Operating Characteristics and Operating Risk: Additional Empirical Evidence

Richard A. Lord*
Montclair State University

William Beranek
University of Georgia, Emeritus

This study provides additional evidence on the relationship between firm operating characteristics and operating risk, defined as the systematic risk of unlevered cash flows. The relevant operating characteristics are (1) operating margin, (2) average income tax rate, (3) firm size, and (4) covariance of output with market returns (or demand beta). Theory and previous empirical evidence suggest that operating risk is negatively related to operating margin, firm size, and the average income tax rate, but linked positively to demand beta. Data limitations imposed by the theory restrict our analysis to electric utility, airline, and automotive industries. A pooled sample for these industries confirms the first three hypotheses. The relationship between demand beta and operating risk is positive as expected, but not significant.

Introduction

Increasingly complex models have been developed to explain the relationship between operating risk, defined as the systematic risk of financially unlevered cash flows, and certain operating parameters. Four elements are identified as influencing operating risk: (1) unit operating margin, (2) the complement of the firm's average tax rate, (3) the covariability of unit output with market returns, and (4) firm size. Testing hypotheses based on these influences has been troublesome because available data almost always come from multi-product firms. We test these hypotheses for a sample of single-product firms.

Studies of operating risk began with Rubinstein (1973) and were extended by Brenner and Smidt (1978), Chance (1982), Conine (1982), Callahan (1985), Mohr (1985), Callahan and Mohr (1989), and Beranek (1990). These studies all identify

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operating margin as a central component of operating risk. While there has been some controversy concerning the nature of this relationship, theory suggests it should be negative. Establishing this empirical relationship is a focus of this study. The second variable, the complement of the firm's average income tax rate, is specified to be positively related to operating risk. Third, the covariability of unit output with returns on the market portfolio, or demand beta, also is predicted to be positively related to operating risk. Finally, theory provides no insight into the relationship between firm size, measured as the market value of equity, and operating risk. Hence, this factor serves as a control variable.[1]

To test these hypotheses, data are collected for the electric utility, automotive, and airline industries, which can be construed as either single product firms or, as shown below, their equivalent. Using the well-established panel-data approach, these data are sorted into four sets, one for each industry, and one composed of an overall, pooled sample.

Consistent with theory and our hypotheses, we find that:

- Operating margin is negatively correlated with operating risk, which confirms predictions by Subrahmanyan and Thomadakis (1980) and Narayanaswamy (1988);
- The complement of the average income tax rate is positively related to operating risk;
- Firm size is negatively correlated with operating risk; and
- Demand beta is positively, but weakly, related to operating risk.

Literature Review
Theoretical Model

The hypotheses of this study follow from theory developed by Callahan (1985) and Callahan and Mohr (1989) that is based on Rubinstein (1973). In these studies operating risk is presented as the product of four factors:

(1) Unit operating margin (unit price minus unit variable cost);
(2) The value of equity;
(3) The complement of the firm's average income tax rate; and
(4) The covariance of firm unit output with returns on the market portfolio or demand beta.

Our hypotheses are derived from a single-period model of an unlevered firm that produces a single product with cash flows to stockholders, $\tilde{x}_u$, defined as:

$\tilde{x}_u = \{[(p - v)\tilde{Q} - F](1 - \tau)$,

[1] Banz (1981) and Reinganum (1981) provide empirical evidence that, for financially leveraged firms, size is negatively correlated with systematic risk.

where:

p = Unit price;

v = Unit variable cost;

$(p - v)$ = Unit operating margin;

$\tilde{Q}$ = The firm's random output. Output is assumed to adjust instantaneously to demand;

τ = The average income tax rate; and

F = Fixed costs (all values are in period t unless otherwise subscripted).

Rate of return on equity is $\tilde{r}_s = \tilde{x}_u / S_{u,t-1}$, where $S_{u,t-1}$ is the value of the firm's equity at the beginning of period t. Expected return becomes:

(1) $E(\tilde{r}_u) = \{[(p - v)E(\tilde{Q}) - F](1 - \tau)\} / S_{u,\,t-1}$,

where:

$E(\tilde{Q})$ = The expected number of units sold in period t.

Given these expressions, systematic risk of an unlevered firm becomes:

(2) $\beta_u = \{[(p - v)(1 - \tau)] / S_{u,t-1}]\}\ \mathrm{cov}(\tilde{Q}, \tilde{r}_m) / \sigma_m^2$,

where:

β_u = A measure of operating risk or operating beta;

$\tilde{r}_m$ = The random return on the market portfolio; and

σ_m^2 = The variance of such returns.

Equation (2) yields the cross-sectional regression model:

(3) $\log(\beta_u) = a_0 + a_1 \log(p - v) + a_2 \log(S_{u,t-1}) + a_3 \log(1 - \tau) + a_4 \log[\mathrm{cov}(\tilde{Q}, \tilde{r}_m) / \sigma_m^2] + \tilde{e}$,

where:

a_i $(i = 0, \ldots, 4)$ = Regression coefficients; and

$\tilde{e}$ = An error term.

The basic hypotheses concern the signs of these four coefficients.

Hypotheses

Theory and historical empirical evidence suggest signs for these parameters. The sign of a_1 is controversial. Lev (1974) and Brenner and Smidt (1978), suggest a positive relationship between unit operating margin and systematic risk. Subrahmanyan and Thomadakis (1980) and Narayanaswamy (1988), however, argue that these studies fail to account for the interaction between unit operating margin and firm value. Following Narayanaswamy, we account for this interrelationship, writing the value of equity as:

$$S_{u,t-1} = [\{[(p - v)E(\tilde{Q}) - F](1 - \tau)\} - \lambda(p - v)(1 - \tau)\mathrm{cov}(\tilde{Q}, \tilde{r}_m)] / (1 + r_f),$$

where:

r_f = The risk-free rate of return; and

λ = The market price per unit of risk.

Substituting this expression for $S_{u,t-1}$ into equation (2) results in:

(4) $\beta_u = K_1 / [K_2 - F/(p - v)]$,

where:

$K_1 = \mathrm{cov}(\tilde{Q}, \tilde{r}_m)(1 + r_f) / \sigma_m^2$; and

$K_2 = E(\tilde{Q}) - \lambda \operatorname{cov}(\tilde{Q}, \tilde{r}_m)$.

The derivative of β_u with respect to operating margin is:

$$\partial \beta_u / \partial (p - v) = -[(K_1 F)/(p - v)^2] / \{K_2 - [F/(p - v)]\}^2.$$

For $K_1 > 0$, and $F > 0$, $\partial \beta_u / \partial (p - v)$ is negative regardless of the sign of K_2. If $K_1 >$ 0 is the predominant empirical condition, we predict that a_1 will be negative.

Theory yields no insight into the relationship between firm size and operating risk or the sign of a_2. For a pooled sample of both levered and unlevered firms, however, Banz (1981) and Reinganum (1981) find evidence of a negative relationship between size and systematic risk. Knowing no a priori reason why this relationship should not hold for purely unlevered firms, we test the hypothesis that a_2 is negative.

The parameter a_3 is associated with the income tax rate. While the expected after-tax cash flow, $\tilde{x}_u$, declines with the tax rate, it can be shown that the variability of cash flows decreases as well. Assume $\tilde{Z}$ is taxable income and τ is the tax rate ($0 \leq \tau \leq 1$). After-tax earnings of $\tilde{Y} = \tilde{Z}(1 - \tau)$ imply $\operatorname{Var}(\tilde{Y}) \leq \operatorname{Var}(\tilde{Z})$, when $\tau \geq 0$. This suggests that the sign of the parameter a_3 should be positive. Callahan and Mohr (1989), following Hamada (1972, p. 161), find a similar result for leveraged firms where the "... tax subsidy to debt" reduces systematic risk. The result developed here, however, holds whether the firm is debt financed or not.

Finally, the sign of the parameter associated with demand beta, a_4, is dependent on the derivative $\partial \beta_u / \partial [\operatorname{cov}(\tilde{Q}, \tilde{r}_m)/\sigma_m^2]$ which, in turn, depends on the sign of $[1 + (p - v)(1 - \tau) \operatorname{cov}(\tilde{Q}, \tilde{r}_m)/\sigma_m^2(1 + r_f)]$. This is positive when $(p - v)$, $(1 - \tau)$, and $\operatorname{cov}(\tilde{Q}, \tilde{r}_m)/\sigma_m^2$ are all positive, which we believe is the likely prevailing empirical condition. Hence a_4 is predicted to be positive.

Data and Methodology

Data Sources and Restrictions

Reported output is our proxy for demand. Such data for single-product firms (or firms that produce multiple products in fixed proportions) are rare, but are essential for estimating both operating margin and demand beta.[2] Data for the electrical utility[3] and automotive industries are available in *Moody's Industrial Guide* and *Moody's Public Utilities Manual* from 1970 until 1988 (19 years per firm). To help satisfy the single-product requirement, the electrical utility sample is limited to firms for which 95 percent of revenue is due to electrical sales (SIC 4911). While automotive firms do not produce a single product, the product mix for these firms is fairly constant over the time horizon for our sample, thus yielding a combination of trucks and passenger vehicles of reasonably fixed proportions that becomes a unit of output for our purposes. For

[2] In previous tests of similar hypotheses, demand beta has been approximated by the covariance of total dollar sales (rather than unit output) with market returns, and total margin has been used as a proxy for unit operating margin.

[3] Callahan(1985) also estimates operating margin and demand beta for electric utilities.

airlines, the product is revenue-passenger-ton-miles which is available monthly from the Civil Aeronautics Board from 1973 to August 1984 and from the Department of Transportation up to 1988 (16 years per firm). This procedure yields 25 electric utilities, seven airlines, and three automotive firms, a total of 35 firms. Only these industries had data that satisfied our restrictions.

Variables and Proxies

Quantities needed to test our hypotheses fall into two broad categories. The first consists of four variables observed at a single point in time: (1) the market value of the unlevered firm's equity; (2) product unit price; (3) unit variable cost of output; and (4) the firm's implied average income tax rate. The second group contains quantities that are estimated from time series observations: (1) operating betas; (2) the proxies for covariance of demand with market return; and (3) variances of market returns.

Unit price and unit variable costs are estimated by taking the ratio of dollar sales to unit sales and the cost of goods sold to unit output, quantities readily obtainable from the COMPUSTAT industrial file.[4] This produces a slight upward bias in unit variable cost because the cost of goods sold generally includes some fixed costs, a bias that is attenuated by the fact that it is systematic. Average income tax rates for each firm are proxied as the ratio of income taxes to estimated taxable income.

The variable $S_{u,t-1}$ represents the equity value of the financially unlevered firm. Current market value of equity, given the firm's current leverage, is obtained from the CRSP tapes. To estimate the unlevered value of equity, the after-tax value of the firm's debt is added to the market value of levered equity (Hamada, 1969, 1972).

Because of data limitations, $\text{cov}(\tilde{Q}, \tilde{r}_m)$ for each firm is estimated indirectly. Covariance of output with the market for each utility and automotive firm is estimated for 13 seven-year moving periods, ending in the years 1976 through 1988. Observations for each of seven years are used to calculate the covariance of output with annual return on the CRSP value-weighted index for that period. These 13 covariance measures are then matched with the variables $(p-v)$, $S_{u,t-1}$ and $1-\tau$ for the last year in each seven-year moving period. For airlines, however, annual output data are not available before 1973, allowing estimates of only 11 covariance figures for each airline ending in 1978 through 1988.

A similar method is used to estimate operating beta and the variance of market returns. Firm annual returns and value-weighted market portfolio returns are obtained from the COMPUSTAT and CRSP tapes, respectively. Following Chance (1982) and Callahan and Mohr (1989), the adjustment suggested by Hamada (1969, 1972) is employed to financially unlever the betas. This approach consists of adding interest payments, less the tax shield, to returns to equity in the calculation of beta. Again,

[4] In studying electric utilities, Callahan (1985) employs a different proxy for operating margin, estimating the coefficient from regressing net operating income on unit output. The mean for her estimates is 20.282 ($/100KwH), similar to our sample mean of 16.767.

seven-year moving periods are used to calculate the covariability of unlevered stock returns with the market using market model betas, and to estimate the variance of market portfolio returns.[5]

Methodology

Our data, consisting of reasonably short time series for a large number of firms, suggest a panel data approach, where all time-series observations for the cross-section of firms are combined into a single set. The potential advantages of such an approach are summarized by Hsiao (1985, 1986, pp. 1-5). Pooling makes more observations available while tending to decrease collinearity between variables. Not only does this approach combine benefits of both time-series and cross-sectional data, it also helps control for dynamically changing elements, such as technological improvement, which can not normally be detected with cross-sectional data alone.[6] Also, the presence of cross-sectional observations reduces the possibility of omission of important firm-specific factors that might not be detected with time-series data alone.

This procedure provides sample sizes of 77 for the airlines, 39 for the automotive industry, and 325 for electric utilities. The fourth data set, the focus of our study, is formed by pooling the three industry samples into one sample containing 441 observations. Selected summary statistics for the variables in the aggregate sample as well as in each industry are presented in Table 1.

Logarithms of observations are employed to capture the multiplicative nature of the relationship between (p-v), $S_{u,t-1}$, $1-\tau$, and $\mathrm{cov}(\tilde{Q}, \tilde{r}_m)/\sigma_m^2$. Because negative values[7] create difficulties in taking logarithms, all observations are squared, a procedure that does not alter the qualitative nature of our hypotheses.

Parameter estimates are made for each of the panel-data sets using a fixed effects model as discussed in Hsiao (1986, pp. 29-32) and Balestra (1992). After time-series data for firms are pooled, dummy variables are introduced to identify the firm, an approach that tends to capture systematic differences between firms by decomposing the intercept term.

[5] Kothari, Shanken, and Sloan (1995) suggest that using annual returns to estimate beta results in parameters that behave more like those predicted in the original capital asset pricing model than estimates based on shorter time horizons.

[6] Time-series data for individual firms are so short that few, if any, changes in production functions are likely to occur.

[7] Observations of β_u, (p - v), and $\mathrm{cov}(\tilde{Q}, \tilde{r}_m)/\sigma_m^2$ can, of course, have negative values. A negative value for an individual annual tax rate can result from a firm using tax loss carryforwards and credits. Finally, the adjustment to produce an estimate of unlevered equity value makes it possible to produce a negative equity value in a year with a negative tax rate of absolute value greater than one.

Table 1—Summary of Sample Statistics

	Mean	Standard Deviation
Panel A: Aggregate Sample (n = 441)		
Operating Beta (β_u)	0.234	0.316
Operating Margin (p-v) ($/unit)	89.406	303.919
Unlevered Firm Equity Value ($S_{u,t-1}$) (M$)	4,646	8,431
Complement of Average Income Tax Rate ($1 - \tau$)	0.728	0.784
Demand Beta ($\mathrm{cov}(\tilde{Q}, \tilde{r}_m) / \sigma_m^2$)	-547,939	5,976,227
Panel B: Electric Utilities (n = 325)		
Operating Beta (β_u)	0.201	0.216
Operating Margin (p-v) ($/100 KwH)	16.767	6.412
Unlevered Firm Equity Value ($S_{u,t-1}$) (M$)	2,941	2,856
Complement of Average Income Tax Rate ($1 - \tau$)	0.674	0.117
Demand Beta ($\mathrm{cov}(\tilde{Q}, \tilde{r}_m) / \sigma_m^2$)	-616,290	5,138,980
Panel C: Automotive (n - 39)		
Operating Beta (β_u)	0.500	0.427
Operating Margin (p-v) ($/vehicle)	846.602	650.747
Unlevered Firm Equity Value ($S_{u,t-1}$) (M$)	23,140	18,223
Complement of Average Income Tax Rate ($1 - \tau$)	0.774	0.278
Demand Beta ($\mathrm{cov}(\tilde{Q}, \tilde{r}_m) / \sigma_m^2$)	-547,020	36,345
Panel D: Airlines (n = 77)		
Operating Beta (β_u)	0.238	0.496
Operating Margin (p-v) ($/RPTM)	12.486	8.355
Unlevered Firm Equity Value ($S_{u,t-1}$) (M$)	2,474	4,237
Complement of Average Income Tax Rate ($1 - \tau$)	0.932	1.844
Demand Beta ($\mathrm{cov}(\tilde{Q}, \tilde{r}_m) / \sigma_m^2$)	-259,909	9,650,846

Imposing these modifications on equation (3) leads to:

$$(5)\quad \log(\beta_u^2) = a_1 \log(p - v)^2 + a_2 \log(S_{u,t-1})^2 + a_3 \log(1 - \tau)^2 + a_4 \log[\mathrm{cov}(\tilde{Q}, \tilde{r}_m) \backslash / \sigma_m^2]^2 + \sum_{i=1}^{n} \delta_i D_i + \tilde{e},$$

where:

n = The number of firms included in each pooled cross-sectional sample;

D_i = Dummy variables coded 1 if the time-series observation is for the ith firm and 0 otherwise; and

δ_i = Regression parameters associated with the n dummy variables.

The parameters δ_i are interpreted as firm specific intercepts for the regression model.[8] To summarize the hypotheses, we expect a_1 and a_2 to be negative, and a_3 and a_4 to be positive.

[8] In the regression of the airline industry, none of the dummy variables are significant. For the electric utilities only one dummy variable is significant. Only in the automotive industry are the dummies significant. In the pooled sample, all dummy variables are statistically significant. This is not surprising, and it would suggest that to a great extent the dummy variables are functioning as a control for the industry in the pooled sample. Parameter estimates for the firm-specific dummy variables are available from the authors upon request.

Table 2—GLS Estimates of Equation (5) for Four Panel-Data Samples

$$\log(\beta_u^2) = a_1 \log(p-v)^2 + a_2 \log(S_{u,t-1})^2 + a_3 \log(1-\tau)^2 + a_4 \log[\mathrm{cov}(\tilde{Q}, \tilde{r}_m)/\sigma_m^2]^2 + \sum_{i=1}^{n} \delta_i D_i + \tilde{e}$$

β_u	=	Operating beta
$p - v$	=	Operating margin
$S_{u,t-1}$	=	Unlevered firm equity value
$1 - \tau$	=	Complement of average income tax rate
$(\mathrm{cov}(\tilde{Q}, \tilde{r}_m)/\sigma_m^2)$	=	Demand beta

Parameter	Regression Coefficients with Associated t-Values in Parentheses			
	Aggregate Sample	Electric Utilities	Automotive	Airlines
a_1	-0.2412 (-4.012)*	-2.5886 (-11.897)*	-0.0523 (-0.998)	-0.0269 (-0.233)
a_2	-1.2272 (-14.242)*	0.5109 (2.614)*	-1.2752 (-9.622)*	0.2024 (1.100)
a_3	0.4420 (3.005)*	-1.5161 (-4.589)*	0.0140 (0.069)	-0.0296 (-0.156)
a_4	0.0158 (-0.688)	0.0153 (0.764)	-0.2915 (-5.506)*	-0.0694 (-1.129)
Diagnostics				
Observations	441	325	39	77
R^2	0.3696	0.3202	0.3112	0.1156
F-Value	173.9592*	128.0943*	14.8194*	8.9010*

*Statistically significant from zero at the 99 percent level for a one-tailed test

A first-stage OLS regression of equation (5) is estimated for each industry sample. Because Goldfeld-Quandt tests revealed the presence of significant heteroskedasticity in all industries, each industry sample is sorted by the magnitude of the error terms and divided into two equal subsets. Second-stage OLS models then are estimated for each of the two subsamples. For each industry all observations in each subsample then are divided by the corresponding sum of squared errors and then recombined into one industry sample. Final parameter estimates for each industry are made from this generalized least squares (GLS) model. For the aggregate sample, the six transformed subsets (two from each industry) are combined into a single-data set to form the pooled 441-observation sample.

Empirical Results

GLS estimates of equation (5) are shown in Table 2. In the aggregate sample, it is striking to observe that parameters a_1, a_2, and a_3 all have their predicted signs and each coefficient is statistically significant. This confirms three of our hypotheses: operating margin and firm size are both negatively related to operating risk, and the complement of the average income tax rate is positively linked to this risk. In the largest industry sample, electric utilities, a_1 is also negative, while in the automotive sample the parameter a_2, associated with firm size, also has the anticipated negative sign.

Convincing evidence of a positive relationship between demand beta and operating risk is lacking in all samples.[9]

Conclusions

A model following Callahan (1985) is used to explain the operating risk of a financially unlevered firm in terms of a number of operating characteristics. Four hypotheses were posited: systematic risk of unlevered cash flows is

(1) Negatively related to unit operating margin;
(2) Negatively correlated to firm size;
(3) Positively related to the complement of the firm's average income tax rate; and
(4) Positively impacted by covariability of unit output with returns on a market portfolio or demand beta.

A panel-data approach employing generalized least squares is used to test these hypotheses for samples of single product firms from the electric utility, automotive, and airline industries.

The important aggregate sample confirms the first three of the above four hypotheses (while the anticipated positive relationship also is found between demand beta and operating risk, it is not significant). In this sample, as well as for utilities, operating beta is negatively related to unit operating margin, as anticipated by Narayanaswamy (1988). Operating risk is positively correlated with the complement of the firm's average income tax rate both in the aggregate sample and in the automotive data. Finally, for the aggregate sample, there is evidence that the negative relationship between firm size and systematic risk found by Banz (1981) and Reinganum (1981) without controlling for leverage, extends to operating risk and therefore holds even for strictly unlevered systematic risk.

References

1. Balestra, P., "Fixed Effect Models and Fixed Coefficient Models," in L. Matyas and P. Sevestre (eds.), *The Econometrics of Panel Data: Handbook of Theory and Applications* (Dordrecht: Kluwer Academic Publishers, 1992), pp. 30-69.

2. Banz, R.W., "The Relationship Between Return and Market Value of Common Stocks," *Journal of Financial Economics*, 9 (March 1981), pp. 3-18.

3. Beranek, W., "Total Shareholder Risk and Residual Risk: Their Properties," in S.G. Rhee and R.P. Chang (eds.), *Pacific Basin Capital Markets*, (Amsterdam: North Holland, Amsterdam, 1990), pp. 547-571.

4. Brenner, M., and S. Smidt, "Asset Characteristics and Systematic Risk," *Financial Management*, 7 (Winter 1978), pp. 33-39.

5. Callahan, C.M., "The Theoretical and Empirical Examinations of the Determinants of Systematic Risk," unpublished dissertation., (Michigan State University, Ann Arbor, 1985).

[9] This is doubtless due, in part, to the presence of a marked number of negative observations of demand beta ($\mathrm{cov}(\tilde{Q}, \tilde{r}_m) / \sigma_m^2$) in our sample. (See page 44.)

6. Callahan, C.M., and R.M. Mohr, "The Determinants of Systematic Risk," *Financial Review*, 24 (May 1989), pp. 157-181.

7. Chance, D.M., "Evidence on a Simplified Model of Systematic Risk," *Financial Management*, 11 (Autumn 1982), pp. 53-63.

8. Conine, T.E., "On the Theoretical Relationship Between Business Risk and Systematic Risk," *Journal of Business Finance and Accounting*, 9 (Spring 1982), pp. 199-205.

9. Hamada, R.S., "Portfolio Analysis, Market Equilibrium and Corporate Finance," *Journal of Finance*, 24 (March 1969), pp. 13-31.

10. Hamada, R.S., "The Effect of the Firm's Capital Structure on the Systematic Risk of Common Stocks," *Journal of Finance*, 27 (May 1972), pp. 435-452.

11. Hsiao, C., "Benefits and Limitations of Panel Data," *Econometric Reviews*, 4 (1985) pp. 121-174.

12. Hsiao, C., *Analysis of Panel Data*, Econometric Society Monograph No. 11 (Cambridge University Press, Cambridge, 1986).

13. Kothari, S.P., J. Shanken, and R.G. Sloan, "Another Look at the Cross-Section of Expected Stock Returns," *Journal of Finance*, 50 (March 1995), pp. 185-224.

14. Lev, B., "On the Association Between Operating Leverage and Risk," *Journal of Financial and Quantitative Analysis*, 9 (September 1974), pp. 627-641.

15. Mohr, R.M., "The Operating Beta of a U.S. Multi-Activity Firm: An Empirical Investigation," *Journal of Business Finance and Accounting*, 12 (Winter 1985), pp. 575-594.

14. Narayanaswamy, C.R., "A Mean Variance Synthesis of Corporate Financial Theory: A Note," *Journal of Finance*, 43 (June 1988), pp. 529-530.

15. Reinganum, M.R., "Misspecification of Capital Asset Pricing: Empirical Anomalies Based on Earnings Yield and Market Values," *Journal of Financial Economics*, 9 (March 1981), pp. 19-46.

16. Rubinstein, M.E., "A Mean-Variance Synthesis of Corporate Financial Theory," *Journal of Finance*, 28 (March 1973), pp. 167-181.

17. Subrahmanyan, M.G. and S.B. Thomadakis, "Systematic Risk and the Theory of the Firm," *Quarterly Journal of Economics*, 94 (May 1980), pp. 437-451.