The Journal of Financial Research • Vol. XXXIII, No. 4 • Pages 373–401 • Winter 2010

RISK AND HEDGING BEHAVIOR: THE ROLE AND DETERMINANTS OF LATENT HETEROGENEITY

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Abstract

The notion of heterogeneous behavior is well grounded in economic theory. Recently it has been shown in a hedging context that the influence of risk attitudes and risk perceptions varies for different segments using a generalized mixture regression model. Here, using recently developed individual risk attitude measurement techniques and experimental and accounting data from investors with differing decision environments, we examine the determinants of heterogeneity in hedging behavior in a concomitant mixture regression framework. Allowing for latent heterogeneity, we find that risk attitudes and risk perceptions do not influence behavior uniformly and that the heterogeneity is influenced by manager's focus on shareholder value and the firm's capital structure.

JEL Classification: D8, G10, G20, G32

I. Introduction

Economic theory suggests that risk attitude and risk perception are important concepts in determining hedging behavior (Holthausen 1979; Rolfo 1980). Notable work by Pratt (1964) and Arrow (1971) also suggests that the interaction between these two concepts influences risk management and hence is expected to affect hedging behavior. These risk variables play an important role in normative models that guide management strategies as well as in positive models that explain

The authors express thanks to Jayant R. Kale, the editor, and Ann Gillette who provided helpful comments on preliminary versions of the manuscript. The authors are grateful for the generous participation of the portfolio managers in the experiments and the companies providing accounting data. Financial support provided by de Algemene Stichting Termijnhandel (AST), the Niels Stensen Foundation, and the Office for Futures & Options Research is gratefully acknowledged. The authors thank seminar participants at INSEAD, Iowa State University, London Business School, Tilburg University, University of California Berkeley, University of California Los Angeles, University of Illinois at Urbana-Champaign, and Wageningen University in the Netherlands, for their comments.

hedging behavior. However, the few studies that compare actual to derived optimal behavior conclude that the models are unable to reflect actual hedging behavior (Hartzmark 1987; Peck and Nahmias 1989). Furthermore, in various positive (descriptive) analyses (e.g., Géczy, Minton, and Schrand 1997; Haushalter 2000), no relation between managerial risk aversion and corporate hedging has been found, a puzzling result that seems counterintuitive. Motivated by these findings, Pennings and Garcia (2004) examine the role of latent heterogeneity in hedging behavior using a generalized mixture regression model that classifies firms into segments such that hedging response is the same within each identified segment but different across segments. Their results indicate the influence of risk attitudes and risk perceptions differs across segments and that these differences result in dissimilar hedging behavior. However, a question arises: What are the determinants of this heterogeneous relation between the risk variables and hedging behavior?

In this article we use organizational literature to gain insight into this question. Research has shown that the environment in which managers operate heavily influences the weights attached to their decision criteria (Aldrich 1979; Rajagopalan, Rasheed, and Datta 1993). This suggests that the influence of risk attitudes and risk perceptions on hedging behavior is moderated by the environment in which decision makers operate. In a hedging context, a firm's capital structure as reflected by the debt-to-asset ratio and the focus on shareholder value are relevant aspects of its internal environment (Smith and Stulz 1985; Froot, Scharfstein, and Stein 1993). To examine our research question empirically, we extend Pennings and Garcia's (2004) modeling framework by introducing concomitant variables (i.e., environmental factors expected to moderate heterogeneity) by collecting experimental field and accounting data from investors who operate in two organizational environments (private investors vs. portfolio managers).

To identify the influence of risk attitude and risk perception and the determinants of hedging behavior is a challenge, complicated by conceptual and empirical issues that require careful examination of the decision-making process. First, risk attitudes and perceptions are difficult to measure; both are psychological constructs, that is, latent variables that cannot be observed directly. In a related sense, risk perception is often conceptualized in hedging models in terms of risk exposure, the volatility in the value of assets or commodities. However, a manager's risk perception differs from risk exposure; it is a subjective or personal interpretation of the probability of being exposed to a specific level of risk. Here we use the framework proposed by Pennings and Smidts (2000) to measure risk attitudes and risk perceptions. They develop reliable and valid risk attitude and risk perception measures rooted in the EU framework and psychometric framework.[1] Second,

[1]Reliability refers to the extent a variable or set of variables is consistent with what it is intended to measure. Validity refers to the extent to which a measure or set of measures correctly represents a concept (e.g., latent variable).

modeling latent heterogeneity and its underlying determinants requires a framework that can simultaneously identify segments of managers in which the influence of risk attitudes and risk perceptions are similar, and identify the factors that cause the heterogeneity. Using recent advancements made in the psychometric and statistical literature (Wedel and Kamakura 2000; Grün and Leisch 2007),we expand on Pennings and Garcia's (2004) framework by estimating a concomitant mixture regression model that reparameterizes the prior probabilities of segment membership in terms of concomitant—a firm's capital structure and focus on shareholder value—factors hypothesized to affect heterogeneity. Because the model classifies decision makers based on the determinants of behavior, the method emphasizes the role of theory.

Using information from 105 managers, we show that the influence of risk on hedging behavior is not homogeneous across managers and that this heterogeneity is indeed driven by focus on shareholder value and the firm's capital structure. This knowledge is important both in theory and in practice. Predictions derived from standard economics and finance theory, such as portfolio theory (e.g., capital asset pricing models), are based on the assumption that risk attitude and risk perception directly influence behavior. From a practical perspective, investment consultants, banks, and insurance companies measure customers' risk attitudes using questionnaires to recommend particular investment portfolios.

II. Hedging Behavior: The Role of Risk Attitudes and Risk Perceptions

The Basic Model

Risk attitude reflects a decision maker's general predisposition to risk. Risk perception reflects the decision maker's interpretation of the chance of being exposed to risk. Theory hypothesizes a positive relation between risk aversion and an individual's hedge ratio (Hicks 1939; Ederington 1979; Stein 1986). Also, it hypothesizes a positive relation between risk perception, which is often approximated by the volatility in the underlying cash market, and the hedge ratio.[2] Furthermore, theory hypothesizes an interaction between the two concepts. In Pratt and Arrow's work, risk management, reflected in the risk premium π, is a function of risk attitude (risk aversion r), the situation (base wealth W), and perceived risk of obtaining additional wealth, which has a mean of $\bar{\varepsilon}$ and variance σ^2. Risk management decisions

[2]Petersen and Thiagarajan (2000) argue that the concept of risk exposure is essential for understanding a firm's risk management strategies. The concept of risk perception reflects risk exposure through the perception of the manager.

are determined such that the risk premium leaves the decision maker indifferent between holding the perceived risky asset or holding its mean value minus the risk premium:

$$EU\,(W+\varepsilon)=U\,(W+\bar{\varepsilon}-\pi)\,,$$

where *EU* is the expected utility. In the expected utility model, this translates into:

$$EU(W+\varepsilon)=\int U(W+\varepsilon)f(\varepsilon)\,d\varepsilon=U(W+\int \varepsilon f(\varepsilon)d\varepsilon-\pi),$$

where $U(.)$ is the Von Neumann–Morgenstern utility and $f(.)$ is the probability density function of additional wealth ε. It can be shown that the risk premium π is equal to

$$\pi=\frac{1}{2}\int \varepsilon^2 f(\varepsilon)d\varepsilon\frac{-U''(W)}{U'(W)},$$

which can be written as: $\pi=\frac{1}{2}\sigma^2 r(W)$, where $r(W)=-U''(W)/U'(W)$ is the Pratt–Arrow coefficient of absolute risk aversion. Interpreting the variance σ^2 of additional wealth ε as a proxy for risk perception, the Pratt (1964) and Arrow (1971) framework shows that risk management behavior depends on risk attitude, risk perception, and their interaction. The greater the perception of risk and the more risk averse the decision maker, the higher the hedge ratio. In mean-variance models the notion of the interaction between risk attitude and risk perception is also apparent; subsequent optimal hedge ratio models include the interaction of risk perception and risk attitude (Levy and Markowitz 1979). Consistent with this framework, managers' decision making regarding their hedge ratio can be expressed by:

$$HR_i=\beta_0+\beta_1 RA_i+\beta_2 RP_i+\beta_3 RA_i * RP_i, \tag{1}$$

where HR_i is the employed hedge ratio by manager i, RA_i is the manager's i risk attitude, RP_i is the manager's i risk perception, and $RA_i * RP_i$ is their interaction.

The Basic Model and Heterogeneity: What Moderates the Influence of the Risk Variables on Hedging Behavior?

The basic hedging model (equation (1)) assumes that the influences of risk attitude, risk perception, and their interaction on hedging behavior are similar for all managers. However, Pennings and Garcia (2004) provide evidence that the influence of risk variables on hedging behavior is not homogeneous. Furthermore, the assumption of homogeneity is challenged by organizational literature that demonstrates a manager's environment influences decision criteria and the importance of these criteria (Aldrich 1979; Rajagopalan, Rasheed, and Datta 1993). Here, we hypothesize the influence of risk attitudes and risk perceptions on hedging behavior is heterogeneous across market participants and that the heterogeneity is driven by the different environments in which managers operate.

In a hedging context, a firm's capital structure and the focus on shareholder value are relevant aspects of the environment. A firm's capital structure as reflected by the debt-to-asset ratio is an important aspect of its internal environment. The expected cost of a firm's financial distress increases as the probability of a firm's insolvency increases. A firm with a higher probability of insolvency may benefit from a decrease in the variance of firm value (Smith and Stulz 1985; Shapira and Titman 1986). A firm's shareholders are also part of the managers' environment. Various authors, including Smith and Stulz (1985) and Froot, Scharfstein, and Stein (1993) focus on the direct relation between hedging and maximizing shareholder value. However, evidence on this relation is mixed; here we examine whether a focus on shareholder value has an indirect effect on hedging behavior.

Heterogeneity, the idea that the influence of managers' risk attitudes and risk perceptions on hedging behavior may differ, can have profound consequences for the interpretation of empirical evidence and for understanding risk management behavior. The notion that heterogeneity must be accounted for when trying to understand actual behavior is not new. In his Nobel Lecture, Heckman (2001, p. 675) indicates that the most important discovery was the evidence on the pervasiveness of heterogeneity and diversity in economic life. The challenge is to model heterogeneity in an appealing way such that variations in economic behavior are influenced by differences in its determinants.

Modeling Latent Heterogeneity and Its Drivers

Heterogeneity in the decision maker's behavior cannot always be observed directly. In our case, differences in the way managers' hedging responds to the risk variables are unobserved before estimation. To accommodate this unobserved (latent) heterogeneity and to examine how shareholder value and the firm's capital structure moderate the influence of the risk variables on actual hedging behavior, we extend the generalized mixture model used by Pennings and Garcia (2004). Their modeling framework identifies segments of market participants such that within a segment the relation between hedging behavior and risk variables are similar, but they are dissimilar across segments. In this article we identify a similar latent heterogeneity but also identify the environmental—concomitant—factors that cause the heterogeneity. The concomitant variables—firm's capital structure and manager's focus on shareholder value—assist in identifying why segments of managers behave differently by allowing latent segment membership to covary with these variables. To accomplish this we reparameterized the prior probabilities in terms of our concomitant variables.

III. Empirical Model

Specification

The generalized mixture model assumes heterogeneity arises from the presence of segments of managers that behave differently. The segments are not observed directly but are recovered from the data by the model. In order to describe the process generating managers' hedge ratios, a statistical distribution is assumed. The distribution describes the probabilities that managers' hedge ratios take certain values, and is characterized by its expectation and variance that are estimated. Given the distribution, the mixture model decomposes the manager population into the underlying segments. The mixture regression framework provides the probability that each manager belongs to the derived segments, and the regression coefficients in each segment that relate the expectation of the managers' hedge ratios to the explanatory variables (Wedel and DeSarbo 1995; Wedel and Kamakura 2000). Formally, we can define the mixture regression model as follows. First, assume the vector of managers responses, y_n (i.e., the hedge ratios), arises from a population that is a mixture of S segments in proportions $\pi_1, \ldots, \pi_s$, where we do not know in advance the segment from which a particular vector of observations arises. The probabilities π_s are positive and sum to one. We assume that the distribution of y_n, given that y_n comes from segment s, $f_s(y_n \mid \theta_s)$, is a member of the exponential or multivariate exponential family, where θ_s is the vector of regression coefficients for each segment. The distribution $f_s(y_n \mid \theta_s)$ is characterized by parameters θ_s, and the means of the s segments (or expectations) are denoted by μ_s.

Because we want to predict the means of the observations in each segment by using the set of explanatory variables (*RA, RP,* and $RA * RP$ in equation (1)), we specify a linear predictor η_{ns}, which is produced by the explanatory variables denoted by$X_1, \ldots, X_P$ ($X_p = (X_{np})$; $p = 1, \ldots, P$; here $P = 3$), and parameter vectors $\beta_s = (\beta_{sp})$ in segment s:

$$\eta_{ns} = \sum_{p=1}^{P} X_{np}\beta_{sp}. \tag{2}$$

The linear predictor is thus the linear combination of the explanatory variables, and the set of betas that are to be estimated (equation (2) is similar to equation (1) but in matrix notation).

The linear predictor is in turn related to the mean of the distribution, μ_s, through a link function g(.) such that in segment s:

$$\eta_{ns} = g(\mu_{ns}). \tag{3}$$

Thus, for each segment, a linear model is formulated with a specification of the distribution in the exponential family, a linear predictor η_{ns}, and a function $g(.)$ that links the linear predictor to the expectation of the distribution. Because the dependent variable, the hedge ratio, is assumed normally distributed, the canonical link is the identity, that is, $\eta_{ns} = \mu_s$, so that by combining equations (2) and (3), the standard linear regression model within segments arises.[3] The unconditional probability density function of an observation vector y_n, can now be expressed in the finite mixture form:

$$f(y_n \mid \varphi) = \sum_{s=1}^{S} \pi_s f_s(y_n \mid \theta_s), \tag{4}$$

where the parameter vector $\varphi = (\pi, \theta_s)$, and $\theta_s = \beta_s$.

Within a latent segment, managers are homogeneous in the sense that they respond similarly to the explanatory variables. Latent segment membership also may covary with other external or moderating factors. As hypothesized, we expect that manager's focus on shareholder value and the firm's debt-to-asset ratio to influence the relation and refer to them as concomitant variables. Formally, the prior probabilities of segment membership can be reparameterized in terms of the concomitant variables z as shown in equation (5):[4]

$$\pi_{s \mid Z} = \frac{\exp\left(\sum_{l=1}^{L} \gamma_{ls} z_{nl}\right)}{\sum_{s=1}^{S} \exp\left(\sum_{l=1}^{L} \gamma_{ls} z_{nl}\right)}, \tag{5}$$

where the parameter γ_{ls} denotes the effect of the lth concomitant variable on the prior probability for segment s.

Equation (5) is referred to as the submodel and formulates the prior probability membership to the segments as a logistic regression function of the variables hypothesized to affect the heterogeneity. The parameters of this multinomial logit

[3] Using the Jarque–Bera test, we can not reject normality of the dependent variable used in the analysis at the 20% level.

[4] An alternative way to accommodate concomitant variables is simply to include them among the independent variable(s) in the mixture model (Langeheine and Rost 1988). Based on our conceptual model, we specify the conditional distribution of the dependent variable given the concomitant variables rather than the standard mixture model that formulates their joint distribution. Several authors argue that simultaneously profiling the derived segments with concomitant variables is a more effective procedure to identify the structure of latent segments (Kamakura, Wedel, and Agrawal 1994).

submodel are specific to each moderating variable and segment: a positive γ_{ls} implies that a higher value of descriptor Z_{ls} increases the probability that a manager belongs to segment s.

The unconditional probability density function of the observation vector y_n is now obtained by combining the unconditional probabilities (equation (4)) with the prior membership probabilities of equation (5) and can be expressed in the finite mixture form:

$$f(y_n \mid \phi) = \sum_{s=1}^{S} \pi_{s \mid z} f_s(y_n \mid \theta_s). \tag{6}$$

Equation (6) shows that the unconditional density function can be decomposed into a weighted average of the latent probability density function, where the weights $\pi_{s \mid z}$ vary systematically as a function of the concomitant variables. Equation (6) provides the link between the concomitant variables (i.e., focus on shareholder value and debt-to-asset ratio) and the probability density function of the decision-making equation (i.e., hedge ratio).

The parameter vector ϕ in equation (6) is estimated via maximum likelihood using the expectation maximization (EM) algorithm (Redner and Walker 1984; Titterington 1990). To accomplish this, the likelihood function is maximized. The likelihood function describes the probability that the data are generated given the specific set of model parameters (i.e., equation (4)). By maximizing the likelihood, the set of parameters is obtained that most likely has given rise to the data. The rationale for using the EM algorithm is that the likelihood function contains missing observations, that is, the 0/1 membership of subjects in the S segments. If these were known, maximization of the likelihood would be straightforward. Assuming that membership in the segments is based on a multinomial distribution, the expectation of the likelihood can be formulated over the missing observations. This involves calculating the posterior membership probabilities according to Bayes rule and the current parameter estimates of ϕ and substituting those into the likelihood. Once this is accomplished, the likelihood is maximized. Given the new estimates of ϕ, new posteriors can be calculated in the next E—expectation—step, followed by a new M—maximization—step to find a new ϕ. The E and M steps are alternated until convergence.[5] Estimates of the posterior probability, p_{ns}, that manager n comes from segment s can be calculated for each observation vector y_n, as shown in equation (7):

$$p_{ns} = \frac{\pi_{s \mid Z} f_s(y_n \mid \theta_s)}{\sum_{s=1}^{S} \pi_{s \mid Z} f_s(y_n \mid \theta_s)}. \tag{7}$$

[5]The EM algorithm is available on request.

Equation (7) shows that the posterior probabilities are also affected by the concomitant variable, and it can be used to classify managers in a particular segment.

To determine the optimal number of segments, Akaike (1974) and Bozdogan (1987) develop information criteria tools. These criteria impose a penalty on the likelihood that is related to the number of parameters estimated. Studies by Bozdogan indicate that the consistent Akaike information criterion (CAIC) is preferable in general for mixture models. An entropy statistic can be used to investigate the degree of separation in the estimated posterior probabilities as defined in equation (8):

$$E_s = 1 - \frac{\sum_{n=1}^{N} \sum_{s=1}^{S} p_{ns} \ln p_{ns}}{N \ln S}. \tag{8}$$

The entropy statistic E_s 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 posteriors probabilities of the managers belonging to specific segments are close to either 0 or 1; the segments are well defined.[6]

Economic Interpretation of the Empirical Model

The empirical model outlined only identifies segments when the decision-making behavior differs across segments. When behavior is heterogeneous, the empirical model discriminates between segments of managers, not on the basis of a single variable but based on the relation between the risk variables and hedging behavior. From an economic perspective, this implies that the marginal effects of risk attitude, risk perception, and their interaction on hedging behavior differ across the identified segments. In addition, the empirical model identifies the drivers of the heterogeneity by allowing segment membership to covary with environmental factors (i.e., concomitant variables).

IV. Research Design

Sample and Data Collection Procedure

To examine the research question, we need experienced decision makers who are actively involved in hedging activities and who work in different business environments. A sample of portfolio managers and private investors was expected to meet

[6]Where only one segment is used, E_s is 1.

these requirements. The portfolio management literature shows that an effective way to manage portfolio risk is to use futures and options contracts (Jarrow and Zhao 2006). This is particularly true when asset allocation constraints exist, which is common for portfolio managers who hold assets that are needed to fulfill future financial obligations of the firm (Frost and Savarino 1988). In this situation, stock index futures and options such as the S&P 500 futures contract and FTSE 100 futures contract play an important role. Stock index futures and options were developed to allow portfolio managers to conveniently hedge portfolio risk, and they are shown to be an effective hedging tool (Butterworth and Holmes 2000; Sarkar and Tripathy 2002; Zafeiropoulos 2005).

Euronext-LIFFE provided us with the names of companies and their portfolio managers, and private investors. The corporations included large banks, oil companies, food processors, and large government pension funds. The private investors were decision makers that manage their own portfolios. Before our data collection we conducted two in-depth interview sessions to gain better insight in the decision-making process of the private investors and portfolio managers and to test our computer-guided interview instrument. The two in-depth sessions consisted of 15 private investors and 15 portfolio managers, respectively. During the in-depth interviews, participants discussed risk management activities when investing and were asked to participate in the computer-guided interview. The in-depth interviews were helpful in reformulating questions and (risk) elicitation experiments and confirmed the notion that risk (attitude and perception) plays a different role depending on the manager's environment.

For the large-scale interview, we approached the managers personally and explained that we were conducting university research and that this research may help to better understand hedging behavior. The participants were not compensated for participating in the field experiment and interview, but we offered a short report of our research findings. Overall, participants were highly motivated, as using derivatives to hedge some of their risks is related to their work activities. Furthermore, many participants expressed interest in their colleagues' or competitor's (hedging) behavior and viewed our report as an opportunity to increase their knowledge. The response rate was high; 90% of the contacted managers indicated their willingness to participate.[7] We collected information from 52 private investors and 53 portfolio managers. In the remainder of the article we use the generic term (portfolio) manager to refer to the entire sample, except where we explicitly differentiate.

The final data collection instrument (computer-guided interview) consisted of two parts. In the first part, demographic data were collected, followed by a series

[7] In terms of their general activities, the firms that chose not to participate were not appreciably different from the sample of respondents.

of questions measuring, among other things, managers' risk perceptions and focus on shareholder value. In the second part, the field experiment, we measured the respondent's risk attitude by eliciting the utility function.

The Concept of Risk Attitude

Risk attitude is a psychological construct that identifies the extent to which the decision makers like or dislike risk. Risk attitude is context specific and needs to be measured in the decision-making context under examination. In the following we describe the procedures used to measure intrinsic risk attitudes for individual decision makers with a global risk attitude measure (e.g., Pennings and Smidts 2000). The global risk attitude reflects the manager's intrinsic risk attitude conditioned by the context in which the manager operates. As discussed, part of the managers are responsible for the assets that companies hold to meet retirement obligations, and for these managers an important factor influencing their work environment is the firm's compensation scheme. Ross (2004) shows that a firm's compensation scheme influences the manager's utility function and hence the manager's global risk attitude. However, the willingness to accept risk is not solely driven by the compensation scheme; the manager's inherent personality also plays an important role. Portfolio managers have their "own style" and are hired by companies because of their style and associated performance. It is not uncommon for a company to employ various types of managers, each with his or her own investment style, which is influenced by the manager's intrinsic risk attitude (Brown and Goetzmann 1997; Ennis 2001). Using a unique and validated procedure, we obtain the manager's global risk attitude measure that reflects differences in compensation schemes and individual styles in the context of managing portfolios.

Several authors provide conditions to minimize response biases when eliciting a decision maker's utility function. Hershey, Kunreuther, and Schoemaker (1982), Harrison (1986), and Holt and Laury (2002) provide useful discussions. These authors stress the importance of constructing relevant choice sets to obtain the decision maker's utility function, and they argue that the response bias is minimized when two conditions are met: (1) decision makers have well-articulated preferences and beliefs, and (2) decision makers use a consistent algorithm.[8] The notion of an appropriate solicitation framework is highlighted by Cox et al. (2008), who show that utility and value functions can differ across applications and that it is difficult to identify the theoretical foundations for decision making under risk.

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[8]There is an extensive body of literature that outlines the potential pitfalls of eliciting utility functions using a hypothetical experimental research design (e.g., Harrison 1986; Holt and Laury 2002). Although the experimental research design for this research is hypothetical because choices do not affect managers' actual wealth or well-being, they reflect daily manager's choices.

We designed the elicitation procedure in accordance with these guidelines so that managers were exposed to a situation they face on a daily basis and hence responded in their managerial role.[9] We accomplished this by exposing managers to portfolios with a 50/50 chance of a high/low return and portfolios with a fixed return. Work by Pennings and Smidts (2000) on the reliability and validity of risk attitude elicitation procedures shows that such a procedure yields reliable and valid risk attitude measures. The research design is appealing because the task reflects the relevant choices made by real decision makers on a daily basis (Smith 1991).

Risk Attitude Elicitation Process

The global risk attitude is derived from the assessed utility function $u(x)$, by means of the certainty equivalence technique (Keeney and Raiffa 1976) and the value function (e.g., strength of preference function) $v(x)$ using the midvalue splitting technique (Smidts 1997). The global risk attitude is determined by relating the functions such that $u(x) = f(v(x))$. The risk attitude measure is defined as $-u''(v(x))/u'v(x))$ (analogue to the Pratt–Arrow coefficient of risk aversion). It represents the remaining curvature in the utility function after eliminating the nonlinear effect related to the value function $v(x)$.[10] The measurement procedure was computerized, took about 45 minutes, and is described in detail in Appendix A. The negative exponential function is used to relate $u(x)$ and $v(x)$ as expressed in equation (9):

$$u(x_i) = \frac{1 - e^{-cv(x_i)}}{1 - e^c} + e_i, \tag{9}$$

where $u(x_i)$ is an element of the vector of certainty equivalents corresponding to utility levels, 0.125, 0.25, . . . , 0.875 assessed by the certainty equivalence technique; $v(x_i)$ is an element of the vector of value equivalents corresponding to value levels, 0.125, 0.25, . . . , 0.875 assessed by the midvalue splitting technique; and e_i is random error.

Measurement and Internal Consistency of the Risk Attitude Measure

To estimate equation (9), the assessed equivalents are used. For the certainty equivalence technique and the midvalue technique, nine points (certainty equivalents for $u(x)$ and value equivalents for $v(x)$) are available for each manager. These nine points correspond to the pairwise levels of utility/value. For example, for $u(x) = v(x) = 0.5$, a certainty equivalent, say x', and a value equivalent, say y', are assessed. For

[9]The choice tasks and the experimental design are available on request.

[10]Dyer and Sarin (1982), Smidts (1997), and others argue that only after removing the nonlinearity in the utility function associated with the nonlinear strength of preference (i.e., value function $v(x)$) for increased outcomes can actual preferences for risk be identified.

each manager, the parameters in equation (9) are estimated using nonlinear least squares and the Fletcher Quasi-Newton method. If parameter $c > 0$, the manager is said to be risk averse, and if $c < 0$, the manager is said to be risk seeking.

In addition, two measurements at $u(x) = 0.5$ and two measurements at $u(x) = 0.625$ were taken when eliciting the manager's utility function to test the internal consistency of the elicitation procedure. If managers respond in a consistent matter, the same certainty equivalents should result except for random response error. Using a pairwise test, the differences between the assessed certainty equivalents for the same utility levels were not significant ($p > .99$) for both consistency measurements. These findings support the notion that the research design elicited well-articulated preferences and that managers use a consistent algorithm to arrive at their responses, ensuring the validity of the measurement procedure. This further substantiates that the research design closely reflects the real business context of the managers, thereby minimizing response mode effects.

Measuring Risk Perception, Managers' Focus on Shareholder Value, and Debt-to-Asset Ratio

Based on previous research (e.g., Pennings and Smidts 2000), a 10-point Likert scale, consisting of three items, was used to measure risk perception. The scale was validated by testing its psychometric properties (Nunnally and Bernstein 1994; Pennings and Smidts 2000). Appendix B describes in detail the scale and its psychometric properties.

The extent to which manager's focus on shareholder value was measured by a Likert scale consisting of one item.[11] Managers were asked to indicate on a nine-point scale ranging from 1 ("strongly disagree") to 10 ("strongly agree") their agreement with the statement "My company focuses predominantly on the interest of our shareholders."

The firm's debt-to-asset ratio was obtained from accounting data.

Dependent Variable: Hedge Ratio

Accounting data provided us with the employed hedge ratio. The hedge ratio in this context reflects the part of the portfolio that is protected against adverse price movement by means of derivative instruments (e.g., stock index and bond futures and options). Specifically, accounting data from the firm identified average face value of the manager's portfolio for the fiscal year 2000. Managers provided confidential information identifying the average face value of the futures and options contracts used to hedge (part) of the manager's portfolio risk.

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[11] We use a Likert scale to measure managers' focus on shareholder value because of its good performance in previous studies. As identified by Nunnally and Bernstein (1994), Likert scales do not suffer from drawbacks in Guttman, and Thurstone and Chave scaling procedures.

V. Empirical Results

Table 1A provides descriptive statistics for the whole sample. The average age of the managers was 40.26 years and the majority had a college (bachelor's) or university (master's) degree. The other statistics reflect a range of work experience, portfolio values, the debt-to-asset ratios, and focus on shareholder value. In Tables 1B and 1C, the descriptive statistics are provided for the private investors and portfolio managers, respectively. On average, portfolio managers are more experienced and more highly educated. They also focus more on shareholder value, manage larger portfolios than private investors, and are more leveraged.

In Table 2A, descriptive statistics for the risk attitude parameter c in equation (9) are presented for the whole sample. The negative exponential function fit the data well, with mean squared errors (MSE) small relative to the mean, and high average R^2s (mean 0.87). This result is in line with Smidts (1997) and Pennings and Smidts (2000, 2003). The results show that risk attitudes vary widely among managers, indicating that the assumption of risk aversion or risk neutrality is not (always) valid. The largest group (55.6% of the total sample) can be classified as risk averse (parameter $c > 0$), and a small group (5.9%) is risk neutral. A relatively large number (38.5%) appears to be risk seeking (parameter $c < 0$). The presence of risk-seeking behavior may seem surprising, but these results are highly consistent with the small but growing literature in the management sciences and psychology. For example, Shapira (1997) and Smidts (1997) find risk-seeking behavior. Several explanations of risk-taking behavior have been advanced depending on the specific domain. For instance, Jaworski and Kohli (1993) find that responding to market developments entails some degree of risk taking. Han, Kim, and Srivastava (1998) find that greater market orientation is associated with higher degrees of risky, innovative behavior.

Tables 2B and 2C show the descriptive statistics for the risk attitude parameter c in equation (9) for the private investors and portfolio mangers, respectively. The negative exponential function fit the data equally well for both private and portfolio managers. There is no significant difference in risk attitudes between private investors and portfolio managers ($p = .186$). The proportions of risk averse, risk neutral and risk seeking are similar between private investors and portfolio managers.

Table 3 presents the risk perception scales—1 = low risk to 10 = high risk—for the samples. Portfolio managers perceive significantly more risk than private investors ($p = .01$), but there appears to be considerable variability in both the private and portfolio's perception of risk.

In Table 4 we first provide the results of equation (1) assuming homogeneous behavior. The results support the puzzling findings in previous studies (Géczy, Minton, and Schrand 1997; Haushalter 2000) that risk attitude, risk perception, and their interaction are not significantly related to the managers' hedge ratios.

TABLE 1A. Descriptive Statistics for Whole Sample ($N = 105$).

Panel A. Work Experience			
Work Experience	%	Value of the Portfolio in Euros (2000)	%
0–1 years	15.4	<0.5 million	28.9
1–2 years	15.4	0.5–5 million	10.6
2–4 years	20.2	5–25 million	10.6
4–8 years	14.4	25–50 million	5.8
8–15 years	14.4	20– 250 million	5.8
>15 years	20.2	250 million–0.5 billion	4.8
		0.5–2.5 billion	13.5
		>2.5 billion	18.3
		Did not disclose	1.9

Panel B. Educational Level			
Highest Educational Degree	%	Debt-to-Asset Ratio	%
High school	1.9	0–20%	36.2
College (BS degree)	54.8	21–40%	15.4
University (MS/MA degree)	39.4	41–60%	13.2
Other	3.8	81–100%	32.8
		Did not disclose	2.4

Panel C. Focus on Shareholder Value	
Company Focuses on the Interest of Shareholders[a]	%
1 (strongly disagree)	27.6
2	17.1
3	9.5
4	8.6
5	3.8
6	8.6
7	2.9
8	5.8
9	6.6
10 (strongly agree)	9.5

Note: This table presents the distribution of the managers' work experience, educational level, the value of their portfolio, the debt-to-asset ratio of the firm, and focus on shareholder value. The sample consists of 105 managers who either managed a part of a firm's assets or who managed their own accounts (e.g., private investors). Work and educational experience were measured during personal computer-guided experiments. The values of the portfolio and the debt-to-asset ratio were obtained from the firm's accounting data, and when the private investors' experiments were administered.
[a]Managers were asked to indicate on a 10-point scale ranging from 1 ("strongly disagree") to 10 ("strongly agree") their agreement with the statement "My company focuses predominantly on the interest of our shareholders."

Because we hypothesized that there might be a number of latent segments in the sample, the model was applied to the data for segments, $S = 1$ to $S = 5$.[12]

[12]For completeness, mean group values for the three observations that did not disclose their debt-to-asset ratio were used. Repeating the analysis without these three observations did not change the results presented qualitatively.

TABLE 1B. Descriptive Statistics for Private Investors ($N = 52$).

Panel A. Work Experience

Work Experience	%	Value of the Portfolio in Euros (2000)	%
0–1 years	28.8	<0.5 million	51.9
1–2 years	28.8	0.5–5 million	19.2
2–4 years	28.8	5–25 million	19.2
4–8 years	5.8	25–50 million	9.6
8–15 years	7.7	20– 250 million	0.0
>15 years	0.0	250 million–0.5 billion	0.0
		0.5–2.5 billion	0.0
		>2.5 billion	0.0
		Did not disclose	0.0

Panel B. Educational Level

Highest Educational Degree	%	Debt-to-Asset Ratio	%
High school	1.9	0–20%	65.4
College (BS degree)	78.9	21–40%	13.5
University (MS/MA degree)	13.5	41–60%	11.5
Other	5.8	81–100%	7.7
		Did not disclose	1.9

Panel C. Focus on Shareholder Value

Company Focuses on the Interest of Shareholders[a]	%
1 (strongly disagree)	28.9
2	28.9
3	17.3
4	15.3
5	3.8
6	5.8
7	0.0
8	0.0
9	0.0
10 (strongly agree)	0.0

Note: This table presents the distribution of the private investors' work experience, educational level, the value of their portfolio, the debt-to-asset ratio of the firm, and focus on shareholder value.
[a]Managers were asked to indicate on a 10-point scale ranging from 1 ("strongly disagree") to 10 ("strongly agree") their agreement with the statement "My company focuses predominantly on the interest of our shareholders."

Based on the minimum CAIC, we select $S = 3$ as the appropriate number of segments. The solution has a log likelihood of 324 and an R^2 of 0.72.[13] The entropy value of 0.95 indicates that the mixture components are well separated. The R^2 has

[13]The three-group solution R^2 is calculated using the method developed by Cameron and Windmeijer (1997) for generalized regression models. The R^2 is defined as the proportionate reduction in uncertainty measured by Kullbac–Leibler divergence due to the inclusion of regressors. Under further conditions concerning the conditional mean function, it can also be interpreted as the proportion of uncertainty explained by the fitted model.

TABLE 1C. Descriptive Statistics for Portfolio Managers ($N = 53$).

Panel A. Work Experience

Work Experience	%	Value of the Portfolio in Euros (2000)	%
0–1 years	1.9	<0.5 million	5.8
1–2 years	1.9	0.5–5 million	1.9
2–4 years	11.5	5–25 million	1.9
4–8 years	23.1	25–50 million	1.9
8–15 years	21.2	20–250 million	11.5
>15 years	40.4	250 million–0.5 billion	9.6
		0.5–2.5 billion	26.9
		>2.5 billion	36.5
		Did not disclose	3.8

Panel B. Educational Level

Highest Educational Degree	%	Debt-to-Asset Ratio	%
High school	1.9	0–20%	7.5
College (BS degree)	30.8	21–40%	17.0
University (MS/MA degree)	65.4	41–60%	15.1
Other	1.9	81–100%	56.6
		Did not disclose	3.8

Panel C. Focus on Shareholder Value

Company Focuses on the Interest of Shareholders[a]	%
1 (strongly disagree)	26.4
2	5.7
3	1.9
4	1.9
5	3.7
6	11.3
7	5.7
8	11.3
9	13.2
10 (strongly agree)	18.9

Note: This table presents the distribution of the portfolio managers' work experience, educational level, the value of their portfolio, the debt-to-asset ratio of the firm, and focus on shareholder value.
[a]Managers were asked to indicate on a 10-point scale ranging from 1 ("strongly disagree") to 10 ("strongly agree") their agreement with the statement "My company focuses predominantly on the interest of our shareholders."

dramatically improved from 0.01 for the aggregate regression model ($S = 1$) to 0.72 for the three-segment solution. Table 5 presents the estimated coefficients for this three-segment solution.

The behavior of Segment 1 is consistent with the decision-making relation identified in equation (1) and the theory outlined earlier.[14] A significant relation

[14]We tested whether the segments differed regarding the managers' risk attitude using analysis of variance. It appears that the managers in the different segments do not significantly differ regarding their risk attitude ($p = .57$). This further substantiates that the heterogeneity is latent and that it is the decision-

TABLE 2A. Summary Results of Estimating the Manager's Risk Attitude ($N = 105$).

	Parameter c	Fit Indices	
Mean	0.247	Mean MSE	0.012
Median	0.198	Median MSE	0.007
St. dev.	4.895	Mean MAE	0.076
Percentile		Median MAE	0.068
25th	−0.757	Mean R^2	0.869
50th	0.198	Median R^2	0.902
75th	0.988		
Classification of respondents			
Risk averse	55.6%		
Risk neutral	5.9%		
Risk seeking	38.5%		

Note: This table presents the summary descriptive statistics of the global risk attitude parameter estimates and the fit statistics from estimating equation (9),

$$u(x_i) = \frac{1 - e^{-cv(x_i)}}{1 - e^{c}} + e_i,$$

for each manager. $u(x_i)$ is an element of the vector of certainty equivalents corresponding to utility levels, 0.125, 0.25, . . . , 0.875 assessed by the certainty equivalence technique. $v(x_i)$ is an element of the vector of value equivalents corresponding to value levels, 0.125, 0.25, . . . , 0.875 assessed by the midvalue splitting technique, and e_i is random error. MSE is mean squared error, and MAE is mean absolute error. R^2 is calculated by squaring the Pearson correlation between actual values and the values predicted from the model. A manager is classified risk neutral when the parameter is not significantly different from $c = 0$ at the .01 level. To perform this test, the residuals must be normally, as well as independently and identically, distributed for each individual. Because it is questionable whether the residuals fit the assumptions, the analysis is for descriptive purposes only.

exists between risk attitude, risk perception, their interaction, and the hedge ratio. Table 5 also shows that the hypothesized drivers of the heterogeneity, the concomitant variables, the debt-to-asset ratio, and the focus on shareholder value are highly significant. The positive coefficients indicate that managers with a high debt-to-asset ratio and an intense focus on shareholder value are likely to belong to this segment. The results suggest that the importance of the risk variables emerges when managers face financial distress, as reflected in a high debt-to-asset ratio. The findings also indicate that risk has more influence on behavior when managers operate in an environment characterized by a relative high focus on shareholder value. One explanation may be that managers who are faced with a high debt-to-asset ratio or focus on shareholder value make the risk–return trade-off more explicitly than managers who do not (Benninga and Sarig 1997; Leland 1998; Borokhovich et al. 2004). The results show that the effect of focus shareholder value and

making behavior (e.g., the influence of risk attitude on behavior) reflected in the regression coefficients that differs across segments.

TABLE 2B. Summary Results of Estimating the Risk Attitude of Private Investors ($N = 52$).

	Parameter c	Fit Indices	
Mean	0.885	Mean MSE	0.011
Median	0.267	Median MSE	0.006
St. dev.	5.330	Mean MAE	0.081
Percentile		Median MAE	0.069
25th	−0.905	Mean R^2	0.869
50th	0.267	Median R^2	0.903
75th	0.171		
Classification of respondents			
Risk averse	55.8%		
Risk neutral	5.7%		
Risk seeking	38.5%		

Note: MSE is mean squared error, and MAE is mean absolute error. R^2 is calculated by squaring the Pearson correlation between actual values and the values predicted from the model. A manager is classified risk neutral when the parameter is not significantly different from $c = 0$ at the .01 level. To perform this test, the residuals must be normally, as well as independently and identically, distributed for each individual. Because it is questionable whether the residuals fit the assumptions, the analysis is for descriptive purposes only.

TABLE 2C. Summary Results of Estimating the Risk Attitude of Portfolio Managers ($N = 53$).

	Parameter c	Fit Indices	
Mean	−0.389	Mean MSE	0.013
Median	0.118	Median MSE	0.008
St. dev.	4.374	Mean MAE	0.072
Percentile		Median MAE	0.067
25th	−0.618	Mean R^2	0.852
50th	0.118	Median R^2	0.901
75th	0.107		
Classification of respondents			
Risk averse	55.6%		
Risk neutral	5.9%		
Risk seeking	38.5%		

Note: MSE is mean squared error, and MAE is mean absolute error. R^2 is calculated by squaring the Pearson correlation between actual values and the values predicted from the model. A manager is classified risk neutral when the parameter is not significantly different from $c = 0$ at the .01 level. To perform this test, the residuals must be normally, as well as independently and identically, distributed for each individual. Because it is questionable whether the residuals fit the assumptions, the analysis is for descriptive purposes only.

debt-to-asset ratio on the employed hedge ratio is an indirect, as opposed to a direct, effect. This result is in line with Tufano (1996), who finds little empirical support for theories that view risk management as a direct means to maximize shareholder value.[15]

[15] To test whether focus on shareholder value and debt-to-asset ratio had a direct effect on the managers' employed hedge ratios, we estimated equation (1) including the focus on shareholder value and the debt-to-asset ratio variables in a simple mixture framework (equation (5)). The MLE estimates indicate that neither

TABLE 3. Summary Results of Estimating the Risk Perceptions of Private Investors ($N = 52$) and Portfolio Managers ($N = 53$).

	Whole Sample	Private Investors	Portfolio Managers
Mean	5.680	4.940	6.420
Median	6.000	5.000	7.000
St. dev.	3.006	2.866	2.986
Percentile			
25th	3.000	3.000	3.000
50th	6.000	5.000	7.000
75th	8.000	7.000	9.000

Note: Risk perception is measured using a 10-point validated scale where low values indicate low risk perception and high values indicate high risk perception. Appendix B describes the risk perception scale in detail and its psychometric properties. The difference in risk perception between private investors and portfolio managers is significant ($p = .01$).

TABLE 4. One-Segment Solution.

Explanatory Variables	Regression Coefficients	t-values
Risk perception	0.13	1.44
Risk attitude	0.83	1.48
Interaction between risk attitude and risk perception	0.18	1.28
Log-likelihood	430	
R^2	0.01	

Note: This table presents the results of the mixture regression model in which the managers' hedge ratio is a function of risk attitude, risk perception, and their interaction. The one-segment solution assumes that the influence of these risk variables on the hedge ratios is homogeneous.

The managers in Segment 2 are highly sensitive to the interaction between risk attitude and risk perception. The main effects of risk attitude and risk perception do not drive their behavior; rather, their interaction is most influential. The more these managers perceive risk, the more risk-averse managers avoid risk and hence the higher the hedge ratio. The effects of the concomitant variables are similar to those identified in Segment 1. The probability of being a member of this segment is higher when the manager focuses on shareholder value and/or is confronted with high debt-to-asset ratios.

For managers in Segment 3, risk does not influence their employed hedge ratios, results that confirm the counterintuitive findings of Géczy, Minton, and Schrand (1997) and Haushalter (2000). The insignificant submodel results support the notion that these managers are hard to classify based on the firm's debt-to-asset

variable was significant in the identified segments, supporting the notion these variables do not have a direct effect on the managers' hedge ratios but instead have an indirect effect as they influence heterogeneity.

TABLE 5. Parameter Estimates for the Three-Segment Model.

	Regression Coefficients		
	Segment 1 ($n = 30$)	Segment 2 ($n = 14$)	Segment 3 ($n = 61$)
Explanatory variables			
Risk perception	0.42***	0.03	0.02
Risk attitude	1.93***	2.54	0.15
Interaction between risk attitude and risk perception	0.45***	0.72**	0.04
Concomitant variables			
Debt-to-asset ratio	2.19***	0.43**	0.14
Focus on shareholder value	2.06***	0.94**	0.11
Relative segment size π	0.29	0.13	0.58
Log-likelihood		−324	
R^2		0.72	
Type of manager in segments			
Portfolio managers	100% ($n = 30$)	64.3% ($n = 9$)	22.9% ($n = 14$)
Working on behalf of company			
Private investors	0% ($n = 0$)	35.7% ($n = 5$)	77.1% ($n = 47$)
Average hedge ratio	90.08%	31.13%	17.74%

Note: This table presents the estimated coefficients for the three-segment solution of the concomitant variable mixture regression model. The managers' hedge ratio is a function of risk attitude, risk perception, their interaction, and the concomitant variables. The table also presents a breakdown of manager type by segment and the average hedge ratio employed by the managers in the three segments. The hypothesis that the means of the managers' hedge ratios of the three segments are equal was rejected at the 1% level using analysis of variance.
***Significant at the 1% level.
**Significant at the 5% level.

ratio, the manager's focus on shareholder value, or the structure of the conceptual model.

Investigating the average hedge ratio employed by managers in the three segments, we find a positive relation between the importance and magnitude of the risk variables and the hedge ratio: Segment 1 has the highest average hedge ratio, whereas Segment 3 has the lowest (Table 5). Further examination of the relation between risk attitude and the hedge ratio indicates that even risk-seeking managers have hedge ratios larger than zero, a finding that can be explained by Schrand and Unal's (1998) coordinated risk management concept.

Examining the distribution of types of managers in the three segments reveals a clear structure (Table 5, lower part). Segment 1 is dominated by managers managing portfolios on behalf of a company, Segment 3 is dominated by private investors (77.1%), and Segment 2 is in between with 64.3% managers working on behalf of a company and 35.7% private investors. These findings suggest that the basic model (equation (1)) hypothesized to explain owner-manager behavior

(Smith and Stulz 1985; Mayers and Smith 1987) is also relevant for managers making decisions on behalf of a company when conditioned by the appropriate concomitant factors. In fact, the risk variables have more influence on hedging behavior of managers that work in a company environment than investors that manage their own portfolio. One explanation of this result is that small and medium enterprises' (SMEs) organizational structure differs from larger companies and that members of the SMEs' decision-making unit significantly affect hedging decisions independent of risk (e.g., Pennings and Garcia 2004).

VI. Conclusion and Discussion

In an uncertain world, the notion that risk influences behavior is pervasive and well grounded in economic theory. Based on management theory, decision makers may develop strategies that permit them to mitigate the effects of risky situations. This notion is particularly well accepted for hedging behavior. Theoretical models have been developed to explain and predict hedging, suggesting that it should be highly influenced by risk attitudes and risk perceptions. However, empirical studies that compare actual and predicted behavior reveal that these models are incapable of explaining actual outcomes. Recent research by Pennings and Garcia (2004) suggests that the influence of risk attitudes and risk perceptions is not homogeneous across market participants. Here, we examine the heterogeneous relation between the risk variables and hedging behavior and the drivers of the heterogeneity. Heterogeneity, referring to the notion that the influence of managers' risk attitudes and risk perceptions on hedging behavior may differ, can have profound consequences for the interpretation of empirical evidence and for understanding risk management behavior. Following Heckman (2001), heterogeneity refers to the idea that decision makers respond differently to similar economic stimuli, which in our context translates into the notion that the influence of risk on hedging varies across decision makers. We show that for some segments risk does indeed influence hedging behavior, but not for others. We further explore the factors that drive this heterogeneity using a concomitant mixture model and find that the debt-to-asset ratio and the firm's focus on shareholder value are important.

The findings have implications for sharpening our understanding of the relevance and structure of theory. First, in uncertain times it seems necessary to collect data to identify how decision makers actually respond. Examining actual behavior in relevant situations can lead to a clearer understanding of the relation between risk and actual choices. Second, in a related context, we need to develop a better understanding of the factors that influence the relation between the risk and actual behavior. Here, the concomitant variables partially address this issue. For example, Segment 3's hedging activities were not sensitive to risk, whereas managers in Segment 1 were highly influenced. Managers in Segment 1 tended to work for companies that have third-party shareholders and high debt-to-asset ratios. This result is consistent with Bernstein's (1999) observation: "The seats on which corporate executives sit today are far hotter than ever before. The penalties are now severe—often terminal—for executives who neglect shareholder interests or just plain err in running their companies. No wonder risk management is on the front burner" (p. 2). At a more general level, the findings emphasize the importance of identifying the moderating factors that affect the heterogeneous relation between behavior and its determinants. Furthermore, the results suggest that knowledge of drivers of the heterogeneous relation between the risk variables and hedging behavior—a client's capital structure and focus on shareholder value—may provide useful information to investment consultants, banks, and insurance companies on how they can customize recommended portfolios for their customers.

In this article we examine the drivers of the hedging ratio, the proportion of the underlying position that is hedged. Standard theory on optimal hedging suggests that there is no relation between portfolio size and hedge ratio; in these models the optimal hedge ratio is independent of the portfolio size. However, portfolio size may have an influence on the optimal hedging ratio by means of transaction costs: firms with larger portfolios may incur relative lower transaction costs per unit hedged.[16] Brown (2001) indicates that the cost of maintaining a hedging program is not trivial and hence may influence whether managers hedge. Brokerage fees can differ across market participants, with fees decreasing with the number of trades. Furthermore, maintenance of an effective hedging program may require additional costs for collecting information and monitoring market movements and positions. Hence, one may expect small firms (private investors) to face higher transaction costs than portfolio managers, influencing their willingness to hedge and their hedge ratios. At the extremes, our results suggest that differences in transaction costs may affect actual hedge ratios. Segment 1, which has the highest average hedge ratio, is solely composed of portfolio managers. Similarly, Segment 3, in which the average hedge ratio is lowest, is composed to a large extent of private investors. However, the findings are less clear for the portfolio managers that are members of Segment 3 and for the mixed group of managers in Segment 2. Further research that examines whether actual hedging behavior is influenced by transaction costs in the presence and measurement of risk is needed. Care will need to be taken to differentiate in an effective manner between risk perceptions, a willingness to accept risk, and actual transactions costs incurred by the firm.

In the empirical study we elicited the intrinsic utility function following Pennings and Smidts (2000). Future research may, in addition to eliciting the intrinsic utility function, elicit hedging probability functions. Cox et al. (2008) provide

[16] In a theoretical context, various authors (see Howard and D'Antonio 2006 for a review) show that transaction costs influence optimal hedge ratios.

useful guidelines on how to calibrate these functions and integrate them into a framework for decision making under risk. Mattos, Garcia, and Pennings (2008) show that probability weighting does influence hedging behavior using an analytical model that is rooted in a non-expected-utility framework. Measuring hedgers' utility functions and probability function simultaneously and relating them to actual hedging behavior is a promising avenue to explore.

Finally, it should be noted that the risk perception measure used here may be subject to some measurement error because it was developed using a self-reporting scale rather than a revealed preference method. Our measure, which was developed in the decision sciences literature and has been used successfully in prior research, demonstrates strong reliability and validity scores. Nevertheless, future research should strengthen our procedures and findings by using risk perception measures based on assessment of respondent's probability function using the interval technique (Hershey, Kunreuther, and Schoemaker 1982; Farquhar 1984; Smidts 1997).

Appendix A. Risk Attitude Measure: Description of Field Experiment

The certainty equivalence technique was formulated in terms of relatively high/low returns with a range of -5% to $+20\%$, with a probability of 0.5 and a fixed return. The assessment of the certainty equivalent was an iterative process. If a manager chose alternative A (the 50/50 high/low return), the computer would randomly generate a higher fixed return (alternative B) than the previous one, thus making alternative B more attractive or would generate a lower fixed return, making alternative A (even) more attractive. If a manager chose alternative B, the computer would randomly generate a lower fixed return (alternative B) the next time, making alternative A more attractive or would generate a higher fixed return, making alternative A less attractive.[17] The next measurement would start after the respondent had indicated an indifference between alternative A or B. Nine points of the utility function were assessed by means of this iterative process. In the midvalue splitting technique, a manager specifies whether a change from x_i to x_j equals in value a change from x_i to x_k, where $x_i < x_j < x_k$. By iteration, a value of x_j can be found so that a manager is indifferent between both changes, and the first midvalue is determined. Similar to the certainty equivalence technique, a sequence of successive bisections results in a number of points of the value function. The procedure used in the midvalue splitting technique resembles the certainty equivalence technique to a large extent. The same boundaries (–5% return and +20% return) and sequence of successive bisections were used. In the experiments, a manager was presented

[17]The randomization was introduced to remove the incentive for individuals to keep choosing A to receive a higher fixed price (Harrison 1986).

with two situations: one concerning a change in return on their portfolio from A to B, and one concerning a change from B to C (with $A < B < C$). This situation was shown on a computer screen by means of a line divided by the three points A, B, and C. Subsequently a respondent was asked to indicate which change in returns was deemed more valuable: the change from A to B or the change from B to C. By adjusting the value C through the computer program, a respondent iterated toward the indifference point. Nine points of the value function were assessed by means of this iterative process.

The $u(x)$, obtained by the certainty equivalence technique, and $v(x)$, obtained by the midvalue technique, are numerically related to obtain the global risk attitude. In the expected utility framework the functional form of the utility function $u(x)$ and value function $v(x)$ is left open. Tsiang (1972) refers to Arrow (1971), who provides four conditions for an acceptable utility function: (1) marginal utility of wealth is positive, (2) marginal utility of wealth decreases with increasing wealth, (3) marginal absolute risk aversion is constant or decreasing with increasing wealth, and (4) marginal proportional risk aversion is constant or increasing with increasing wealth. The negative exponential, power, and logarithmic function meet all four conditions. Keeney and Raiffa (1976) and Fishburn and Kochenberg (1979) demonstrate that the negative exponential and power functions perform well relative to the logarithmic function. Moreover, both functions are straightforward to use. After scaling the boundaries of the functions, the estimation of only one parameter suffices to characterize a manager's risk attitude. Pennings and Smidts (2000) find that the negative exponential function performed slightly better than the power function; therefore, we use the negative exponential function to relate $u(x)$ and $v(x)$ as expressed in equation (9) in the text:

$$u(x_i) = \frac{1 - e^{-cv(x_i)}}{1 - e^{c}} + e_i, \tag{9}$$

where $u(x_i)$ is an element of the vector of certainty equivalents corresponding to utility levels, $0.125, 0.25, \ldots, 0.875$ assessed by the certainty equivalence technique, $v(x_i)$ is an element of the vector of value equivalents corresponding to value levels, $0.125, 0.25, \ldots, 0.875$ assessed by the midvalue splitting technique, and e_i is random error.

Appendix B. Risk Perception Measure: Psychometric Properties

We use a Likert scale to measure managers risk perception because of its good performance in previous studies. As identified by Nunnally and Bernstein (1994), Likert scales do not suffer from drawbacks in Guttman, and Thurstone and Chave scaling procedures. The items of the scale were based on the validated risk perception scale developed by Pennings and Wansink (2004).

Managers were asked to indicate their agreement with the following items using a 10-point scale that ranged from "strongly disagree" to "strongly agree":

1. I am able to predict the value of my portfolio over time.
2. My portfolio is not at all risky.
3. I am exposed to a large amount of risk with my portfolio.

Confirmatory factor analysis was used to assess the psychometric measurement quality of the risk perception scale. The analytical model underlying factor analysis assumes that the observed indicators (questions 1–3) are generated by a one-latent factor (risk perception). The relation between the indicators and the latent variable can be represented by the following matrix equation:

$$\mathbf{x} = \boldsymbol{\Lambda}\boldsymbol{\kappa} + \boldsymbol{\delta}, \tag{B1}$$

where $\mathbf{x}$ is the $q \times 1$ vector of the n sets of observed variables (i.e., indicators), $\boldsymbol{\kappa}$ is the $n \times 1$ vector of underlying factor (risk perception), $\boldsymbol{\Lambda}$ is the $q \times n$ matrix of regression coefficients relating the indicators to the underlying factors, and $\boldsymbol{\delta}$ is the $q \times 1$ vector of error terms of the indicators. The overall fit of the model provides necessary and sufficient information to determine whether our set of questions accurately describes risk perception. All factor loadings (i.e., the regression coefficients, $\boldsymbol{\Lambda}$) were significant ($p < .001$) and greater than 0.4. These findings support the convergent validity of the indicators (Anderson and Gerbing 1988). The average sum score of the indicators are used in the analyses to measure risk perception. In addition, we measured the reliability of the risk perception scale. The value of the construct reliability, which ranges between 0 and 1, with higher values indicating higher reliability (see Hair et al. 1995), was 0.80.

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