© Academy of Management Journal
1996, Vol. 39, No. 1, 91–122.

CORPORATE RISK-RETURN RELATIONS: RETURNS VARIABILITY VERSUS DOWNSIDE RISK

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This study tested a model of firm risk-return relations in which risk was conceptualized in terms of downside outcomes. Drawing on the behavioral theory of the firm, we developed a set of hypotheses involving downside risk, return, and organizational slack. The hypothesized risk and return relations were tested using both downside risk and the conventional standard deviation of returns. The results indicate downside risk results in improved subsequent performance. Performance shows a negative relation with subsequent downside risk.

During the 1980s, strategic management and organization researchers gave increased attention to risk. Bowman's (1980, 1982, 1984) research pointed out the theoretical and empirical contradictions between firm-level risk-return relations and the positive risk-return relation derived from financial portfolio theory. Bowman drew attention to behavioral theory as a possible explanation for the paradoxical patterns observed in corporate risk-return data. Following Bowman's suggestion, other researchers sought to empirically test hypotheses derived from behavioral explanations of managerial risk avoidance and risk seeking. Fiegenbaum and Thomas (1988), Fiegenbaum (1990), and Jegers (1991) appealed to prospect theory (Kahneman & Tversky, 1979) to explain corporate risk-return relations. Singh (1986) and Bromiley (1991b) tested models grounded in Cyert and March's (1963) behavioral theory of the firm.

Although these studies sought to test propositions drawn from behavioral theory, their substantive findings have often been discounted because of skepticism regarding the appropriateness of using variance measures of corporate risk. Marsh and Swanson (1984) contended that risk-return relations computed as variance-mean relations in corporate accounting returns data may be statistical artifacts rather than valid tests of behavioral relations. Ruefli (1990, 1991) sought to further this line of argument, contending on statistical grounds that variance-mean relations were not meaningful. Bromiley (1991a) disputed this contention. This debate regarding the appro-

Philip Bromiley, Thomas Brush, and Javier Gimeno Gascon, along with anonymous reviewers, provided helpful comments on earlier drafts.

priateness of variance measures is critical to evaluating the findings of prior behavioral research and may also prompt a reevaluation of the findings of other branches of strategy research incorporating variance measures of risk, such as research on corporate diversification.[1]

This controversy regarding appropriate measures of organizational risk has largely suppressed the question of the conceptual validity of variance measures. We bring the validity question to the forefront by questioning whether variance measures adequately capture the concept of risk relevant to managers. In the opening section of this article, we contend that rather than supporting variance concepts of risk, management theory and studies of managers' understandings of risk point to the potential for poor performance as the essence of risk.

The primary objective of this study was to test a behavioral model of firm risk-return relations in which risk is conceptualized in terms of downside outcomes rather than outcome variance. We drew from the behavioral theory of the firm (Cyert & March, 1963) to develop testable hypotheses regarding relations between downside risk and organizational performance. These relations become explicit in a two-equation model of relations between downside risk and return allowing for moderating effects associated with organizational slack.

The behavioral theory of the firm has been around for more than three decades, but empirical studies such as those by Singh (1986) and Bromiley (1991b), examining risk-return models directly incorporating the constructs of performance, aspirations, and slack and using actual organizational data, are quite rare.[2] March's own work based on the behavioral theory of the firm has concentrated on simulations (cf. March, 1988a). Other researchers (Lant, 1992; Lant & Montgomery, 1987) have looked at group decisions in simulated organizations (i.e., using a marketing strategy game). The theory merits further investigation using actual organizational data.

In developing operational measures of the variables in our behavioral model, we introduce a general category of measures of firm downside risk; these measures are specified as weighted functions of below-target returns. The particular class of downside measures examined in this study incorporates historical accounting returns.

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[1] Despite the unresolved state of this debate, the criticisms of variance measures have prompted researchers to explore alternative risk proxies. Bromiley (1991b) advocated the use of risk measures capturing the ex ante uncertainty of returns reflected in the variance among stock analysts' earnings forecasts. Oviatt and Bauerschmidt (1991) measured risk as the variability in returns around the time trend in a firm's accounting returns data. Ruefli and Wiggins (1994) subsequently criticized the measure used by Oviatt and Bauerschmidt on the basis that under certain conditions it converges to returns variance—an inappropriate measure for examining risk-return relations if Ruefli's earlier (1990, 1991) contentions are accepted (see Appendix B).

[2] Singh's (1986) cross-sectional model of risk taking found performance to have a negative relation. Bromiley (1991b) found performance reduced subsequent firm risk, and risk reduced subsequent performance. Results regarding organizational slack differed across these two studies.

Tests of the behavioral model indicate downside risk results in improved subsequent performance. Performance, however, shows a negative relation with subsequent downside risk. Correlation and regression analyses using data from U.S. manufacturing companies indicate the choice between downside and variance measures has substantive implications for estimated risk-return relations. This finding alerts strategy and organization researchers to the need to explicitly consider the conceptual validity of variance and downside measures in specifying and testing theoretical models.

THEORY AND HYPOTHESES

Behavioral Theory and Downside Risk

In the behavioral theory of the firm, Cyert and March (1963) sought to describe the way in which organizations make decisions. The theory focuses on internal organizational decision criteria and processes. In developing it, Cyert and March gave extensive attention to organizational performance and aspirations as determinants of managerial choices, indicating that organizations measure performance along multiple dimensions, including production, inventory, sales, market share, and profitability. The degree of emphasis on any particular dimension of performance is driven by top management priorities and previous experience. Following the stream of research on risk-return relations, we focused on a profitability measure of performance; however, the discussion could be extended to other organizational performance dimensions.

Not only do managers measure performance—they also formulate aspirations as benchmarks for assessing performance. Performance that falls short of aspirations motivates organizational change. Describing the adaptation of organizational aspirations, Cyert and March stated the following: "We assume, therefore, that organizational goals in a particular time period are a function of (1) organizational goals of the previous time period, (2) organizational experience with respect to that goal in the previous period, and (3) experience of comparable organizations with respect to the goal dimension in the previous time period. Initially at least, we would assume a simple linear function, $G_t = a_1G_{t-1} + a_2E_{t-1} + a_3C_{t-1}$, where G is the organizational goal, E the experience of the organization, C a summary of the experience of comparable organizations, and where $a_1 + a_2 + a_3 = 1$" (1963: 123). Subsequent research supported the contention that managers' assessments of performance are framed in terms of aspiration levels (Lant, 1992; Lant & Montgomery, 1987; Milliken & Lant, 1991).

Studies of managers indicate the performance and aspiration constructs found in the behavioral theory of the firm are central to managers' concepts of risk. Mao (1970) found executives characterized risk in terms of failure to meet a target rather than in terms of variance. March and Shapira (1987) reported that 80 percent of the executives they surveyed considered only negative outcomes when thinking about risk. Baird and Thomas's (1990) survey results indicated financial analysts specializing in six different industries considered the size and probability of a loss the most important of seven risk definitions. Hence, managerial surveys suggest that downside concepts of risk—those specified in terms of failure to perform at an aspired-to level—are much more relevant to practicing managers than performance variability, which includes both upside and downside outcomes.

Furthermore, discussions of risk in the strategy literature frequently reflect the view of risk as failure to perform at an aspired level. For example, as Aaker and Jacobson stated, "Marketing and strategy are primarily concerned with avoiding decreases in expected return" (1990: 153). They noted that although new entry into an industry may leave the returns variability of incumbent firms unchanged, entry can lower expected returns. It is this potential for reduced future performance, rather than a change in the variability of future returns, that constitutes risk. Similarly, Porter, in discussing corporate risk management, stated the following: "Risk is a function of how poorly a strategy will perform if the 'wrong' scenario occurs" (1985: 476). Hoskisson, Hitt, and Hill (1991) asserted loss aversion, rather than variance aversion, characterizes strategic decision makers' risk preferences.

Despite the apparent relevance of downside risk for managers and strategy theorists, empirical strategy and organizational research continue to employ operational measures of risk reflecting variability in accounting or stock returns. Such variability measures fail to differentiate upside and downside outcomes—a distinction fundamental to the risk assessments of managers. Noting this inconsistency, March and Shapira 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). Recognition of the discrepancy between downside and variability concepts of risk raises questions about the validity of variance risk measures and the conclusions obtained from empirical research using such measures.

Hypotheses

Focusing on a downside concept of risk requires rethinking the implications of behavioral theory for risk-return relations. The discussion in this section generates a set of hypotheses grounded in the behavioral theory of the firm (Cyert & March, 1963). The hypotheses relate downside risk and organizational performance. Following behavioral theory, the hypotheses also reflect the role of organizational slack in determining risk-return relations. Unlike previous research, this study tested behavioral hypotheses conceptualizing risk in terms of below-target outcomes rather than performance variability.

According to Cyert and March (1963), when performance falls below the level of aspirations, organizations respond by initiating searches for alternative routines. Such managerial attention to performance that falls short of a target level is consistent with downside conceptualizations of risk. Deficiencies in performance relative to aspirations stimulate searches designed to generate alternatives that will resolve performance shortfalls.[3] Since searching is costly, failure to achieve a desired performance level may reduce short-term performance. However, the behavioral theory of the firm suggests that search continues in a sequential fashion until the organization encounters an alternative with an expected performance exceeding the aspiration level. It is assumed that the profit generated by this solution more than offsets the short-term cost associated with search. As a result, the behavioral theory of the firm suggests a failure to reach aspired-to performance levels will result in new routines that lead to improved subsequent performance.[4]

The hypothesized positive relation between downside risk and subsequent performance is unlikely to be evident in cross-sectional research unless a control for prior performance is included. Although there could be exceptions, firms that consistently perform above their aspiration levels are likely to maintain higher performance than those that perform at levels lower than they have aspired to. Thus, in the absence of a control for prior performance, cross-sectional analysis is likely to render a negative relation between downside risk and performance. The more interesting issue is whether or not downside risk results in a relative improvement in a firm's own performance. By controlling for prior performance, we isolate the effect of downside risk on performance relative to a firm's own prior performance.

> *Hypothesis 1: With prior performance controlled, downside risk has a positive relation with subsequent financial performance.*

The behavioral argument underlying Hypothesis 1 rests on the assumptions that downside risk focuses managers' attention on problem solving and that the ensuing search results in the identification and implementation of a performance-enhancing alternative organizational strategy.[5] These are disputable assumptions. A plausible alternative to Hypothesis 1 is that organizations are dominated by inertia and fail to respond to downside risk with performance-enhancing changes. The view that inertia, rather than managerial strategic choice, characterizes organizations is most strongly asserted in population ecology (e.g., Hannan & Freeman, 1977). Elsewhere in organization theory, there is a recognition that although organizations have inertial

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[3] Puffer and Weintrop (1991) found shortfalls in actual financial performance relative to analysts' forecasts were associated with CEO turnover, a finding consistent with the contention that performance shortfalls motivate change.

[4] We are indebted to an anonymous reviewer for drawing attention to the importance of the time dimension in specifying relations between downside risk and return. In an earlier version of this work, we assumed a relatively short time frame and, owing to adjustment costs, hypothesized a negative relation between downside risk and subsequent performance. By contrast, the present statement of Hypothesis 1 is in agreement with Cyert and March's (1963) behavioral theory of the firm and is consistent with the five-year time frame used in our empirical analyses.

[5] As Cyert and March stated, "We have argued that failure induces search and search ordinarily results in solutions" (1963: 278).

tendencies, a concerted effort for change is, nevertheless, possible (e.g., Hedberg, Nystrom, & Starbuck, 1976). The absence of empirical support for a positive relation between downside risk and subsequent performance would be consistent with the inertial hypothesis.

The behavioral theory of the firm contains no explicit statement about the nature of the particular strategic changes adopted in response to downside risk. It does not address what strategies enhance organizational performance. The behavioral theory of the firm is a theory of organizational choice, not competitive advantage. It should be acknowledged, however, that changes in strategy mediate the relation between downside risk and subsequent financial performance and, hence, the hypothesized relation between downside risk and financial performance is not directly causal.

A further implication of the behavioral theory of the firm is that firms with strong financial performance will not undertake searches for alternative strategies. Firms avoid uncertainty unless performance shortfalls motivate problemistic search (Cyert & March, 1963). Thus, high-performance firms avoid the cost and performance uncertainty associated with searching for alternative strategies and should experience less subsequent downside risk than low-performance firms.

Behavioral theorists (e.g., Singh, 1986) motivated by prospect theory (Kahneman & Tversky, 1979) have also contended that poor performers are more likely than high performers to engage in risky strategies. Kahneman and Tversky found individuals exhibit risk-averse behavior for probabilistic choices involving gains and risk-seeking behavior for choices involving losses. Bowman (1980, 1982, 1984) and Fiegenbaum and Thomas (1986, 1988) extended prospect theory from analysis at the individual level to organization-level risk preferences. Prospect theory suggests that poorly performing firms may take greater risks than strongly performing firms. Such risky strategies may have low expected values, but the firms expect eventually that some strategic gamble will improve firm performance. Strong performers, on the other hand, may reduce their risk-taking strategic initiatives. Hence, both the behavioral theory of the firm and prospect theory arguments support the contention that strong financial performance decreases organizational downside risk and that poor performance increases it.

Since downside risk is a function of performance relative to an aspiration level, empirical results supporting a negative relation between performance and subsequent downside risk could be due simply to autocorrelation in firms' returns data. Hence, testing this relation requires controlling for prior downside risk. In so doing, we isolate the changes in downside risk attributable to prior performance. The following illustrates the reasoning behind controlling for prior downside risks: in any given period, it is quite possible for two firms to have the same level of downside risk yet very different average performance levels. This pattern could be a result of one firm's having some large positive deviations from its aspiration level during the period while the other does not. We would expect the firm with higher average performance to experience a greater reduction in downside risk than the firm with lower average performance. Thus, if we control for prior downside risk, finding performance has an impact on subsequent downside risk would be a substantive result.[6]

> *Hypothesis 2: With prior downside risk controlled, financial performance has a negative relation with subsequent downside risk.*

The behavioral theory of the firm introduces organizational slack as a moderator of organizational responses. Hence, a well-specified behavioral model of downside risk-return relations must incorporate organizational slack. Organizational slack resources accumulate during periods of performance above aspirations and diminish during periods of unsatisfactory performance. As such, slack provides a cushion allowing organizations to maintain more stable aspirations when faced with performance variability than would be possible without slack resources (cf. Cyert & March, 1963: 36–38). Slack determines an organization's motivation to seek out revenue-enhancing changes in operating routines and strategies in response to performance shortfalls. The intensity of search is greater where organizational slack is low than when it is high (Cyert & March, 1963: 80). Since high-slack firms are less likely to undertake searches for new strategies when faced with downside risk, downside risk has a less positive impact on subsequent financial performance for high-slack firms than for low-slack firms. Sharfman Wolf, Chase, and Tansik (1988) also made the claim that slack absorption allows firms to postpone changes when short-term performance falls below aspirations.

> *Hypothesis 3: Slack attenuates the positive effect of downside risk on subsequent financial performance.*

Although slack is expected to be a significant moderator of the impact of downside risk on financial performance, the total effect of slack on financial performance is unclear. Cyert and March (1963: 278–279) proposed that organizations benefit from "slack innovation," that is, innovation that arises through experimentation that would not be undertaken in a slack-constrained organization. The possibility of slack innovation argues for a positive direct effect of slack on subsequent performance. Cyert and March were careful to characterize slack innovation as distinct from problem-driven innovation, the primary focus of their theory. Although slack may allow firms to experiment and take advantage of opportunities, its buffering effect serves to reduce "problem-oriented innovation" (Hypothesis 3). The net result of these offsetting effects is not apparent. Hence, we did not expect the combined effects

[6] This approach is consistent with that of Lant and Montgomery (1987), who found risk taking (formulated as variance or uncertainty) to be positively related to past risk and negatively related to past attainment discrepancy (performance minus aspiration level) for players of a marketing strategy game.

of slack on performance (both direct and in interaction with downside risk) to be significant.

Slack was expected to have both a direct and a moderating effect on subsequent downside risk.[7] These relations are summarized in Hypotheses 4 and 5. First, regarding the direct effect of slack on downside risk, the presence of slack resources is expected to allow firms to undertake investments reducing subsequent downside risk. Firms with slack resources formulate responses to a greater range of environmental contingencies than do resource-constrained firms (Cohen, March, & Olsen, 1972). In so doing, high-slack firms reduce their downside risk relative to low-slack firms. This argument coincides with Thompson's (1967) contention that firms use slack resources to buffer their "technological cores."[8]

Hypothesis 4: Slack reduces subsequent downside risk.

Slack should also demonstrate a moderating effect on the relation between firm performance and subsequent downside risk. Risk reduction through investment of slack resources is likely to be particularly evident in high-performance firms. That is, the managers of organizations performing well should be more predisposed than managers of poorly performing organizations to use slack resources to buffer their organizations from downside risk. By contrast, managers of poor performers may not be inclined to buffer their maladapted organizations through slack investments.

Hypothesis 5: Slack enhances the negative effect of financial performance on subsequent downside risk.

In addition to testing these five hypotheses, this study had the further objective of contrasting the empirical implications of using downside and variability measures of risk. In the earlier discussion of variability and downside risk, we argued that downside risk is the more managerially relevant concept of risk. If downside measures have greater validity than variability measures, the former should provide greater explanatory power than the latter in a behavioral model of risk-return relations. We did not develop specific hypotheses relating variability risk measures and return, but the empirical results presented below are based on both downside and variance risk measures. This approach allows comparisons between the measurement properties of downside and variability risk in behavioral models.

[7] Bromiley (1991b) specified a model with nonlinear effects of slack on risk and performance. The estimated coefficients associated with slack squared were generally not significant at the .05 level. Given the lack of empirical evidence and convincing theoretical arguments for the inclusion of slack squared and the potential for collinearity problems with the inclusion of both direct and quadratic forms in the same model, we have chosen not to include a quadratic slack variable.

[8] This hypothesis contrasts with Jensen's (1986) free cash flow hypothesis, which would lead to the alternative hypothesis, that organizational slack increases downside risk because of agency problems.

RESEARCH DESIGN

Model Specification

The model consisted of two equations. The primary relations are those between risk and subsequent return and the effect of return on subsequent risk. The time period subscripts indicate the time lags incorporated into the model. The bilinear moderating effect of slack on the relations between risk and return is incorporated as a multiplicative term in each equation (cf. Jaccard, Turrisi, & Wan, 1990). Slack also enters the model as a direct effect. Partialing the direct effect from the product terms is necessary for interpreting the t-statistic associated with the risk-by-slack and return-by-slack interaction terms (Cohen, 1978). The two equations are as follows:

$$Return_t = \mathrm{b}_0 + \mathrm{b}_1 risk_{t-1} + \mathrm{b}_2 slack_{t-1} + \mathrm{b}_3 risk_{t-1} \times slack_{t-1} + \mathrm{b}_4 return_{t-1} + \mathrm{b}_5 industry\ return_t + \mathrm{e}_t. \quad (1)$$

For Hypothesis 1, $\mathrm{b}_1 + \mathrm{b}_3 slack_{t-1} > 0$; for Hypothesis 3, $\mathrm{b}_3 < 0$.

$$Risk_t = \mathrm{c}_0 + \mathrm{c}_1 return_{t-1} + \mathrm{c}_2 slack_{t-1} + \mathrm{c}_3 return_{t-1} \times slack_{t-1} + \mathrm{c}_4 risk_{t-1} + \mathrm{c}_5 industry\ risk_t + e_t. \quad (2)$$

For Hypothesis 2, $\mathrm{c}_1 + \mathrm{c}_3 slack_{t-1} < 0$; for Hypothesis 4, $\mathrm{c}_2 + \mathrm{c}_3 return_{t-1} < 0$; for Hypothesis 5, $\mathrm{c}_3 < 0$.

The hypotheses under each regression equation summarize the expected relations developed in the previous section. In Equation 1, the t-statistic for the coefficient b_3 provides a test for Hypothesis 3, positing a moderating effect of slack_{t-1}. Risk_{t-1} has both a direct and a slack-moderated effect on return. Hence, the total effect of risk_{t-1} on return_t is given by the partial derivative of Equation 1 with respect to risk_{t-1}, that is, $\mathrm{b}_1 + \mathrm{b}_3 slack_{t-1}$. This expression makes clear that the relation of risk_{t-1} on return_t is a linear function of slack_{t-1}. Similarly, in Equation 2, the total effects of return_{t-1} and slack_{t-1} are given by the partial derivatives with respect to each of these terms.

Controls. Previous strategy research indicates that numerous firm-specific and industry variables affect organizational risk and return. Our focus was on developing a parsimonious model consistent with the behavioral theory of the firm, but it was important to include appropriate organizational and industry controls. The lagged dependent variable and contemporaneous industry effects are included as controls for other varibles that have an impact on risk and return but are not explicitly considered in the behavioral theory of the firm. The lagged dependent variable controls for firm-specific factors affecting return or risk across time periods. Thus, the lagged risk and return variables are expected to be positively related with the same variables in the subsequent period ($\mathrm{b}_4 > 0$, $\mathrm{c}_4 > 0$). As noted in the development of the first two hypotheses, the lagged dependent variables express the downside risk-return relations in the context of a firm's prior risk and return.

The contemporaneous industry effect controls for differences in performance and risk across industry categories. Previous research has indicated the importance of industry controls in modeling risk-return relations (Bowman, 1980; Fiegenbaum, 1990; Fiegenbaum & Thomas, 1985, 1986). Contemporaneous measures of risk and return serve as proxies for the attractiveness of an industry's structure. The industry return term in the return equation includes contemporaneous performance by all other firms in the same two-digit Standard Industrial Classification (SIC) industry. That is, a firm's own return is not included in the industry return for that observation. If industry structure affects performance, average returns by other firms in the industry should be positively related to returns for any particular firm ($b_5 > 0$).

Similarly, the risk equation incorporates a measure of contemporaneous average risk for all other firms in a two-digit SIC industry. High average industry downside risk indicates the presence of firms with large performance deviations below aspirations. The persistence of such firms in an industry may indicate high exit barriers and, hence, higher risk for all firms in the industry. A general decline in industry performance would raise average industry downside risk. Average downside risk is expected to be positively related to downside risk for a particular firm in the industry ($c_5 > 0$).

Lag structure. Although it has been widely argued that risk affects return and vice versa, one of the difficulties in specifying a model of risk-return relations is inadequate understanding of the timing of these effects. As Bromiley (1991b) pointed out, most previous studies in the strategy field have used cross-sectional data to estimate risk-return relations. These studies make causal arguments relating risk and return but model risk and return as having contemporaneous effects on each other. An alternative to estimating contemporaneous risk-return relations is to specify a lagged model in which risk affects subsequent return and vice versa. Although model specification with temporal ordering of risk and return variables does not necessarily indicate causality, reverse causation can be ruled out (Kenny, 1979: 2–4). That is, a variable measured in one period does not cause variables measured in earlier periods.

Specifying a model with lagged relations between risk and return is consistent with causal theoretical arguments, such as those of the behavioral theory of the firm, but the appropriate lag structure for such models is unclear. Miller and Bromiley (1990) found significant relations using a model in which risk in one five-year time period explained return in the subsequent five-year period. Bromiley (1991b) modeled risk in one year as affecting return in the following year and vice versa.

Given the unique characteristics of organizations and investment projects, it would be difficult to make any generalization regarding the appropriate lag structure for risk-return relations. Although other lag structures may be reasonable, this study used five-year periods to specify the lags in modeling risk-return relations. The first equation models average return over a five-year period as a function of downside risk measured over the previous five-year period. The risk equation uses average return in a period to explain risk in the subsequent five-year period. The slack, industry risk, and industry return variables were also computed as five-year period averages.

Since lagged effects of downside risk on return and vice versa are consistent with the behavioral theory of the firm, we did not model a contemporaneous risk-return relation. Hence, the proposed cross-sectional model differs from the theoretical perspective reflected in other research modeling contemporaneous risk and return as a system of simultaneous equations (e.g., Oviatt & Bauerschmidt, 1991). Since cross-sectional estimation of Equations 1 and 2 involves no endogenously determined explanatory variables, use of ordinary-least-squares estimates was appropriate (Kennedy, 1985: 126–127).

Temporal stability. Fiegenbaum and Thomas (1986) found risk-return relations differed over time. Ruefli (1991) and Baucus, Golec, and Cooper (1993) also questioned the temporal stability of corporate risk-return relations. Hence, each of the regression models was estimated cross-sectionally for three distinct periods to allow testing for the stability of the regression coefficients over time.

Measures and Sample

Return. Return on equity (ROE) and return on assets (ROA) are two common accounting-based measures of performance. Both measures are highly correlated. Furthermore, both have been used to compute highly correlated accounting-based risk measures in previous strategy research (Miller & Bromiley, 1990). This study used average ROA over the five-year period as the return measure. ROA does not vary with changes in financial leverage, as does ROE.

Risk. For each firm, downside risk was measured as a function of the magnitude of performance shortfalls relative to an aspiration level. We computed downside risk using five-year periods of annual firm ROA data. Computation involved a two-stage process. For each year *t*, we computed the downside performance discrepancy (δ_{jt}) as a function of the aspired-to target return (τ_{jt}) and the actual return for firm j (r_{jt}). The performance discrepancy takes on the value $\delta_{jt} = \tau_{jt} - r_{jt}$ if $\tau_{jt} > r_{jt}$. If $\tau_{jt} \leq r_{jt}$, then $\delta_{jt} = 0$. Next, we aggregated the five years of performance discrepancy values using the functional form of a root lower partial moment:

$$\mathrm{RLPM}_{\alpha}(\tau;j) = [(1/5)\sum_{t=1}^{5}\delta_{jt}^{\alpha}]^{1/\alpha}. \tag{3}$$

The parameter alpha reflects the relative importance of small and large deviations from the target. First-order ($\alpha = 1$) and second-order ($\alpha = 2$) root lower partial moments were calculated. Although the first- and second-order root lower partial moments were expected to be highly correlated, both measures were generated in order to evaluate the sensitivity of corporate downside risk to the choice of the parameter alpha. For the interested reader, Appendix A contains further background on the specification of downside risk measures as lower partial moments.

To accommodate alternative assumptions about the evolution of firms' target performance levels over time, we adopted four alternative assumptions: (1) firms update their target levels annually and set them equal to their own performance in the previous year; (2) firms update their target levels annually and set them equal to the average performance in their two-digit SIC industries in the previous year; (3) firms base their target levels for any five-year period on the average performance of all firms in their two-digit SIC industries in the previous five-year period; and (4) firms are loss-averse and thus maintain a constant target return of zero. A target level corresponding to lagged industry average performance (assumptions 2 and 3 above) is consistent with theoretical discussions of adaptive aspirations (Cyert & March, 1963: 123). Such a target level consists of weighted sum of own-firm past performance and the past performance of other industry participants, a relevant reference group for determining a firm's target level. By contrast, assumption 1 allows for the possibility that firms look only to their own past performance in setting aspirations. Under assumption 4, firms' aspirations do not evolve over time. Rather, firms consistently aspire to avoid financial losses.

The use of first- and second-order root lower partial moments and four alternative assumptions about target levels generated a total of eight RLPM measures. Initial correlations indicated that the choice for the scaling parameter of alpha equals 1 or alpha equals 2 did not have a significant effect on the value of the downside risk measures. Risk measures differing only in this scaling parameter were significantly correlated at the .001 level, with a correlation coefficient greater than .96 in all four periods studied. Because of this very high correlation and for consistency in comparing results with those based on standard deviation risk measures, which are of order two, we retained only the (four) second-order root lower partial moments for our remaining analyses. In Table 1, we refer to the downside risk measure calculated using a firm's own previous year returns as the target level as RLPM(previous year target). RLPM(industry target) refers to the downside risk measure using previous year industry performance (which includes own-firm performance) as the target level. RLPM(fixed target) designates the downside measure with the target level in each period fixed at the industry average performance in the previous five-year period. Finally, the measure incorporating the assumption of loss aversion ($\tau_{it} = 0$) is labeled RLPM (zero target).

For comparing downside measures with the risk measures commonly used in strategy research, two returns variability measures were generated. The first of these was the common standard deviation of return on assets over a five-year period. The second measure was similar to the standard-deviation-around-returns trend used by Fisher and Hall (1969) and Oviatt and Bauerschmidt (1991). Appendix B contains computational details for the trend standard deviation and responds to concerns regarding variability measures expressed by Ruefli (1990, 1991) and Ruefli and Wiggins (1994).

Five years of returns data were required to calculate the four downside risk and two standard deviation measures of risk. Firms with fewer than five return observations were eliminated from the data set for that period.

Furthermore, the RLPM(fixed target) measure could not be generated in the first period (1972–76) since the required five years of lagged performance data were unavailable.

Slack. Bourgeois (1981) and Sharfman and colleagues (1988) provided conceptual treatments of slack. Bourgeois and Singh (1983) specified eight measures of organizational slack. They differentiated measures of available, recoverable, and potential slack. Singh (1986), Hambrick and D'Aveni (1988), and Bromiley (1991b) used accounting-based slack measures similar to those suggested by Bourgeois and Singh. We identified 13 distinct accounting-based slack measures from previous research.

There is theoretical support for the relevance of reference levels in specifying slack indicators, a concern that is not reflected in the operational measures of slack used in previous research. Bourgeois (1981) contended that changes in the amount of organizational slack over time, rather than absolute levels of slack, are relevant to explaining firm behavior. Similarly, March and Shapira (1987) and Bromiley (1991b) argued the influence of slack on performance and risk depends not on the absolute level of slack but on slack relative to a target level.

Financial ratios such as those commonly used as slack indicators differ across industries. Ratios that are the norm in one industry may be exceptionally high or low in another. Hence, slack measures may not generalize across industries. According to Lev (1969), average industry financial ratios offer reasonable proxies for target levels. We measured slack as the ratio of a firm's own accounting measure to its industry average (at the two-digit SIC level). Following Bourgeois and Singh (1983), we measured recoverable slack using the following ratios: accounts receivable/sales, inventory/sales, and selling, general, and administrative expenses/sales. In each case, our normalized measures consisted of a firm's ratio divided by the two-digit SIC industry average ratio.

Bourgeois and Singh also identified measures of both available and potential slack. We chose to focus on recoverable slack, for two reasons. First, recoverable slack is the most relevant concept of slack for many organizational stakeholders. The levels of accounts receivable to sales and of inventory to sales are directly relevant to a firm's capability to meet customer demands. The level of overhead expenses affects employee satisfaction through nonpecuniary benefits. Because of the immediate impact of recoverable slack on operations, constraints on recoverable slack are likely to be more salient to managers than constraints on potential or available slack.

Second, exploratory factor analysis indicated the available and potential slack measures found in previous research did not load on two distinct and consistent factors over the years included in the data set. Using the available and potential slack ratios normalized by their respective industry averages did not improve the stability of the factor loadings. By contrast, the three normalized recoverable slack indicators did load on a single factor with a great deal of consistency over 20 years of annual data. This finding supports the use of the three recoverable slack measures as indicators of a common construct but also calls into question the reliability of the available and potential slack measures found in previous research.

The aggregate recoverable slack measures for a given year consisted of an unweighted sum of the three standardized recoverable slack indicators. The slack measure used for model estimation was a firm's mean recoverable slack calculated over a five-year period.

Sample. The sample consisted of all manufacturing firms in SIC codes 3000 to 3999 for which the necessary accounting data were available in the COMPUSTAT primary, secondary, and tertiary files during the years 1971 through 1991.[9] We defined four periods corresponding to the five-year time segments of 1972–76, 1977–81, 1982–86, and 1987–91. Firms with returns or any recoverable slack indicator beyond three standard deviations from the annual mean across all firms were considered outliers and eliminated from that year's data set. We included 1971 data solely for the purpose of calculating the 1972 target return level, assuming that firms set the target level to the industry mean performance in the previous year. The sample provided at least ten firms for each two-digit SIC industry in each year.

RESULTS

Table 1 presents descriptive statistics and cross-sectional correlations between return, the various risk measures, slack, and the control variables for each of the four periods. Industry return, industry standard deviation, and industry downside risk denote the average ROA, standard deviation of ROA, and RLPM(industry target) for all firms in the same two-digit SIC industry (excluding the firm under observation). These three industry average variables serve as controls in the regression models.

Table 1 indicates significant negative correlations between all six risk indicators (four RLPM and two standard deviation measures) and five-year mean ROA.[10] The two standard deviation measures had positive correlations of at least .87 across the four time periods. The RLPM using one-year lagged own-firm performance as the aspiration level, RLPM(previous year target), was unique among the four downside measures in being more highly correlated with the variance measures (standard deviation and trend standard deviation) than with the other RLPM measures in each period. The other three RLPM measures [RLPM(industry target), RLPM(fixed target), and RLPM(zero target)] maintained significant positive correlations of at least .78 in each period. Hence, with the exception of the assumption of annual updating of

[9] The focus on manufacturing firms in SIC codes 3000–3999 corresponds with Bromiley's (1991b) sample selection. We concur with Bromiley's observation that focusing on manufacturing firms mitigates discrepancies in the data resulting from differences in accounting practices across single-digit SIC categories.

[10] Collins and Ruefli's (1992) study of the airlines industry also found a negative relation between ordinal downside risk in a five-year period and ROA rank position in the fifth year of the period.

targets based solely on own-firm past performance, the RLPM measure appears robust to a range of target-level assumptions.

Given the consistently high correlations among three of the four RLPM measures and between the two standard deviation measures, we retained just two measures for the regression analyses. These were the second-order RLPM with aspirations updated annually based on industry performance [RLPM(industry target)] and the standard deviation of returns. Using these two measures allowed us to make direct comparisons between the risk-return relations obtained using the common standard deviation measure and those obtained using the previously untested RLPM measure. The RLPM(industry target) measure was chosen over the RLPM(fixed target) and RLPM(zero target) measures because of two appealing characteristics: (1) the assumption of annual updating of aspirations is consistent with the planning cycle of many organizations, and (2) incorporating both past own-firm and industry competitors' performance in the aspiration level is consistent with previous theoretical treatments of adaptive aspirations (Cyert & March, 1963; Herriott, Levinthal, & March, 1985). In the remainder of this article, we refer to RLPM(industry target) as simply "downside risk."

Initial regression results for Equations 1 and 2 indicated outlier observations may have unduly influenced the estimated coefficients. Outliers were eliminated if their influence statistics, DFFITS, indicated very influential observations.[11] Elimination of outliers resulted in deletion of 6.3 to 8.9 percent of the original sample observations in each of the 12 estimated regression models. A comparison of the regression results before and after elimination of outliers indicated no substantive differences in the signs or magnitudes of the estimated coefficients.

Tables 2 and 3 present ordinary-least-squares results (after elimination of outliers) for the return and risk regression equations, respectively. The first section of each table presents the downside risk results and the second section shows the standard deviation results. The column headings indicate the period of the dependent variable. The left-hand column of each period reports the estimated coefficients and their standard errors (in parentheses). Significance levels are not indicated for the direct effects of variables that also appear in interaction terms to avoid unwarranted interpretation of the coefficients of these variables.[12] The appropriate test for the significance of the combined effect of a variable both through the direct effect and the interaction term is an F-test (Kmenta, 1986). The F-statistic tests the hypothe-

[11] The DFFITS statistic is a scaled measure of the change in the predicted value for a given observation with and without including the observation in the model estimation. Large DFFITS values indicate very influential observations. Observations are thought to unduly affect model estimations when their DFFITS value exceeds $2\sqrt{p/n}$, where p is the number of parameters in a model and n is the number of observations (Belsley, Kuh, & Welsch, 1980).

[12] Although t-values for the interaction terms are meaningful (i.e., they are equivalent to a hierarchical F-test), the t-values for the two direct effect terms included in an interaction are not invariant to linear transformations of the variables (Cohen, 1978).

TABLE 1
Descriptive Statistics and Correlations by Period[a]

Variables	Mean	s.d.	1	2	3	4	5	6	7	8	9	10
Period 1: 1972–76												
1. Return	0.067	0.040										
2. Standard deviation	0.026	0.021	−.20***									
3. Trend standard deviation	0.027	0.019	−.21***	.94***								
4. RLPM(previous year target)	0.019	0.017	−.18**	.81***	.78***							
5. RLPM(industry target)	0.021	0.026	−.77***	.64***	.61***	.58***						
6. RLPM(fixed target)												
7. RLPM(zero target)	0.005	0.015	−.51***	.71***	.69***	.64***	.85***					
8. Industry return	0.065	0.007	.16**	−.04	−.03	−.06	−.06		−.06			
9. Industry standard deviation	0.026	0.004	−.01	.23***	.23***	.20***	.18**		.21***	−.08		
10. Industry downside risk	0.020	0.005	−.03	.21***	.21***	.21***	.21***		.20***	−.22***	.88***	
11. Slack	0.000	2.134	−.15**	−.06	−.04	−.08	.06		.02	−.07	−.01	.00
Period 2: 1977–81												
1. Return	0.075	0.038										
2. Standard deviation	0.026	0.022	−.23***									
3. Trend standard deviation	0.028	0.019	−.17***	.87***								
4. RLPM(previous year target)	0.022	0.020	−.27***	.83***	.74***							
5. RLPM(industry target)	0.023	0.026	−.78***	.67***	.58***	.66***						
6. RLPM(fixed target)	0.019	0.024	−.74***	.71***	.61***	.68***	.98***					
7. RLPM(zero target)	0.004	0.013	−.47***	.75***	.70***	.67***	.78***	.83***				
8. Industry return	0.073	0.008	.21***	−.08	−.05	−.02	−.03	−.09†	−.16**			
9. Industry standard deviation	0.026	0.004	−.07	.21***	.19***	.19***	.11*	.13*	.17***	−.31***		
10. Industry downside risk	0.023	0.003	−.06	.20***	.17***	.19***	.11*	.12*	.17***	−.24***	.95***	
11. Slack	0.000	2.165	−.01	−.06	−.01	−.06	−.05	.07	−.06	.00	.09†	.09†

TABLE 1 (continued)

Variables	Mean	s.d.	1	2	3	4	5	6	7	8	9	10
Period 3: 1982–86												
1. Return	0.045	0.056										
2. Standard deviation	0.046	0.047	−.55***									
3. Trend standard deviation	0.044	0.041	−.58***	.96***								
4. RLPM(previous year target)	0.042	0.042	−.64***	.92***	.91***							
5. RLPM(industry target)	0.041	0.055	−.85***	.87***	.87***	.87***						
6. RLPM(fixed target)	0.054	0.061	−.89***	.84***	.85***	.87***	.98***					
7. RLPM(zero target)	0.023	0.048	−.77***	.90***	.89***	.90***	.97***	.95***				
8. Industry return	0.044	0.016	.29***	−.09†	−.13**	−.19***	−.15**	−.23***	−.19***			
9. Industry standard deviation	0.045	0.011	−.11**	.25***	.25***	.25***	.23***	.25***	.24***	−.38***		
10. Industry downside risk	0.040	0.013	−.18***	.23***	.24***	.26***	.25***	.28***	.26***	−.61***	.92***	
11. Slack	0.000	2.152	−.14**	.01	−.00	.06	.11*	.08†	.09†	.04	−.16**	−.15**
Period 4: 1987–91												
1. Return	0.035	0.055										
2. Standard deviation	0.051	0.044	−.56***									
3. Trend standard deviation	0.042	0.036	−.52***	.92***								
4. RLPM(previous year target)	0.041	0.044	−.57***	.91***	.87***							
5. RLPM(industry target)	0.042	0.052	−.85***	.86***	.79***	.83***						
6. RLPM(fixed target)	0.045	0.053	−.86***	.84***	.77***	.81***	.98***					
7. RLPM(zero target)	0.028	0.046	−.80***	.88***	.81***	.84***	.98***	.97***				
8. Industry return	0.034	0.011	.21***	−.16***	−.18***	−.16***	−.12***	−.15**	−.20***			
9. Industry standard deviation	0.049	0.010	−.16***	.21***	.25***	.21***	.15**	.11*	.21***	−.78***		
10. Industry downside risk	0.041	0.009	−.16***	.21***	.24***	.21***	.16***	.14***	.21***	−.80***	.97***	
11. Slack	0.000	2.116	−.09†	.01	.03	.06	.07	.05	.06	−.03	.07	.06

[a] Sample sizes are as follows: period 1, 295; period 2, 385; period 3, 406; period 4, 445.

† $p < .10$

* $p < .05$

** $p < .01$

*** $p < .001$

TABLE 2
Results of Regression Analyses for Return[a]

Variables	1977–81 Parameter Estimate	1977–81 F	1982–86 Parameter Estimate	1982–86 F	1987–91 Parameter Estimate	1987–91 F
Return$_t$ as a function of downside risk$_{t-1}$						
Intercept	−.021		−.046***		−.023*	
	(.014)		(.010)		(.009)	
Return$_{t-1}$	.483***		.702***		.672***	
	(.063)		(.076)		(.078)	
Downside risk$_{t-1}$	.193	9.407***	.193	3.548*	.314	7.621***
	(.088)		(.117)		(.085)	
Slack$_{t-1}$	.001	7.141***	−.001	2.949†	−.000	2.441†
	(.001)		(.001)		(.001)	
Downside risk$_{t-1}$ × slack$_{t-1}$	.062**		.050†		.039*	
	(.021)		(.026)		(.018)	
Industry return$_t$	.831***		.875***		.547**	
	(.198)		(.122)		(.194)	
R^2	.266		.382		.271	
Regression F	25.310***		45.029***		30.529***	
N	355		370		417	

TABLE 2 (continued)

Variables	1977–81 Parameter Estimate	1977–81 F	1982–86 Parameter Estimate	1982–86 F	1987–91 Parameter Estimate	1987–91 F
Return$_t$ as a function of standard deviation $_{t-1}$						
Intercept	−.021		−.032***		−.011	
	(.014)		(.008)		(.008)	
Return$_{t-1}$	.395***		.617***		.505***	
	(.040)		(.050)		(.047)	
Standard deviation$_{t-1}$	.117	5.593**	.075	0.667	.165	3.735*
	(.059)		(.094)		(.065)	
Slack$_{t-1}$	.002	7.004***	−.001	1.536	−.001	1.383
	(.001)		(.001)		(.001)	
Standard deviation$_{t-1}$ × slack$_{t-1}$	.050**		.024		.026	
	(.019)		(.028)		(.018)	
Industry return$_t$	.917***		.777***		.558**	
	(.195)		(.127)		(.192)	
R^2	.275		.365		.284	
Regression F	26.502***		42.130***		31.949***	
N	355		373		409	

[a] Standard errors are in parentheses.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

TABLE 3
Results of Regression Analyses for Risk[a]

Variables	1977–81 Parameter Estimate	1977–81 F	1982–86 Parameter Estimate	1982–86 F	1987–91 Parameter Estimate	1987–91 F
Downside $risk_t$ as a function of $return_{t-1}$						
Intercept	.021*		.029***		.027**	
	(.009)		(.008)		(.010)	
Downside $risk_{t-1}$	.144*		.220*		.090	
	(.059)		(.102)		(.069)	
$Return_{t-1}$	−.125	5.291**	−.250	8.537***	−.242	8.068***
	(.038)		(.064)		(.065)	
$Slack_{t-1}$	−.001	3.919*	.001	1.499	−.000	0.828
	(.000)		(.001)		(.001)	
$Return_{t-1}$ × $slack_{t-1}$	−.003		−.012		.014	
	(.007)		(.009)		(.011)	
Industry downside $risk_t$	.162		.411**		.355†	
	(.350)		(.126)		(.207)	
R^2	.173		.198		.194	
Regression F	14.655***		18.248***		19.390***	
N	357		375		409	

TABLE 3 (continued)

Variables	1977–81 Parameter Estimate	1977–81 F	1982–86 Parameter Estimate	1982–86 F	1987–91 Parameter Estimate	1987–91 F
Standard deviation$_t$ as a function of return$_{t-1}$						
Intercept	.013*		.016*		.016†	
	(.005)		(.007)		(.009)	
Standard deviation$_{t-1}$	.108**		.552***		.228***	
	(.039)		(.067)		(.048)	
Return$_{t-1}$	−.056	4.074*	−.082	2.980†	−.090	2.865†
	(.021)		(.036)		(.038)	
Slack$_{t-1}$	−.000	0.240	−.000	0.767	−.001	0.579
	(.000)		(.001)		(.001)	
Return$_{t-1}$ × slack$_{t-1}$	.003		−.009		−.001	
	(.005)		(.008)		(.010)	
Industry standard deviation$_t$	.404*		.325*		.466**	
	(.185)		(.135)		(.169)	
R^2	.080		.205		.158	
Regression F	6.019***		18.865***		15.359***	
N	352		372		414	

[a] Standard errors are in parentheses.
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

sis that the coefficients of the direct effect and the corresponding interaction are jointly zero. The second column of each period's regression results reports F-statistics for terms included in interactions and their significance levels.

The significant correlations among the independent variables evident in Table 1 motivated assessment of potential collinearity problems. Examinations of both the variance inflation factors and conditioning index statistics provided diagnostics well below the suggested guidelines, indicating collinearity did not present serious problems for model estimation.[13]

Hypothesis 1 states that downside risk should have a positive relation with subsequent financial performance. The F-statistics for downside risk are significant in each period. Furthermore, the signs of both the direct and moderated effects of downside risk are positive, supporting Hypothesis 1. A firm that takes downside risks tends to improve its performance in the subsequent period. Contradicting the negative risk-return relations supported by some previous research using variability measures of risk, we found that downside risk is rewarded with higher subsequent performance.

Hypothesis 3 states that the downside risk-by-slack interaction term would be negatively related to subsequent performance. The significant, positive coefficients on the interactions between downside risk and slack contradict this hypothesis. Rather than making firms sluggish in responding to downside risk, slack facilitates organizational responses, enhancing subsequent performance. Low-slack firms may be constrained in their ability to implement successful searches for new organizational strategies.

The F-statistics indicate that slack influenced return in the first period as expected but had a weaker ($p < .10$) effect in the later periods. The relative magnitudes of slack's moderating and direct effects indicate its primary role is moderating the relation of downside risk to return rather than directly affecting return.

The control variables, lagged return and contemporaneous industry return, have the expected significant, positive relations with return.

The second section of Table 2 provides mixed evidence regarding the relation between risk, as measured by returns standard deviation, and returns. Although the first and third periods reveal a significant positive relation, the standard deviation F-statistic was not significant in the second period. The relative weakness of the relation between standard deviation and returns

[13] One approach to assessing collinearity is the calculation of variance inflation factors (VIFs). A VIF greater than 10 is often interpreted as an indication of collinearity problems (Neter, Wasserman, & Kutner, 1985: 392). However, if several near dependencies exist among explanatory variables, collinearity assessments based on large bivariate correlations or VIF factors may not provide adequate grounds for assessing collinearity. In these instances, conditioning indexes provide a supplemental collinearity diagnostic. Belsley and colleagues (1980) suggested that conditioning indexes in the neighborhood of 15 to 20 tend to result from an underlying near dependency and that indexes in excess of 100 cause substantial variance inflation and potential large distortions in regression coefficients. For the 12 regressions reported in Tables 2 and 3, the maximum VIF was 4.03. The maximum conditioning index was 3.81.

indicates downside risk is a more consistent predictor of subsequent financial performance than returns standard deviation. Whereas standard deviation identifies risk associated with the volatility of past returns, it fails to discriminate between upside and downside performance volatility. The results provide initial evidence that discrimination between downside and upside volatility is relevant to explaining subsequent performance.

The slack-by-standard deviation interaction was significant only in the 1977–81 period. This interaction was not significant in the final two periods for the standard deviation model. Unlike the results using the downside risk measure, the standard deviation results provide little empirical support for the behavioral proposition that slack moderates the relations between risk and return.

As in the downside risk equation, the two control variables, lagged return and contemporaneous industry return, are significant and have the expected positive signs. Moreover, the ability of the standard deviation model to explain return is largely due to the presence of these two control variables.

The results shown in Table 3 shed light on Hypotheses 2, 4, and 5. Hypothesis 2 states that financial performance should have a negative relation with subsequent downside risk. As the behavioral theory of the firm suggests, organizations performing well avoid the cost and uncertainty associated with searching for alternative strategies. The downside risk model provides strong support for this hypothesis in all three periods.

Hypotheses 4 and 5 proposed slack acts as a buffer allowing firms to reduce subsequent downside risk. Hypothesis 4 states that the combined effect of slack (both direct and moderating) is to reduce downside risk. The *F*-statistic for the combined effect of slack is significant in just the first of the three periods, where the slack effect has the expected negative sign. Hypothesis 4 was not supported in the other two periods. Hypothesis 5 states that slack enhances the negative effect of financial performance on downside risk. The insignificant coefficients for the interaction terms do not support this hypothesis.

Although contemporaneous industry and lagged own-firm downside risk had the expected positive signs, they were not significant in all periods. Contemporaneous industry risk has the expected significant, positive sign in the first two periods studied. Lagged downside risk was significant in the last two periods. These results support inclusion of both controls; however, the relative influences of lagged downside risk and contemporaneous industry downside risk differ across periods.

The standard deviation results shown in the second section of Table 3 present some interesting contrasts to the downside risk results. Return had a significant, negative effect at the .05 level only in 1977–81. The sign was also negative in the other two periods but significant at only the .10 level. Slack showed no significant effects in any of the periods in the standard deviation model. None of the return-by-slack interactions were significant.

The coefficient on the lagged standard deviation of returns was positive and significant in all three periods. This result indicates more consistent correlation across time for the standard deviation measure than for the downside measure. Contemporaneous industry risk, as measured by the average standard deviation across all other firms in an industry, also showed a significant, positive relation.

As with the results in the second section of Table 2, the standard deviation risk equations show consistent relations with the control variables but only weak relations with the substantive variables based on behavioral theory. This finding held both before and after elimination of outliers. Given the weak risk-return relations in the models incorporating the standard deviation measure, it is difficult to make generalizations regarding the behavioral theory relations summarized in the five hypotheses.

The positive relation of risk and subsequent return using the downside measure and the negative influence of return on risk are, however, consistent and significant across all periods. This pattern suggests an interesting sequence in agreement with the behavioral theory of the firm: taking downside risk results in higher performance, but higher performance leads to less risk taking. Thus, using downside risk, we have a self-correcting cycle that contrasts with the downward spiral hypothesized in previous research on Bowman's (1980) risk-return paradox. Research applying prospect theory has contended that poorly performing firms take bad risks and that worse performance results (Bowman, 1982; Fiegenbaum, 1990; Fiegenbaum & Thomas, 1988; Jegers, 1991). Such a downward spiral ultimately would result in the demise of a firm. Using downside risk, we did not find evidence that poor performers take "bad risks." On the contrary, we found that poor performers often take "good risks" and that the existence of slack resources may allow them to seek out even "better risks."

Tables 2 and 3 indicate that within each of the four sets of regression estimates, the signs of the significant coefficients were consistent across the three time periods. We conducted formal tests for stability of the regression parameters over the three periods using Chow tests (Kennedy, 1985: 87–88). These tests indicated that the coefficients for the four models were unstable over the three time periods. All F-statistics for the Chow tests were significant at the .01 level. Hence, although the signs of the significant model parameters were consistent within each of the four sets of regression analyses, the magnitude of the effects differed across periods.

DISCUSSION

Strategy researchers have given much attention in recent years to studying risk-return relations in corporate data. This study, however, is the first to elaborate a theoretical perspective on organizational downside risk grounded in behavioral theory. Research on managers' concepts of risk indicates managers conceptualize risk in terms of failure to achieve targets. This finding provides a compelling argument for shifting the focus of empirical strategy research from performance variability to downside risk.

Our tests of the behavioral model challenge a major contention of previous research based on prospect theory, namely, the idea that poor performers take on high variance strategies with low expected values. Such risk-seeking behavior can be shown to increase the probability of firm survival despite reducing expected returns (Aron & Lazear, 1990; Singh, 1986). Using a fundamentally different concept of risk—downside risk—results in a very different pattern of risk-return relations. The evidence from this study indicates downside risk leads to organizational strategic changes that improve, rather than diminish, subsequent firm performance. Our results indicate that this relation is strengthened by the presence of slack resources. This finding contradicts the notion of a downward spiral in which poor performance increases risk taking, which further erodes subsequent performance.[14]

Nevertheless, firms with exceptionally high performance avoid downside risk in the subsequent period. Such downside risk avoidance does, in turn, drive down subsequent performance. Combining the results from the return and downside risk equations indicates a self-correcting, rather than downward spiraling, cycle involving performance and downside risk.

The regression results also shed light on the role of slack resources in determining organizational performance and downside risk. The empirical evidence indicates the primary role of slack is to facilitate organizational responses to downside risk, thus improving subsequent performance. By contrast, slack does not appear to play a role in determining organizational risk taking. These findings contradict the contention that slack acts as a buffer reducing organizational performance and risk taking.

This initial exploration of accounting-based downside risk measures indicated some attractive properties. First, RLPM downside risk measures proved quite robust to alternative assumptions about firm target levels (τ_{jt}) and order specification (i.e., values of the RLPM parameter alpha, an indicator of risk preference). Four different assumptions about the time path of firm performance targets and both first- and second-order moments resulted in eight alternative RLPM measures. Despite the specification differences, the eight measures were highly positively correlated in each of the time periods examined. Whereas the functional form of the RLPM (Equation 3) indicates

[14] Since the standard deviation of returns and the standard deviation of stock analysts' earnings forecasts are significantly correlated (Miller & Bromiley, 1990), we would expect the accounting returns standard deviation results to be similar to those reported by Bromiley (1991b) using the forecast measure. Whereas the standard deviation results reported here indicate weak positive relations between risk and subsequent return, Bromiley found a negative effect of risk on return. Both studies find performance reduces subsequent risk. Differences in model specification, lag structure (one-year versus five-year lags), and estimation approach (cross-sectional versus pooled cross-sectional and time series data) may account for the divergent results. Bromiley's single-year lagged model produced results similar to the negative cross-sectional correlations between returns and standard deviation reported in Table 1.

Despite contradictory findings, both studies raise questions about whether substantive feedback loops exist in estimated risk-return relations using variability measures in behavioral models. As reported in Tables 2 and 3, the risk-return relations were not significant (at the .05 level) in three of the six standard deviation regressions. In assessing the substantive impact of risk-return feedbacks in the model, Bromiley concluded, "Thus, the relations of performance and risk do create a negative feedback loop, but it is of such small magnitude that other factors overwhelm it" (1991b: 54).

an entire class of measures, the results in Table 1 indicate little difference in the empirical properties of RLPM measures falling within the guidelines offered by existing theory for specifying target levels and the parameter alpha (Appendix A). The one exception to this general conclusion was the RLPM measure specifying the target level as the one-year lagged own-firm performance, which tended to be more highly correlated with the standard deviation measures than with the other downside measures.

Tests of the behavioral model indicated more consistently significant risk-return relations when downside risk was used than when the standard deviation of return was used. This result was evident before we eliminated outlier observations as well as after. With returns standard deviation as the risk proxy, the relations between risk and return were often not significant (at the .05 level). In contrast, downside risk exhibited a consistently significant, positive relation with subsequent performance (Table 2). Performance had a consistent, and highly significant, negative relation with subsequent downside risk (Table 3). Although the positive relation between downside risk and subsequent performance can be partially explained as regression toward the mean (Kenny, 1979: 21), the negative relation between performance and subsequent downside risk contradicts that explanation.

These observations should motivate broader interest in downside risk among empirical strategy researchers. Whereas strategy theorists and managers have indicated a propensity to think about risk in terms of downside outcomes, empirical strategy research has not previously incorporated downside measures based on the concept of lower partial moments. The initial results from this study encourage wider theoretical and empirical treatments of downside risk.

As a theory of organizational risk-return relations, the behavioral theory of the firm suffers from two important shortcomings. First, since behavioral theory seeks to explain risk as a managerial choice, it neglects unchosen risks. A more complete perspective on organizational risk would acknowledge that risks can occur that are environmentally determined and result in deviations from managers' risk preferences. This acknowledgment suggests the need for further research on downside risk incorporating organization-environment interactions. Such a perspective acknowledges that managers and environments jointly determine risk-return relations. Second, strategic actions mediate the relations between downside risk and performance from one period to the next. The behavioral theory of the firm, however, does not illuminate the content of these strategic actions. Explicit attention to the mediating strategic responses is essential to advancing research on organizational risk.

These two observations suggest downside risk measures have applications beyond the parsimonious behavioral model tested here. Most important, strategy and organization theorists need to break away from focusing on the indirect relation between risk and return to the exclusion of their managerial and environmental determinants. Although research on risk-return relations has revealed the measurement properties of alternative risk measures, it has done little to inform managerial decisions. The relations between firm strategy, industry structure, risk, and performance raised in previous research (e.g., Aaker & Jacobson, 1987; Amit & Wernerfelt, 1990; Cool, Dierickx, & Jemison, 1989; Oviatt & Bauerschmidt, 1991; Woo, 1987) could be reanalyzed from a downside risk perspective.

Diversification and investments in research and development affect organizational risk (e.g., Hoskisson & Johnson, 1992). Recent theoretical developments in financial economics and strategy conceptualize such strategic moves as options (cf. Dixit & Pindyck, 1994; Sanchez, 1993). Like financial options, these investments provide the opportunity to take advantage of upside gains but avoid downside outcomes. Option theory offers a basis for explaining strategic investments under uncertainty when decision makers have an aversion to downside outcomes and, as such, may provide a fruitful direction for theory building.

Agency theory presents another domain for extending research on organizational downside risk. This article focused on the managerial perspective and emphasized firm-specific downside risk measures incorporating accounting returns, but shareholders may be more interested in the downside stock returns variability of a diversified portfolio (cf. Harlow, 1991). Hence, we might postulate that steps taken to address agency problems, such as changes in governance structures, monitoring, and management compensation systems, can result in managerial attention to maximizing shareholder returns rather than minimizing downside risk. For example, compensation based on employee stock ownership plans results in managers being exposed to both downside and upside stock price movements. By contrast, compensation through stock options provides the potential for unlimited gains while limiting downside risk. Hence, organizations using employee stock ownership plans may exhibit less downside risk than organizations providing stock options. Future research may shed light on the moderating effects of agency theory variables on managerial decisions affecting downside risk and return.

CONCLUSION

In this study, we questioned the conceptual validity of the variability measures of risk commonly used in strategy research and proposed downside risk as an alternative. Hypotheses based on the behavioral theory of the firm motivated a parsimonious model of downside risk-return relations. The empirical results contrasted models using root lower partial moments and the conventional standard deviation of returns as risk proxies. Risk measured as root lower partial moments demonstrated more consistent significant relations with return than did returns standard deviation.

Consistent with the behavioral theory of the firm, the results support a positive effect of downside risk on subsequent performance and a negative effect of performance on downside risk. This self-correcting cycle is an interesting contrast to the downward spiral proposed by previous risk-return research based on prospect theory. Rather than acting as a buffer, slack enhances the subsequent organizational performance of firms experiencing downside risk. Future research should shed light on the specific strategic actions that mediate risk-return relations.

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APPENDIX A

Stone (1973), Fishburn (1977), and Laughhunn, Payne, and Crum (1980) specified downside risk measures at the individual level as lower partial moments. We adapt their measures to organizations.

Consider the returns distribution for a given firm j. For a sample of n observations from this returns distribution, we can express downside risk in terms of the return observations (r_j), a target return, denoted τ, and the relative importance of returns below the target, measured by a parameter α. Downside risk for firm j is a function of below-target returns specified as a lower partial moment:

$$\mathrm{LPM}_\alpha(\tau;j) = (1/n)\sum_{r_j<\tau}^{\tau} (\tau - r_j)^\alpha, \quad \alpha \geq 0. \tag{A1}$$

The term lower partial moment (LPM) refers to the inclusion of only the left-hand (downside) tail of the returns distribution in the calculation. The value of the parameter α reflects the importance of small deviations below target relative to large deviations. If small deviations below target are unimportant relative to large deviations, the appropriate value for α would be greater than one. As the value of alpha approaches zero, small and large deviations below target are weighted more equally in assessing downside risk. Although α could take on any nonnegative value, 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.

Stone (1973) offered a variant of the LPM risk measure, the root lower partial moment ($\mathrm{RLPM}_\alpha[\tau;j]$), defined as the α-order root of $\mathrm{LPM}_\alpha(\tau;j)$:

$$\mathrm{RLPM}_\alpha(\tau;j) = \mathrm{LPM}_\alpha(\tau;j)^{1/\alpha} = [(1/n)\sum_{r_j<\tau}^{\tau} (\tau - r_j)^\alpha]^{1/\alpha}, \quad \alpha > 0. \tag{A2}$$

For $\alpha = 2$, this measure is termed "target semideviation" (Harlow, 1991). As Stone pointed out, $\mathrm{RLPM}_\alpha(\tau;j)$ is linearly homogeneous (that is, homogeneous of degree one). Linear homogeneity indicates proportional changes in the aspiration level and returns change $\mathrm{RLPM}_\alpha(\tau;j)$ by an equivalent proportion. By contrast, LPM measures are not homogeneous of degree one when $\alpha \neq 1$. This study specified downside risk measures as root lower partial moments because of their desirable property of being homogeneous of degree one.

Only under very restrictive conditions will estimated risk-return relations using downside measures be proportional to risk-return relations using central moments. Consider, for example, the common standard deviation measure of risk (the second-order root central moment). Estimated risk-return relations using returns standard deviation and the second-order RLPM measures are 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 conditions, returns standard deviation is equal to two times the second-order RLPM measure. If, however, some target level other than the mean return is chosen or the return distribution is skewed, or both, the downside and standard deviation measures will yield different risk-return relations. This discrepancy between the standard deviation and second-order RLPM measures motivates the comparisons between these two measures presented in the empirical portion of this study.

Computing the RLPM measure used in this study required choosing an appropriate aspiration target level. The LPM measures specified by Fishburn (1977) and Stone (1973) assumed a fixed target level for determining downside deviations. This assumption is inconsistent with previous research on the evolution of organizational aspirations. Cyert and March (1963), Levinthal and March (1981), and Herriott, Levinthal, and March (1985) portrayed organizational aspirations as evolving over time. Subsequent studies by March (1988b) and March and Shapira (1987) indicated organizational aspirations change with experience. In order to accommodate adaptive aspirations, we specified downside risk as a function of a time-specific target level (τ_{jt}). Doing so gave rise to the RLPM specification indicated as Equation 3 in the text.

APPENDIX B

Apart from the lower partial moment measures, two variability measures of risk were also computed. These were the common standard deviation of returns and a measure of the variability of a firm's returns around its time trend, each computed using five years of firm returns (ROA) data. Fisher and Hall (1969) and Oviatt and Bauerschmidt (1991) presented the measure:

$$\text{Trend standard deviation} = [(1/n)\sum_{t=1}^{n}(r_{jt} - r'_{jt})^2]^{1/2}, \quad \text{(B1)}$$

where r_{jt} and r'_{jt} are the actual and the predicted return to firm j in year t, respectively. For our calculations, predicted returns, r'_{jt}, were estimated by the autoregressive time series model $r'_{jt} = b_{0j} + b_{1j}t + u_{jt}$, where t is the year, and u_{jt} assumes a first-order autocorrelation of errors, i.e., $u_{jt} = e_{jt} - a_1 u_{jt-1}$. Rather than using n as the divisor in Equation B1, we used $n - 2$, which results in an unbiased estimator of the variance of the error term, u_{jt} (Neter et al., 1985: 110).

Ruefli and Wiggins (1994) criticized the measure used by Oviatt and Bauerschmidt (1991) on the grounds that if the trend line in a firm's returns is relatively flat, the measure is effectively equivalent to the returns standard deviation. This potential for convergence between trend and familiar standard deviations is problematic if we accept Ruefli's (1990, 1991) concerns about the appropriateness of estimating risk-return relations using contemporaneous means and variances (or standard deviations) generated from firm returns data. It should be noted that this criticism is not directly applicable to this study since we estimated lagged rather than contemporaneous mean-standard deviation relations. Nevertheless, we believe this criticism has unnecessarily deterred researchers from using the standard deviation measure and, as such, warrants response.

Although it can be shown that the sample mean and sample variance are independent for a particular normal distribution (cf. DeGroot, 1975: 326–333), it does not follow that the sample means and sample variances are unrelated across different firms in cross-sectional research (Bromiley, 1991a). The treatment of heteroskedasticity in econometric research provides a basis for the validity of estimating mean-variance relations. One common form of heteroskedasticity, termed dependent variable heteroskedasticity, involves the assumption that the variance of the disturbance is proportional to the squared mean of the dependent variable (Kmenta, 1986: 287). That is, for the simple regression model $Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$, we specify $\varepsilon_i \sim N(0, \sigma_i^2)$, where $\sigma_i^2 = \sigma^2[E(Y_i)]^2$, or equivalently, $\sigma_i = \sigma[E(Y_i)]$. Thus, this form of heteroskedasticity assumes a simple linear relation between the standard deviation of the error term and the expected value of Y_i, with an unknown but estimable parameter σ. In other words, for any subset of observations with expected value $[E(Y_i)]$, the standard deviation of the error term is directly proportional to the expected value. Since σ_i (the standard deviation of ε_i) is, by definition, the standard deviation for the subset of dependent variable observations with expected value $[E(Y_i)]$, we see that this common form of heteroskedasticity implies a direct relation between mean and standard deviation across subsets of normally distributed data with different means. Hence, there is a precedent in econometric research for the estimation of standard deviation-mean relations as found in many strategy studies of risk-return relations.

Estimating mean-standard deviation relations in returns data across firms simply involves postulating a theoretical relation of the form $\sigma_j = \beta\mu_j + \nu_j$, where σ_j is the standard deviation of the returns for firm j, μ_j is the mean return, ν_j is the normally distributed error term with mean zero and constant variance, and β is the parameter to be estimated. A sample mean and standard deviation can be computed from multiple observations for each firm. For any firm j, the sample mean and standard deviation are unbiased estimators of μ_j and σ_j, respectively. Hence, ordinary-least-squares regression generates an unbiased estimate of β. We agree with Ruefli (1990) that in order to estimate the relations between sample mean returns and the standard deviations of returns the relation must be stable over the data collection period. As Bromiley (1991a) pointed out, this is a fundamental assumption necessary for model identification in general and is not unique to mean-variance relations.

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