership of which reflected a manager's highest posterior probability of belonging to a particular segment based on (Eq. (10)). The opinions and practices provide a way to profile the manager's predisposition to hedging, and to identify how active market participation, and the implicit costs of using derivatives affect hedging practices.

Table 5 tabulates the responses to the additional questions for the three segments.

Segment 1 is characterized by respondents who do not use risk-spreading techniques extensively, who believe that derivatives do not yield good prices, perform poorly at reducing price risk, and who perceive derivatives as difficult to use and hence costly in a transactional sense. The large proportion of producers in this segment (89.6% of the respondents in this group) with low levels of derivative usage is consistent with findings in other commodity-related industries. Lence (1996) and others have identified the low level of producer participation in hedging activities

Table 5
Profile of the three segments using age and manager opinions as profile variables

	$s = 1$		$s = 2$		$s = 3$	
	Mean	SD	Mean	SD	Mean	SD
Age	42	9.8	42	8.7	43	10.1
Using risk-spreading activities	3	1.5	4	1.4	5	1.4
Derivatives yield good prices	2	1.4	4	1.6	3	1.7
Follow the market prices closely	3	1.3	4	1.2	6	1.2
Risk reduction performance	2	1.4	4	1.3	5	1.1
Ease of use	3	1.7	5	1.4	6	1.2

SD is the standard deviation.
All profile variables, except for age, were measured on a 7-point Likert scales. We asked managers to identify the extent to which: (a) they use risk-spreading techniques, e.g., sell to more than one buyer (1 = no use and 7 = extensive use); (b) derivatives yield good prices (1 = yield very bad prices and 7 = yield very good prices); (c) they follow market prices closely (1 = do not follow and 7 = follow very closely); (d) derivatives are able to reduce price risk (1 = not at all and 7 = able to eliminate price risk); and (e) derivatives are easy to use (1 = not easy at all and 7 = very easy to use).

in US futures markets. Furthermore, Lence (1996) has demonstrated that even small transactions costs can impose a high barrier to small producer participation in futures markets. This segment can be described as "focusing on production, rather than on marketing their products", which further explains the relatively low use of derivatives. This orientation also helps to explain why the DMU is so important in this segment (see Table 4). These managers appear to rely heavily on the expertise of consultants and bank account managers when the use of derivatives is concerned. Furthermore, these managers, who are not heavily involved in the use of derivatives as a hedging tool, might not be well informed about derivatives, which is consistent with the fact that this segment shows the lowest levels of education. Managers who think that derivatives are easy to use but are neutral regarding their risk reduction and pricing performance form segment 2. In this segment, risk-management behavior is not driven by their risk attitudes and risk perceptions. Segment 3 has a rather positive attitude towards derivative usage. Managers find derivatives easy to use, believe that derivatives are able to reduce risk, but are neutral as to whether derivatives produce high prices. It appears that this segment uses derivatives as a hedging tool, not for receiving high prices. Managers in this segment follow market prices closely, which might explain the influence of the interaction term between their perceived risk and risk attitudes on derivative use. This segment seems to use "financial structure" characteristics (as imbedded in the debt-to-asset ratio, risk attitude and risk perception) in their decisions to engage in derivatives. In addition, the DMU is a determinant significantly associated with derivative usage.

The organizational structure, marketing practices, and the influence of the DMU also affect the heterogeneity across the groups. The ownership structure differs significantly across the three segments (see Table 6). [17] It appears that segment 3 (the segment in which the fundamental risk variables are most important) is dominated by limited and public companies, i.e., companies that have third-party (outside) shareholders. These companies are inclined to optimize their risk-return trade off in order to maximize shareholder value, and hence it seems logical that the fundamental risk variables play a role for this segment. This contrasts with segments 1 and 2, which are dominated by private companies and where derivative use is less extensive.

This finding empirically confirms the notion of Haushalter (2000) and Graham and Rogers (2002), who conjecture that hedging decisions and capital structure decisions are intertwined. [18]

As indicated, the influence of the DMU is related to hedging use, which seems to separate the segments effectively. The results from Table 4 suggest that the influence of the DMU is non-linearly related to hedging use within the context of the model. Recall that the hedging use of segment 3 > segment 2 > segment 1, and that the influence of the DMU is significant in defining segments 3 and 1, though not segment 2. Hence,

[17] We thank an anonymous reviewer for bringing this to our attention.

[18] Interestingly, including the Likert scale and ownership variables in our model does not produce significant findings. This suggests that they do not have a direct effect on managers' derivative usage, but an indirect effect instead, as they influence heterogeneity. Further research that incorporates factors that drive heterogeneity is warranted.

Table 6
Profile of the three segments using ownership structure as profile variable

	$s = 1$	$s = 2$	$s = 3$
Ownership structure[a]			
Private	90.7%	80.6%	34.3%
Private limited	8.7%	16.1%	54.4%
Public traded	0.6%	3.3%	11.3%

[a] 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 shares are not traded publicly; and publicly traded companies whose shares are publicly traded.

the influence of the DMU on hedging behavior is important to SMEs, as the organizational behavior literature suggests, but the relationship is not linear and is highly influenced by the environment of the firm, as well as by the managers' characteristics.

7. Discussion

Previous research has identified that various factors, such as the size of the firm, risk exposure and its financial structure, influence the derivative usage of large corporations. These factors also play a role for segments of SMEs. In addition, our analysis has revealed that the SME's decision-making unit, the manager's risk attitude, the manager's risk perception and the manager's education level play an important role in explaining SME derivative usage. The role of the decision-making unit is particularly important for private companies (i.e., segment 1), confirming the findings in organizational behavior that the members of the decision-making unit influence managers' decision-making behavior (Moriarty and Bateson, 1982). The importance of the risk variables is consistent with theoretical hedging models that identify risk as a determinant of hedging behavior, and suggests the need to account for a manager's risk attitude and risk perception in order to fully understanding derivative usage at the firm level.

The analysis also reveals the presence of multiple segments that can be interpreted on the basis of existing theory of hedging behavior. Risk exposure, size of firm, the firm's decision unit, leverage, risk attitude, risk perception, the interaction between risk attitude and risk perception, and level of education are the factors related to derivative usage. However, these factors are not equally important throughout the industry. Assuming homogeneity in managers' responses and estimating a pooled model yields a poor fit, and leads to the conclusion that only risk exposure, size of firm, the manager's decision-making unit and the interaction between risk attitude and risk perception are determinants of SMSs' derivative usage. Allowing for heterogeneity in managers' responses, increases the model's statistical coherence dramatically, and demonstrates that the importance of the determinants varies significantly across the segments. The heterogeneity at the segment level appears to have been masked at the aggregate level, notably the effects of risk attitude, risk perception, leverage, and the manager's level of education.

In our analysis, heterogeneity is not based on observable variables, such as region or company type, but is latent instead and imbedded in the influence of the determinants on the decision to participate in derivative contracts. In order to identify these latent segments, procedures must be used that simultaneously identify segments based on the influence that the determinants have on hedging behavior, and estimate the effect of the independent variables on derivative use for each identified segment. In this paper, we have used a mixture model that classifies managers into segments, and estimates a different structure for each segment (i.e., different coefficients that reflect the relationship between hedging use and the independent variables), based on the observations with the highest probability of conforming to that structure.

The merit of the segmentation technique becomes apparent when we look at the different company types present in each segment. Segment 1, for example, consists of producers, wholesalers, and processors. If we had not used the unobserved heterogeneity approach, but instead had segmented the sample based on company type, we would have eliminated the possibility that heterogeneity is a function of the relationship between the determinants of derivative use and hedging behavior.

Some caveats of our analysis should be mentioned. Ex ante risk exposure is a key variable when studying risk management behavior. We have conceptualized and measured ex ante risk exposure in an intuitively appealing way by focusing on the managers' perception of the commodity price volatility and the number of times an SME enters the volatile spot market (Strong, 1991). Recently Tufano (1998), among others, has shown that risk exposure can be influenced by "exogenous" characteristics such as a firm's cost structure, as well as by market volatility. Research is needed to determine the relative usefulness of these two procedures in reflecting the role of ex ante risk exposure in SME decisions.

The influence of the DMU was measured in terms of whether the manager was influenced by individuals who favor the use of derivatives. Managers who use derivatives are assumed to be influenced by those around them. However, it is possible that managers are more likely to associate with those that have similar ideas and perceptions of the world, creating a subtle form of endogeneity or selective bias. Accounting for this possibility is a challenge, and research on the interface between finance and organizational behavior is needed to effectively deal with it. It should also be noted that the nature of the interaction between the manager and the DMU may differ among segments. For smaller SMEs, DMUs may consist of consultants and individuals. For larger SMEs, managers may be influenced by members of their own management team. This could explain the findings that the DMU variable is significant in segments 1 and 3. Furthermore, the composition, actual operations, and management dynamics of these management units may influence their recommendations and their effectiveness. For smaller SMEs, consultants and individuals may only possess limited information about the functioning of derivative markets. For larger SMEs, managers may be influenced by highly trained members of a management team that understand the functioning and usefulness of derivative markets. Additional work is needed to further develop our understanding of the composition, operations, and role of DMUs in financial decision making in SMEs.

The measurement of risk attitude is a complex and challenging task, as it is a psychological construct. Risk attitude is context specific, and hence it is important to measure individual risk attitudes in the appropriate context to identify the decision-maker's risk attitude that is influencing behavior. In this paper, we followed closely the recent developments in the decision sciences on measuring risk attitudes in a reliable and valid way (e.g., Pennings and Smidts, 2000). Measuring the managers' risk attitudes in experiments that closely reflect their daily work environment, ensured that we obtained a global risk attitude construct that is consistent across managers and drives hedging behavior. However, questions remain that may be of interest to further enhance our knowledge about the relationship between risk attitudes and hedging behavior: How are risk attitudes formed in different environments (owner–manager versus manager of public company)?; How might this formation influence hedging behavior?; and How qualitatively compatible are the findings based on the procedures of direct measurement of risk attitudes used here with those procedures that incorporate factors which affect hedging behavior, such as compensation schedules?

Finally our work has at least two implications for financial institutions. First, the importance of the DMU in derivative use decisions suggests that managers of SMEs rely heavily on the expertise and advice of consultants and bank account managers. Hence, the use of derivatives among SMEs can be stimulated through targeted programs that promote the advantages of derivatives to the members of these support groups. Research in economics is emerging that shows the important role of market advisory services in producers' decisions to use derivatives (e.g., Schroeder et al., 1998). Second, the heterogeneity of derivative usage suggests that financial institutions need to use different tools to attract different segments. Identifying the different segments is a challenge. With this information, the financial institution is able to target their marketing efforts and design customized financial products. Fridson (1992), Angel et al. (1997), and Nesbitt and Reynolds (1997) show the importance of customizing financial services. Based on the characteristics of the different segments, financial institutions can select a group of potential customers, to whom they offer risk reduction services designed to match the customer's derivative usage profile. This implies differentiation of services offered by financial institutions. The findings indicate that a single observable variable like the type of firm or firm size (which can be observed) is not necessarily a strong predictor of derivative usage, but rather the combination of the determinants of derivative usage (which is unobserved), as reflected in the regression coefficients of each segment. Thus, having identified the segments and having gained information about the segments' profiles, the financial institution is able to target these segments and design securities that better fit the segments' needs.

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Appendix A. Description of the risk-perception scale

To examine the measurement quality of the constructs, confirmatory factor analysis was performed using LISREL 8 (Jöreskog and Sörbom, 1993).

SMEs were asked to indicate their agreement with the following items using a 9-point scale that ranged from "strongly disagree" to "strongly agree":

(1) I am able to predict hog spot prices.
(2) The hog spot market is not at all risky.
(3) I am exposed to a large amount of risk when I buy/sell hogs in the spot market.

The value of the construct reliability, which ranges between 0 and 1, with higher values indicating higher reliability (see Hair et al., 1998), was 0.72.

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