Strategic Management Journal, Vol. 17, 671–691 (1996)

MEASURING ORGANIZATIONAL DOWNSIDE RISK

KENT D. MILLER and JEFFREY J. REUER
Krannert Graduate School of Management, Purdue University, West Lafayette, Indiana, U.S.A.

Despite widespread incorporation of risk measures in strategy research, there is little consensus regarding the meaning and measurement of risk. In contrast to the variability measures widely used in strategy studies, this paper draws from behavioral decision theory, finance, and management theory to present an alternative perspective on organizational risk—downside risk. The paper explains three categories of organizational downside risk measures based on the concept of lower partial moments. The latter sections of the paper present considerations involved in specifying operational measures of downside risk and an empirical comparison of alternative downside risk measures.

Risk has become an important variable in many areas of strategy research. Measures of risk have been included in research on corporate product diversification (e.g., Amit and Livnat, 1988; Bettis, 1981; Bettis and Hall, 1982; Bettis and Mahajan, 1985; Chang and Thomas, 1989; Chatterjee and Lubatkin, 1990; Montgomery and Singh, 1984), international geographic diversification (e.g., Kim, Hwang, and Burgers, 1993), vertical integration (e.g., Chatterjee, Lubatkin, and Schoenecker, 1992; D'Aveni and Ilinitch, 1992; Lubatkin and O'Neill, 1987), business strategy and industry characteristics (e.g., Cool, Dierickx, and Jemison, 1989; Cool and Schendel, 1988; Oviatt and Bauerschmidt, 1991; Woo, 1987), organizational processes (e.g., Jemison, 1987), and corporate structures (e.g., Hoskisson, 1987; Singh, 1986).[1] These studies use a variety of risk measures derived from accounting and stock returns data seeking to capture the variability of company performance. The most common measures are the variance of return on equity or return on assets, and systematic (i.e., beta) and unsystematic risk derived from historical stock returns.

Despite the widespread incorporation of risk in empirical strategy research, there is little consensus regarding the meaning of the concept and its measurement. Within strategy, debate regarding the appropriate specification of risk measures began with Bowman's (1980) study indicating that in the majority of industries studied, average company ROE was negatively related to variance in ROE. Subsequent research scrutinized Bowman's risk measure, methodology, and findings. Marsh and Swanson (1984) criticized Bowman's methodology and proposed a transformed return on equity measure which, in general, did not demonstrate significant relations between ROE mean and variance.

Fiegenbaum and Thomas (1986) raised questions about the robustness of Bowman's finding across different time periods and different risk measures. Fiegenbaum and Thomas (1988) and

Key words: risk measurement; risk–return; behavioral decision theory

[1] The studies cited are intended to be indicative of the various kinds of strategy research incorporating measures of risk. The list is not comprehensive.

CCC 0143–2095/96/090671–21

Received 1 September 1994
Final revision received 22 January 1996

Fiegenbaum (1990) studied the role of firms' target levels in explaining risk–return relations. Despite Marsh and Swanson's (1984) criticism, these studies relied on variance in accounting returns to measure risk. Other strategy studies examining risk–return relations have used systematic risk (i.e., beta) and unsystematic risk based on stock returns (Amit and Livnat, 1988) and accounting returns (Aaker and Jacobson, 1987). Bromiley (1991b) used the standard deviation of stock analysts' earnings per share forecasts as a measure of the risk associated with future earnings.

Examining the various measures used in previous strategy research, Miller and Bromiley (1990) found that different risk proxies result in different estimated corporate risk–return relations. This finding cautioned against arbitrary selection of risk proxies in empirical research. Furthermore, the debate between Ruefli (1990, 1991) and Bromiley (1991a) regarding the estimation of mean–variance relations has called into question the appropriateness of variance measures of risk. Ruefli and Wiggins (1994) extended the criticisms of variance measures to Oviatt and Bauerschmidt's (1991) measure of risk as the variability of returns around a time trend. Baucus, Golec, and Cooper's (1993) research on the implications of using beginning-of-period vs. end-of-period accounting returns pointed to the sensitivity of risk–return relations to the specification of risk measures.

This study seeks to respond to calls for explicit attention to the definition and measurement of risk in strategy research (e.g., Baird and Thomas, 1990; Bromiley, 1991b; Fiegenbaum and Thomas, 1988). This research was conducted from the perspective that assessing the conceptual and empirical properties of alternative measures is a prerequisite for substantive strategy research incorporating risk proxies. While this perspective has not always been appreciated by strategy researchers, who have tended to favor substantive questions over psychometric concerns, the need for explicit attention to measure assessment is recognized within the field (e.g., Venkatraman and Grant, 1986).

While much of the controversy surrounding risk measures has revolved around the empirical properties of alternative measures, the conceptual validity of existing strategic risk measures also remains in question (Aaker and Jacobson, 1990; Baird and Thomas, 1990; Collins and Ruefli, 1992). Despite the widespread use of variability measures as risk proxies, behavioral decision theory suggests such an approach may not reflect managers' and investors' conceptualizations of risk. Criticisms of variability measures of risk can be found in the finance and strategic management literature also. As an alternative, researchers in these various fields propose that managers and investors are averse to downside risk, i.e., below-target performance.[2] If downside risk is more relevant to managerial behavior than performance variability, empirical strategy research using downside risk may provide greater explanatory power than previous studies using variability measures of risk.

The first portion of this paper draws from behavioral decision theory, finance, and management perspectives to motivate downside conceptualizations of risk. We know of no other research drawing together these three distinct streams of research on downside risk. The discussion then turns to the specification of organizational downside risk measures and the decisions involved. This study introduces three categories of downside risk measures not found in previous strategy research. Indeed, the proposed measures of organizational downside risk based on accounting returns and stock analysts' earnings forecasts are unique to this study. Specification of these measures requires addressing the conceptual and empirical issues associated with adapting individual-level measures to the organizational level. Only after addressing the issues associated with this shift in the level of analysis is it possible to make comparisons with the organizational-level downside version of beta from finance theory. The latter portion of the paper provides an empirical comparison of downside measures and the variability measures found in previous strategy research. These comparisons shed light on the measurement properties of alternative organizational risk measures and serve as a basis for providing guidance to researchers interested in incorporating downside risk measures in strategy and organization theory research.

[2] Other terms related to downside risk are loss aversion (Kahneman and Tversky, 1982) and regret aversion (Bell, 1983).

DECISION THEORY, FINANCE, AND MANAGEMENT PERSPECTIVES ON DOWNSIDE RISK

Behavioral decision theory

Much of the work on risk in behavioral decision theory can be viewed as a reaction against economists' portrayal and conclusions. Behavioral theorists have criticized economists' portrayal of risk preferences in terms of stable concave individual utility functions (Schoemaker, 1982, 1993). While behavioral theorists have offered interesting critiques of treatments of risk in economics, their research indicates risk preferences defy simple specifications. Behavioral research has emphasized heuristics and biases in individual evaluations of probabilistic outcomes (Kahneman, Slovic, and Tversky, 1982; Slovic, Fischoff, and Lichtenstein, 1977). By focusing on any particular conceptualization of risk—as we do here by focusing on downside risk—we sacrifice some of the richness of the behavioral characterizations in order to generate tractable empirical measures.

Evidence from behavioral research indicates the importance of reference levels in determining risk preferences (Kahneman and Tversky, 1979; March and Shapira, 1987). Recognition that individuals' risk preferences are formulated relative to reference levels motivated the specification of downside measures of risk. Stone (1973), Fishburn (1977) and Laughhunn, Payne, and Crum (1980) specified risk as a probability-weighted function of deviations below a target level. Fishburn notes:

> The idea of a mean-risk dominance model in which risk is measured by probability-weighted dispersions below a target seems rather appealing since it recognizes the desire to come out well in the long run while avoiding potentially disastrous setbacks or embarrassing failures to perform up to standard in the short run (1977: 118).

Aversion to downside outcomes may be due to individuals' desire to avoid postdecision regret (Bell, 1982, 1983; Loomes and Sugden, 1982).

Laughhunn *et al.* (1980), Libby and Fishburn (1977), and March and Shapira (1987) argue that management theory ought to incorporate valid assumptions about the way managers actually perceive and evaluate risk. Libby and Fishburn (1977) cite several studies supporting the relevance of individual risk viewpoints to group decisions. They contend that groups respond to the same risk parameters as individuals, but the specific parameter values may be subject to risky or cautious shifts (see Wallach and Wing, 1968; Levinger and Schneider, 1969). With risky shifts, a group displays greater risk-taking propensity than any individual in the group.

Finance theory

Very early in the field's development, finance research acknowledged the relevance of downside risk for investment decisions. Even the pioneering work by Markowitz (1959), which advanced mean–variance portfolio models, acknowledged the relevance of risk associated with failure to achieve a target return. Markowitz actually argued that semivariance analyses produce better portfolios than variance analyses but chose to work with variance analyses because of their computational ease.[3] Hogan and Warren (1972, 1974) showed how the computational difficulties associated with semivariance as a risk measure could be overcome.

Despite early recognition of the semivariance definition of risk, incorporation of downside risk into finance portfolio models has been limited. Harlow and Rao explain: '...empirical tests of these models (e.g., Jahankani (1976) and Bawa, Brown, and Klein (1981)) have not led to substantive improvements over the results offered by the standard Sharpe (1964)–Lintner (1965)–Mossin (1966) Capital Asset Pricing Model (CAPM)' (1989: 285–286). In contrast to the previous empirical research on downside risk, Harlow and Rao (1989) developed and tested a downside risk model of equity returns and found its ability to explain stock returns exceeded that of the traditional CAPM. Their research is discussed in greater detail below.

Harlow (1991) discussed asset allocation to minimize portfolio downside risk for any given level of expected return. The downside risk approach is more attractive than traditional mean–variance approaches because of its consistency with the observation that investors are averse to

---

[3] Semivariance refers to a second-order moment considering only downside outcomes below a target level. This contrasts with the second-order central moment (i.e., variance) considering both upside and downside deviations from the mean. See the discussion of Equation 1 below for a precise definition.

downside results but not to upside variability. Furthermore, Harlow points out that the downside risk approach requires less restrictive assumptions about the distribution of returns and investor utility functions than mean–variance models. Leibowitz and Henriksson (1989) and Garcia and Gould (1987) offer alternative approaches to incorporating downside risk in portfolio asset allocation decisions.

Management theory

Several management studies have explored how managers conceptualize risk. Mao's (1970) interviews with executives indicated managers characterize risk as failure to meet some target rate of return rather than variance. MacCrimmon and Wehrung (1986) identified the magnitude of loss, the chance of loss, and the exposure to loss as the essence of risk. March and Shapira reported that when managers were asked whether they viewed risk in terms of a distribution of all possible outcomes, just the negative ones, or just the positive ones, 80 percent indicated they considered only the negative outcomes. They concluded, 'There is, therefore, a persistent tension between "risk" as a measure (e.g., the variance) on the distribution of possible outcomes from a choice and "risk" as a danger or hazard' (1987: 1407).

Baird and Thomas (1990) provided an overview and critique of the various definitions and operational measures of risk used in strategy research. Their survey results indicated financial analysts specializing in six different industries considered size of loss and loss probability the most important of seven risk definitions.

Aaker and Jacobson state: 'Marketing and strategy are primarily concerned with avoiding decreases in expected return' (1990: 153). They use the example of new entry into an industry to illustrate the deficiency of variance risk measures. As they explain, while new entry into an industry may leave incumbent firms' return variabilities unchanged, entry can lower expected returns. The potential for reduced returns due to competitor actions or environmental factors is the essence of risk as discussed in most strategy literature. For example, Porter states: 'Risk is a function of how poorly a strategy will perform if the "wrong" scenario occurs' (1985: 476). Firms invest in financial and real options to reduce downside risk while maintaining upside potential (Bowman and Hurry, 1993; Kogut, 1991; Sanchez, 1993). The use of variance measures of risk in empirical strategy research conflicts with the understanding of risk as performance below expectations found in much of the strategy literature.

A recent study by Collins and Ruefli (1992) advocated the strategy field adopt operational measures of risk formulated in terms of organizational losses. They proposed ordinal measures capturing the probability of losing rank position relative to other industry competitors. A downside concept of risk is also implicit in strategy studies incorporating Altman's Z (Altman, 1983), a bankruptcy risk discriminant score, as a proxy for organizational risk (e.g., D'Aveni and Ilinitch, 1992).

The behavioral decision theory, finance, and management studies mentioned in this section provide a strong basis for shifting strategy researchers' attention from variance measures of risk to downside measures. The discussion now turns to three categories of organizational downside risk measures. The three categories include measures based on (1) historical performance, (2) a downside version of the capital asset pricing model (CAPM), and (3) stock analysts' earnings forecasts. Each category makes use of the concept of lower partial moments.

THREE CATEGORIES OF DOWNSIDE RISK MEASURES

Lower partial moments

Fishburn (1977) modeled downside risk at the individual level of analysis using lower partial moments. The term lower partial moment (LPM) refers to the inclusion of only the left-hand (downside) tail of the return's distribution in the calculation. Adapting lower partial moment measures to the organizational level, risk can be defined in terms of a target level of return, denoted τ, and the relative importance of returns below the target measured by a parameter α. Risk for a given firm j is a probability weighted function of below target returns:

$$\mathrm{LPM}_{\alpha}(\tau;j) = \int_{-\infty}^{\tau} (\tau - r_j)^{\alpha} f(r_j)\,dr_j, \qquad \alpha \geq 0 \tag{1}$$

where $f(r_j)$ is the probability density function for firm j returns. $LPM_\alpha(\tau;j)$ is the general formula for a set of organizational risk measures specified as lower partial moments.

The value of α reflects the relative importance of the magnitude of deviations below the target level, τ. If small deviations below target are unimportant relative to large deviations, the appropriate value for α is greater than 1. If risk is conceptualized as deviations below target with little concern for the magnitude of the target shortfall, then a small value of α (i.e., less than 1) is appropriate. Fishburn (1977) demonstrated that specifying $0 < \alpha < 1.0$ is consistent with the decision-maker having a convex utility function for returns below target (i.e., risk seeking). If $\alpha > 1.0$, the utility function is concave, indicating risk aversion; $\alpha = 1$ indicates risk neutrality. For $\alpha = 0$, LPM_α reduces to the probability of loss, whereas $\alpha = 1$ and $\alpha = 2$ imply expected target shortfall and target semivariance concepts of risk, respectively. If $\alpha = 0$ and τ = survival level return, the probability of ruin model results.[4]

Extending Fishburn's (1977) measure of downside risk from the individual to the organizational level requires an implicit assumption that an organization's risk preferences can be represented by a unique and relatively simple organizational utility function. Specifying such an organizational utility function requires suppressing the problems of aggregating stakeholders' preferences (Arrow, 1963; March, 1981). While simplistic assumptions about preference aggregation may be troubling to some microeconomic and behavioral theorists, public economists have often found specification of well-behaved social welfare functions to be a useful theoretical construct (see, for example, Atkinson and Stiglitz, 1980). In the same way, specifying a simple organizational utility function focuses on the relevant level of analysis, while skirting the problem of aggregating individual preferences.

Using discrete historical returns data, Equation 1 can be rewritten as:

$$LPM_\alpha(\tau;j) = (1/N) \sum_{r_j<\tau}^{\tau} (\tau - r_j)^\alpha, \qquad \alpha \geq 0 \tag{1'}$$

[4] Holthausen (1981) provides a critique and extension of the theoretical perspective reflected in Fishburn's (1977) lower partial moment model.

where N is the number of return observations. Such a measure could be incorporated easily in empirical research using historical accounting or stock returns data.

Only under very restrictive conditions will estimated risk–return relations using downside measures be proportional to risk–return relations using central moments. Estimated risk–return relations using the second-order ($\alpha = 2$) downside risk measures (1′) and sample variance to measure risk will be proportional only if (1) the mean return for each firm is chosen as the target level, and (2) returns are symmetrically distributed about the mean. Under these two conditions, the second-order LPM is directly proportional to the variance.[5] If, however, some target rate other than the firm-specific mean return is chosen and/or the return distributions are skewed, the downside and variance approaches yield different risk–return relations.

Figure 1 illustrates the return distributions for two different firms, a and b. The two firms have symmetric (normal) distributions but different means. Both distributions have identical variances. That is, both firms have the same level of risk when the traditional variance (or standard deviation) measure is used. If, however, we use the LPM_0 (probability of loss) measure, risk is measured as the area under the curve to the left

[5] The second central moment (variance) is defined as:

$$M_2(j) = \int_{-\infty}^{\infty} (\mu - r_j)^2 f(r_j) dr_j$$

where μ is the mean of the distribution of firm j returns. We can rewrite this expression as:

$$M_2(j) = \int_{-\infty}^{\mu} (\mu - r_j)^2 f(r_j) dr_j + \int_{\mu}^{\infty} (\mu - r_j)^2 f(r_j) dr_j$$

By symmetry around μ,

$$\int_{-\infty}^{\mu} (\mu - r_j)^2 f(r_j) dr_j = \int_{\mu}^{\infty} (\mu - r_j)^2 f(r_j) dr_j$$

Hence,

$$M_2(j) = 2\int_{-\infty}^{\mu} (\mu - r_j)^2 f(r_j) dr_j = 2LPM_2(\mu;j)$$

The variance, $M_2(j)$, is therefore directly proportional to the second-order lower partial moment, $LPM_2(\mu;j)$.

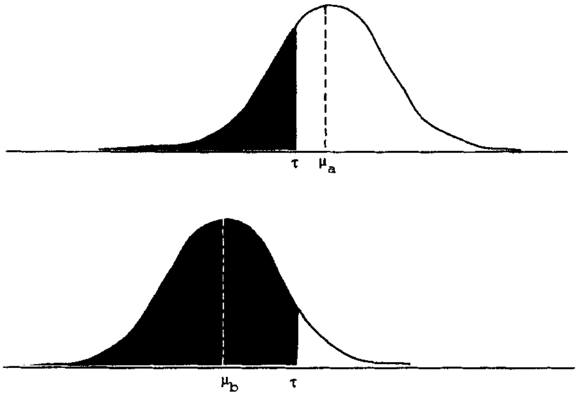

Figure 1. LPM_0 downside risk for two different firms

of a particular target level, τ. For any given target level within the range of the two distributions, the LPM_0 measures clearly differ across the two firms. More generally, the two firms' risk levels would differ using any LPM_α measure ($0 \leq \alpha < \infty$). Similarly, two firms with identical means and variances but different third moments (skewnesses) would have different LPM risks. This contrasts with variance measures which are invariant to the direction of return distribution skewness. Differences in variances across two firms are neither necessary nor sufficient to produce differences in LPM risk.

Stone (1973) offers a variant of the LPM risk measure:

$$RLPM_\alpha(\tau,j) = LPM_\alpha(\tau;j)^{1/\alpha} = [\int_{-\infty}^{\tau} (\tau - r_j)^\alpha f(r_j)dr_j]^{1/\alpha}, \quad \alpha > 0 \qquad (2)$$

$RLPM_\alpha(\tau;j)$ is the root of $LPM_\alpha(\tau;j)$.[6] For $\alpha = 2$, this measure is termed 'target semideviation' (Harlow, 1991). As Stone points out, $RLPM_\alpha(\tau;j)$ has the property that it is homogeneous of degree one. If, for example, the return measure of interest is return on equity, changes in financial leverage resulting in proportional changes in both the target return (τ) and realized return (r_j) change $RLPM_\alpha(\tau;j)$ by an equivalent proportion. By contrast, LPM measures are not homogeneous of degree one when $\alpha \neq 1$.

In presentations of portfolio theory, the use of homogeneous of degree one measures (typically, the standard deviation of returns) is a popular way to graphically represent risk–return relations (see, for example, Brealey and Myers, 1991). When using homogeneous of degree one risk measures, combinations of a portfolio of risky assets and a risk-free asset lie along a straight line (Stone, 1970). Linearity also holds for combinations of a portfolio of risky assets and a risk-free asset plotted in $RLPM_\alpha(\tau;j)$-mean return space (Bawa and Lindenberg, 1977; Hogan and Warren, 1974).

Mean-lower partial moment CAPM

Bawa and Lindenberg (1977) used a mean-lower partial moment (MLPM) framework to derive a downside variant of the CAPM. They considered portfolio evaluation using both $\alpha = 1$ ($MLPM_1$) and $\alpha = 2$ ($MLPM_2$), and specified investors' target as the risk-free rate of return. Use of the risk-free rate of return is a convenient, but by no means the only possible, solution to the choice of investors' target return. Harlow and Rao (1989) generalize the MLPM CAPM to other possible target return levels, τ. Their model for an individual firm j is specified as:

$$E(r_j) - r_f = \beta_j^{MLPM_\alpha(\tau)}[E(r_m) - r_f] \qquad (3)$$

where r_m is the return to the market portfolio and r_f is the risk-free return.[7]

[6] For a sample of N observations using historical data from a given firm, we can write:

$$RLPM_\alpha(\tau;j) = LPM_\alpha(\tau;j)^{1/\alpha} = [(1/N)\sum_{r_j<\tau}^{\tau}(\tau - r_j)^\alpha]^{1/\alpha}, \alpha > 0 \qquad (2')$$

[7] The beta coefficient:

$$\beta_j^{MLPM_\alpha(\tau)} = GCLPM_\alpha(\tau,r_f;m,j)/GLPM_\alpha(\tau,r_f;m) \qquad (3a)$$

differs from the traditional CAPM beta obtained in a mean–variance framework, $\beta_j^{MV} = cov(r_m,r_j)/var(r_m)$. In Equation 3a, $GCLPM_\alpha(\tau,r_f;m,j)$ is the generalized colower partial moment of order α between the returns to security j and the market portfolio, m, given by:

$$GCLPM_\alpha(\tau,r_f;m,j) = \int_{r_m=-\infty}^{\tau}\int_{r_j=-\infty}^{\infty}(\tau - r_m)^{\alpha-1}(r_f - r_j)f(r_m,r_j)dr_jdr_m \qquad (3b)$$

$GLPM_\alpha(\tau,r_f,m)$, the generalized LPM of order α for the market about τ and r_f is:

$$GLPM_\alpha(\tau,r_f;m) = \int_{r_m=-\infty}^{\tau}(\tau - r_m)^{\alpha-1}(r_f - r_m)df(r_m) \qquad (3c)$$

According to the MLPM CAPM, a firm would have a beta between zero and one if during periods in which the market underperformed the target rate, the firm also underperformed the target rate but generally by less than the market. That is, in periods in which $\tau - r_m > 0$, it is generally the case that, $\tau - r_m \geq \tau - r_j > 0$. A $\beta_j^{MLPM}\alpha(\tau)$ greater than one results when a firm tends to underperform the market in periods in which market performance is below the target level. The other possibility, in which the firm's returns typically exceed the target return when the market underperforms the target rate, results in a negative $\beta_j^{MLPM}\alpha(\tau)$.

The less general Bawa–Lindenberg MLPM$_\alpha$ and standard Sharpe–Lintner–Mossin CAPM models are special cases of the Harlow–Rao model. Bawa and Lindenberg's model occurs when the target return equals the risk-free rate. The traditional CAPM makes the two additional assumptions that returns on all assets are normally distributed and that $\alpha = 2$. The Harlow–Rao beta, $\beta_j^{MLPM}\alpha(\tau)$, shares the desirable property of the traditional CAPM beta of invariance to corporate capital structure.

Harlow and Rao (1989) show that a second-order ($\alpha = 2$) MLPM beta (β_j) can be estimated from historical returns data for a given firm j using the simple regression model:

$$r_{jt} = \beta_{0j} + \beta_j r_{mt} + \epsilon_{jt},\ \epsilon_{jt} \sim N(0,\sigma_j^2) \quad (4)$$

estimated over all periods, t, in which the market return, r_{mt}, is less than the target level, τ. Historical stock returns data can be used to estimate firm-specific MLPM β_js.

Harlow and Rao (1989) found that, on average, MLPM beta estimates were higher than CAPM betas for 'low beta' stocks (i.e., CAPM betas less than 1.00). For high CAPM beta stocks, MLPM betas were lower than CAPM estimates. Price, Price, and Nantell (1982) reported similar results using the risk-free return as the target rate ($\tau = r_f$).

Lower partial moments based on performance forecasts

Bettis (1982) and Bromiley (1991b) argued that *ex ante* measures of risk are preferable to *ex post* measures. Measures of past performance variability, or even downside variability, may not accurately estimate organizational risk in subsequent periods. Bromiley measured risk as the standard deviation of security analysts' earnings per share (EPS) forecasts. This measure associates unpredictability of future earnings with risk. A number of previous finance and accounting studies used the divergence of analysts' forecasts to generate risk measures (e.g., Carvell and Strebel, 1984; Givoly and Lakonishok, 1988; Imhoff and Lobo, 1984; Malkiel, 1982; Pari and Chen, 1985).

The problem with using the standard deviation of analysts' EPS forecasts as a risk proxy is that it is not invariant to the number of outstanding shares. For example, doubling the number of outstanding shares cuts the standard deviation of analysts' EPS forecasts in half.[8] Despite this shortcoming of the standard deviation measure, examples of its use can be found in Conroy and Harris (1987), Givoly and Lakonishok (1988), and Malkiel (1982).

The coefficient of variation of EPS forecasts is invariant to the number of outstanding shares. This measure is the standard deviation of analysts' EPS forecasts divided by the mean of the forecasts.[9] The property of invariance to the number of outstanding shares allows comparison of coefficients of variation of EPS forecasts over

[8] More generally, we can show that multiplying earnings per share by a positive coefficient γ results in an equivalent change in the magnitude of the standard deviation of EPS forecasts. The estimated standard deviation of analysts' EPS forecasts for a company, is given by:

$$D = \{[1/(N-1)]\sum_{i=1}^{N}(x_i - x_m)^2\}^{1/2}$$

where x_i is an individual analyst's forecast, x_m is the sample mean forecast, and N is the number of analysts. Multiplying the analysts' forecasts by a constant γ, we have:

$$\{[1/(N-1)]\sum_{i=1}^{N}(\gamma x_i - \gamma x_m)^2\}^{1/2}$$

$$= \{[1/(N-1)]\sum_{i=1}^{N}[\gamma^2(x_i - x_m)^2]\}^{1/2}$$

$$= \gamma\{[1/(N-1)]\sum_{i=1}^{N}(x_i - x_m)^2\}^{1/2} = \gamma D$$

[9] If the sample of firms includes companies with negative mean forecasts, then it is necessary to take the absolute value of the coefficient of variation to ensure comparability across firms.

time and across firms. Carvell and Strebel (1984), Pari and Chen (1985), and Rivera (1991) used the coefficient of variation of EPS forecasts to measure risk.[10] The coefficient of variation is, by construction, positively related to the variance of analysts' forecasts and negatively related to the mean of the distribution. Hence, implicit in this measure is the notion that, for any given level of variance in expected performance, firms with higher mean expected returns have lower risk. This is consistent with the downside approach to risk as illustrated in Figure 1.

For purposes of constructing a downside risk measure, it is useful to normalize EPS in such a way that is is both interpretable as a returns measure, and comparable across firms and time. This can be done in several different ways depending on the financial returns ratio of interest. One simple normalization is to divide forecasted EPS by the current price per share of common stock. The resulting ratio, the inverse of the price/earnings (P/E) ratio, measures expected returns to shareholders. Alternatively, EPS forecasts can be multiplied by the number of outstanding shares of common stock, yielding total expected earnings forecasts. Total expected earnings can be divided by total assets or stockholders' equity to generate expected return on assets and return on equity ratios. Whereas the E/P ratio uses the market-determined stock price to value shareholders' investment, expected ROA and ROE estimates misstate financial returns when historical book values of assets and stockholders' equity deviate from current market values.

Any of these three expected returns ratios can be used to construct a downside risk measure of the form given in Equation 1′. For $\alpha = 0$, such a measure indicates the proportion of analysts predicting earnings below target τ. Choosing $\alpha = 1$, or $\alpha = 2$, yields measures of the expected target shortfall and target semivariance. For $\alpha > 0$, the measure can be converted into its homogeneous of degree 1 counterpart, by taking the α order root. Such a transformation is similar to that indicated in Equation 2′ (in footnote 6).

The most widely used source of data on stock analysts' annual EPS forecasts is the Institutional Brokers Estimate System (IBES). For many firms, 20 or more analysts provide annual EPS predictions. For each company, IBES reports the mean EPS forecast for the current and next fiscal year, the number of forecasters, and the standard deviation about the mean forecast. Data on the individual forecasts are not readily available. This complicates the derivation of a downside risk measure but does not preclude the use of IBES data.

If we assume normality in the distribution of stock analysts' EPS forecasts for any given firm, we can generate a downside risk measure. The first step, as discussed above, is to convert the mean EPS into a financial returns ratio (such as expected E/P, ROA, or ROE). The same conversion should be used to scale the standard deviation of analysts' forecasts.[11] Call the resulting mean forecasted return r_{mean} and the standard deviation around the mean forecasted return s_r. For any given target return level τ, we can calculate a standardized variable $(\tau - r_{\text{mean}})/s_r$. The value of the standard normal cumulative distribution at $(\tau - r_{\text{mean}})/s_r$ is the total probability of falling short of the target return τ. Thus, under the assumption of normality, we can readily generate a downside LPM_0 measure of the form given in Equation 1. This measure is interpreted as the *ex ante* probability of failure to reach the target level.

The proposed downside measure based on analysts' earnings forecasts assumes normality in the distribution of return forecasts. Alternative assumptions regarding the distribution of forecasts (e.g., lognormal distribution) could be used to allow for deviations from normality.

SPECIFICATION OF OPERATIONAL MEASURES

The previous section identified three classes of downside risk measures: lower partial moments based on historical returns data, mean-lower partial moment CAPM beta, and lower partial moments using analysts' earnings forecasts. The purpose of the latter portion of this paper is to

[10] Miller and Bromiley (1990) examined the empirical properties of both the standard deviation and coefficient of variation measures derived from analysts' EPS forecasts.

[11] If the returns measure r is multiplied by a scalar γ, the variance of the rescaled variable is given as $\text{Var}(\gamma r) = \gamma^2\text{Var}(r)$. Hence the standard deviation of the rescaled variable is equal to γ times the standard deviation of r.

provide an empirical comparison of these various downside measures and existing risk measures used in strategy research. Whereas the measures were presented earlier as general categories of measures, empirical comparison forces precise specification of the downside measures. For each of the measures, full specification requires identification of the measure of returns, and specification of appropriate values for the moment of interest, α, and the target level, τ. This section indicates considerations relevant to the selection of the parameters α and τ, and describes the actual operational measures used for empirical comparison.

Alpha

Theory, research on managers' understandings of risk, and academic convention provide considerations influencing the choice of a value for the LPM parameter α.

Theoretical considerations arise because, as noted earlier, specification of α makes implicit assumptions about the nature of organizational utility. Theoretical considerations generally give rise to values of α ranging from zero to two. If organizations are assumed to have a convex utility function for returns below target, then the appropriate value for α falls between zero and one. This specification is consistent with risk seeking in the domain of below-target returns (Kahneman and Tversky, 1979). On the other hand, $\alpha > 1.0$ implies risk aversion and concavity of the organizational utility function. The choice of $\alpha = 1$ indicates risk neutrality.

Empirical research on managers' definitions of risk indicates probability of downside outcomes ($\alpha = 0$) and expected loss ($\alpha = 1$) are relevant to managers (Baird and Thomas, 1990) and, as such, may be relevant risk proxies for organizational research.

Behavioral decision theory and finance conventions also provide some guidance regarding appropriate values for α. Behavioral decision theorists (see for example, Libby and Fishburn, 1977) have given credence to the use of lower partial moment measures corresponding to probability of loss ($\alpha = 0$), expected loss ($\alpha = 1$), or semivariance ($\alpha = 2$). Finance studies on downside risk have used LPM_2 measures of downside risk. Semivariance (or semideviation) and $MLPM_2$ CAPM beta are the conventional downside risk measures in finance research. An industrial organization economics study by Stonebraker (1976) used expected loss ($\alpha = 1$), relative to the normal rate of return, of small firms in an industry as an indicator of entry risk.

This research had the additional objective of making empirical comparisons between downside and variability measures of organizational risk. Existing accounting-based measures of risk generally use the second-order root central moment (i.e., the standard deviation of ROE or ROA). For consistency in making comparisons with standard deviation measures, we constructed all lower partial moment measures as second-order RLPM measures.

The second-order MLPM beta can be computed with ease using the simple regression model given earlier in Equation 4. The methodology for computing the second-order MLPM beta is equivalent to that of the standard CAPM beta, with the exception that the former uses only data from those periods in which the market return underperforms the target level. Hence, the second-order MLPM beta has the advantage of being conceptually and computationally comparable to the standard CAPM beta.

Our lower partial moment based on analysts forecasts used the $\alpha = 0$ specification described earlier. This measure captures the *ex ante* probability of loss.

Tau

Cyert and March (1963) introduced organizational aspirations in their behavioral theory of the firm. They identified three variables influencing aspirations: 'the organiztion's past goal, the organization's past performance, and the past performance of other "comparable" organizations. The aspiration level is viewed as some weighted function of these three variables' (Cyert and March, 1963: 115). Herriott, Levinthal, and March (1985) discussed adaptive organizational goals as a function of past goals and past performance. Fishburn (1977) identified four possible values for a firm's target level: (1) ruinous return, (2) zero profit return, (3) return from an insured safe investment, and (4) acceptable firm performance. A zero profit target return could be specified in either nominal or real terms.

Aspirations change with experience (March, 1988). March and Shapira (1987) contend managers attend to (1) a target performance level and (2) a survival level, and the focus of attention shifts between these two levels over time. Both articles by March and Shapira (1987, 1992) indicate an organization's target level for slack resources may be relevant to risk taking. In March and Shapira's (1992) model, the focus of attention shifts between the aspiration and survival points depending on the relation between current resources and the aspired resource level. If this proposition is correct, then the appropriate target level for explaining firm risk will differ across slack levels.

The contention that organizational target levels evolve over time (i.e., adaptive aspirations) is inconsistent with the downside measures specified earlier. Rather than allowing for period-specific target levels, the LPM and MLPM CAPM beta measures specified earlier assume a constant target return level over time (see Equation 1 and footnote 7). The assumption of a constant target rate over time is unlikely to hold when macroeconomic cycles create variable inflation, interest, and economic growth rates. Industry cycles also affect aspirations. Hence, the assumption of a constant target level over time may be invalid.

One way to handle this problem is to shorten the time period for measuring returns so that the assumption of a constant target level is valid throughout the entire period. The shortcoming of this approach is that performance in the context of varying macroeconomic and industry cycles is important to determining organizational downside risk.

An alternative is to allow the target return to vary over time. That is, incorporate period-specific targets, τ_t, in LPM and MLPM CAPM measures.

In formulating RLPM measures, we assumed adaptive aspirations. Our accounting returns measures incorporated the assumption that organizations update their target returns on an annual basis. We assumed firms' target returns consisted of a weighted average of the previous year's own-firm performance and the previous year performance of other firms in the same 2-digit SIC industry. Not knowing how firms might weight their own previous performance relative to industry competitors in formulating their target levels, we made the simplifying assumption that firms look at the industry average performance. This makes the implicit assumption that firms in industries with many competitors weight their own past performance less than those in concentrated industries when formulating target levels.

For generating LPM measures based on stock returns, we generated two alternative measures under the assumptions that target returns were set equal to (1) the current return to the overall stock market, and (2) the current risk-free rate of return. Each of these targets was updated on a monthly basis to correspond with the periodicity of individual stock returns.

The LPM measures based on analysts' earnings forecasts eliminate entirely the problem of intertemporal differences in a firm's target return. Since measures based on analysts' earnings forecasts are generated in a single period from a cross-section of forecasts, just a single target needs to be specified for a firm in any period.

Summary of operational measures

Root lower partial moments

Four second-order RLPM measures were calculated. Computation of these measures involved data from three different sources: (1) the Center for Research on Security Prices (CRSP); (2) International Financial Statistics (IFS); and (3) COMPUSTAT.

The two RLPM measures based on stock returns data involved differing assumptions regarding firms' target levels: RLPM_MKT used a value-weighted market return as the target level while RLPM_INT incorporated the risk-free rate of return as a target level. Stock returns data were obtained from CRSP, a widely used data base containing daily stock prices as well as monthly, quarterly, and annual financial data for publicly held firms. This data set provided firms' monthly stock returns and the monthly returns for a value-weighted stock index during the period 1988–92. The IFS CD-ROM package, an electronic version of IFS written publications, provided monthly U.S. Treasury bill rates, which served as a proxy for the risk-free rate of return. Firms without complete data for each of the 60 months were excluded from the analysis.

The two RLPM measures based on accounting returns, RLPM_ROA and RLPM_ROE, used the previous year industry average for ROA and ROE, respectively, as proxies for organizational targets. Industries were defined as 2-digit SIC categories. Firms in 2-digit SIC codes containing less than five companies were deleted from the analysis. The two measures were constructed using annual accounting data from the COMPUSTAT data base for the period 1988–92. Companies with missing data were excluded from the analysis, as were outlier firms with ROA or ROE values beyond three standard deviations from the respective means.

Downside beta

The mean lower partial moment beta, MLPM_BETA, was constructed from monthly firm and market stock returns data from CRSP, and the U.S. Treasury bill rate (i.e., our risk-free interest rate proxy) provided by the IFS data base. MLPM_BETA was calculated by estimating the market model provided in Equation 4 for all periods in which the market return was less than the risk-free interest rate, which served as the target level τ_t. Companies that did not have complete data for the 60 months (1988–92) were excluded from the analysis.

IBES measures

For each firm in their data set, the Institutional Brokers Estimate System (IBES) reports the mean earnings per share forecast for the coming year, the standard deviation of these forecasts, and the number of analysts reporting on a given firm. For comparability with the time period ending 1992 used to generate RLPM measures and MLPM beta, we used analysts' 1992 forecasts of 1993 earnings per share as a basis for generating our IBES downside measures. Two zero-order downside risk measures were constructed from the IBES data base: (1) IBES_EP, a downside risk measure based on the predicted earnings–price ratio; and (2) IBES_ROA, a downside risk measure based on predicted ROA. Firms with fewer than three analysts' forecasts were excluded from the analysis. Because industry averages are required, companies which have fewer than five firms in their 2-digit SIC code were deleted as well.

The first of the two downside IBES measures, IBES_EP, used the estimated earnings to price (E/P) ratio as the returns measure. We converted each firm's mean EPS forecast to an E/P ratio by dividing the mean EPS forecast by the 1992 year-end stock price. Likewise, the standard deviation of analysts' EPS forecasts were divided by1992 year-end stock price. IBES_EP was calculated as the value of the cumulative standard normal density function at $(\tau - r_{\mathrm{mean}})/\mathrm{sd}_r$, where r_{mean} and sd_r are the mean and standard deviation of the forecasted E/P ratio. The target level τ was the 1992 industry average E/P ratio at the 2-digit SIC code level.

The second IBES measure, IBES_ROA, involved computing a forecasted return on assets. We adjusted the mean 1993 EPS forecast to an ROA measure by multiplying by the number of outstanding shares at year-end 1992, and dividing by the value of 1992 year-end total assets. The same procedure was used to adjust the standard deviation of analysts' EPS forecasts. IBES_ROA was calculated as the value of the cumulative standard normal density function at $(\tau - r_{\mathrm{mean}})/\mathrm{sd}_r$, where r_{mean} and sd_r are the mean and standard deviation of the forecasted ROA. The target level τ was the 1992 industry average ROA at the 2-digit SIC code level.

Comparison measures

While downside measures are conceptually distinct from variability measures, it remains to be seen whether the two categories of measures exhibit substantively different empirical properties. In order to make such comparisons, we generated six measures of organizational risk used in strategy research—five variability measures and one bankruptcy risk measure.

The variability measures included the common risk proxies standard deviation of ROA (SDROA) and ROE (SDROE), beta (BETA) and unsystematic risk (UNSYS), and the absolute value of the coefficient of variation of stock analysts' forecasts (IBES_CV).

The standard procedure for estimating the CAPM beta involves estimating the CAPM market model, Equation 4, including all periods regardless of whether the market portfolio exceeds or falls short of the risk-free target return. UNSYS, the firm's unsystematic risk, was estimated as the standard deviation of the residuals for the CAPM market model.

The coefficient of variation for forecasted earnings per share (IBES_CV) was computed as the absolute value of the ratio of the standard deviation to mean of stock analyst's EPS forecasts.

Because forecasted earnings per share were negative for some firms, the traditional coefficient of variation erroneously indicates very low risk levels for such firms, particularly if the dispersion of analysts' forecasts is high. We consequently used the absolute value of the coefficient of variation as our *ex ante* variability risk measure.

The bankruptcy risk proxy was Altman's Z, an established measure of credit default risk. Altman's *Z* is defined as: ALTMANZ = (1.2 × LIQ) + (1.4 × RE) + (3.3 × ROA) + (0.6 × MED) + (1.0 × CAPINT), where LIQ is working capital divided by total assets, RE is retained earnings divided by total assets, ROA is earnings before interest and taxes divided by total assets, MED is the market value of equity divided by the book value of total liabilities, and CAPINT is sales divided by total assets (Altman, 1983). This weighted sum of financial ratios is based on Altman's research generating a discriminant function distinguishing firms with high bankruptcy risk from those with low risk. Altman's *Z* is actually an inverse indicator of bankruptcy risk. That is, the higher ALTMANZ, the less likely is bankruptcy. Hence, we expected to find ALTMANZ to be negatively correlated with the other measures—both the downside and variability measures. Values for Altman's Z were calculated using 1992 COMPUSTAT data.

Methodology and results

The empirical analysis sought to determine the covariance relationships among the risk measures. To this end, we present correlations and factor analysis results. Analysis of the risk measures' distributions indicated that outliers were prevalent in the measures' upper tails. The issue of outlying observations was addressed by eliminating observations for all risk measures except IBES_EP and IBES_ROA which exceeded the 99th percentile. No observations were deleted for IBES_EP and IBES_ROA since these two measures are cumulative standard normal probabilities, and many firms had values equal to the maximum of one.[12] This screen of outlying observations reduced the sample size from 454 to 422 firms.

[12] While values for the IBES measures never actually attain 1.0, some firms had values which were inconsequentially different from 1.0.

Table 1 provides a correlation matrix for the risk measures. As expected, the significant correlations between Altman's *Z* and the downside risk measures were negative in sign. It is peculiar, however, that two variability measures, the standard deviation of ROA and CAPM beta, show significant positive correlations with Altman's Z. For the sampled firms, high variability of accounting and stock returns is associated with lower expected probability of bankruptcy. This finding suggests strategy studies using Altman's *Z* as a risk proxy may produce conclusions regarding risk that are inverse to those using variability measures. This observation is an important extension of Miller and Bromiley's (1990) work, which did not consider Altman's *Z* among the risk proxies examined.

Table 2 provides the results of a principal components factor analysis after varimax rotation. Factors were retained if their corresponding eigenvalues exceeded one. Together, the five factors explained 77.2 percent of the variation in the data. Communalities generally exceeded 0.50, with the exception of the IBES coefficient of variation (IBES_CV), which had a communality of just under 0.40.

The first thing to note is that most of the factors combine high loadings for both downside measures and the measures used in previous strategy research. Only factor four contains downside risk measures exclusively.

Variables with high positive loadings on factor one were unsystematic risk and the two stock returns RLPM measures reflecting the risk of underperforming the market return and risk-free rate of return. Like CAPM unsystematic risk, the stock returns downside measures reflect firm-specific risk that could be diversified by holding a broad stock and bond portfolio. Hence, factor one was labeled *unsystematic risk*.

The standard deviations of ROE and ROA, the RLPM measure based on ROA, and the IBES coefficient of variation measure show high positive loadings on factor two. The standard deviation of accounting returns and the IBES coefficient of variation measures are recognized measures of income stream risk (Miller and Bromiley, 1990)—the two standard deviation measures being *ex post*, and the IBES measure an *ex ante* proxy for income stream variability. We refer to factor two as *income stream risk*.

From factor two, we observe that using ROA to

Table 1. Correlations among risk measures[a]

Measures	1	2	3	4	5	6	7	8	9	10	11	12
1. RLPM__MKT												
2. RLPM__INT	0.936***											
3. RLPM__ROA	0.453***	0.447***										
4. RLPM__ROE	0.111*	0.152**	0.090†									
5. MLPM__BETA	0.072	0.269***	−0.030	0.112*								
6. IBES__EP	0.108*	0.089†	0.134**	−0.088†	0.066							
7. IBES__ROA	0.099*	0.078	0.235***	−0.108*	0.094†	0.330***						
8. SDROE	0.390***	0.390***	0.653***	0.129**	−0.011	0.111*	−0.017					
9. SDROA	0.441***	0.416***	0.592***	−0.057	−0.074	0.083†	−0.133	0.762***				
10. BETA	0.311***	0.594***	0.179***	0.190***	0.492***	0.030	0.004	0.138***	0.083†			
11. UNSYS	0.910***	0.898***	0.378***	0.135**	0.138**	0.075	0.046	0.319***	0.358***	0.408***		
12. IBES__CV	0.382***	0.364***	0.320***	0.042	0.006	0.247***	0.102***	0.395***	0.348***	0.130**	0.270***	
13. ALTMANZ	−0.010	0.029	−0.199***	−0.252***	−0.044	−0.063	−0.338***	−0.082†	0.167***	0.102*	0.054	−0.144**

[a] $N = 422$. Outliers are eliminated from the upper tails of the measures' distributions (except IBES__EP and IBES__ROA) using a 99 percentile cutoff.
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Key to measure names:

RLPM__MKT: Root lower partial moment using stock returns, market return target.
RLPM__INT: Root lower partial moment using stock returns, risk-free return target.
RLPM__ROA: Root lower partial moment using ROA, lagged industry average ROA target.
RLPM__ROE: Root lower partial moment using ROE, lagged industry average ROE target.
MLPM__BETA: Mean lower partial moment systematic risk.
IBES__EP: Standard normal probability of underperforming lagged average industry E/P.
IBES__ROA: Standard normal probability of underperforming lagged average industry ROA.
SDROE: Standard deviation of ROE.
SDROA: Standard deviation of ROA.
BETA: CAPM systematic risk.
UNSYS: Unsystematic risk, calculated by the standard deviation of the residuals of the CAPM market model.
IBES__CV: Coefficient of variation for forecasted earnings per share.
ALTMANZ: Altman's *Z*.

Table 2. Rotated factor pattern[a]

Variables	Factor one: Unsystematic risk	Factor two: Income stream risk	Factor three: Systematic risk	Factor four: *Ex ante* Downside risk	Factor five: Bankruptcy risk	Communalities
UNSYS	**0.936**	0.187	0.121	0.001	0.001	0.925
RLPM_MKT	**0.932**	0.289	0.020	0.072	0.025	0.959
RLPM_INT	**0.894**	0.284	0.309	0.036	0.019	0.977
SDROE	0.128	**0.911**	0.044	−0.040	−0.083	0.857
SDROA	0.210	**0.867**	−0.039	−0.125	0.229	0.866
RLPM_ROA	0.267	**0.743**	−0.018	0.185	−0.198	0.697
IBES_CV	0.235	**0.506**	0.020	0.285	−0.068	0.398
MLPM_BETA	0.015	−0.065	**0.875**	0.118	−0.060	0.788
BETA	0.364	0.072	**0.787**	−0.050	−0.006	0.760
IBES_ROA	0.086	−0.063	−0.022	**0.817**	−0.209	0.723
IBES_EP	−0.018	0.183	0.121	**0.715**	0.177	0.591
ALTMANZ	0.062	−0.040	0.112	−0.359	**0.801**	0.788
RLPM_ROE	0.093	0.064	0.222	−0.327	**−0.735**	0.709
Var. Explained	2.884	2.642	1.576	1.570	1.364	
Proportion	0.222	0.203	0.121	0.121	0.105	
Cumulative	0.222	0.425	0.546	0.667	0.772	

[a] $N = 422$. For each variable, bold print highlights the factor loadings with the largest absolute values.

measure returns, the choice between the standard deviation and RLPM does not appear to be critical. This is not the case, however, when returns are measured as ROE. The factor loading for RLPM_ROE is just 0.064 on factor two.

Downside beta and the traditional CAPM beta have high positive loadings on factor three. Both of these measures capture the sensitivity of firms' returns to movements in the market portfolio. In the case of beta, this sensitivity is measured in all periods irrespective of whether the market portfolio exceeds or underperforms the risk-free rate of return. In the case of downside beta, this sensitivity is measured only in periods in which the market portfolio underperforms the risk-free rate of return. Factor three represents *systematic risk*.

Both of the downside risk measures constructed from IBES data had high positive loadings on factor four. This pair of variables captures the *ex ante* probability of underperforming the lagged industry average performance, where performance is measured in terms of the earnings to price ratio and ROA. Both the *ex ante* nature of these measures as well as the choice of the zero order (i.e., $\alpha = 0$) moment may account for the distinct measurement properties of the two downside IBES measures relative to the other measures. Factor four was labeled *ex ante downside risk*.

Altman's *Z* and the RLPM measure using ROE have high, oppositely signed loadings on factor five. As noted earlier, high values of Altman's *Z* indicate a low risk of default. Thus, it is not surprising that the signs for Altman's *Z* and RLPM_ROE would be opposite in the factor five loadings. Unlike the RLPM measure using ROA, using ROE to generate the RLPM results in a measure which appears to capture the likelihood of jeopardizing a firm's equity, resulting in possible bankruptcy. We labeled the fifth factor *bankruptcy risk*.

DISCUSSION

Interpretation of the empirical results

While there is no guarantee that results from exploratory factor analyses will be interpretable, in this case the factor loading pattern was straightforward and the assigned labels are unlikely to be controversial. In general, the results suggest many of the downside risk measures proposed in this research have measurement properties similar to those of existing risk measures used in previous strategy research. That is, in general, the downside risk measures do not capture risk factors distinct from those associated with variability measures and Altman's *Z*. The one clear exception was the pair of *ex ante* downside measures constructed from stock analysts' earnings forecasts which loaded on a unique factor (*ex ante* downside risk).

The finding that downside and existing strategic risk measures often loaded on common factors does not necessarily render the choice among measures within a given factor irrelevant. For example, Table 2 indicates the standard deviation and RLPM measures constructed from ROA data are each indicators of the common income stream risk factor. Their correlation of 0.592, yielding a coefficient alpha of 0.74,[13] satisfies generally accepted criteria for item reliability (Nunnally, 1978). However, either variable accounts for just $(0.592)^2$ or approximately 36 percent of the variability of the other (see Black, 1993: 136). Hence, researchers employing the standard variability measures may also want to use a comparable downside measure to determine whether research findings are robust to the choice of risk measure within a risk factor. In modeling the relations of risk to other variables, we would generally expect the signed relations to be consistent among the various measures within any risk factor; however, the significance of estimated relations may differ.

The five factors presented in Table 2 can be interpreted as representing distinct stakeholder perspectives on organizational risk (Miller and Bromiley, 1990). These distinct stakeholder perspectives may inform the choice of risk proxies in future research. Unsystematic risk (factor 1) focuses on stock returns and would be of interest to investors holding narrow, undiversified portfolios. The diversified investor is likely to be most concerned with indicators of systematic risk (factor 3)—either the CAPM or MLPM beta. Both the widely used CAPM beta and the less widely known MLPM beta reflect stock returns volatility relative to the overall market. As such, these measures reflect the well-established perspective of financial portfolio theory. Bankruptcy risk (factor 5) holds the greatest interest for creditors concerned with default on debt obligations.

Income stream risk (factor 2) would be of interest to managers, buyers, suppliers, and other stakeholders with sunk investments in a firm. The ability of the firm to follow through on commitments to these diverse stakeholders may be directly related to short-term cash flows. Like income stream risk, *ex ante* downside risk (factor 4) has potential implications for a variety of organizational stakeholders. The two *ex ante* downside measures are, however, distinct from the indicators of income stream risk in their focus on future returns and only downside outcomes. None of the four correlations between the two downside measures based on analysts' forecasts (IBES_ROA and IBES_EP) and the two measures most highly correlated with the income stream risk factor (SDROE and SDROA) is significant at the 0.05 level. Hence, the income stream risk and *ex ante* downside risk factors appear to capture two distinct aspects of accounting returns risk of interest to a variety of organizational stakeholders.

These observations regarding the various stakeholder perspectives reflected in the downside risk measures raise interesting questions for future research. Agency theory research could consider the implications of downside risk aversion for elaborating management compensation contracts. Not only may stockholders, creditors, and managers have distinct views on the relevant performance measures, they may also differ in their target aspiration levels. The various stakeholder views on downside risk raise new issues regarding the alignment of managerial incentives and corporate risk management policies. Jensen's (1986) free cash flow hypothesis suggests the availability of slack resources may reduce organizational performance relative to stockholders' target level and, hence, increase subsequent stockholders' downside risk. Managers, on the other hand, may be quite willing to reduce their aspirations when organizational slack is high.

Choosing risk measures

This research introduced three categories of organizational downside risk measures: (1) lower partial moments from historical returns data; (2) downside capital asset pricing model beta; and (3) lower partial moments from stock analysts' earnings forecasts. Apart from the distinct stakeholder perspectives reflected in the various downside risk measures, other considerations may influence researchers' choices among the three categories. This section offers further guidance for researchers inter-

[13] Computation of the coefficient alpha was based on the formula provided by Cronbach (1951: 321).

ested in incorporating downside risk measures in future research. As in all empirical research, the choice among the measures depends on both theoretical considerations and the constraints imposed by available data.

The level of analysis constrains the choice among the three categories of downside risk measures. Researchers studying corporate-level strategy may have access to the data necessary to employ any of the downside risk measures. Strategy researchers interested in measuring downside risk at the business unit level are largely confined to lower partial moment measures based on past accounting returns since the measures employing stock returns or earnings forecast data are only meaningful for measuring corporate risk. Another alternative at the business unit level would be to generate MLPM betas using accounting rather than stock returns data. This method would be similar to the stock returns MLPM beta presented earlier but would substitute individual business unit accounting returns and aggregate accounting returns across firms for corporate shareholder returns and market portfolio returns.

We turn now to specific assessments regarding each of the three categories of downside risk measures.

Lower partial moments from historical returns

A potential shortcoming of this category of lower partial moments is that, by using historical data, LPM measures may be only rough proxies for the *ex ante* downside risk experienced by managers at any point in time. That is, retrospective LPMs may not always be reasonable proxies for the current downside risk experienced by managers and investors.

Accounting returns LPM measures may be distorted because of their reliance on historical book values of equity and assets which often deviate from market values. Inflation results in underreporting of equity and asset values relative to current market prices. Undervaluing equity and assets increases the volatility of ROE and ROA. Hence, understated book values of equity and assets relative to current market values distort both variance and downside risk measures. Constructing ROE and ROA using market valuations of shareholder equity and debt may provide more accurate returns data than can be derived using historical values. Using market valuations may increase the comparability of returns data across firms and within firms across time.

For corporate-level research on publicly traded companies, an alternative approach that avoids the distortions in accounting data is the use of historical stock returns to generate LPM measures. As reported in Table 2, the LPM measures based on stock returns loaded on a single factor which included neither the ROA nor ROE LPM measures. Hence, there is evidence for significant discrepancies between LPM measures using accounting returns and those using stock returns. The reasonableness of using stock returns data depends on the efficiency of capital markets. Given the potential for distortions in stock returns as well as accounting returns, strategy researchers seeking to determine the robustness of their empirical results may do well to incorporate indicators of downside risk based on both accounting and stock returns.

Lower partial moment CAPM betas

Portfolio theory provided the context for developing the MLPM CAPM. As such, the MLPM CAPM reflects the perspective of a downside risk-averse investor holding a diversified portfolio of assets. A downside beta measures the tendency of a firm to perform above or below the general market during periods in which the market as a whole underperforms a target level. While such a beta is of interest to an investor concerned about reducing portfolio losses during bear markets, it is unlikely such a measure captures managers' perspectives on risk. Hence, MLPM CAPM betas may be better suited to financial portfolio analysis than to strategy research on managerial risk assessment and risk-taking behavior. Based on the factor analysis results in Table 2, we would also have to extend this critique of MLPM beta to the traditional CAPM beta.

Management compensation packages tied to shareholder returns may improve the alignment of managers' risk considerations with those of diversified shareholders. Hence, the nature of management compensation may be an important moderator of the correspondence between MLPM betas and managers' perspectives on risk. Nevertheless, managers have firm-specific human capital investments which preclude portfolio diversification to the same extent as shareholders (Amit and Wernerfelt, 1990). Thus, managers' risk preferences may diverge from those of shareholders even when management compensation is tightly linked to shareholder returns. As such, managerial behavior may be linked to downside risk relative to a firm-specific target level independent of the performance of the market as a whole. If so, this argues for incorporating shareholder returns in LPM measures rather than MLPM CAPM betas when seeking to measure risk from a managerial perspective.

Lower partial moments from analysts' earnings forecasts

We know of no previous studies proposing downside measures generated from stock analysts' forecasts. Hence, the introduction of such measures is a unique contribution of this study.

An advantage of lower partial moments from stock analysts' earnings forecasts is the *ex ante* nature of the downside risk measures. This category of measures avoids the need to assume that future downside risk is consistent with past experience. Significant shifts in strategy and/or the external environment may invalidate the assumption that future risk will be similar to past risk. It is on this basis that Bromiley (1991b) and finance researchers who have used risk measures incorporating stock analysts' forecasts argue their superiority over measures using historical returns. The empirical results in Table 2 indicate the *ex ante* downside risk measures have very distinct measurement properties from downside measures based on historical returns and, hence, the choice between *ex ante* and *ex post* downside risk measures may substantively affect research results.

While the theoretical argument for *ex ante* measures of risk is compelling, the data for generating such measures have shortcomings. IBES is the most widely used source of data on stock analysts' forecasts. As discussed earlier, generation of LPM measures requires making assumptions about the distribution of analysts' forecasts. In this study, we assumed normality but alternative assumptions about the distribution could be easily accommodated. The central limit theorem indicates the assumption of normality is more likely to be reasonable for stocks followed by a large number of analysts than those followed by few.

Returns based on stock analysts' earnings forecasts will generally be more tightly bunched than historical returns. Analysts' presumably estimate the expected return while the actual returns constitute a set of single observations on the return variable. As such, stock analysts' predictions of earnings over the next year have a much smaller standard deviation than historical returns. Hence, the LPM measures based on stock analysts' forecasts are much more sensitive to the choice of the target level, τ, than the measures based on historical returns. This was evident in our analysis from the many firms attaining values for the IBES LPM measures at the extreme values of zero and one. This indicated that for many firms analysts were tightly bunched together in their forecast of returns either above or below the target level.

This section has suggested that considerations of theory and data availability are relevant to the choice of a downside risk measure. Each of the three categories of downside risk measures requires trade-offs along these two criteria. No single category of downside risk measures dominates the other two on both criteria.

Implications for strategic management research

As noted at the outset of this article, risk has been recognized as both an important outcome and an explanatory variable in strategic management research. Reconceptualizing risk as a downside construct rather than variability may have important theoretical and empirical (as well as, managerial) implications. The downside perspective calls for rethinking the propositions regarding risk raised in prior research. Work on topics where risk is already recognized as a key construct (e.g., product and international market diversification, vertical integration, business strategy and industry characteristics, organizational processes, and corporate structure) may result in important new insights. By presenting operational measures of downside risk, we hope to encourage such research.

As an example of how research questions might be altered by shifting from variability to downside risk, consider Bowman's work (1980, 1982) and the subsequent studies exploring the risk–return paradox (e.g., Fiegenbaum, 1990; Fiegenbaum and Thomas, 1986, 1988). These studies reflect standard empirical treatments of risk as variability. Whereas these studies asked how mean–variance relations in firm data differ for above and below median performers, a downside perspective would not motivate the same question. Using a lower partial moment accounting measure, if firms in an industry share a common aspiration level such as the median performance level, a firm that consistently underperforms the industry median will, by definition, have a higher risk level than a firm that consistently outperforms the industry median.[14] Hence, the downside perspective does not motivate the question addressed in research on Bowman's risk–return paradox. Rather, the downside risk perspective incorporates aspirations into the computation of the risk measure itself. Prior discussions of the role of discrepancies between organizational performance and aspirations (e.g., Cyert and March, 1963; Lant, 1992; Lant and Montgomery, 1987) may be more helpful than the variability studies of risk–return relations in motivating behavioral propositions regarding organizational responses to downside risk.

CONCLUSION

Previous research indicates that managers conceptualize risk in downside rather than variance terms. Despite this observation, strategy scholars have given little attention to downside risk in empirical research.[15] This paper lays the groundwork for introducing lower partial moment measures of organizational downside risk into strategy research. The empirical results and discussion provide specific guidance for researchers interested in measuring downside risk as an organizational construct. Further theoretical and empirical work addressing specific strategic management questions is needed to determine the implications of conceptualizing risk in downside rather than variance terms. By specifying downside risk measures, this paper serves as a precursor to empirical research linking downside risk to organizational strategy, structure, process, and environment variables.

[14] Alternatively, if we simply correlated firms' mean returns with their semivariances using their own mean returns as the target level, we would generate exactly the same results as estimating mean–variance relations. This is because semivariance using the mean as the target value is directly proportional to the variance (i.e., half the value of the variance).

[15] Apart from those studies using Altman's Z as a proxy for bankruptcy risk, we know of no other empirical strategy research than the study by Collins and Ruefli (1992) that incorporates an operational measure of downside risk. The ordinal measure they developed is, however, quite distinct from the LPM measures presented here.

ACKNOWLEDGEMENTS

The authors wish to thank Philip Bromiley, David Deephouse, Javier Gimeno-Gascon, Michael Leiblein, Hemant Merchant, Carolyn Woo, and the anonymous reviewers for comments on earlier drafts of this article. The authors also gratefully acknowledge I/B/E/S Inc. for providing earnings per share forecast data, available through the Institutional Brokers Estimate System.

REFERENCES

Aaker, D. A. and R. Jacobson (1987). 'The role of risk in explaining differences in profitability', *Academy of Management Journal*, **30**, pp. 277–297.

Aaker, D. A. and R. Jacobson (1990). 'The risk of marketing: The roles of systematic, uncontrollable and controllable unsystematic, and downside risk'. In R. A. Bettis and H. Thomas (eds.), *Risk, Strategy, and Management*. JAI Press, Greenwich, CT, pp. 137–160.

Altman, E. I. (1983). *Corporate Distress: A Complete Guide to Predicting, Avoiding, and Dealing with Bankruptcy*. Wiley, New York.

Amit, R. and J. Livnat (1988). 'Diversification and the risk-return trade-off', *Academy of Management Journal*, **31**, pp. 154–166.

Amit, R. and B. Wernerfelt (1990). 'Why do firms reduce business risk?', *Academy of Management Journal*, **33**, pp. 520–533.

Arrow, K. J. (1963). *Social Choice and Individual Values* (2nd ed.). Wiley, New York.

Atkinson, A. B. and J. E. Stiglitz (1980). *Lectures on Public Economics*. McGraw-Hill, New York.

Baird, I. S. and H. Thomas (1990). 'What is risk anyway? Using and measuring risk in strategic management'. In R. A. Bettis and H. Thomas (eds.), *Risk, Strategy, and Management*. JAI Press, Greenwich, CT, pp. 21–52.

Baucus, D. A., J. H. Golec and J. R. Cooper (1993). 'Estimating risk–return relationships: An analysis of measures', *Strategic Management Journal*, **14**(5), pp. 387–396.

Bawa, V. and E. Lindenberg (1977). 'Capital market equilibrium in a mean, lower partial moment framework', *Journal of Financial Economics*, **5**, pp. 189–200.

Bawa, V., S. Brown and R. Klein (1981). 'Asymmetric response asset pricing models: Testable alternatives to mean-variance', mimeo.

Bell, D. E. (1982). 'Regret in decision making under uncertainty', *Operations Research*, **30**, pp. 961–981.
Bell, D. E. (1983). 'Risk premiums for decision regret', *Management Science*, **29**, pp. 1156–1166.
Bettis, R. A. (1981). 'Performance differences in related and unrelated diversified firms', *Strategic Management Journal*, **2**(4), pp. 379–393.
Bettis, R. A. (1982). 'Risk considerations in modeling corporate strategy'. In K. H. Chung (ed.), *Academy of Management Best Paper Proceedings*, pp. 22–25.
Bettis, R. A. and W. K. Hall, (1982). 'Diversification strategy, accounting-determined risk, and accounting-determined return', *Academy of Management Journal*, **25**, pp. 254–264.
Bettis, R. A. and V. Mahajan (1985). 'Risk/return performance of diversified firms', *Management Science*, **31**, pp. 785–799.
Black, T. R. (1993). *Evaluating Social Science Research: An Introduction*. Sage, London.
Bowman, E. H. (1980). 'A risk/return paradox for strategic management', *Sloan Management Review*, **21**(3), pp. 17–31.
Bowman, E. H. (1982). 'Risk seeking by troubled firms', *Sloan Management Review*, **23**(4), pp. 33–42.
Bowman, E. H. and D. Hurry (1993). 'Strategy through the option lens: An integrated view of resource investments and the incremental-choice process', *Academy of Management Review*, **18**, pp. 760–782.
Brealey, R. A. and S. C. Myers (1991). *Principles of Corporate Finance* (4th ed.). McGraw-Hill, New York.
Bromiley, P. (1991a). 'Paradox or at least variance found: A comment on "Mean-variance approaches to risk-return relationships in strategy: Paradox lost", *Management Science*, **37**, pp. 1206–1210.
Bromiley, P. (1991b). 'Testing a causal model of corporate risk taking and performance', *Academy of Management Journal*, **34**, pp. 37–59.
Carvell, S. and P. Strebel (1984). 'A new beta incorporating analysts' forecasts', *Journal of Portfolio Management*, **11**, pp. 81–85.
Chang, Y. and H. Thomas (1989). 'The impact of diversification strategy on risk-return performance', *Strategic Management Journal*, **10**(3), pp. 271–284.
Chatterjee, S. and M. Lubatkin (1990). 'Corporate mergers, stockholder diversification, and changes in systematic risk', *Strategic Management Journal*, **11**, (4), pp. 255–268.
Chatterjee, S., M. Lubatkin and T. Schoenecker (1992). 'Vertical strategies and market structure: A systematic risk analysis', *Organization Science*: **3**, pp. 138–156.
Collins, J. M. and T. W. Ruefli (1992). 'Strategic risk: An ordinal approach', *Management Science*, **38**, pp. 1707–1731.
Conroy, R. and R. Harris (1987). 'Consensus forecasts of corporate earnings: Analysts' forecasts and time series methods, *Management Science*, **33**, pp. 725–738.
Cool, K., I. Dierickx and D. Jemison (1989). 'Business strategy, market structure and risk–return relationships: A structural approach', *Strategic Management Journal*, **10**(96), pp. 507–522.
Cool, K. and D. Schendel (1988). 'Strategic group formation and performance: The case of the U.S. pharmaceutical industry, 1963–1872', *Management Science*, **33**, pp. 1102–1124.
Cronbach, L. J. (1951). 'Coefficient alpha and the internal structure of tests', *Psychometrika*, **16**, pp. 297–334.
Cyert, R. M. and J. G. March (1963). *A Behavioral Theory of the Firm*. Prentice-Hall, Englewood Cliffs, NJ.
D'Aveni, R. A. and A. Y. Ilinitch (1992). 'Complex patterns of vertical integration in the forest products industry: Systematic and bankruptcy risks', *Academy of Management Journal*, **35**, pp. 596–625.
Fiegenbaum, A. (1990). 'Prospect theory and the risk–return association: An empirical examination in 85 industries', *Journal of Economic Behavior and Organization*, **14**, pp. 187–204.
Fiegenbaum, A., and H. Thomas (1986). 'Dynamic and risk measurement perspectives on Bowman's risk–return paradox for strategic management: An empirical study', *Strategic Management Journal*, **7**(5), pp. 395–407.
Fiegenbaum, A., and H. Thomas (1988). 'Attitudes toward risk and the risk–return paradox: Prospect theory explanations', *Academy of Management Journal*, **31**, pp. 85–106.
Fishburn, P. C. (1977). 'Mean-risk analysis with risk associated with below target returns', *American Economic Review*, **67**, pp. 116–126.
Garcia, C. B. and F. J. Gould (1987). 'A note on the measurement of risk in a portfolio', *Financial Analysts Journal*, **43**(2), pp. 61–69.
Givoly, D. and J. Lakonishok (1988). 'Divergence of earnings expectations: The effect on stock market responses to earnings signals'. In E. Dimson (ed.), *Stock Market Anomalies*. Cambridge University Press, New York, pp. 272–289.
Harlow, W. V. (1991). 'Asset allocation in a downside-risk framework', *Financial Analysts Journal*, **47**(5), pp.28–40.
Harlow, W. V. and R. K. S. Rao (1989). 'Asset pricing in a generalized mean-lower partial moment framework', *Journal of Financial and Quantitative Analysis*, **24**, pp. 285–311.
Herriott, S. R., D. Levinthal and J. G. March (1985). 'Learning from experience in organizations', *AEA Papers and Proceedings*, **75**, pp. 298–302.
Hogan, W. W. and J. M. Warren (1972). 'Computation of the efficient boundary in the E-S portfolio selection model', *Journal of Financial and Quantitative Analysis*, **7**, pp. 1881–1896.
Hogan, W. W., and J. M. Warren (1974). 'Toward the development of an equilibrium capital-market model based on semivariance', *Journal of Financial and Quantitative Analysis*, **9**, pp. 1–11.
Holthausen, D. M. (1981). 'A risk-return model with risk and return measured as deviations from a target return', *American Economic Review*, **71**, pp. 182–188.
Hoskisson, R. E. (1987). 'Multidivisional structure and performance: The contingency of diversification strategy', *Academy of Management Journal*, **30**, pp. 625–644.

Imhoff, E. A., Jr. and G. J. Lobo (1984). 'Information content of analysts' composite forecast revisions', *Journal of Accounting Research*, **22**, pp. 541–554.

Jahankhani, A. (1976) 'E-V and E-S capital asset pricing models: Some empirical tests', *Journal of Financial and Quanitative Analysis*, **11**, pp. 513–528.

Jemison, D. (1987). 'Risk and the relationship among strategy, organizational processes, and performance', *Management Science*, pp. 1087–1101.

Jensen, M. C. (1986). 'Agency costs of free cash flow, corporate finance and takeovers', *American Economic Review*, **76**, pp. 323–329.

Kahneman, D. and A. Tversky (1979). 'Prospect theory: An analysis of decision under risk', *Econometrica*, **47**, pp. 262–291.

Kahneman, D. and A. Tversky (1982). 'Variants of uncertainty', *Cognition*, **11**, pp. 143–157.

Kahneman, D., P. Slovic and A. Tversky (eds.) (1982). *Judgment under Uncertainty: Heuristics and Biases*. Cambridge University Press, Cambridge, UK.

Kim, W. C., P. Hwang and W. P. Burgers (1993). 'Multinationals' diversification and the risk-return trade-off', *Strategic Management Journal*, **14**(4), pp. 275–286.

Kogut, B. (1991). 'Joint ventures and the option to expand and acquire', *Management Science*, **37**, pp. 19–33.

Lant, T. K. (1992). 'Aspiration level adaptation: An empirical exploration', *Management Science*, **38**, pp. 623–644.

Lant, T. K. and D. B. Montgomery (1987).'Learning from strategic success and failure', *Journal of Business Research*, **15**, pp. 503–517.

Laughhunn, D. J., J. W. Payne and R. Crum (1980). 'Managerial risk preferences for below-target returns', *Management Science*, **26**, pp. 1238–1249.

Leibowitz, M. L. and R. D. Henriksson (1989). 'Portfolio optimization with shortfall constraints: A confidence-limit approach to managing downside risk', *Financial Analysts Journal*, **45**(2), pp. 34–41.

Levinger, G. and D. J. Schneider (1969). 'Test of the "risk is a value" hypothesis', *Journal of Personality and Social Psychology*, **11**(2), pp. 165–169.

Libby, R., and P. E. Fishburn (1977). 'Behavioral models of risk taking in business decisions: A survey and evaluation', *Journal of Accounting Research*, **15**, pp. 272–292.

Lintner, J. (1965). 'Security prices, risk and maximal gains from diversification', *Journal of Finance*, **30**, pp. 657–675.

Loomes, G. and R. Sugden (1982). 'Regret theory: An alternative theory of rational choice under uncertainty', *Economic Journal*, **92**, pp. 805–824.

Lubatkin, M. and H. M. O'Neill (1987). 'Merger strategies and capital market risk', *Academy of Management Journal*, **30**, pp. 665–684.

MacCrimmon, K. R. and D. A. Wehrung (1986). *Taking Risks*. Free Press, New York.

Malkiel, B. G. (1982). 'Risk and return: A new look'. In B. M. Friedman (ed.), *The Changing Roles of Debt and Equity in Financing U.S. Capital Formation*. University of Chicago Press, Chicago, IL, pp. 27–45.

Mao, J. C. T. (1970). 'Survey of capital budgeting: Theory and practice', *Journal of Finance*, **25**, pp. 349–360.

March, J. G. (1981). 'Decision making perspective'. In A. H. Van de Ven and W. F. Joyce (eds.), *Perspectives on Organization Design and Behavior*. Wiley, New York, pp. 205–244.

March, J. G. (1988). 'Variable risk preferences and adaptive aspirations', *Journal of Economic Behavior and Organization*, **9**, pp. 5–24.

March, J. G. and Z. Shapira (1987). 'Managerial perspectives on risk and risk taking', *Management Science*, **33**, pp. 1404–1418.

March, J. G. and Z. Shapira (1992). 'Variable risk preferences and the focus of attention', *Psychological Review*, **99**, pp. 172–183.

Markowitz, H. M. (1959). *Portfolio Selection*. Wiley, New York.

Marsh, T. A. and D. S. Swanson (1984). 'Risk-return tradeoffs for strategic management', *Sloan Management Review*, pp. 35–51.

Miller, K. D. and P. Bromiley (1990). 'Strategic risk and corporate performance: An analysis of alternative risk measures', *Academy of Management Journal*, **33**, pp. 756–779.

Montgomery, C. A. and H. Singh (1984). 'Diversification strategy and systematic risk', *Strategic Management Journal*, **5**(2), pp. 181–191.

Mossin, J. (1966). 'Equilibrium in a capital asset market', *Econometrica*, **34**, pp. 768–783.

Nunnally, J. C. (1978). *Psychometric Theory* (2nd ed.). McGraw-Hill, New York.

Oviatt, B. M. and A. D. Bauerschmidt (1991). 'Business risk and return: A test of simultaneous relationships', *Management Science*, **37**, pp. 1405–1423.

Pari, R. A. and S. Chen (1985). 'Estimation risk and optimal portfolios', *Journal of Portfolio Management*, **12**(1), pp. 40–43.

Porter, M. E. (1985). *Competitive Advantage: Creating and Sustaining Superior Performance*. Free Press, New York.

Price, K., B. Price and T. J. Nantell (1982). 'Variance and lower partial moment measures of systematic risk: Some analytical and empirical results', *Journal of Finance*, **37**, pp. 843–855.

Rivera, J. M. (1991). 'Prediction performance of earnings forecasts: The case of U.S. multinationals', *Journal of International Business Studies*, **22**, pp. 265–288.

Ruefli, T. W. (1990). 'Mean-variance approaches to risk-return relationships in strategy: Paradox lost', *Management Science*, **36**, pp. 368–380.

Ruefli, T. W. (1991). 'Reply to Bromiley's comment and further results: Paradox lost becomes dilemma found', *Management Science*, **37**, pp. 1210–1215.

Ruefli, T.W. and R. R. Wiggins (1994). 'When mean square error becomes variance: A comment on "Business risk and return: A test of simultaneous relationships"', *Management Science*, **40**, pp. 750–759.

Sanchez, R. (1993). 'Strategic flexibility, firm organization, and managerial work in dynamic markets: A strategic-options perspective'. In P. Shrivastava, A.

Huff, J. Dutton (eds), *Advances in Strategic Management*, Vol. 9. JAI Press, Greenwich, CT, pp. 251–291.

Schoemaker, P. J. H. (1982). 'The expected utility model: Its variants, purposes, evidence and limitation', *Journal of Economic Literature*, **20**, pp. 529–563.

Schoemaker, P. J. H. (1993). 'Determinants of risk-taking: Behavioral and economic views', *Journal of Risk and Uncertainty*, **6**, pp. 49–73.

Sharpe, W. (1964). 'Capital asset prices: A theory of market equilibrium under conditions of risk', *Journal of Finance*, **19**, pp. 425–442.

Singh, J. V. (1986). 'Performance, slack, and risk taking in organizational decision making', *Academy of Management Journal*, **29**, p. 562–585.

Slovic, P., B. Fischoff and S. Lichtenstein (1977). 'Behavioral decision theory', *Annual Review of Psychology*, **28**, pp. 1–39.

Stone, B. K. (1970). *Risk, Return and Equilibrium: A General Single Period Theory of Asset Selection and Capital Market Equilibrium*. MIT Press, Cambridge, MA.

Stone, B. K. (1973). 'A general class of three-parameter risk measures', *Journal of Finance*, **28**, pp. 675–685.

Stonebraker, R. J. (1976). 'Corporate profits and the risk of entry', *Review of Economics and Statistics*, **58**, pp. 33–39.

Venkatraman, N. and J. H. Grant (1986). 'Construct measurement in organizational strategy research: A critique and proposal', *Academy of Management Review*, **11**, pp. 71–87.

Wallach, M. A. and C. W. Wing, Jr. (1968). 'Is risk a value?', *Journal of Personality and Social Psychology*, **9**, pp. 101–106.

Woo, C. Y. (1987). 'Path analysis of the relationship between market share, business-level conduct and risk', *Strategic Management Journal*, **8**, pp. 149–168.