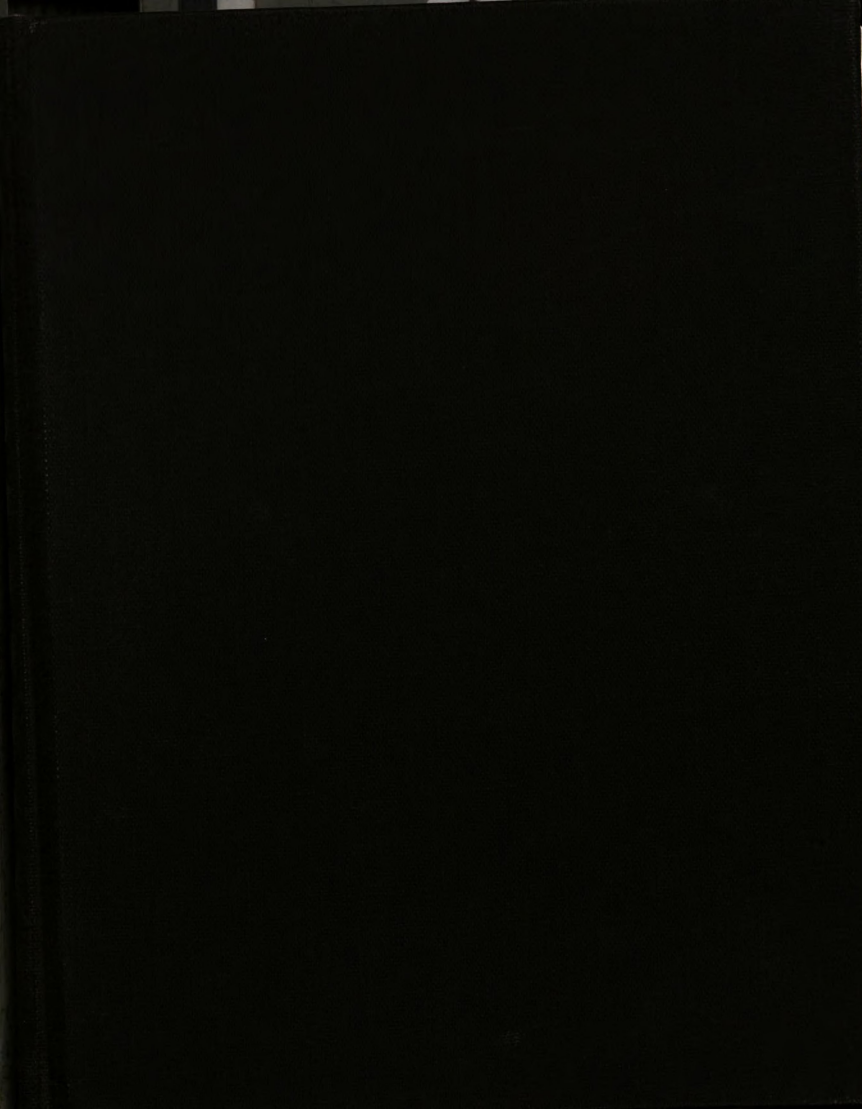






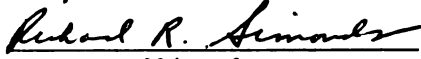
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INDUSTRY BETAS AND
SEGMENTAL ACCOUNTING INFORMATION

By
KIRT CHARLES BUTLER

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Submitted to
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ABSTRACT

INDUSTRY BETAS AND SEGMENTAL ACCOUNTING INFORMATION

By

Kirt Charles Butler

This study develops an alternative estimate of the systematic risk of a financially levered, multi-segment firm. The firm is viewed as a portfolio of industry segments. The systematic risk or segmental beta of the firm is constructed as a weighted average of the component segmental industry betas.

The segmental industry betas are estimated using a variant of the "pure-play" strategy of matching each industry segment with an equivalent single segment firm. An equal weighted portfolio of single segment firms in each industry is formed to represent the average business risk of each industry in which the multi-segment firm is engaged. The betas of the firms in each industry are averaged (using equal weights) to form levered industry betas representing the systematic risk of the average firm in the industry.

An explicit adjustment for financial leverage is then performed. The industry portfolio betas are unlevered by applying Hamada's or Conine's leverage adjustment according to the debt-to-equity ratio of each industry. These betas represent the systematic operating risk of the average firm in each industry. To form the equivalent of the pure-play security, the leverage adjustments are then reversed using the

Kirt Charles Butler

multi-segment firm's debt-to-equity ratio to 'lever-up' the unlevered industry betas.

These segmental betas are compared to OLS betas in terms of their ability to explain and to predict security returns. The cross-sectional correlation between segmental betas combining market and accounting information and market-based OLS betas provides evidence of a significant association. A multiple regression F-test demonstrates that OLS and segmental beta estimates provide nearly the same set of information in explaining security returns. The segmental betas also exhibit more stability over time than the OLS estimates. A test of the ability of the segmental and OLS betas to predict security returns is also performed and evaluated using mean square forecast error as a measure of forecast accuracy.

The objective of this study is to provide a test of the financial theory of the firm as a portfolio of assets. Simultaneously, a test of the Conine and Hamada models of the capital structure of the firm is provided. In the process, an alternative estimate of the systematic risk of a multi-segment firm is created which proves to be more stable than an OLS estimate. This segmental beta does not depend on the historical asset and financing mix of the firm and hence is more responsive to changes in the financing and investment characteristics of the firm.

DEDICATION

This dissertation is dedicated to my beloved wife Erika for her patience and loving consideration through too many long nights.

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Industry Betas and Segmental Accounting Information

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Chapter 1 Introduction

1.1 Motivation for the Study

In the context of the Capital Asset Pricing Model (CAPM) of Sharpe [1964], Lintner [1965], and Mossin [1966], identifying the systematic risk (beta) of a share of common stock is essential to determining an equity investor's required rate of return and the firm's cost of equity capital. The estimation of the systematic risk, or beta, of the firm thus has significance both for the investor attempting to place a value on common stock and for the financial manager in setting hurdle rates for investment projects. The manager of a firm invested entirely in one industry segment¹ has several alternatives for estimating the systematic risk of equity. Like a single segment firm, individual divisions or industry segments require unique hurdle rates to reflect their different systematic risks. The required rate of return on oil exploration is quite different from that on oil refining and marketing, for example, and the divisional cost of capital should reflect this difference in systematic risk. Yet many

¹ An industry segment refers to that portion of a company involved in a single industry or line of business. Technically, a segment may not be the same as a division since a division may be broken down along a functional line such as target market, distribution channel or geographic area. In this study, the terms segment and division are used interchangeably to refer to a firm's investment in a particular industry or line of business.

financial variables, such as returns to debt and equity, are only observable for the firm as a whole and not for the individual industry segments. Therefore, a multi-division firm invested in several industry segments faces unique problems in estimating its component segmental betas.

1.1.1.a Cost of Capital and the "Pure Play"

The single segment firm has available several ways to estimate its cost of equity capital, but ultimately the calculated cost is still only an estimate. Historical rates of return may be used, but these will be incorrect estimates of the cost of equity if either the firm, its investors, or the economy have changed from their former levels. The financial manager may estimate expected future dividends and use the current price to solve for the implicit expected rate of return of shareholders. The resulting equity cost of capital will be incorrect if the manager's estimate of the random future dividend stream is not identical to that of investors in the market. Another estimate could be arrived at by adding a risk premium to the firm's cost of debt to reflect investor risk aversion and the nondiversifiable risk of the firm. Similarly, the firm's beta could be estimated by regressing historical returns on historical market returns (or historical risk premia) to determine the systematic risk of equity. Through an application of the CAPM, estimates of the expected return on the market and of the riskless rate of return then yield an estimate of the required rate of return on equity.² All of these estimates of the equity cost of capital or required rate

² Rosenberg and Guy [1976] use accounting and financial information to supplement historical return information to arrive at an estimate of beta and hence of the required rate of return of investors.

of return of investors will be incorrect in the presence of changes in the level of interest rates, in investor attitudes toward risk, or in the systematic risk composition of the individual firm.

If none of these alternatives is acceptable, an estimate of the cost of equity capital for a nearly identical firm may provide a proxy for the systematic risk and required rate of return of equity investors. A "pure-play" firm is matched along relevant financial characteristics, especially business and financial risk. The pure-play firm should be in the same industry and should be of similar size, operating and financial leverage, management philosophy, distribution networks, and so forth. This approach to estimating the divisional costs of capital of multi-segment firms has figured prominently in the financial and accounting literature.¹ The cost of equity capital or required rate of return of investors is estimated for this pure-play firm, usually by applying the CAPM. The unobservable divisional cost of capital is then assumed equal to the cost of capital of the pure-play. In this manner a cost of capital for the entire firm may be found as the weighted average of the segmental betas, where the weights are ideally the (unobservable) proportional market values of the segments. That is, by treating the firm as a portfolio of segments or divisions, the systematic risk of the entire firm

1 See, for instance, "Estimating the Divisional Cost of Capital: An Analysis of the Pure-Play Technique", by Fuller and Kerr [1981].

may be found as the weighted average of the component segmental betas.

1.1.b Special Situations

If segmental betas prove to be an accurate representation of the systematic risk of the firm, then there may arise occasions when these estimates are preferable to OLS betas as measures of the systematic risk of the firm. Historical ordinary least square betas will be inappropriate for any firm which has undergone changes in the composition of its asset mix or of its financing mix. When a firm undergoes a sudden change in its financing characteristics, the systematic risk of the firm is likely to change as well. Using the Conine [1980] relationship and the multi-segment results found in Chapter 3, we may take any new information about the changed financial condition of the firm and 'relever' the unlevered segmental industry betas, thus forming a revised estimate of the systematic risk of the firm. Such a sudden change in financial structure may occur when a firm buys treasury stock with a new issue of debt, retires debt with a new issue of stock, forces conversion of a convertible bond issue, has warrants exercised, or for any of a number of other reasons.

A change in systematic risk may also occur when the firm experiences a change in its asset mix, such as a new investment, acquisition, or divestiture. When a firm acquires

or merges with another firm or spins off one of its operating divisions or subsidiaries, it undergoes an instantaneous change in the operating characteristics of its asset mix. In an acquisition or merger, a revised estimate of the systematic risk of the firm may be formed by recalculating the beta of the new portfolio of assets. The post-merger or acquisition market values of the segments are ideally used to weight the segmental betas of the firm. In a divestiture, the beta of the surviving firm is found as the weighted average of the levered industry segmental betas where the weights are the proportional market values of the surviving segments.

The segmental beta is also conceptually adaptable to the situation where the firm undergoes a simultaneous change in both the mix of its operating components and its capital structure. Since the segmental beta estimate may be mixed anew as needed, an estimate of the systematic risk of the firm may always be constructed according to the current mix of operating segments adjusted for the current financing package. A sudden change in any of these components represents no threat to the segmental beta, whereas historical OLS betas will be tied to the systematic risk of the original firm.

1.1.c Forming a Stable Risk Surrogate

An OLS estimate of systematic risk composed from several industry portfolios should have the additional advantage of

being more stable than an OLS beta estimate of an individual firm. Combining securities into portfolios substantially eliminates the unsystematic component of security return. Historical OLS beta estimates of portfolio risk thus reflect the remaining nondiversifiable or systematic component of portfolio return and should fluctuate much less over time. If these beta estimates accurately represent the systematic risk of an industry, then these stable estimates may be preferable to a single firm or segment beta which exhibits less stability. This portfolio effect is also operative when combining several industry segments into a risk surrogate for the multi-segment firm. Once again, variations in segmental industry betas will tend to cancel out when combined into a portfolio of industry segments. The resulting beta composed as a portfolio of industry segments should be a more stable estimate of the firm's systematic risk than a historical OLS beta estimate.

Individual investors can eliminate diversifiable risk by combining securities into portfolios. These well-diversified investors will not receive the full benefit of a more stable estimate of systematic risk since firm-specific variation in beta estimates will be eliminated at this portfolio level of investment. But there are important classes of people that have a need for more stable risk estimates. These include the financial manager of the firm, government regulators, active investors attempting to "beat the market" and achieve superior

returns, and passive investors trying to balance the mix of systematic risk classes in their portfolio. Increased stability may be highly desirable to all of these groups in their search for a better estimate of beta.

The financial manager makes critical financing and investment decisions based on his estimate of the cost of capital to the firm. While investors can combine the firm with other firms in a portfolio and hence eliminate firm-specific risk, the financial manager must be concerned with accurately estimating the risk and cost of capital for a single firm. Any error in this estimate will create the possibility of sub-optimal financing and investment decisions. The financial manager will thus benefit from a more stable estimate of systematic risk (and hence cost of capital) so long as this more stable estimate does indeed reflect the systematic risk of the firm. Similarly, the manager of a diversified firm has a need for stable estimates of the divisional costs of capital.

Just as the financial manager of the firm must accurately estimate the systematic risk of a single firm, government agents involved with regulated industries deal with individual firms and hence have a need for more stable beta estimates. Regulators in the electric utility industry, for instance, must determine the cost of capital to the regulated firm in order to determine rate schedules. Rate schedules must be set to supply an adequate return of capital to investors while at the same time keeping rates as low as possible for the utility's

consumers. If rates are set too high, investors receive a windfall at the expense of the utility's customers. If rates are set too low, investors suffer and the utility may have difficulty raising the capital needed for fuel, maintenance, and expansion. A more stable estimate of the systematic risk of a regulated firm will allow public utility commissions to more accurately and confidently set rate schedules.

Active investors following a fundamental approach to security valuation attempt to select mispriced securities to achieve superior investment performance. Advertisements for stock selection techniques and buy/sell recommendations are prominent in almost every financial publication available today. The persistence of these hot-lines and newsletters indicates that there is an active market for these investment tips. A more stable beta estimate may be desirable to these active investors in stock valuation and in performance evaluation.

Passive investment strategies hold a diversified portfolio of securities in a long-term buy-and-hold approach. Most passive portfolios, such as the College Retirement Equity Fund (CREF), invest in a broad range of risk classes within a certain type of securities market. Smaller funds of this type do not possess the capital to fully diversify across the entire spectrum of securities. Since many of the benefits of diversification can be achieved with a small number of different securities, these funds select a few securities in

several risk classes to achieve nearly the same degree of diversification as the larger funds. A more stable and responsive beta estimate may be useful in ensuring that these funds are not overly invested in a particular risk class.

Thus, the approach of this study should provide additional insight into the systematic risk, cost of capital, and required return of multi-segment firms. The study should also provide a more stable and responsive estimate of systematic risk, and hence should be of value to financial managers, financial institutions, investors, and government regulators.

1.2 Objective of the Study

This study develops an alternative estimate of the systematic risk of a multi-segment firm. In the context of the CAPM, identifying the systematic risk of a share of common stock simultaneously determines equity investors' required rate of return and the firm's cost of equity capital.⁴ The estimate of systematic risk in this study should exhibit, relative to the traditional OLS estimate, both increased stability and increased responsiveness to changes in the financing and asset composition of the firm.

For a single firm, there is a large amount of month-to-month variation in beta when using a 60-month moving window to calculate historical OLS beta estimates due to the large random component in security returns. Forming the pure-play variant as a portfolio of securities in an industry

⁴ It is not self evident that systematic risk is the appropriate or the only measure of risk for the firm. In an efficient CAPM market, the firm and its managers are unable to do anything for the investor which the investor is unable to do for himself. The managers, however, may be in a position to do something for themselves which the investors will not necessarily do for them and may not wish to do for them. If the managers' contract with shareholders does not include the proper incentives to guarantee their acting in the shareholders interests, agency theory [Shavell, 1979 and Holmstrom, 1979] suggests the financial managers of the firm may have an incentive to minimize the total risk of the firm rather than the systematic risk to investors. Given some level of expected return which satisfies the owners of the firm and avoids undue probability of financial distress, minimizing the total risk of the firm will coincidentally maximize the probability of the managers maintaining their position in the firm. Management may then remain entrenched and hence maximize their own personal welfare.

segment should increase the stability of the beta estimates via the portfolio effect. Segmental beta estimates of the systematic risk of the multi-segment firm should thus be more stable than a single market-based OLS beta.

Segmental betas are compared to OLS beta on their ability to explain and to predict security returns. The variance over time for each of these beta estimates, while not measuring the accuracy of the estimates, provides a measure of their stability. The correlation between segmental betas combining market and accounting information and market-based historical OLS betas measures the extent to which these estimates share common information. A multiple regression F-test is performed to determine if OLS and segmental beta estimates provide the same set of information in explaining security returns. A test of the ability of segmental and OLS betas to predict security returns is also performed and evaluated on forecast accuracy. Evidence of the usefulness of line-of-business or segmental accounting information in forming estimates of the systematic risk of the firm is also provided.

The objective of this study is, then, to provide a test of the financial theory of the firm as a portfolio of assets. Simultaneously, a test of the Conine and Hamada models of the capital structure of the firm is provided. In the process, an alternative estimate of the systematic risk of a multi-segment firm is created which should be more stable than OLS estimates and more responsive to changes in the financing and investment

characteristics of the firm. The approach should provide additional insight into the systematic risk, cost of capital, and required return of multi-segment firms.

1.3 Overview of the Study

The firm is viewed as a portfolio of individual industry segments. The systematic risk, or segmental beta, of the firm is constructed as a weighted average of the segmental industry betas. The systematic risk of each industry segment of the multi-segment firm is estimated by determining the average OLS beta of all single-segment firms invested in the industry. This industry average represents a pure play of the firm's industry segment. The weights used in the portfolio construction are a surrogate for the proportional market values of the firm's industry segments (see Sections 2.1 and 4.1.c). The resulting estimate of the firm's systematic risk should exhibit greater stability and be more responsive than historical OLS estimates to changes in the operating and financial characteristics of the firm. It may also provide information about the systematic risk of the firm beyond that provided by OLS betas.

The industry segmental betas are estimated using a variant of the pure-play strategy of matching each industry segment with an identical single segment firm. The pure-play approach matches on business and financial risk (or sometimes on systematic risk). A portfolio of single segment firms in each industry segment is formed to represent the average business risk of each industry in which the multi-segment firm is engaged. Industries are identified by the Standard Industry

Classification (SIC) code. Monthly industry returns are compiled by equal weighting the single segment firms comprising each industry. Industry betas are then estimated by OLS regression of each industry's returns on the market return.

An explicit adjustment for capital structure is then performed. The segmental industry betas of both the firm and of the pure-play industry average are adjusted for financial leverage to reflect the additional financing risk accepted by shareholders. A vector of monthly OLS beta estimates is calculated for each industry as described above. These industry betas are then unlevered by applying Conine's [JF, 1980] relationship:

$$\beta_U = [\beta_L + \beta_{DEBT} (1-T) (D/SL)] / [1 + (1-T) (D/SL)] \quad (1.1)$$

according to the debt-to-equity ratio of each individual firm. The systematic risk of debt is approximated by an approximate beta for investment-quality corporate bonds (see Section 2.3).

To form the equivalent of the pure-play security, Conine's relationship is reversed:

$$\beta_L = \beta_U (1 + (1-T) (D/SL)) - \beta_{DEBT} (1-T) (D/SL) \quad (1.2)$$

using the multi-segment firm's debt-to-equity ratio to 'lever-up' the unlevered industry betas. The Conine segmental betas are compared to Hamada [JF, May, 1972] segmental betas which do not adjust for risky corporate debt ($\beta_{DEBT}=0$) as well as to historical OLS betas and to segmental betas which have had no leverage adjustment.

Of course, this approach is not without estimation problems. Some difficulties in applying the theory to real-world situations with limited data are immediately apparent. Divisions within a firm are often not broken down along industry lines. Reported divisional assets, earnings, and sales figures may include several different industry segments and corporate functions. Even if segmental financial reports do represent a single industry, the business risk in a particular segment will in general not be identical to that of the industry average or to the average of single-segment firms in the industry. We also need to use some proxy, such as segmental sales, assets, or historical replacement cost for the unobservable segmental market values when value-weighting the industry segments. The leverage adjustment models are also misspecified since they assume perfect markets and perpetual cash flows. Yet, the proposed approach offers some interesting advantages and insights.

Chapter 2 Literature Review

The literature review in this chapter provides ample evidence that "If you laid all the economists in the world end-to-end, they would still not reach a conclusion." Some consistent results nevertheless emerge from the academic literature. These include:

2.1 Disclosure of segmental information, particularly segmental sales, provides valuable information to financial statement users. Furthermore, such accounting information may be useful in predicting the systematic risk of common stock. These results can be linked to the literature on the theory of the firm as a portfolio of assets.

2.2 The traditional view of the optimal capital structure of the firm as the point where the marginal benefits of reduced taxes are equal to the marginal costs of financial distress provides the benchmark against which other theories are compared.

2.3 The systematic risk of debt is generally less than that on common stock. Empirical estimates range from 0.15 to 0.4, depending on the bonds and the market portfolio surrogate.

2.1 Line-of-Business (LOB) Accounting Studies and Market Risk and Return

The Securities Act of 1933 empowered the Securities and Exchange Commission (SEC) with the responsibility to ensure a "full and fair disclosure of the character of securities sold in interstate and foreign commerce." To this end, the SEC in 1970 required the disclosure of line-of-business (LOB) or "segmental" sales and earnings in SEC registration statements and annual 10K reports. In 1976, the Financial Accounting Standards Board (FASB) further required diversified firms to include the sales, operating profits, identifiable assets on a historical cost basis, depreciation, and capital expenditures of each reportable¹ industry segment in the firm's published annual report. These disclosure requirements were intended to allow financial statement users to better evaluate the risk and expected return of the diversified firm, as evidenced in the following quote from SFAS No. 14:

"The evaluation of risk and return is the central element of investment and lending decisions...the evaluation of risk involves assessment of the uncertainty surrounding both the timing and the amount of the expected cash flows to the enterprise...uncertainty also results, in part, from factors unique to the

¹ A "reportable" industry segment is defined by SFAS No. 14, "Financial Reporting for Segments of a Business Enterprise", as a segment which comprises at least 10% of total segmental revenues, operating profits or losses, or identifiable assets. Additionally, the total revenues of the reportable segments must equal at least 75% of consolidated sales to unaffiliated customers. A maximum of up to 10 segments is suggested.

particular...investment." (SFAS No 14, 1976, paragraph 57).

Mohr [1983] presents a comprehensive review of the academic research on segmental disclosure. She employs the "Fineness Theorem" of the information economics literature (e.g., Marschak and Radner [1971], pgs. 53-59) as a theoretical rationale for segmental disclosure. Theoretically, the disclosure of "finer" sets of disaggregated information provides an information set which is at least as valuable as consolidated or aggregated information. The disaggregated information will be of value to decision makers so long as the costs of gathering, reporting, and analyzing the information do not offset the theoretical benefits of the "finer" information system. If segmental disclosure indeed allows a more accurate assessment of the risks and expected returns of diversified firms, then the disclosure should improve market estimates of risk and expected return. The structure supplied by the Fineness Theorem helps place the disparate academic inquiries into a consistent and logical perspective with respect to the costs and benefits of segmental disclosure. The following discussion closely parallels Mohr's presentation.

2.1.a LOB Disclosure and Expected Returns

Several studies concluded that the "finer" information provided by segmental disclosure had no discernible effect on the market's assessment of the expected return to common

stock. Horwitz and Kolodny [1977], Twombly [1979], and Ajinkya [1980], employing several different methodologies, searched for a change in expected return around the time of the initial 1970 disclosure of LOB data. All concluded that there was no statistically significant difference in expected return (either mean return or residual return in a market-model context) in single or multi-segment firms either before or after the 1970 SEC-required disclosure rules. However, Collins and Simonds [1979] and Ajinkya [1980], among others, note that the direction of change in many accounting and financial variables from segmental disclosure is dependent on the additional information provided by the "finer" information set. Since it is not possible, a priori, to predict the direction of change, any change in expected return at the individual firm level that resulted from the segmental disclosure may have been lost at the portfolio level.

Financial analysts' earnings predictions and earnings predictions based on various statistical models were found to be improved by the disclosure of segmental information. Kinney [1971], Collins [1976], and Silhan [1982] examined the predictive ability of various statistical forecasting models using both segmental and consolidated sales and earnings data. All three studies concurred that segmental earnings data had limited usefulness beyond segmental sales data in predicting the earnings of multi-segment firms. However, Kinney and Collins found that segmental sales disclosure allowed many

models of earnings prediction to achieve greater forecast accuracy than models based on consolidated sales and earnings alone. Barefield and Comiskey [1975], Baldwin [1976], and Smith [1979] found that the availability of segmental information, including both segmental sales and earnings, improved the forecast accuracy of financial analysts' earnings predictions.

Finally, in stating that disaggregated or segmental information is at least as valuable as aggregated or consolidated information, the Fineness Theorem predicts that the disaggregated or "finer" information should contribute to a greater consensus among market participants. This greater consensus was in fact observed with segmental disclosure in studies by Ortman [1975], Dhaliwal [1978], and Ajinkya [1980].

2.1.b LOB Disclosure and Systematic Risk

Just as the above studies attempted to detect changes in the expected return of multi-segment firms around the initial date of segmental disclosure, Horwitz and Kolodny [1977] searched for a shift in the systematic risk or beta of a firm that disclosed segmental earnings data for the first time in 1970. They found that the average change in beta around the 1970 disclosure date of their treatment sample of multi-segment firms was not significantly different from the beta change in their control sample of single-segment firms. Collins and

Simonds [1979] and Dhaliwal [1978], on the other hand, detected a downward shift in the beta of multi-segment firms around the original 1970 disclosure date. In the Dhaliwal study, the beta shift was due to changes in both the return variance and the return covariance with the market.

Ajinkya [1981] expanded the Collins and Simonds study to investigate the possibility that mean reversion and nonstationarity in beta contributed to the observed downward beta shift. Ajinkya concluded that the higher observed beta of the multi-segment treatment group exhibited a tendency to revert to the mean of 1.0, and that attributing the downward shift to segmental disclosure, as Collins and Simonds had, was unfounded. Beta nonstationarity may have also confounded Collins and Simonds' result.² As such, the presence of changes in the assessment of systematic risk due to the 1970 SEC disclosure requirements remains an unresolved issue.

2.1.c LOB Disclosure and the Diversified Firm

² Several authors, including Blume [1975], Fisher [1978], and Sunder [1980], have concluded that beta is nonstationary over time. All of these studies used approximate procedures to test for nonstationarity. Simonds, LaMotte, and McWhorter ["Stationarity of Market Risk: An Exact Test", forthcoming, JFQA, March, 1986] applied a test developed by LaMotte and McWhorter ["An Exact Test for the Presence of Random Walk coefficients in a Linear Regression Model", JASA, 1978, Vol. 73, No. 364, pp. 816-820], and were able to detect statistically significant nonstationarity in market risk.

2.1.c LOB Disclosure and the Diversified Firm

Application of the Capital Asset Pricing Model (CAPM) to the divisional cost of capital has profound implications for the selection of capital investment proposals by the diversified firm. Discounted cash flow (DCF) techniques require an estimate of the cost of capital specific to each project or division of the firm. This risk-adjusted asset-specific cost of capital is then used to discount expected future cash flows to determine the value of the investment to the owners of the firm.

Industry has recently incorporated more asset-specific discounting techniques into their capital budgeting procedures. Gitman and Mercurio [1982], in their mail questionnaire sent to the Fortune 1000 firms, report that nearly 60% of the 177 respondents individually classify projects according to risk and use some form of risk-adjusted discount rate or risk-adjusted cash flows to evaluate project worth.³ Van Horne [1980] presents a real-world application of the CAPM to divisional costs of capital at a high technology company with two principle lines of business. Implicit in such applications is the concept of the firm as a portfolio of assets each with unique risk and return characteristics.

³ Gitman and Mercurio point out that the 177 responses may not represent a true cross-section of the Fortune 1000 firms. Firms with sophisticated DCF and capital budgeting procedures, for instance, are more likely to respond to such a questionnaire.

Rubinstein [1973] developed the theoretical relationship between the operating or unlevered beta, β_U , of a multi-segment firm and the operating characteristics of its segments:

$$\beta_U = [\sum_i X_i (p_i - v_i) \text{corr}(q_i, r_m) \sigma(q_i / (X_i U))] / \sigma(r_m) \quad (2.1)$$

where i = industry segments 1, 2, ..., n,
 X_i = proportion of the firm's total assets,
devoted to segment i ($\sum_i X_i = 1$),
 $(p_i - v_i)$ = contribution margin in industry segment i ,
 q_i = units of output from industry segment i (a random variable),
 r_m = return on the market index (a random variable),
 U = market value of the total assets of the firm,
 corr = correlation coefficient,
 σ = standard deviation.

Several studies have found evidence consistent with this model of the firm's systematic risk. Lev [1974] found a negative correlation between beta and average per unit variable cost v , a result consistent with the $(-v_i)$ term in the Rubinstein relationship. Bowman [1979] demonstrated analytically the existence of a relationship between the operating beta β_U and the firm's "accounting beta" (defined as the covariability of the firm's accounting earnings with the earnings of the market as a whole). Bowman then demonstrated empirically that the beta of the unlevered firm, β_U , is closely related to the accounting beta. The accounting beta has also been shown to be associated with market-based estimates of beta by Ball and Brown [1969], Beaver, Kettler, and Scholes [1970], and Beaver and Manegold [1975]. While none of these studies examined the operating beta of a multi-segment firm, they nevertheless provide support for the Rubinstein expression as it applies to the single-segment firm.

Mohr [1983] examined the relationship between the unlevered market-based beta, calculated as

$$\beta_U = \beta_L / (1 + (D/SL)), \quad (2.2)$$

and the operating beta of the diversified firm, calculated as

$$\beta_O = \sum_i X_i \beta_i, \quad (2.3)$$

where β_L = the beta or systematic risk of the levered firm,
 β_U = the unlevered beta of the firm,
 β_O = the operating beta of the diversified firm,
 β_i = the operating beta of segment i,
 D = the value of debt and preferred stock,
 SL = the value of levered equity,
 and X_i = the proportional investment in segment i.

The operating beta of segment or industry i (β_i) was formed by calculating the beta of a portfolio of single-segment firms. The single-segment firms were selected from the CRSP (Center for Research in Security Prices) return tapes and were weighted with the Rosenberg and Marathe [1975]⁴ weighting scheme. The operating beta of the diversified firm (β_O) was then calculated as the beta of a portfolio of industry or segmental betas. The unlevered beta β_U and the operating beta β_O when using a matched pair t-test, however, were significantly positively and linearly related. Mohr also found statistically significant evidence of $\beta_U < \beta_O$. She presents several possible explanations for this unexpected relationship, including the assumption of

⁴ Rosenberg and Marathe assign a weight to each segment i which is inversely proportional to the residual variance of the regression used to calculate each industry beta. The industry involvements are thus weighted according to the "confidence" of the beta estimates. In this study, the Rosenberg and Marathe weighting scheme will not be used. Instead, a proxy will be chosen for the market value investment in each industry segment.

risk-less debt in the Hamada relationship (2.2) and the possibility of errors in this particular operationalization of the model.

Mohr also fit the multiple regression model

$$\beta_L = a + b_1[1+(D/SL)] + b_2[\beta_o] + e. \quad (2.4)$$

The regression coefficients b_1 and b_2 of the model were both positive and statistically significant, indicating that both financial leverage and the operating beta contribute information about the systematic risk of the levered multi-segment firm. The addition of the operating beta term significantly improved the explanatory power of the regression model over a simple regression model containing only the leverage factor.

The Rubinstein expression (2.1) provides a direct link between the unlevered beta of the firm and the characteristics of its component industries. The evidence of Section 2.2 indicates that the systematic risk of common stock is also positively related to the degree of financial leverage employed by the firm.

2.2 Capital Structure: Theory and Evidence

2.2.a Capital Structure Theory

In 1958, Modigliani and Miller [1958, 1963, 1969] formulated their famous MM Proposition I:

"If $T_c = 0$, then $U_L = U_U$ ",

where U_L = the value of the levered firm,
 U_U = the value of the unlevered firm, and
 T_c = the corporate tax rate.

That is, in a world without taxes, the equilibrium value of a firm is independent of its capital structure.

In deriving this result, MM made several key assumptions which established the conventional methodology followed in most later analyses. Among the assumptions which have become standard in the finance literature are the following list of perfect capital market conditions:

- a) competitive markets with many perfect substitutes available for all securities,
- b) frictionless markets including infinite divisibility and marketability of financial assets, costless capital markets with no transaction costs or taxes, no constraining government regulations, and no bankruptcy costs or costs of financial distress (although financial distress and bankruptcy may occur),
- c) informationally efficient markets (information is costless and is received simultaneously by all individuals),
- d) all individuals are rational expected utility maximizers and have homogeneous expectations with regard to future events,
- e) equal access to funds (all investors and firms can borrow, lend, and issue claims on the same terms).

In addition, MM assumed that all cash flows were perpetual

streams, including returns from investment and payments to debt and equity.

Finally, MM assumed that the firm belongs to a risk-class where the investment of each firm in the risk-class is proportional: $X_j = (1+P) * X_i$, where X represents the operating cash flow of a firm in the risk-class. Thus, each firm in a risk class differs only in the scale of operations and represents a "chip off the old block". Cash flow returns from investment are identical or differ only by a scale factor P . Since firms in the same risk-class are perfect substitutes per dollar invested, the equilibrium behavior of all such firms is necessarily identical. The risk-class assumption allowed MM to use an arbitrage argument to determine the equilibrium value of the firm.

Next, MM relaxed the restriction on corporate taxes and demonstrated the MM Proposition I with corporate taxes:

$$\begin{aligned} \text{If } T_c > 0, \text{ then } V_L &= V_U + PV \text{ (tax shield)} \\ &= V_U + T_c * D, \end{aligned}$$

where D = market value of debt,
 PV = present value operator.

In equilibrium, in a world with corporate taxes, the value of a levered firm is equal to the value of the equivalent risk-class unlevered firm plus the present value of the tax shield from the tax deductibility of interest payments. In such a world, financial managers would finance investment entirely with debt and thereby maximize the value of the firm. Of course, Modigliani and Miller did not believe that this is how

real-world firms should actually finance investment. In the idealized MM world, however, this is the optimal financing policy. The simple MM world served to structure the task of relaxing the restrictive assumptions of the model to bring it into concert with reality.

Subsequent analyses used the MM Proposition I as a base case, relaxed one or more of the assumptions, and derived the resulting equilibrium behavior of the firm and of investors. Hamada [1972] began this process by combining the original MM analysis with the Capital Asset Pricing Model (CAPM). Suppose the cash available to meet fixed interest payments is always greater than the fixed interest cost so that debt is risk free. Alternatively, assume tax losses can be sold in the market for $T_c D$, their value to a tax-paying firm. In an MM world with risk-free corporate debt and corporate taxes (but no personal taxes or bankruptcy costs), the relationship between the systematic risk of a levered firm and an otherwise identical unlevered firm is the same as in the original MM corporate tax case. Hamada reformulates this result as:

$$V_L = V_U + T_c \cdot D.$$

By assuming either quadratic utility or normally distributed security returns, Hamada derived the systematic risk of common stock as:

$$\beta_L = \beta_U + \beta_U \cdot [(1-T) (D/L)],$$

where D = the market value of debt,
 L = the market value of common stock,
 β_U = the systematic risk of the identical unlevered firm,

and β_L = the systematic risk of levered common stock. Finally, it is important to note that Hamada's result is contingent upon the independence of the financing and investment decisions of the firm.

Bierman and Oldfield [1979] extended the Hamada result to determine the value of the firm issuing risky debt in the presence of corporate taxes. Bankruptcy costs and costs of financial distress are assumed to be absent. If default does occur the firm is allowed to continue operation and the actual payment to debtholders is the random variable I such that $0 \leq I \leq C$, where C is the promised coupon payment. The CAPM is invoked to simultaneously determine equilibrium required rates of return for levered equity, unlevered equity, and debt. The equilibrium value of the levered firm is shown to be:

$$\begin{aligned} V_L &= V_U + IC \{ (I/RF) - [\text{cov}(I, k_M) * (k_M - RF) / \text{var}(k_M)] / RF \} \\ &= V_U + (IC * D / RF) * \{ (I/D) \\ &\quad - [\text{cov}(I, k_M) * (k_M - RF) / \text{var}(k_M)] / D \} \\ &= V_U + (IC * D / RF) * \{ k_D \\ &\quad - \text{cov}(k_D, k_M) * (k_M - RF) / \text{var}(k_M) \} \\ &= V_U + (IC * D) * (RF / RF) \\ &= V_U + IC * D, \end{aligned}$$

where k_D = the required rate of return on debt (a random variable),
 k_M = the required rate of return on the market portfolio including both the debt and equity securities (a random variable),
 RF = the risk-free rate of return,
 I = the (random) payment to debt.

The required rates of return k_D , k_L , and k_U are linked together through the Capital Asset Pricing Model. The MM Proposition I result with taxes is again achieved with the restriction that the value of debt is:

$$D = \{ (I/Rf) - [\text{cov}(I, km) * (km - Rf) / \text{var}(km)] / Rf \},$$

an amount that is simultaneously determined and linked to the value of levered and unlevered equity through the CAPM. If debt is risk-free as in the Hamada relationship, then $k_D = R_f$ and the analysis again collapses to the MM case with corporate taxes.

Conine [1980] extended the Bierman and Oldfield analysis to demonstrate:

$$\begin{aligned} \beta_L &= \beta_U (SU/SL) - \beta_D \{ (1-TC)D/SL \} \\ &= \beta_U + \beta_U \{ (1-TC)D/SL \} - \beta_D \{ (1-TC)D/SL \}, \end{aligned}$$

where β_D = the systematic risk of debt.

When debt is risk-free, bonds have no systematic risk and $\beta_D = 0$. The model then reduces to the Hamada result:

$$\begin{aligned} \beta_L &= \beta_U (SU/SL) \\ &\quad \beta_U + \beta_U \{ (1-TC)D/SL \}. \end{aligned}$$

Because the random return to debt I is a truncated distribution in the presence of risk of default, the assumption of a normal return distribution is violated. As such, within the extended analysis of Conine and Bierman and Oldfield, quadratic utility must be assumed in order to salvage the CAPM as a pricing mechanism. This is discussed in more depth in the section reviewing the literature on the systematic risk of corporate bonds.

Miller [1977] extended the original MM model to include taxes on personal equity (TE) and debt (TD). In such a world, the value of the levered firm is:

$$V_L = V_U + [1 - ((1 - IC)(1 - IE)/(1 - ID))] * D,$$

where IC = the corporate tax rate,

IE = the personal tax rate on equity income, and

ID = the personal tax rate on interest (debt) income.

Within this model, Miller argues that there is a single optimal use of debt for the entire economy, but that due to the wide array of personal tax rates, there is no optimal financing policy for an individual firm. The market is only interested in the total supply of debt and individual firms may have different and still optimal capital structures. The economy-wide use of debt is determined by the level of the various tax rates. So long as the equilibrium supply of debt and equity streams exists in the market, each individual firm may maintain any desired financial structure. Each capital structure class has a clientele of investors with a given set of personal tax rates. Interestingly, this resurrects the no-tax MM Proposition I that the value of the firm is independent of its capital structure. Miller's analysis is appealing because it allows firms to select heterogeneous debt ratios and is consistent with the myriad of corporate financial policies that are observed in the market.

Kim [1978] presented the traditional view that costs of bankruptcy and financial distress offset the benefits of the tax deductibility of interest payments. Costs of financial distress include both direct (legal and administrative) and indirect (lost sales, management time spent on avoiding

bankruptcy) costs. In Kim's analysis, financial leverage should be utilized until the present value of the costs of financial distress and bankruptcy exactly offset the increase in present value from the tax deductibility of interest payments. The objective of the financial manager is to select that capital structure which maximizes the value of the firm:

$$VL = VU + PV(\text{tax shield}) - PV(\text{costs of financial distress}).$$

Maximizing VL with respect to the use of debt D yields the result:

$dPV(\text{tax shield})/dD = dPV(\text{costs of financial distress})/dD$;
 ie. at the optimal capital structure, the marginal benefit of the tax shield equals the marginal cost of financial distress. As the probability of incurring costs of financial distress rises, the question becomes one of "Who chickens out first...the equityholders, the debtholders, or the managers of the firm?"

DeAngelo and Masulis [1980] follow a similar approach by including tax shields from other sources. These include depreciation, depletion allowances, pension fund contributions, the immediate expensing of investments in intangible assets, and investment tax credits. As firms use these other methods of shielding income from taxation, taxable income and hence the available tax shields from interest payments are reduced. They demonstrate that the firm may have an optimal capital structure which is neither entirely debt nor entirely equity even in the

absence of bankruptcy costs so long as the availability of tax shields differs across firms.

Yagill [1982] integrated the MM and CAPM approaches and included risky debt, corporate and personal taxes, and bankruptcy costs. The resulting model, representing the logical extension of the original MM analysis, identified the following relationships:

$$\begin{aligned} V_L &= V_U + D \cdot (1-Z) - q \cdot D \\ &= V_U + Q \cdot D, \end{aligned}$$

where $Z = (1-TC)(1-TE)/(1-TD)$ as in Miller [1977],
 q = a function of debt D designed to represent
 bankruptcy costs,
 and $Q = (1 - Z - q)$.

Also, Yagill showed that:

$$\begin{aligned} k_L &= k_U + Z \cdot [k_U - k_D (1-TD)] \cdot D / SL, \\ \text{and } \beta_L &= \beta_U \cdot (SU/SL) - \beta_D \cdot Z \cdot (D/SL) \\ &= \beta_U + Z \cdot [\beta_U ((1+Q)/Z) - \beta_D] \cdot (D/SL). \end{aligned}$$

If debt is risk-free, the systematic risk of debt again reduces to:

$$\begin{aligned} \beta_L &= \beta_U \cdot [1 + Z \cdot (D/SL)], \\ &= \beta_U + \beta_U [Z \cdot (D/SL)], \end{aligned}$$

which is the Hamada [1969] expression adjusted for personal taxes ala Miller [1977].

2.2.b Capital Structure Evidence

The optimal capital structure of the firm is one of the unresolved problems in financial theory. While there is a rich body of theoretical work (as discussed above), empirical support for these models is sparse. Empirical examinations of

several models of optimal corporate financial leverage are examined in this section. These examinations focus primarily on the debt tax shield-bankruptcy cost tradeoff, the existence and importance of direct and indirect costs of financial distress, the importance of non-debt tax shields such as depreciation, depletion and investment tax credits, and the size of the tax advantage of debt.

Costs of financial distress include a diverse array of direct and indirect costs. Legal and administrative costs are direct costs associated with liquidating or reorganizing the firm. Indirect costs include lost sales and greater expenses suffered as the probability of default increases. The bank runs experienced by depository institutions as bankruptcy approaches represent probably the most dramatic example of these indirect costs.⁵ Other indirect costs include agency costs (Jensen and Meckling [1976]), moral hazard costs (Holmstrom [1979]), and the costs of contracting debt covenants and monitoring conformity of the firm to the debt covenants. Agency costs and moral hazard costs are sufficient to require debt covenants to protect the debtholders from detrimental financing and investment decisions by management. Attempts to

⁵ The indirect cost of a bank run can impact both large money center banks like Continental Illinois as well as smaller institutions, as recently occurred with Ohio's Savings and Loan industry. While Continental had the financial reserves and political connections to weather the storm, many of the Ohio S&Ls were not so fortunate.

measure the existence and size of the direct and indirect costs of financial distress have met with limited success.

Warner [1977], in the most widely cited reference on the costs of bankruptcy, measured direct legal and administrative costs for eleven bankrupt railroads. These direct costs averaged 5.3% of the market value of the railroads at the time of liquidation or reorganization. They averaged only 1% of the market value of the railroads as measured 7 years prior to the judgement. In addition, distribution of the proceeds of the liquidation was often delayed up to 10 years by litigation. Warner recognized that these direct costs of bankruptcy applied specifically to the railroad industry which is composed of large firms possessing primarily tangible assets. Nevertheless, Warner suggests that these bankruptcy costs are too small to allow an interior solution using the traditional tax shield-bankruptcy cost argument. The Warner study did not address, however, the issue of the size and importance of indirect costs of bankruptcy.

Measurements of the indirect costs of bankruptcy are particularly difficult because these costs are often opportunity costs and hence they defy specification and measurement. Altman [1984] used a regression method for determining indirect bankruptcy costs which he defined as unexpected losses. On average, direct and indirect (unexpected losses) costs of bankruptcy ranged from 11% to 17% of the value of the firm up to three years prior to bankruptcy. Bankruptcy costs

were frequently over 20% of firm value. Altman compared the expected present value of bankruptcy costs with the expected present value of tax benefits from leverage and concluded that bankruptcy costs were indeed significant.

Castanias [1983] examined the relationship between financial leverage and the historical failure rates of various lines of business. Firms in lines of business with high failure rates tended to make less use of financial leverage. (This is consistent with the results of Bradley, Jarrell and Kim [1984] mentioned below.) Castanias found ex ante default costs to be especially significant for small firms. The observed negative relationship between leverage and bankruptcy is again consistent with the tax shield-bankruptcy cost model of optimal capital structure.

Masulis [1983] examined the response of share prices to pure capital structure changes. He focused on issuer exchange offers and recapitalizations which changed financial leverage without a simultaneous change in asset structure. Stock price and firm value were positively related to increases in financial leverage. Nonconvertible senior security prices were negatively related to increases in financial leverage and the magnitude of these price changes was greater when the exchange offer or recapitalization involved securities of equal or greater seniority than those outstanding. This suggests changes in financial structure induce wealth transfers across security classes and bond indenture agreements are designed to

reduce or eliminate the risk of these wealth transfers. Masulis concluded that his results were consistent with the tax-based models of optimal capital structure.

There have also been several recent efforts at specifying alternative models of the optimal capital structure of the firm. Bradley, Jarrell and Kim [1984] develop a single-period model of the firm incorporating corporate and personal taxes, costs of financial distress (including direct bankruptcy costs and agency costs of debt), non-debt tax shields (eg. depreciation), and uncertain cash flows to the firm. The optimal use of debt is theoretically shown to be inversely related to the expected costs of financial distress and to the amount of non-debt tax shields. Further, if costs of financial distress are significant, a greater variability of firm earnings theoretically results in a lower optimum use of financial leverage. Bradley, Jarrell and Kim then found empirically that the variability of firm earnings helped explain both inter- and intra-industry variations in financial leverage. Firms and industries with a greater variability of earnings generally used less debt in their capital structure.

Kalaba, Langetieg, Rasakhoo, and Weinstein [1984] develop a partial differential equation model of firm value to estimate the bankruptcy costs implicit in security prices. Simulation was then performed to demonstrate that their "quasilinear estimation" may be a viable technique for estimating implicit bankruptcy costs. Kane, Marcus, and McDonald [1984] propose an

option valuation model with corporate and personal taxes to determine the size of the tax advantage of debt. Simulation results then indicate that variations in the size of bankruptcy costs across firms are insufficient to account for the existence of both levered and unlevered firms. Both of these model simulation approaches, however, are highly sensitive to model misspecification. Nevertheless, they do represent innovative approaches to the determination of optimal capital structure.

In summary, the preponderance of evidence supports the theoretical view of the optimal capital structure of the firm as a balancing of the tax advantage of debt against the various leverage-related direct and indirect costs of financial distress and the loss of non-debt tax shields. Furthermore, this balancing occurs in the presence of differential personal taxes on capital gains and ordinary income.

2.2.c Models Examined in this Research

In this study, both the Hamada and Conine models are incorporated into the methodology and empirically examined:

a. Hamada - corporate tax case

$$\beta L = \beta U + \beta U * (1 - TC) * (D / SL),$$

b. Conine - corporate taxes and risky debt

$$\beta L = \beta U + \beta U * ((1 - TC) * (D / SL)) - \beta D * ((1 - TC) * (D / SL)).$$

Reflecting their theoretical evolution, the models hopefully represent progressively more accurate portrayals of the systematic risk of common equity.

The models of financial structure of Section 2.2 are not tested beyond the Conine equation with risky corporate debt and corporate taxes. Although Yagill, for instance, has developed a theoretical model which incorporates costs of financial distress and personal tax rates, his model is difficult to empirically test. The exact functional form of the costs of financial distress is not known, and perhaps also varies across both industries and firms and over time. Heterogeneous personal tax rates likewise hamper investigations into the aggregate effects of personal taxes on systematic risk. This research is thus an attempt to extend the empirical literature beyond the Hamada relationship. No claim is made that this study represents or should represent the final word on the empirical relationship between capital structure and systematic risk.

2.3 The Systematic Risk of Corporate Bonds

The theoretical models and empirical results of Section 2.2 indicate that the riskiness of debt is a key factor affecting firm value and systematic risk. Since capital structure models including risky debt are examined in the present research, studies that have investigated the determinants and measurement of risky corporate debt are reviewed in this section.

2.3.a Firm Characteristics and the Systematic Risk of Debt and Equity

Early studies of risk in corporate bonds attempted to demonstrate a relationship between the business and financial risk of the firm and market-based estimates of the debt and equity beta. Fisher [1959] found that earnings variability, reliability in meeting financial obligations, financial leverage, and bond marketability all played a part in determining the risk premium on corporate bonds. The operating and financial decisions of the firm also affect the market expectations of investors and hence should contribute to the volatility of the firm's equity securities. Another early study by Beaver, Kettler, and Scholes examined the "Association between Market Determined and Accounting Determined Risk Measures" [1970]. Statistically significant correlations were discovered between the systematic risk of common stock and

several accounting measures. These included the dividend payout ratio, financial leverage, earnings variability, and earnings covariability with the earnings of other firms (or the 'accounting beta'). These two studies would indicate that the systematic risk of corporate debt is related to the internal operating and financial characteristics of the firm.

Reilly and Joehnk [1976] noted the relationship between internal corporate variables and the systematic risks of debt and common stock that had been demonstrated in the Fisher and Beaver, et.al. studies. The same internal corporate variables (financial leverage is of particular importance for this study) were then related to bond ratings and risk premiums on corporate debt. Noting that bond ratings (Moody's and Standard and Poor's) should reflect the internal risk characteristics of the firm, Reilly and Joehnk tested the hypothesis that systematic risk is an appropriate risk measure for a bond. That is, if the hypothesis is true, market-based measures of systematic risk should be inversely related to bond ratings. Seventy-three investment quality bonds (Moody's ratings Aaa to Baa) with maturities of 20 to 35 years were examined over a six year period. The market-determined systematic risk,

$$\beta_D = \text{corr}(\text{debt}, \text{market}) [\sigma(\text{debt}) / \sigma(\text{market})],$$

was calculated using market indices comprised entirely of either stock or of bond returns. No attempt was made to form an index combining the separate markets for stocks and bonds. As a result of their research, Reilly and Joehnk failed to find

an association between bond ratings and either the systematic risk or the total risk of the bonds.

This curious lack of association between bond ratings and the systematic risk of bonds deserves some further discussion. Reilly and Joshnk suggest that the market risk of a bond issue should be related to the financial characteristics of the firm. The reason for the observed lack of association then lies in the bond pricing mechanism and in the definition of systematic risk. Bond price changes arise primarily from changes in the level of interest rates. Macroeconomic variables, including changes in anticipated inflation, in Federal Reserve Board policy, and in the supply and demand for loanable funds, conspire to move interest rates. In contrast, new information regarding changes in the risk characteristics of a bond result in relatively fewer price changes. The correlation coefficient between bond price changes and price changes in the level of the market portfolio surrogate then depends primarily on changes in the macroeconomic determinants of interest rates and not on the riskiness of a particular offering. Also, for a high-quality bond offering, it is likely that the standard deviation of bond returns is likewise more closely linked to macroeconomic factors than to factors specific to the firm. Reilly and Joshnk's result is then not surprising. High-grade corporate bond yields move together and different corporate bonds have similar systematic risks irrespective of differences among the firms.

Weinstein [1981] investigated the systematic risk of corporate bonds in terms of default risk (bond ratings) and interest rate risk. He corroborated Reilly and Joehnk's bond rating results with many more bonds and an extended time period. The systematic risk of bonds was unrelated to bond ratings for investment quality bonds rated Aaa to Baa. For bonds rated Ba and below, however, there was a statistically significant correlation with beta. Lower rated bonds with higher risk of default exhibited higher systematic risk. Weinstein concluded that default risk does play some role in determining the beta of a medium or low-quality issue, but does not discriminate between the investment quality issues.

In order to examine interest rate risk, Weinstein regressed β_D on term to maturity and coupon rate. Term to maturity was positively related to the bond beta reflecting higher interest rate risk on long-term bonds. β_D was negatively related to the coupon rate. Higher coupons shorten the duration or effective maturity of the bond and thus reduce the exposure to unanticipated changes in the level of interest rates. In fact, bond price volatility is linearly related to the duration of a bond [Hopewell, M. and G. Kaufman, 1973]. Weinstein concluded that interest rate risk plays a key role in the determination of the systematic risk of corporate bonds. This result is consistent with Reilly and Joehnk's explanation of the lack of variation in the systematic risk of high-quality corporate bonds. Weinstein [1983] subsequently empirically

demonstrated that long term bonds have greater systematic risk than short term bonds, but that systematic risk is also positively related to the level of financial leverage and to the variability in firm value for bonds below investment quality.

Weinstein's results are consistent with Reilly and Joehnk's intuitive argument that bond ratings and bond betas should be inversely related. McEnally and Ferri [1982] claim that the relationship between the bond betas and their determinants is obscured because the *ceteris paribus* conditions seldom hold.⁶ That is, corporate bonds differ in coupon rate, term to maturity, marketability, the risk of call, sinking fund requirements, and other provisions of the bond indenture. They also differ in their response to changes in interest rates, risk premia, corporate leverage, tax clienteles, and other characteristics of the corporate and market environments. Finally, they differ in duration, which is a function of the coupon rate, term to maturity, and yield. And, of course, even the choice of market index affects both the level of bond betas and their sensitivity to changes in other factors. The real world is not a laboratory. The problem lies in the difficulty of examining changes in a single variable while holding all else constant.

⁶ McEnally and Boardman [1979] initially found that lower bond ratings are often associated with lower bond betas. In a later analysis, McEnally and Ferri [1982] reversed this finding in a multivariate setting and claimed that, *ceteris paribus*, bond ratings and the systematic risk of bonds are inversely related.

In sum, these studies indicate that the systematic risk of corporate debt is related to i) bond ratings, ii) maturity, and iii) the characteristics of the firm, including the use of financial leverage by the firm. More pertinent to this study, researchers have observed that, within rating classes, there is little variation in the systematic risk and required return of debt. Between rating classes, there is a small but statistically significant difference in systematic risk. This difference, however, appears to be dominated by the duration of the bond and by provisions of the bond issue.

2.3.b The Actual Estimation of β_D

An excellent place to begin a discussion of the actual estimation of bond betas is with a study by Alexander [1980]. Alexander investigated the shortcomings of applying the market model

$$R_{it} = a_i + b_i r_{mt} + e_{it},$$

to risky corporate debt. His sample included 63 investment quality (Moody's rating Aaa to Baa) corporate bonds with a term-to-maturity between 20 and 30 years over the six year period 1967 through 1972. Continuously compounded monthly returns adjusted for accrued interest were regressed on various market indices.⁷

⁷ In the presence of violations of the distributional assumptions on returns to debt, quadratic utility must be assumed to preserve the interpretation of the debt beta. Pratt [1965]

Theoretically, the choice of a market portfolio index should include a combination of marketable assets consisting of common and preferred stock, government and corporate bonds, commodities such as gold and silver, Old Masters paintings, and so forth. Human capital, a nontransferable asset, might also be included [see Fama and Schwert, 1977]. Most applications of the market model have, however, focused on the market for common stocks. A stock market index is then selected to represent this class of securities. When the market model is applied to corporate debt, a choice must be made as to the relevant market surrogate. Alexander selected the CRSP (Center for Research in Security Prices, University of Chicago) value weighted NYSE stock return index (including dividends and capital gains) to represent the stock market. As a proxy for high-grade corporate bonds, Ibbotson and Singuefield's Long - Term Corporate Bond Index was chosen. A third index was

has shown that quadratic utility exhibits increasing absolute risk aversion,

$$R(W) = - [u''(W) / u'(W)],$$

where W represents wealth. An individual exhibiting this behavior will assume less risk the larger his wealth. Since this conflicts with our intuition and with our observation of individual behavior, quadratic utility is of limited usefulness in explaining or predicting behavior. On the other hand, the use of quadratic utility has a long tradition in uncertainty analysis. It is roughly consistent with our observations of individual behavior. Individuals do prefer more to less, and its mathematical simplicity makes it a convenient and powerful tool in the analysis of decisions under uncertainty. While our assumption of quadratic utility is not a completely satisfactory solution to the problems encountered in applying the market model, it does salvage the interpretation of a bond beta as the contribution of debt to the total riskiness of a well-diversified portfolio.

constructed to represent the combined stock and bond markets. This index was a linear combination of the aforementioned stock and corporate bond indices and of Ibbotson and Sinquefeld's long-term government bond index. This aggregate index was composed of 60% common stock, 30% long-term corporate debt, and 10% long-term government debt. The market value weights were taken from the Federal Reserve Board "Flow of Funds" data.

Alexander then examined the distributional assumptions of in the market model. In the above market model regression equation, the following assumptions should hold:

- 1) Normal residuals $\epsilon_{it} \sim N(0, \sigma(\epsilon_{it}))$
- 2) No residual autocorrelation $\text{cov}(\epsilon_{it}, \epsilon_{it-1}) = 0$
- 3) Independent regressor and residuals
 $\text{cov}(\epsilon_{it}, r_{mt}) = 0$
- 4) Homoskedastic residuals $\sigma(\epsilon_{it}) = \sigma(\epsilon_{it-1})$

The assumption of zero mean residuals always holds in a simple regression model with a single independent variable. The OLS estimators of beta β and standard deviation $\sigma(e)$ are then unbiased and consistent [Schmidt, 35-38].

Residual nonnormality alone is not a serious problem since the OLS estimators maintain their unbiasedness and consistency. Nonnormality in the residuals does, however, have consequences for the distributions of the estimates of β and $\sigma(e)$. These estimates are no longer efficient (or even asymptotically efficient) estimators of beta and of the residual standard deviation. β is no longer normally

distributed, so interpretation of the standard error of the estimate is impaired. Tests of hypotheses concerning β and $\sigma(e)$ are no longer valid [Schmidt, 55-64]. Alexander used the studentized range test statistic of Fama [1976, pg 8]

$$SR = [\max(e_i) - \min(e_i)] / \sigma(e_i),$$

to test the hypothesis of normality. He was unable to reject normality when using either the stock or combined indices. However, when using the debt index, nearly half of his sample bonds demonstrated significant residual nonnormality.

Next, Alexander used the Durbin Watson statistic to test for autocorrelation in the error terms. The residuals e_{it} reflect the influence of all factors not explicitly included in the independent variable r_{mt} . When autocorrelation exists in the error term it means that all explanatory factors have not been captured in the independent variable. In the presence of residual autocorrelation, the estimate of beta remains unbiased but the confidence intervals around β can no longer be trusted because the estimate of the residual variance is no longer unbiased. Alexander concluded from the Durbin-Watson statistic that the autocorrelation assumption holds when using either the stock index or the combined index. However, when using the debt index, again nearly half of the bonds examined exhibited serial correlation in the residuals. Reilly and Joehnk [1976] also found significant autocorrelation when using a bond index and no significant autocorrelation when using a stock index.

The assumption of independence of the error term e_{it} and the independent variable r_{mt} is not of consequence under OLS since

$$\begin{aligned} \text{cov}(e_{it}, r_{mt}) &= \text{cov}(r_{it} - a_i - b_i r_{mt}, r_{mt}) \\ &= \text{cov}(r_{it}, r_{mt}) - \text{cov}(a_i, r_{mt}) - b_i * \text{cov}(r_{mt}, r_{mt}) \\ &= \text{cov}(r_{it}, r_{mt}) - [\text{cov}(r_{it}, r_{mt}) / \text{var}(r_{mt})] * \text{var}(r_{mt}) \\ &= 0. \end{aligned}$$

Regarding the last assumption, Alexander found no serious evidence of heteroskedasticity in the residual variance for any of the three market indices. He applied the Goldfeld-Quandt test (see Johnston, 1972) which determines if residual variance is an increasing function of r_{mt} . A more exact test may have revealed evidence of heteroskedasticity, but none was performed.

Nonstationarity in beta was also observed. Bond betas tended to rise over the early years of their life and decline in later years. The rise in the early years was apparently due to the rise in bond yields over the time period studied. The subsequent decline was due to the decreased interest rate risk and probability of default as the maturity date approached.

Thus, Alexander found serious violations of the regression conditions when a bond index was used. Less serious violations, primarily in the stability of beta over time, were observed with the stock and combined stock and bond portfolios. As such, violations of the regression assumptions are not severe when using a broad market index.

Nonstationarity in beta is the most worrisome, although nonstationarity is to be expected in fixed income, finite-maturity assets. Alexander concluded that caution should be exercised in the interpretation of results from bond market applications of the market model, especially when using a bond portfolio as the market surrogate. Applications of the market model to corporate debt when using a stock or combined market surrogate suffer the same limitations as when applied to common stocks alone.⁸

⁸ The choice of a market portfolio surrogate index is an important and difficult decision. Roll [JFE, 1977] has demonstrated the consequences of our inability to measure the ex ante or expected return on the market portfolio. All testable implications of the theory follow from the ex ante efficiency of this market portfolio. Without knowledge of the true market portfolio expected return, we are unable to test the market model or the CAPM. If an ex-post efficient index is used as the market return, then all securities will fall on the security market line and no security will exhibit abnormal performance. If an ex-post inefficient index is chosen, then the choice of a specific inefficient index will determine the measure of abnormal performance. Different ex-post inefficient indices will result in different rankings of abnormal performance. The validity of the CAPM must be jointly tested with market efficiency. Any test of a theory is necessarily dependent upon the accuracy of the empirical data used to test the theory. When the empirical data only approximates the true market portfolio expected return, this approximation also impairs the validity of our test of theory.

The market index should ideally consist of all marketable and nonmarketable risky assets, including stocks, bonds, commodities, Old Master paintings, human capital, and so forth. Returns for many of these assets do not conform to our assumption of normality, so we are forced to assume quadratic utility to preserve the CAPM. Even neglecting violations of the assumptions regarding the distribution of returns on assets, it is still virtually impossible to construct a market portfolio including all risky assets. This has prompted Ross [JF, 1978] to conclude "...for empirical work we are going to have to settle for looking at subsets of the whole set of assets."

In the literature, actual estimates of the systematic risk of bonds are fairly consistent when a stock portfolio or a combined stock and bond portfolio is used as the market surrogate. Table 2.1 presents several estimates of bond betas for various market indices and bond ratings. The range of estimates when using a stock portfolio is from 0.16 in the McEnally and Ferri study to 0.252 in the Sharpe study. Using a combined stock and bond market surrogate, the range was from 0.190 in the Weinstein study to 0.372 in the Alexander study. The studies used different market surrogates as well as bond samples and thus would be expected to yield slightly different estimates of the systematic risk of bonds. More importantly, the standard deviations (in parentheses) around each of the estimates consistently describe a distribution which does not vary much from the estimate itself. Thus, debt issues within a given rating class and, to an extent, between ratings classes, exhibit much the same levels of systematic risk.

The conclusion that may be drawn from this literature is that the systematic risk of corporate bonds is relatively uniform within a bond rating category. Consequently, when estimating the systematic risk of a levered firm by the Conine relationship,

$$\beta_L = \beta_U (1 + (1-TC) D/SL) - \beta_D ((1-TC) D/SL),$$

we do not need an estimate of β_D which is specific to each firm. At the most, all that is required is an estimate of the

systematic risk of bonds that are in the same rating class as the firm's bonds.

In this study, rather than generating a separate bond beta for each firm, a single beta estimate was applied to all of the sample firms. In accord with the results of Table 2.1, a bond beta of .30 (consistent with the use of a stock and bond market index) was selected. This choice provides a convenient and supportable means of empirically testing the Conine model.

Table 2.1 Previous Estimates of Bond Betas*

Researcher(s)	Market Index	Description	Estimated Bond Beta
Alexander [1980]	CRSP NYSE (Value Weighted)		0.2239 (0.0820)
	Aggregate:	ala Friend, 60% common stock et. al. 30% corp bonds 10% govt bonds	0.3719 (0.1177)
Friend, Westerfield, and Granito [1978]	Aggregate:	60% common stock 30% corp bonds 10% govt bonds	0.362 (0.139)
McEnally & Ferri [1982]	S&P 500	Aaa-Baa	0.186 (0.081)
	S&P 500	Aaa	0.160 (0.040)
	S&P 500	Baa	0.224 (0.123)
Reilly & Joehnk [1976]	S&P 500	Moody's Aaa-Baa Public Utilities	0.25
	S&P 500	Industrials	0.17
Sharpe [1973]	DJIA	Postwar 1946-1971	0.252
	DJIA & Keystone B-2 bond fund index		0.286
Weinstein [1981]	CRSP NYSE Value-Weighted	1962-1974	0.198
	Aggregate:	1962-1974 70% CRSP NYSE 30% Ibbotson and Singuefield Long-Term Corporate Bonds	0.190

* standard deviations in parentheses (where available)

Chapter 3 Systematic Risk - Underlying Theory

3.1 The Multi-Segment Firm

The Capital Asset Pricing Model (CAPM) of Sharpe[1964], Lintner[1965], and Mossin[1966] specifies a relationship between the systematic risk of an asset and its expected return:

$$E[k] = R_F + \beta (E[k_m] - R_F), \quad (3.1)$$

where

- $E[]$ = the expectations operator
- k = the random return on an asset
- R_F = the rate of return on riskless borrowing and lending
- k_m = the random return on the market portfolio
- β = the systematic (nondiversifiable) risk of an asset

Many firms, however, are comprised of several operating divisions. These conglomerate or multi-segment firms may be considered as a portfolio of individual assets. If a multi-segment firm includes n divisions or segments of industry i , then the total expected return of the portfolio of industries is

$$E[k] = \sum_i X_i * E[k_i], \quad (3.2)$$

where the X_i represent the proportion of the entire firm's assets invested in industry i . It follows that the systematic risk of the multi-segment firm is:

$$\beta = \sum_i X_i * \beta_i, \quad (3.3)$$

ie., a weighted average of the betas of the component assets where the market value proportions of the invested assets are

used as weights. Rather than treat the multi-segment firm as a single asset, we may consider it to be a portfolio of assets each with unique risk-return characteristics.

To demonstrate that $\beta = \sum_i X_i \cdot \beta_i$, define the covariance of return between two assets a and b as

$$\text{cov}(k_a, k_b) = \sum_o P_o \cdot (k_a - E[k_a])(k_b - E[k_b]) \quad (3.4)$$

where

$$\begin{aligned} \text{cov}(k_a, k_b) &= \text{covariance of return between a and b,} \\ k_a, k_b &= \text{return on assets a and b in state o,} \\ E[k_a], E[k_b] &= \text{expected return on assets a and b,} \\ P_o &= \text{probability of event o occurring } (\sum_o P_o = 1). \end{aligned}$$

Then the covariance of return between a portfolio c with expected return $E[k_c] = \sum_i X_i \cdot E[k_i]$ and the market portfolio m is

$$\begin{aligned} \text{cov}(k_c, k_m) &= \sum_o P_o (k_c - E[k_c]) (k_m - E[k_m]) \\ &= \sum_o P_o (\sum_i X_i \cdot k_i - \sum_i X_i \cdot E[k_i]) (k_m - E[k_m]) \\ &= \sum_o P_o [\sum_i X_i (k_i - E[k_i])] (k_m - E[k_m]) \\ &= \sum_i X_i [\sum_o P_o (k_i - E[k_i]) (k_m - E[k_m])] \\ &= \sum_i X_i \cdot \text{cov}(k_i, k_m). \end{aligned} \quad (3.5)$$

$$\begin{aligned} \text{Since } \text{cov}(k_c, k_m) &= \text{corr}(k_c, k_m) \cdot \sigma(k_c) \cdot \sigma(k_m) \\ &= \text{corr}(k_c, k_m) \cdot \sigma(k_c) \cdot \sigma^2(k_m) / \sigma(k_m) \\ &= \beta_c \cdot \sigma^2(k_m), \end{aligned} \quad (3.6)$$

where $\sigma(\)$ represents the standard deviation of the asset's returns, then

$$\begin{aligned} \beta_c \sigma^2(k_m) &= \sum_i X_i \cdot \beta_i \cdot \sigma^2(k_m) \\ \text{or } \beta_c &= \sum_i (X_i \cdot \beta_i). \end{aligned} \quad (3.7)$$

3.2 The Levered Firm with Risky Debt and Corporate Taxes

In 1958, Modigliani and Miller (MM) wrote their seminal paper on "The Cost of Capital, Corporate Finance, and the Theory of Investment". In this paper, MM established a methodological framework that has been followed by many subsequent studies of the cost of capital, capital structure, and the valuation of corporate securities. The conventions established by MM include the following set of assumptions:

- 1) Capital markets are frictionless
- 2) There are no costs of bankruptcy
- 3) Firms issue only equity and fixed-income debt securities
- 4) All cash flow streams are level perpetuities

The last assumption allows the use of the Gordon Valuation model with no growth; i.e.,

$$k = CF/Value \quad \text{or} \quad Value = CF/k,$$

where k is the required or expected return of investors and the before-tax cost of capital to the company, CF is the cash flow level of the perpetuity, and U is the present value or price of the claim. The cash flow streams may be random variables, in which case they must be stationary through time with a constant expected value $E[CF]$.

In addition, MM assumed that firms can be categorized into risk classes. Two firms a and b are in the same risk class if and only if their net operating returns are proportional;

i.e. $NOI_a = z * NOI_b$. The firms' operating cash flows differ only by a scale factor z . While MM's analysis relies heavily on this assumption, Mossin [1973, 119-124] has shown that, if quadratic utility is assumed, it is possible to value investments with completely arbitrary return distributions within the framework of the CAPM. Since proceeds to debt are nonnormal, we need to assume quadratic utility anyway to preserve our asset valuation model. As such, the MM assumption of the proportionality of operating returns will not be necessary in the subsequent CAPM analysis.

The following analysis is based primarily on Bierman and Oldfield's [1979] and Yagill's [1982] augmented MM model with risky corporate debt, but also draws from Conine [1980]. The following definitions describe the framework and are used throughout the analysis. Let u be an unlevered firm with cash operating income or cash flow before taxes X (a random variable). Let L be an otherwise identical levered firm with the same business risk and identically distributed operating cash flow X . After-tax proceeds from the infinite flow of earnings X are distributed to debt holders in the amount I (a random variable) with the residual after-tax cash flow distributed to equity holders. There are no personal taxes on interest income or dividends. No earnings are reinvested in the firm.

Next, define the following:

k_u, k_L	random equity returns such that $E[k]$ is expected return and k is required return
------------	--

kd	random return on debt
I	random interest payment to debt
D	market value of debt such that $D = E[I] / kd$
km,Rf	random after-tax market return and risk-free rate of return
Su,SL	market value of equity
Vu,UL	total firm value such that $Vu=Su$ and $UL=SL+D$
Z	the market price of risk such that $Z = (E[km]-Rf)/var(km)$
cov(s,t)	covariance between random variables s and t
T	corporate tax rate
E[]	expected value

The random cash flow available to the unlevered firm is

$X(1-T)^1$. Using the Gordon no growth relationship and the CAPM,

$$\begin{aligned} k_u &= E[CF]_u / \text{Value}_u \\ &= E[X] (1-T) / S_u, \end{aligned} \quad (3.8)$$

$$\text{so that} \quad E[X] (1-T) = k_u * S_u. \quad (3.9)$$

¹ This tax rate is in fact an average tax rate over the taxable income of the firm. Consider the case where there are M marginal tax rates $t_1, t_2, \dots, t_M$ such that $0 \leq t_1 \leq \dots \leq t_M \leq 1$ over the marginal taxable income brackets $X_1, X_2, \dots, X_{M-1}, X_M$ (X_M could be set equal to infinity, the maximum income the firm may earn). Let the underscore character "_" denote a vector dimensioned $1 \times M$ so that $\underline{X} = [X_1, X_2, \dots, X_M]'$ and $\underline{I} = [t_1, t_2, \dots, t_M]'$. Let $\underline{N} = [1, 1, \dots, 1]'$ be an identity matrix dimensioned $1 \times M$. If the corporation earns operating income

$$X = X_1 + X_2 + \dots + X_M = \underline{X}' * \underline{N}$$

over the M brackets, then total after-tax corporate income is

$$\begin{aligned} &X_1(1-t_1) + X_2(1-t_2) + \dots + X_M(1-t_M) \\ &= \underline{X}' * (\underline{N} - \underline{I}) \\ &= \underline{X}' * (1 - t_{avg}) \\ &= X * (1-T) \end{aligned}$$

where T = the average tax rate over all income of the firm. The total after-tax corporate income is simply the before-tax income times the average tax rate. Similarly, for a firm with interest payments on debt I, after-tax income may be defined as $(X-I)*(1-T)$ where T is again the average tax rate over the (levered) taxable income $(X-I)$. The following proofs are based on cash flows to the levered and unlevered firms and are thus correct in a world with marginal tax brackets so long as T is interpreted as the average tax rate over all taxable income of the firm. If the corporate tax rate is a single flat rate tax, then this is the average tax rate as well.

If the financing and investment decisions of the firm are independent so that $X_u = X_L = X$, then for a firm with corporate taxes and risky corporate debt such that $D = E[I]/k_d \Rightarrow E[I] = k_d * D$,

$$\begin{aligned} k_L &= [(E[X] - E[I])(1-T)] / SL \\ &= [E[X](1-T) - E[I](1-T)] / SL \\ &= [E[X](1-T) - (k_d * D)(1-T)] / SL \end{aligned}$$

so that

$$E[X](1-T) = (k_L * SL) + (k_d * D)(1-T). \quad (3.10)$$

Equating equations (3.9) and (3.10) gives

$$k_u * S_u = (k_L * SL) + (k_d * D)(1-T). \quad (3.11)$$

Note that $U_L = U_u + ID$

so that $SL + D = U_u + ID$

$$= S_u + ID,$$

and $S_u = SL + D(1-T). \quad (3.12)$

Solving (3.11) for the required return on the levered equity,

$$\begin{aligned} k_L &= ((k_u * S_u) / SL) - k_d (D / SL)(1-T) \\ &= k_u (SL + D(1-T)) / SL - k_d (D / SL)(1-T) \\ &= k_u [1 + (D / SL)(1-T)] - k_d (D / SL)(1-T). \end{aligned} \quad (3.13)$$

According to the CAPM,

$$k_L = R_f + Z \text{ cov}(k_L, k_m),$$

$$k_u = R_f + Z \text{ cov}(k_u, k_m),$$

and $k_d = R_f + Z \text{ cov}(k_d, k_m). \quad (3.14)$

Substituting equations (3.14) into equation (3.13) and simplifying,

$$k_L = [R_f + Z * \text{cov}(k_u, k_m)] [1 + (D / SL)(1-T)]$$

$$\begin{aligned}
& - [R_f + Z \cdot \text{cov}(k_d, k_m)] [(D/SL)(1-T)] \\
= & R_f [1 + (D/SL)(1-T) - (D/SL)(1-T)] \\
& + Z \cdot \text{cov}(k_u, k_m) \\
& + Z \cdot \text{cov}(k_u, k_m)(D/SL)(1-T) \\
& - Z \cdot \text{cov}(k_d, k_m)(D/SL)(1-T) \\
= & R_f + Z \cdot \text{cov}(k_u, k_m) \\
& + Z \cdot \text{cov}(k_u, k_m)(D/SL)(1-T) \\
& - Z \cdot \text{cov}(k_d, k_m)(D/SL)(1-T) \tag{3.15}
\end{aligned}$$

$$= R_f + Z \cdot \text{cov}(k_L, k_m). \tag{3.16}$$

Subtracting the risk-free rate R_f from both sides of (3.15) and (3.16),

$$\begin{aligned}
[Z \cdot \text{cov}(k_L, k_m)] = & Z \cdot \text{cov}(k_u, k_m) \\
& + Z \cdot \text{cov}(k_u, k_m)(D/SL)(1-T) \\
& - Z \cdot \text{cov}(k_d, k_m)(D/SL)(1-T). \tag{3.17}
\end{aligned}$$

But, from the definition of Z ,

$$\begin{aligned}
Z \cdot \text{cov}(k_L, k_m) = & [(E[k_m] - R_f) / \text{var}(k_m)] \text{cov}(k_L, k_m) \\
= & \beta_L [E[k_m] - R_f],
\end{aligned}$$

$$Z \cdot \text{cov}(k_u, k_m) = \beta_u [E[k_m] - R_f],$$

$$\text{and } Z \cdot \text{cov}(k_d, k_m) = \beta_d [E[k_m] - R_f]. \tag{3.18}$$

Substituting equations (3.18) into equation (3.17), and solving for the systematic risk of the levered firm's equity,

$$\beta_L = \beta_u + \beta_u (D/SL)(1-T) - \beta_d (D/SL)(1-T),$$

$$\text{or } \beta_L = \beta_u [1 + (D/SL)(1-T)] - \beta_d [(D/SL)(1-T)] \tag{3.19}$$

$$= \beta_u [(SL + D(1-T))/SL] - \beta_d [(D/SL)(1-T)],$$

which is precisely the relationship derived by Conine [1980]2,

$$\beta_L = \beta_U (S_u/SL) - \beta_D (D/SL)(1-T). \quad (3.20)$$

In equation (3.19), it is evident that the systematic risk of a levered firm with risky debt and corporate taxes consists of an operating risk component β_U , a financial risk component which reflects corporate taxation $[1+(D/SL)(1-T)]$, and a risk component arising from the use of risky debt in the presence of corporate taxation $[\beta_D(D/SL)(1-T)]$.

Multiplying each side of equation (3.19) by $[E[km]-R_f]$ and adding the risk free rate of return, we obtain the required equity rate of return for the levered firm L:

$$\begin{aligned} k_L &= R_f + \beta_L [E[km]-R_f] \\ &= R_f + [\beta_U (1+(D/SL)(1-T))] [E[km]-R_f] \\ &\quad - [\beta_D (D/SL)(1-T)] [E[km]-R_f]. \end{aligned} \quad (3.21)$$

2 Recall from footnote 1 that T represents the average tax rate of the firm. Similarly, beta represents the average systematic risk of equity over all assets of the firm.

3.3 The Levered Multi-Segment Firm with Risky Debt and Corporate Taxes

Given the systematic operating risk components $i\beta_u$ of the unlevered firm with $i = 1, 2, \dots, n$ segments, the unlevered systematic risk of the entire firm as a portfolio of segments is .

$$\beta_u = \sum_i X_i * i\beta_u.$$

To 'lever-up' this β_u by the previously derived relationship, let

$$\begin{aligned} \beta_L &= \beta_u [1 + (D/SL)(1-T)] - \beta_d (D/SL)(1-T) \\ \text{or } \beta_L &= [1 + (D/SL)(1-T)] [\sum_i X_i * i\beta_u] \\ &\quad - \beta_d (D/SL)(1-T) \end{aligned} \quad (3.22)$$

The systematic risk of a levered multi-segment firm is composed of a financial risk component $[1 + (D/SL)(1-T)]$, the weighted sum of the segmental systematic operating risks $i\beta_u$ using market value proportions X_i as weights, and an adjustment for risky corporate debt in the presence of corporate taxes $\beta_d(D/SL)(1-T)$. Notice the implicit assumption that all segments of the multi-segment firm share in the financial leverage of the firm. If the investment and financing decisions of the firm are independent, this is not a debilitating assumption. A more intensive investigation of the debt capacity of the individual segments of the firm will not be undertaken.

3.4 The Levered Multi-Segment Firm with Risky Debt, Corporate and Personal Taxes, and Bankruptcy Costs

Yagill [1982] extends the above analysis to include:

te = personal tax rate applicable to equityholders
 td = personal tax rate applicable to debtholders
 qD = bankruptcy costs as a function of the amount of debt
 (Yagill assumes this is a linear function of debt)

The after-tax cash flow available to the unlevered firm's equityholders is $X(1-T)(1-t_e)$. If k_u is the after-tax required return on the common stock value of S_u , then, under the perpetuity model,

$$\begin{aligned} U_u &= S_u \\ &= E[X] (1-T) (1-t_e) / k_u, \end{aligned} \quad (3.23)$$

which implies

$$\begin{aligned} k_u &= X (1-T)(1-t_e)/S_u \\ &= R_f + Z \text{ cov}(k_u, k_m), \end{aligned} \quad (3.24)$$

so that

$$\begin{aligned} X (1-T)(1-t_e) &= k_u * S_u \\ &= S_u * [R_f + Z \text{ cov}(k_u, k_m)]. \end{aligned} \quad (3.25)$$

The expected after-tax cash flow to equityholders of the levered firm is $[(E[X]-E[I])(1-T)(1-t_e)]$. The value of the levered firm with risk-free debt in this case has been shown by Miller [1977] to be:

$$U_L = U_u + D * \{1 - [(1-T)(1-t_e)/(1-t_d)]\}. \quad (3.26)$$

When debt is risky and bankruptcy costs exist, the value of a levered firm will be the value of the unlevered firm plus the

value of the tax shield from the tax deductibility of interest expense minus the value of the bankruptcy costs:

$$\begin{aligned}
 V_L &= V_U + D * (1 - [(1-T)(1-t_e)/(1-t_d)]) - qD \\
 &= V_U + QD \\
 &= S_U + QD
 \end{aligned} \tag{3.27}$$

where $Q = \{ 1 - [(1-T)(1-t_e)/(1-t_d)] - q \}$ adjusts for leverage and bankruptcy costs. The required rate of return of equityholders is then given by:

$$\begin{aligned}
 k_L &= [(E[X] - E[I])(1-T)(1-t_e) / SL \\
 &= [E[X](1-T) - E[I](1-T)](1-t_e) / SL \\
 &= [E[X](1-T)(1-t_e) - (k_d * D)(1-T)(1-t_e)] / SL \\
 &= R_F + Z \text{ cov}(k_L, k_M),
 \end{aligned} \tag{3.28}$$

so that

$$E[X](1-T)(1-t_e) = (k_L * SL) + k_d (D/SL) (1-T) (1-t_e). \tag{3.29}$$

Equating equations (3.25) and (3.29) gives

$$k_U * S_U = (k_L * SL) + k_d (D/SL) (1-T)(1-t_e). \tag{3.30}$$

Next, note that $V_L = S_L + D$

$$\begin{aligned}
 &= S_U + D * [1 - (1-T)(1-t_e)/(1-t_d)] - q * D \\
 &= S_U + QD,
 \end{aligned}$$

$$\text{so that} \quad S_U = S_L + D(1-Q). \tag{3.31}$$

Solving (3.30) for the required return on levered equity,

$$\begin{aligned}
 k_L &= [k_U (S_L + D(1-Q)) / S_L - [k_d (D/SL) (1-T)(1-t_e)]] \\
 &= k_U [1 + (D/SL)(1-Q)] - [k_d (D/SL) (1-T)(1-t_e)] \\
 &= k_U + [k_U(1-Q) - k_d(1-T)(1-t_e)] (D/SL),
 \end{aligned} \tag{3.32}$$

which is precisely the relationship derived by Yagill.

Yagill then develops the systematic risk of the levered and unlevered equity and of debt as follows. The after-tax cash flows to the owners are

$$\begin{aligned} Y_u &= X (1-T)(1-t_e) \\ Y_d &= I (1-t_d) \\ Y_L &= (X-I)(1-T)(1-t_e), \end{aligned} \quad (3.33)$$

so the after-tax required rates of return are

$$\begin{aligned} k_u &= E[Y_u] / S_u \\ k_d &= E[Y_d] / D \\ k_L &= E[Y_L] / S_L. \end{aligned} \quad (3.34)$$

The systematic risk of each security is then:

$$\beta_u = \text{cov}(k_u, k_m) / \text{var}(k_m), \quad (3.35)$$

$$\beta_d = \text{cov}(k_d, k_m) / \text{var}(k_m), \quad (3.36)$$

$$\beta_L = \text{cov}(k_L, k_m) / \text{var}(k_m). \quad (3.37)$$

Expanding the equations,

$$S_u \beta_u = (1-T)(1-t_e) \text{cov}(X, k_m) / \text{var}(k_m) \quad (3.38)$$

$$(D \beta_d) / (1-t_d) = \text{cov}(I, k_m) / \text{var}(k_m) \quad (3.39)$$

$$\begin{aligned} S_L \beta_L &= (1-T)(1-t_e) \text{cov}(X, k_m) / \text{var}(k_m) \\ &\quad - (1-T)(1-t_e) \text{cov}(I, k_m) / \text{var}(k_m) \end{aligned} \quad (3.40)$$

and substituting (3.38) and (3.39) into (3.40), yields

$$S_L \beta_L = \beta_u * S_u - [(1-T)(1-t_e) \beta_d * D / (1-t_d)] \quad (3.41)$$

which simplifies to

$$\beta_L = [\beta_u * S_u / S_L] - [\beta_d * \{(1-T)(1-t_e) / (1-t_d)\} (D / S_L)]. \quad (3.42)$$

$$\text{Since } V_L = V_u + QD, \quad (3.43)$$

$$\text{then } V_u = S_u = V_L - QD$$

$$= (SL + D) - QD$$

$$= SL + D(1-Q). \quad (3.44)$$

Finally, substituting for S_u in (3.42),

$$\beta_L = \beta_u + [(1-T)(1-t_e)/(1-t_d)]$$

$$\cdot [\beta_u(1+(q/[(1-T)(1-t_e)/(1-t_d)])) - \beta_d] \cdot D/SL, \quad (3.45)$$

which is the levered beta relationship of Yagill.

Chapter 4 Research Design and Methodology

4.1 Operationalizing the Model

Information was obtained from Ibbotson and Sinquefeld's Stocks, Bonds, Bills, and Inflation: 1984 Yearbook, from the University of Chicago's CRSP (Center for Research in Security Prices) monthly stock return tapes, and from Value Line's database tapes. Ibbotson and Sinquefeld provide monthly holding period returns on several market indices including common stocks, small capitalization stocks, long-term U.S. corporate bonds, and U.S. Treasury bills. The CRSP database provides monthly holding period returns for approximately 3000 firms from 1926 through the present. The Value Line database contains accounting and financial information for over 1600 major companies. To be included in the single or multi-segment samples, a firm must have information available both on the CRSP and the Value Line databases.

Variables available on the Value Line database include:

Field	Description
-----	-----
1	Cusip #: unique identifier assigned and maintained
2	Cusip suffix #: by American Bankers Association
3	Ticker symbol
5	ISIC Standard Industry Classification
7	Data year
56	Total reported liabilities
94	Income tax rate
157	Average annual price (of weekly highs and lows)
160	Common shares outstanding at end of fiscal year
287,288	Division A VL Industry Code and Restated Sales

291,292	Division B UL Industry Code and Restated Sales
.	.
.	.
323,324	Division J UL Industry Code and Restated Sales
416	IULSIC Value Line assigned Standard Industry Classification

Value Line provides line-of-business data for only the most recent four year period. The sample period includes January, 1979 through December, 1982, the most recent four year period for which complete information is available. The sample period and the associated beta estimation periods are illustrated in Figure 4.1.

The discussion which follows outlines the sample selection, describes the construction of each of the variables utilizing data from the Value Line and CRSP data bases, and specifies any concessions made in the data selection. While an empirical study should utilize the most accurate and representative data available, budget and data force some simplifications.

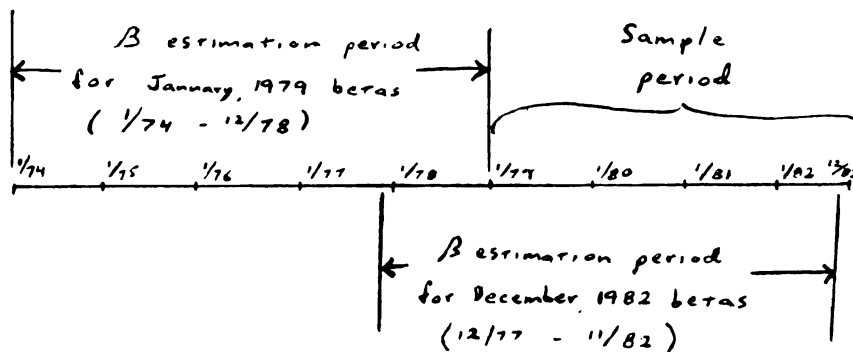


Figure 4.1

4.1.a Standard Industry Classifications

The Standard Industry Classification (SIC) code is a four-digit code which classifies each firm in the data base into an industry category. Four-digit codes represent the most restrictive classification, three-digit codes represent a broader industry classification, and two-digit codes represent the broadest classification. For instance, 4900 is the 2-digit code for Electric, Gas, and Sanitary Services, 4920 is the three-digit code for Gas Production and Distribution, and 4922 is the four-digit code for Natural Gas Transmission.

Value Line provides two firm-wide standard industry classifications, ISIC (field 5) and IVLSIC (field 416), for each firm in the database. The ISIC classification is self-assigned by the firm and its auditors, while Value Line independently assigns the IVLSIC code. Unfortunately, these industry classification codes are not often in agreement. In addition, Value Line provides an industry classification for each segment of the multi-segment firm (fields 287, 291, ..., 323).

Individual firms handle their segmental disclosure in different ways. FASB No. 14 (paragraph 10a) defines an industry segment in terms of products and services that are sold primarily to unaffiliated customers. Vertically integrated companies with many intracompany sales, such as General Motors, are thus not required to disaggregate their

operating divisions or profit centers into segments unless the products or services of these profit centers are a significant proportion (defined as greater than 10%) of the total operations of the firm. FASB No. 14 (paragraph 100) also sets up standards for determining industry segment classifications according to the nature of the product, the nature of the production process, and the markets or marketing methods used.

This variety of suggested classification standards impairs the comparability of segments across firms. The assignment of each segment to a standard industry classification may not be uniform across firms. Further, similar single segment firms may be classified in different industries.

The industry classifications assigned by Value Line are used throughout the empirical analysis of this study. At a minimum, this ensures that the assignment of each firm or segment of a firm to an SIC code has been performed on some sort of a consistent basis. The following discussion provides further evidence that the Value Line industry codes are a better choice in the present application.

Based on the sample selection criteria of the next section, 235 firms were classified as multi-segment firms. There are 885 yearly observations available from the Value Line database on the multi-segment sample over the four year sample period 1979-1982. The ISIC and IUSIC codes fail to match for 492 of the 885 observations (56%). The remaining 393 observations match at least at the 2-digit level (eg. 48xx).

Of these, 171 match at the 3-digit level (19% of the observations) and only 74 match on all four digits (8%).

Upon inspection of the sample of multi-segment firms, Value Line's segmental industry classification codes are in fact more closely related to their IVLSIC codes than to the ISIC codes assigned by the firm. Of the 885 multi-segment firm observations over the sample period (235 firms over four years), the segmental industry code of the primary segment based on sales matches the Value Line IVLSIC code at the two digit level in 456 of the cases and the SIC code in 391 of the cases. These overlap, of course, whenever the primary segment and the IVLSIC and SIC codes are identical. The multi-segment firm's IVLSIC code and primary segment industry code match at the three and four digit levels for 376 (42%) and 335 (38%) of the firms, respectively. The ISIC matches the primary segment's industry code for 164 firms at the 3-digit level and for only 58 of the firms at the four digit level.¹ For this reason, the Value Line IVLSIC code is used throughout the analysis to classify single segment firms and the industry segments of multi-segment firms.

1 The 235 multi-segment firms included 3436 different lines-of-business over the four year sample period. Of these industry segments, the number of matches with the IVLSIC code at the 2-, 3-, and 4-significant digit level are 997, 658, and 557 segments, respectively. The corresponding matches with the ISIC code are only 850, 314, and 91 segments. This provides further motivation for using industry codes assigned by Value Line to identify industry segments and single segment firms.

4.1.b Sample Selection

Since an adjustment for financial leverage is central to all of the theoretical systematic risk relationships, the empirical analysis is restricted to multi-segment firms that are primarily non-financial in nature. Financial companies (banks, insurance companies, and so forth) possess unique leverage positions because of the financial nature of their assets. Many commercial banks, for instance, have equity capital positions of only five or six percent, while the average equity to total capital ratio for U.S. retailing and manufacturing firms is closer to fifty percent (Federal Trade Commission, Quarterly Financial Reports). Including both financial and nonfinancial firms and performing leverage adjustments on the combined sample would mix two very different forms of business enterprise.

Firms were classified as non-financial if their primary segment industry classification based on sales was not finance-related. The standard industry classification codes between 6000 and 6999 include the banking, credit, brokerage, insurance, and real estate industries as well as financial holding companies and conglomerates. Any firm with a primary segment based on sales with a 6XXX SIC code was eliminated from the sample. By eliminating companies that are primarily financial, focus is placed on a more homogeneous set of multi--

segment firms in terms of the use of financial leverage and the nature of their assets.

The sample of multi-segment firms should ideally include those firms which are the most broadly diversified across major industry boundaries. The sample of single segment firms should in contrast include those firms which are primarily invested in a single line of business and should exclude firms which have a significant investment in several lines of business. As would be expected of the very large and often diversified firms on the major exchanges, most of the firms on the Value Line data base report more than one segment. Many of these firms, however, are primarily invested in the same general type of business and have the same 2-, 3- or 4-digit standard industry classification code assigned to many or all of their segments. In this study, these segments were assumed to be in the same industry.²

Several filters were applied to determine an acceptable trade-off between maximizing the resolution of the statistical tests through a large sample size and minimizing the

2 Inclusion of firms which are almost entirely invested in a single industry, even though reporting several segments, might tend to increase the correlation coefficient between market-based and segmental beta estimates. Klemme [1983] hypothesized but failed to find this relationship in a study of accounting- and market-based betas. She concluded that there was simply too much noise in the accounting-based LOB betas to discover the relationship. The present study, however, is not intended to focus on the homogeneity of systematic risk within standard industry classifications. Although some homogeneity in the operating component of systematic risk (B_u) is assumed, the primary emphasis will be on developing an alternative measure of systematic risk for the multi-segment firm.

consequences of an inappropriate classification of multi-segment and single segment firms. An initial screening of the Value Line data base categorized the firms according to the percent of sales in the primary segment for all four years in the sample period. Summary statistics are shown in Table 4.1 for those firms reporting line-of-business data.

Based on this profile, it was decided to define the multi-segment firms as those firms which had less than or equal to sixty percent of sales in their primary segment. After eliminating financial companies and companies with missing data, the sample consisted of 235 firms. A list of this sample of multi-segment firms appears in Appendix B. A list of industries by SIC code in which the multi-segment firms are engaged appears in Appendix C.

In forming the industry portfolios, single-segment firms were defined as those firms included in both the CRSP and the Value Line databases which either do not report line-of-business data or report multiple segments each with the same 2-, 3- or 4-digit SIC code. This included approximately 1000 firms in the industry portfolios. After elimination of financial firms and firms in industries which were not referenced in the multi-segment sample, the sample of single segment firms was reduced to 653 firms. Also shown in Appendix C are the number of single segment firms in each industry classification.

Each industry segment in the sample of multi-segment firms was matched with a corresponding industry portfolio containing

at least three single-segment firms. In matching each industry segment with the corresponding industry portfolio, an industry segment of 4920 was matched with an industry portfolio including all single-segment firms having a Value Line SIC code of 4920. (Note that the 3-digit SIC code 4920 includes the 4-digit codes 4921 through 4929.) If there were less than three single segment firms included in this portfolio, then the industry segment was matched with firms in the more general 4900 industry classification. In this fashion, each segment was matched with a corresponding industry portfolio which approximated the underlying business of the segment. Simultaneously, the benefits of the portfolio effect in forming the pure play industry portfolios were retained.

TABLE 4.1 PERCENT OF SALES IN PRIMARY SEGMENT *

Year	0-10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	TOTAL
1979	0	0	6	49	84	106	115	101	142	85	688
1980	0	0	10	58	109	138	135	123	162	113	848
1981	0	0	13	66	101	135	139	128	163	103	848
1982	0	0	16	62	95	140	151	125	153	105	847

* cell entries represent number of firms from the Value Line database

4.1.c Operationalizing the Variables

Market-based historical OLS beta estimates for the multi-segment firms in the sample are obtained by using monthly data in the market model regression equation:

$$R_{jt} = \alpha_j + OLS\beta_j * (R_{mt}) + e_{jt}. \quad (4.1)$$

The market index is a composite index combining 70% Ibbotson and Sinquefeld's value-weighted common stock returns³ (including dividends and capital gains) with 30% Ibbotson and Sinquefeld's Long-Term Corporate Bond Index.⁴ These weights represent the approximate proportional values of outstanding corporate debt and equity as recorded in the Federal Reserve Board's "Flow of Funds" data.

Monthly holding period return vectors are formed for each industry by equal weighting the returns of the component securities. The vector of arithmetic mean returns for the industry is then calculated as the arithmetic average of the single segment firms in the industry, and the industry beta is

³ Recently, Elgers and Murray [1982] suggested that beta-association studies may be enhanced by the use of an equal-weighted market return index, while beta-prediction studies may benefit from the use of a value-weighted index. This study focuses not just on the correlation of OLS and segmental beta estimates but also on the relative predictive and explanatory power of alternative beta estimates. The emphasis here is on the differences as well as the similarities of OLS and segmental beta estimates.

⁴ Since Conine's leverage adjustment (equations 4.2 and 4.4) includes bond betas, the market index should include both debt and equity markets. The combined debt and equity market index follows Weinstein [1981]. See the discussion in Section 2.3.

estimated with regression equation (4.1) by using a 60-month moving average for each month in the sample period. The beta at time t is calculated using returns for the prior 60 months (time $t-60$ through $t-1$), so each beta estimate is based on return information available from the preceding periods (see Figure 4.1).

Another approach considered was the value weighting of the single-segment firms to reflect the average industry beta in market value terms. This would, however, allow a single large firm to dominate an industry and would mitigate the portfolio effect of combining many firms into an industry portfolio. The equal weighting scheme forms an estimate of systematic risk which is equal to the average firm in the industry rather than the market value industry average. The equal weighting scheme also greatly reduces the computational requirements of combining the single segment firms into industry portfolios with up to 4 years of 60-month moving average data.

Rosenberg and Marathe [1975] alternatively suggest assigning firm weights which are inversely proportional to the residual variance of the market model regression used to calculate the firm betas. This weighting scheme places more weight on those firms with the greatest beta estimation efficiency. The Rosenberg-Marathe weights would, however, require the calculation of 60-month moving average betas for each firm and for all four years and the subsequent weighted

averaging of the firm betas in each industry. In contrast, equal weighting allows first the simple aggregation arithmetic averaging) of industry returns and then the calculation of a single 60-month moving average monthly industry beta vector over the four year period. It is also noted that the Rosenberg-Marathe approach relies on a statistical rather than an economic rationale.

The calculated vector of monthly industry betas was then unlevered according to the Hamada and the Conine leverage adjustments. For example, industry betas are adjusted for financial leverage using the Conine equation as

$$IND\beta CON = [\beta L + \beta D(1-T)(D/SL)]/[1 + (1-T)(D/SL)]. \quad (4.2)$$

The average industry debt/equity ratio (D/SL) is determined by dividing total industry debt by total industry equity.⁵ Total industry debt and equity are calculated by summing Value Line field 56 (total reported liabilities) and the product of fields 157 and 160 (number of shares outstanding times share price) across all firms in each industry.

Bowman [1978, 1980] examined the relationship between accounting and market values of debt and equity in a beta association context. He found that book values of debt and market values of equity provide debt-to-equity ratios that correlate most closely with market-determined beta measures.

⁵ Since the debt-to-equity ratio is non-linear, i.e. $D/S = D/(U-D)$, the average industry debt-to-equity ratio is not equal to the average of the individual firm i debt-to-equity ratios. That is,

$$(INDD/INDS) \neq (1/n) \left(\sum_i (D_i/S_i) \right).$$

Following this result, the book value account "total reported liabilities" (field 56) is used as a proxy for the market value of debt in the leverage adjustment equations. The market value of equity is calculated directly as the average annual price (field 157) times the number of common shares outstanding at the end of the fiscal year (field 160). These surrogates then represent an acceptable approximation to the average market value of debt and equity in equation (4.2).

While the levels of debt and equity are fairly constant over time for most firms in the sample, the tax rates vary widely over time and hence have a much greater impact on the leverage adjustments to systematic risk. The income tax rate T (field 94) is defined by Value Line as "federal, foreign, state and local income taxes, including deferred taxes and tax credits, divided by pretax income" and represents the actual (or average) tax rate on accounting income.

Value Line also provides the reported tax rate defined as "federal, foreign, state and local income taxes, including deferred taxes reported to stockholders, divided by pretax income". The difference between the reported and actual tax rate lies in the exclusion of tax credits in the reported tax rate. Actual tax rates are used in the leverage adjustments since they represent the percentage of pre-tax accounting income actually paid in taxes.

Marginal rather than average tax rates are generally used in investment and financing decisions where a decision may

change the assets, cash flow, or capital structure of the firm. But since the Conine relationship (4.2) is descriptive of the systematic risk of the entire levered firm's debt and equity, it is a description of the average systematic risk of all the assets of the firm. As such, in this application of the Conine relationship, the actual (average) tax rate rather than the marginal tax rate is used (See footnote 3 in Section 3 for a formal argument).

Most firms report actual tax rates (Value Line field 94) of between 20-50% for the period 1979-1982. The average tax rate for the period was approximately 35-40% for both the multi-segment firm sample and the single segment firms comprising the industry pure-play portfolios. A summary of the single and multi-segment firms' tax rates for the years 1979-1982 appears in Table 4.2.

A potential problem arises upon inspection of the table. Actual tax rates reflect taxes on operations as well as deferred taxes, tax credits, and taxes on extraordinary items. Because of these special items, actual tax rates are negative for about 2.5% of the firms and greater than 100% of pretax income for about 0.3% of the firms. In fact, the range of tax rates for single segment firms is from +1406% (ticker symbol CUM, fiscal year 1980) to -856% (ticker symbol SPY, 1982). The tax rates are unavailable from the Value Line tapes for between five and ten percent of the firms during the four year sample period.

The MM model is based on perpetual cash flows from operations. If special tax items and the attendant extreme tax rates are used in the leverage adjustment equations, the unlevered or industry operating betas will be grossly misrepresented. A value of $T=14.06$ or $T=-8.56$ in the Conine equation, for instance, will yield nonsense values for the unlevered industry betas. Similarly, nonrecurring extreme tax rates for multi-segment firms are inappropriate when relevering the pure-play divisional betas to form the multi-segment firms' segmental beta estimates.

In such circumstances, since the size of any special tax item in such a circumstance dominates the tax rate on operations, a best guess of the actual tax rate from operations may simply be the average tax rate in the sample. To accommodate the financial leverage models while retaining as many firms in the sample of single and multi-segment firms as possible, a tax rate of 40% (approximately equal to the average tax rate for all the firms in the single and multi-segment samples) was assumed for any year and any firm with an actual tax rate of either less than zero percent, greater than 60%, or one which is missing from the database. This assumed tax rate is reasonable, if somewhat arbitrary.

From section 2.3, it is clear that the single most influential determinant of the systematic risk of corporate debt, B_d , is a change in the level of interest rates. Individual bonds within a particular rating class differ only

slightly in terms of systematic risk. Empirical beta estimates reported in the literature and based on stock and bond market indices range from 0.17 to 0.37 (see Table 2.3). To maintain consistency with these estimates, a debt beta of 0.3 is assumed throughout this study.

The segmental beta estimates for each multi-segment firm in the sample are then formed by weighting the betas of the leverage-unadjusted pure-play industries and by applying either the Hamada or the Conine leverage adjustments. For example, using the Conine relationship,

$$\beta_{CON} = \beta_{UNCON} * [1 + (1 - T)(D/SL)] - \beta_{DEBT}(1 - T)(D/SL). \quad (4.4)$$

In this expression, the unlevered beta of the multi-segment firm (β_{UNCON}) is the beta of the portfolio of unlevered industry segmental betas. That is,

$$\beta_{UNCON} = \sum_i X_i * \beta_{UNCONi}, \quad (4.5)$$

where X_i is the proportion of firm sales in segment i and β_{UNCONi} is the unlevered industry beta of segment i according to the Conine relationship. The debt/equity ratio, income tax rate, and beta of debt are as described above. The resulting segmental beta estimate is recalculated every month in the sample period using the monthly unlevered industry moving average betas. The debt/equity ratio and the income tax rate change annually. The beta of debt is assumed constant at 0.3.

Ideally, the market value proportion of assets invested in each industry segment should be used as the X_i weight in calculating the beta of the firm as the weighted average of

segmental industry betas. The SEC in 1970 required the disclosure of segmental sales and earnings for multi-segment firms, although the classification into segments and the allocation of costs and revenues was left primarily to the judgement of management. The Financial Accounting Standards Board (FASB) Statement No. 14, "Financial Reporting for Segments of a Business Enterprise" (1976), required diversified companies to disclose information on "reportable"⁶ segments in their audited financial statements. It also standardized somewhat the accounting rules for classification of industry segments and allocation of costs, revenues, and so forth.

Required segmental disclosures per FASB Statement No. 14 are:

- 1) revenue,
- 2) operating profit,
- 3) identifiable assets on a historical cost basis,
- 4) depreciation, and
- 5) capital expenditures.

Segmental replacement cost of assets would be preferred for use as a portfolio weight, but FASB Statement No. 33, "Financial Reporting and Changing Prices", only requires replacement cost disclosure for the firm as a whole and not for individual segments. The next best alternative might be to use the disclosed identifiable assets from the published reports, even though these assets are reported on a historical cost

⁶ A "reportable" segment as defined by SFAS No. 14 is a segment which comprises at least 10% of total segmental revenues, operating profits or losses, or identifiable assets. Additionally, the total segmental revenues of the reportable segments must equal at least 75% of consolidated sales to unaffiliated customers. A maximum of 10 segments is suggested.

basis.¹ Identifiable assets on a historical cost basis can be retrieved from the firms' 10K reports. The associated data collection task, however, motivates a search for an alternative and more readily accessible surrogate for the segmental market values.

The Value Line data base, initially created before the 1976 issuance of FASB Statement No. 14, reports segmental sales and earnings for up to 10 industry segments for each company in the data base. Several studies have indirectly addressed the choice of segmental sales or earnings as a proxy for segmental market value. These studies examined the relative ability of segmental sales and earnings data to predict consolidated sales and earnings. Kinney [1971] compared the predictive ability of earnings forecast models utilizing consolidated income data only, consolidated income and segmental sales data, and consolidated income and segmental sales and income data.

Kinney concluded that

- a) segmental sales data improved predictive ability over consolidated sales and earnings alone, but that
- b) segmental income data provided no predictive information beyond that of consolidated earnings and segmental sales.

Collins [1976] confirmed these results using a larger set of firms and many more forecast models. He extended Kinney's

¹ Mohr [1981] found that unlevered market-based firm betas were more closely related to weighted average betas derived from the reported historical cost of identifiable assets than to weighted average betas derived from segmental sales. However, Mohr also detected a significant relationship between market-based betas and segmental betas derived from sales data.

results to include the prediction of consolidated earnings and sales as well as the first differences of consolidated earnings and sales. Again, segmental sales information provided better prediction than did consolidated information alone, and segmental earnings provided only nominally better forecasts than did models which used only consolidated data.

Silhan [1982] employed Box and Jenkins' (BJ) time series methodology to select the consolidated earnings forecast models with the most predictive accuracy. By aggregating the quarterly earnings data of a sample of single segment firms, a series of "diversified" firms was simulated. The BJ methodology was then employed to determine the predictive ability of models incorporating either consolidated earnings alone or disaggregated "segmental" earnings. Silhan concluded that segmental earnings data provided no better predictions than did consolidated earnings alone. In conjunction with the Kinney and Collins studies, Silhan concluded [page 256]: "Together, these studies seem to imply that (segmental) earnings may be of limited usefulness in making predictions of enterprise profits."

In the long run, segmental earnings are closely linked to the market value of segmental investment; i.e. to each segment's after-tax cash flow discounted back to the present at the appropriate segmental or divisional cost of capital. But the variability of segmental earnings, especially the possibility of zero or negative earnings, makes this measure unsuitable as

a proxy for segmental asset values. Segmental profit data also suffer from a lack of uniformity across companies due to differences in the transfer pricing of intra-firm sales and the allocation of common costs among segments.

Alternatively, segmental sales provide a approximation to segmental asset values. Different segments will have different profit margins, resulting in some segments with high sales having lower market values than other segments. Yet segmental sales do enjoy more stability than earnings, do not suffer from negative and zero values, are expressed in current dollars, and are readily available from the Value Line data base. Additionally, the Kinney [1971], Collins [1976], and Silhan [1982] studies indicate that segmental sales may provide as much information as segmental earnings with regard to relative segmental market values. Consequently, segmental sales are used in this study as weights in the firms' segmental beta calculations. It is recognized, however, that the sales amounts are only an approximation to the theoretically preferred but unobservable segmental market values.

Value Line reports divisional or segmental sales for the most recent four fiscal years, so the sample period consists of the four calendar years 1979-1982. The reported segmental sales, long term debt, income tax rate, year-end number of shares outstanding, and average annual price are for the company's fiscal year. For some firms, the fiscal year is different than the calendar year (see Figure 4.2). Value Line

defines a fiscal year as a 12-month period ending between May first of one year and April thirtieth of the subsequent year. As such, sales for the Value Line year 1978 would include sales for firms with fiscal years ending during the period May 1978 through April 1979. Similarly, the fiscal year over the period May 1979 through April 1980 would be reported as Value Line year 1979. Using the Value Line sample period from January 1979 through December 1982 means the Value Line yearly sales will not always represent yearly fiscal sales. This is not a problem if the proportional sales in each division remain fairly constant over time, in which case the proportional sales weights would not change.

A scan through the first 100 firms on the data base indicates that for a small number of firms the proportional sales in each segment vary by as much as 20% over the four-year sample period. But since most of the companies have a fiscal year which runs from January through December, it appears that using yearly fiscal sales as the calendar year sales does not significantly contaminate the proportional sales weights.

This discrepancy between fiscal and calendar years also impacts the levels of debt and equity and the tax rate used in the leverage adjustments to systematic risk. While empirical debt/equity ratios are somewhat volatile, the observed tax rates fluctuate widely. Thus, the segmental beta leverage adjustments of this study are inexact to the extent that the

debt/equity ratios and tax rates from fiscal years are applied to non-overlapping calendar years.

Of course, the adjustment equations themselves are misspecified since they assume perpetual cash flows in a perfect market. The objective, again, is to create an alternative estimate of the systematic risk of the levered, multi-segment firm. The usefulness of the estimate derives from its properties as an alternative to the historical OLS beta estimate. It is important to remember that both β_{SEG} and β_{OLS} are merely estimates. The state of current financial theory and its application to an imperfect world precludes these estimates from representing the true systematic risk of the firm.

TABLE 4.2 Actual Tax Rates (UL field 94) 1979-1982

Tax Rate	Single Segment Sample	Percent	Multi- Segment Sample	Percent
< 0%	72	2.5%	24	2.7%
10-20%	72	2.5%	12	1.4%
20-30%	123	4.4%	38	4.3%
30-40%	285	10.2%	93	10.5%
40-50%	567	20.3%	242	27.3%
50-60%	1249	44.8%	394	44.5%
60-70%	116	4.2%	31	3.5%
70-80%	22	.8%	5	.6%
80-90%	8	.3%	0	0%
90-100%	0	0%	0	0%
> 100%	9	.3%	3	.3%
MISSING	265	9.5%	43	4.9%
TOTAL	2788	100.0%	885	100.0%
AVERAGE TAX RATE		35.7%		37.5%

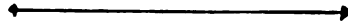
Table 4.3 OLS Debt Betas: $\beta_D = \text{cov}(r_D, r_M) / \sigma^2(r_M)$

Mean	0.5097
Standard Deviation	0.1048
Range	0.3576 to 0.6944

Figure 4.2 Value Line Calendar and Fiscal Years

FISCAL YEARS

6/1/80 - 5/31/81
FISCAL 1981



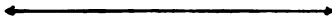
4/1/80 - 3/31/81
FISCAL 1980



6/1/81 - 5/31/82
FISCAL 1982



5/1/80 - 4/30/81
FISCAL 1980



1/1/82 - 12/31/82
FISCAL 1982



jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec	jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec	jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec
1980												1981												1982											

CALENDAR YEARS

4.1.d Alternative Estimates of Systematic Risk

The end result of the above beta estimation procedures is a set of historical OLS beta estimates and a set of segmental beta estimates constructed as portfolios of industry segments for a sample of nonfinancial, multi-segment firms. Several variants of the segmental beta are also calculated. A listing of the calculated estimates of the systematic risk of the levered, multi-segment firm follows:

β_{OLS}	historical OLS beta estimate,
β_{SEG}	segmental beta estimate with no adjustment for financial leverage,
β_{PSEG}	segmental beta estimate based solely on the primary industry segment,
β_{HAM}	segmental beta estimate adjusted according to the Hamada leverage equation,
β_{CON}	segmental beta estimate adjusted according to the Conine leverage equation,
$\beta_{HAM}(T)$	Hamada levered segmental beta with an assumed forty percent tax rate rather than the reported tax rate of β_{HAM} ,
$\beta_{CON}(T)$	Conine levered segmental beta with an assumed forty percent tax rate rather than the reported tax rate of β_{CON} .

The estimates of systematic risk of the industry portfolios are as follows:

$IND\beta$	industry betas as an equal weighted average of single segment firms in the industry (without a leverage adjustment),
$IND\beta_{HAM}$	industry betas unlevered according to the Hamada leverage adjustment,
$IND\beta_{CON}$	industry betas unlevered according to the Conine leverage adjustment,
$IND\beta_{HAM}(T)$	Hamada's unlevered industry betas with an assumed tax rate of forty percent,
$IND\beta_{CON}(T)$	Conine's unlevered industry betas with an assumed tax rate of forty percent.

The β OLS sample represents the market-based historical ordinary least square beta estimates. β SEG, β PSEG, β HAM, β HAM(I), β CON, and β CON(I) are the segmental beta estimates derived from segmental sales data and industry pure play surrogate portfolios. The industry portfolios represent the pure play segmental beta estimates.

No adjustment for financial leverage is made in the calculation of β SEG. The segmental beta of the multi-segment firm is simply calculated as the sales-weighted average of the betas of the component levered industry portfolios. This segmental beta estimate serves as the base case estimate of the systematic risk of the multi-segment firm. Other segmental estimates are elaborations on this basic measure.

The primary segment betas β PSEG are identical to the segmental beta estimates β SEG except that only the primary segment based on sales is considered. Other segments carry no weight in the portfolio aggregation process.

The Hamada (β HAM) and Conine (β CON) leverage adjustments unlever the industry portfolios ($\text{IND}\beta$ HAM and $\text{IND}\beta$ CON, respectively) and then relever these pure plays to form segmental beta estimates as the sales-weighted average of the component industry portfolios. These beta estimates use the annual tax rates from the Value Line database. However, as noted in Section 4.1.c and Table 4.2, the actual tax rates reported on the Value Line tapes are often quite volatile. Occasionally, special tax items cause the actual tax rate to be

very large in absolute value (the range in the multi-segment sample was -836% to +1405%). Since these extreme tax rates are not representative of average tax rates from operations, such values were set to a minimum tax rate of zero or a maximum rate of sixty percent (actual tax rates include federal, state, and local taxes) in the calculation of β_{HAM} and β_{CON} .

The Hamada and Conine leverage adjustments, however, are based on perpetual cash flow models. In an attempt to bring the application of the leverage adjustments more into line with the underlying theory and to avoid large shifts in beta based solely on a shifting tax rate, the leverage adjustments were also performed using the approximate average tax rate of the firms in the single and multi-segment samples. The average tax rate for the single and multi-segment samples was 35.7% and 37.5%, respectively. As such, a tax rate of forty percent was assumed for all firms for the Hamada and Conine leverage adjustments and the resulting beta estimates are represented by $\beta_{HAM}(T)$ and $\beta_{CON}(T)$. The unlevered industry pure play beta estimates using an assumed tax rate of forty percent are $IND\beta_{HAM}(T)$ and $IND\beta_{CON}(T)$, respectively.

In the next section, procedures are described for comparing these alternative estimates of the systematic risk of a levered multi-segment firm on similarity, on explanatory power, and on forecast accuracy.

4.2 Tests of the Theory

Two applications of the Capital Asset Pricing Model are considered. The first application considers the extent to which the segmental estimate of beta (β_{SEG}) supplies incremental information beyond that supplied by the OLS estimate (β_{OLS}) in explaining the returns to common stocks. Next, the ability of the alternative beta estimates to predict the return to common stock is examined within the Capital Asset Pricing Model. The two applications of the CAPM thus involve both the explanation and the prediction of equity security returns.

4.2.a The Cross-Sectional Behavior of β_{OLS} and β_{SEG}

To investigate whether β_{OLS} and β_{SEG} are independent random variables,⁸ the following null hypothesis is proposed:

$$H_{A0}: \text{corr}(\beta_{OLS}, \beta_{SEG}) = 0.$$

If β_{OLS} and β_{SEG} measure different characteristics of equity returns, and if they are not linked through some omitted variable, then β_{OLS} and β_{SEG} should be unrelated and the null hypothesis will not be rejected. On the other hand, if both estimates provide similar information about the systematic risk

⁸ The cross-sectional behavior of β_{OLS} is examined with respect to all of the segmental beta estimates β_{SEG} , β_{PSEG} , β_{HAM} , β_{CON} , $\beta_{HAM}(I)$, and $\beta_{CON}(I)$. In section 4.2.a, β_{SEG} is assumed to represent all of these segmental beta estimates.

of equity, then the null hypothesis should be rejected and the alternative hypothesis:

$$H_{A1}: \text{corr}(\beta_{OLS}, \beta_{SEG}) \neq 0$$

accepted. This test provides information on the association between market-based and segmental betas. The null hypothesis is tested cross-sectionally using each firm's average OLS and segmental beta over the four year sample period.

A further comment on the independence of the OLS and segmental betas is necessary. It is possible that two random variables A and B may be independent, such that $\text{corr}(A, B) = 0$, and yet both may be related to another variable. Consider the relationship

$$X = c + a \cdot A + b \cdot B,$$

where A and B are orthogonal and $\text{corr}(A, B) = 0$. The standard presentation of the Capital Asset Pricing Model assumes that there is a single market-wide factor which accounts for market risk [for instance, Rudd and Rosenberg, 1980] and that this factor cannot be broken down into orthogonal components. The above two-factor model then cannot hold and we needn't be concerned about independent risk factors being correlated through an omitted variable X.

Arbitrage Pricing Theory (APT), developed by Ross [1976], postulates a K-factor model of the stochastic process generating asset returns over a specified time interval:

$$R_i = E_i + b_{i1}d_1 + \dots + b_{iK}d_K + e_i;$$

where

R_i = the return on asset i ,
 $E_i = E[R_i]$ = the expected return on asset i ,
 b_{ik} = the reaction coefficient in asset i 's returns to movements in the common factor k ,
 k = a common factor with zero mean that influences the returns on all assets, $k=1,2,\dots,K$
 dk = the rate of change in the common factor k ,
 e_i = the zero mean, firm-specific, diversifiable component of asset i 's returns.

In contrast to the CAPM, where only an asset's covariance with the market portfolio contributes to the systematic risk and required return of the firm, the APT provides for multiple factors contributing to security returns. The K terms represent the common factors which may have an impact on security prices. Examples of k include such macroeconomic factors as inflation, the growth rate of GNP, and the price of oil. The b_{ik} term reflects the impact of the common factor k on security i 's returns. For instance, security i may be interest rate sensitive such that $b_{ik} \neq 0$.

In such a world, the nondiversifiable risk of securities is multi-dimensional. Then, even if the correlation between β_{SEG} and β_{OLS} is zero and the measures are independent, they may both contribute information in the determination of the required return on equity, R_i . In the present study, β_{SEG} and β_{OLS} are correlated through their common relationship to the fundamental characteristics of the firm. Sections 4.2.c and 4.2.d attempt to determine if these two estimates of systematic risk contribute unique information concerning the required return on equity.

4.2.b The Intertemporal Behavior of β OLS and β SEG

Historical ordinary least square beta estimates exhibit a substantial degree of variability due to estimation error. Even if the true underlying beta is constant over time, the unsystematic risk of the firm results in beta estimates which fluctuate around this true beta.

Combining firms of similar risk into a portfolio tends to reduce the variability of the portfolio risk estimates over time. The segmental beta estimate is composed of a portfolio of industry segments. Combining these industry segments into a portfolio should reduce the variability of the beta estimate. The industry beta estimates, being composed of several single segment firms, should also exhibit a substantial degree of stability.

The following null hypothesis

$$H_0: \sigma(\beta_{OLS}) = \sigma(\beta_{SEG})$$

detects some, but not all, types of differences in the variability of the beta estimates. Figure 4.3 gives some examples of variability in beta estimates which a test statistic should capture. In Figure 4.3.a, the true beta is constant and the beta estimate has a standard error of σ . Figure 4.3.b represents an example where the true beta is increasing over time but the standard error is again constant at σ . In Figure 4.3.c, the true beta is fluctuating randomly

over time. The standard error is again shown as constant. Other situations are, of course, possible.

If a firm's true underlying beta is constant as in Figure 4.3.a, then an unbiased estimate of this beta with a smaller standard error is preferable to one with a larger standard error. The null hypothesis H_0 is appropriate in this case. If the segmental beta estimate is biased and the OLS estimate is unbiased, the segmental estimate may still be preferable under some statistical criteria if the estimate is more efficient than the OLS estimate (see Section 4.2.d). In this case, similar to a ridge regression, the tighter standard error around the estimate overcomes the a degree of bias. In any case, the financial manager of the firm and investors in the market both have a practical preference for a more stable beta estimate, preferably one which is also unbiased.

Applying the null hypothesis to the examples of Figure 4.3.b and 4.3.c also detects a difference in the variability of the beta estimates. In these cases, however, the standard error of the beta estimates over time overstates the true standard error because of the fluctuation in the true beta itself. The null hypothesis applied to these situations provides only a rough measure of the variability of the beta estimates.

Figure 4.3 Variability in Estimates of Beta

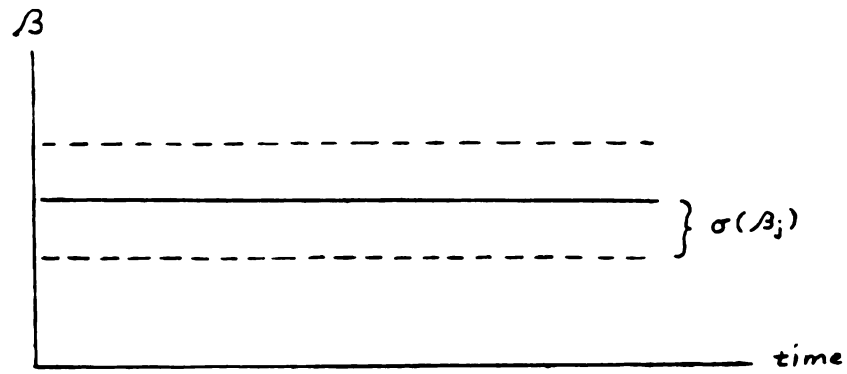


Figure 4.3.a

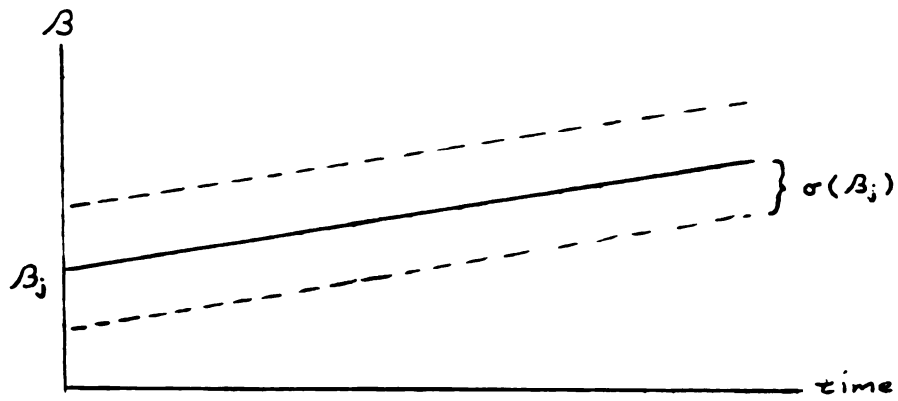


Figure 4.3.b

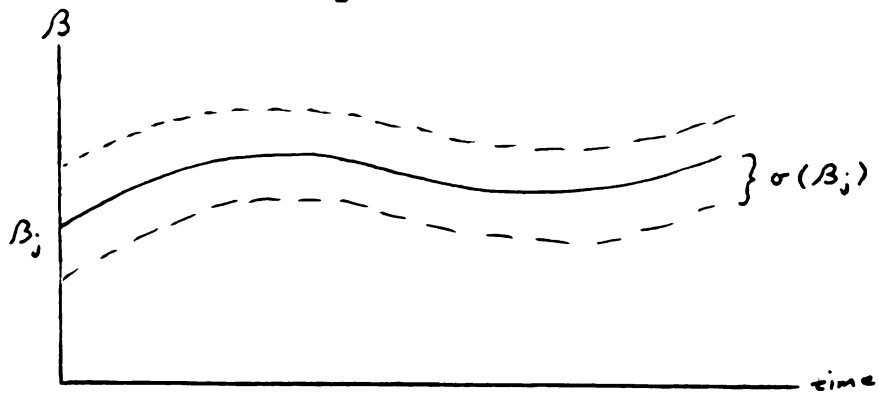


Figure 4.3.c

4.2.c The Incremental Explanatory Power of β OLS and β SEG

One reason for examining β SEG is to determine the usefulness of segmental data in forming estimates of the systematic risk of common stock. The segmental beta β SEG may provide information about systematic risk not provided by the historical OLS beta β OLS. If so, then the segmental beta may be used to augment a market-based beta in forming an improved estimate of the systematic risk of common stock. Several tests are undertaken to determine the extent to which β SEG and β OLS provide common and/or unique information in the explanation of security returns.

A test of the incremental information provided by β SEG beyond that provided by β OLS may be obtained by estimating the equation:

$$(R_{it}-R_{ft}) = a[\beta_{OLS,t-1}(R_{mt}-R_{ft})] + b[\beta_{SEG,t-1}(R_{mt}-R_{ft})]. \quad (4.1)$$

where $(R_{it}-R_{ft})$ is the rate of return of firm i over and above the riskless rate of return R_{ft} . Ibbotson and Sinquefeld's monthly holding period rate of return on 30-day Treasury bills is used as the risk-free rate R_f . If β OLS and β SEG are collinear, the OLS estimates of the individual regression parameters a and b may have very large variances. Consequently, even though the parameter estimates remain minimum variance and unbiased, they may be too imprecise to be of much use. An examination of the chi-square distributed

partial F statistic, however, supplies a test of the null hypothesis:

$$H_0: b = 0.$$

If $\beta_{SEG} \cdot (R_m - R_f)$ does not provide any additional information about the return $(R_i - R_f)$, then the partial F statistic assumes a value near 1. If in fact $\beta_{SEG} \cdot (R_m - R_f)$ does provide significant information about the firm's return, then we should be able to reject the null hypothesis even though we may not place any confidence in the parameter estimate b due to the collinearity of the OLS and segmental beta estimates.

The regression is performed using contemporaneous R_{it} , R_{mt} , and R_{ft} observations at time t . The beta estimates $\beta_{SEG,t-1}$ and $\beta_{OLS,t-1}$ are calculated from historical OLS time-series regressions

$$R_{it} = \alpha_i + \beta_i \cdot R_{mt} + \epsilon_{it} \quad (4.2)$$

using the immediately preceding 60 month period; i.e., from time $t-60$ through time $t-1$.⁹ The multiple regression (4.2) is performed on the pooled sample including all multi-segment firms over all 48 months (a total of 8808 observations). (See the statistical note in Appendix A for a discussion of the

⁹ In order to focus on the use of beta in each of the above forecasts, beta is estimated with a 60-month moving average using data from the immediately preceding 60 months. The choice of a 60-month window is an attempt to balance the competing objectives of timeliness and accuracy in the beta estimates. Using more months in the estimation of beta reduces the standard error of the statistical estimates but uses return information from years when the firm is likely to have been of significantly different character.

hazards of pooling time series and cross-sectional observations).

The multiple regression is run separately for each of the 48 months. The 48 monthly 2SLS regressions test whether the OLS or the segmental beta estimates provide incremental information about the security returns ($R_i - R_f$) for a single cross-section of firms. These cross-sections are not independent since the 60 month moving average beta estimation technique for firm i employs substantially the same information for adjacent beta estimates. The 48 realizations of the results are simply reported. No attempt is made to combine the 48 separate regressions and make inferences from them because of the lack of independence.

The regression is also performed on several of the sample firms separately over the 48 monthly observations. If β_{SEG} and β_{OLS} are both stationary and perfectly positively correlated over this time interval, then the partial F statistic of the multiple regression will not uncover any incremental explanatory power. If the firm undergoes a change in its financing or asset mix or if the betas are nonstationary over time or imperfectly correlated, then there is a possibility that either β_{OLS} or β_{SEG} possess some incremental information content. There are only 48 observations on each firm and this may not be sufficient to obtain significant results. However, since β_{SEG} may be more responsive to changes in asset and financing mix, the approach may prove fruitful in identifying

firms undergoing changes in systematic risk that arise from these sources. The major obstacle here is the large estimation error at the single firm level. Again, no attempt is made to form summary statistics combining the individual regressions.

The regression approach is also applied to the 9600 observations in the pooled sample. Pooling data in this fashion requires rather strict conditions on the regression (see Appendix A). Regression coefficients must be constant for all 200 firms and across all 48 months. The residuals must also possess constant variance. Since these conditions are certainly not met, the results are simply presented. No attempt is made to justify the appropriateness of the procedure. The application is, however, supplied as corroboration for the other results.

4.2.d The Predictive Power of β OLS and β SEG

The above approaches yield information on the incremental ability of β SEG and of β OLS to explain the return to common equity. Several tests are also performed to determine the extent to which the segmental beta estimates augment or increase the predictive power of the OLS estimates. The predictions are compared against several benchmarks using mean error (ME) as a measure of prediction bias and mean square error (MSE) and mean absolute deviation (MAD) as measures of forecast accuracy:

$$ME: \quad \sum_i e_{it}, \quad (4.3)$$

$$MAD: \quad \sum_i [\text{ABSOLUTE VALUE } (e_{it})], \quad (4.4)$$

$$MSE: \quad \sum_i (e_{it})^2, \quad (4.5)$$

$$\text{where } e_{it} = R_{it} - E[R_{it}]. \quad (4.6)$$

In order to focus on the predictive power of BSEG and BOLS, actual returns are compared to forecast returns.¹⁰

The Security Market Line states that the expected return to a security j is composed of the general level of interest rates R_F , the market risk premium ($R_M - R_F$), and the systematic risk of the security β_j . The general level of interest rates and the average level of investor risk aversion measured by the market risk premium are market-wide factors. The systematic risk factor β_j is specific to the individual firm j .

To test the null hypothesis,

$$H_0: e_{it} = R_{it} - E[R_{it}] = 0,$$

the following forecasts are compared on forecast accuracy:

- a) a naive forecast of the risk-free rate,

$$e_{it} = R_{it} - E[R_{it}] = R_{it} - R_{ft} = 0 \quad (4.7)$$

- b) a forecast of the market return,

$$\begin{aligned} e_{it} &= R_{it} - E[R_{it}] = R_{it} - R_{ft} - \beta_M(R_{mt} - R_{ft}) \\ &= R_{it} - R_{ft} - (1.0)(R_{mt} - R_{ft}) = 0 \end{aligned} \quad (4.8)$$

¹⁰ The forecast returns at time t , however, are derived from the Security Market Line using actual market index and risk-free returns at time t . The resulting forecasts R_{it} represent predictions for time t based on information available at time $t-1$ ($\beta_i, t-1$) as well as at time t (R_{mt} and R_{ft}) and are thus unattainable in a real-world setting. This framework is like that of portfolio performance evaluation where risk-adjusted performance is measured relative to ex-post market performance on a risk-adjusted basis.

c) a forecast of the average equity return,

$$\begin{aligned} e_{it} &= R_{it} - E[R_{it}] = R_{it} - R_{ft} - \beta_{CS} * (R_{mt} - R_{ft}) \\ &= R_{it} - R_{ft} - (1.43) * (R_{mt} - R_{ft}) = 0 \end{aligned} \quad (4.9)$$

d) a forecast using only the OLS estimate,

$$\begin{aligned} e_{it} &= R_{it} - E[R_{it}] \\ &= R_{it} - R_{ft} - \beta_{OLS_{it-1}} * (R_{mt} - R_{ft}) = 0 \end{aligned} \quad (4.10)$$

e) a forecast using only the segmental estimate,

$$\begin{aligned} e_{it} &= R_{it} - E[R_{it}] \\ &= R_{it} - R_{ft} - \beta_{SEG_{it-1}} * (R_{mt} - R_{ft}) = 0 \end{aligned} \quad (4.11)$$

Three predictions based on market-wide information (forecasts 4.7 to 4.9) are provided for comparison to the returns predicted by the firm-specific beta estimates (forecasts 4.10 and 4.11) of this study. A naive forecast

$$E[R_{jt}] = R_{ft} \quad (4.7)$$

(ie. $\beta=0$) is equivalent to estimating the return on a share of common stock as the risk-free rate of return on 30-day Treasury bills. This return forecast represents compensation for inflation and a real rate of return on a risk-free security as a base case. The prediction

$$E[R_{jt}] = R_{mt} \quad (4.8)$$

corresponds to setting $\beta=1$ and estimating the equity returns as the average rate of return on debt and equity securities in the market index. The market index of this study is composed of 70% stock and 30% long-term corporate bond returns as reported by Ibbotson and Sinquefeld [1984]. A forecast

$$\begin{aligned} E[R_{jt}] &= R_{ft} + \beta_{CS} * (R_{mt} - R_{ft}) \\ &= R_{ft} + (1.43) * (R_{mt} - R_{ft}) \end{aligned} \quad (4.9)$$

of the average equity return based on the average equity beta of the multi-segment firm sample ($\beta=1.43$) provides the best return estimate in the absence of firm-specific information.

Since β OLS and β SEG are updated monthly for each firm in the sample, the prediction is performed using the pooled sample including both cross-sectional and time series data. A comparison of the ME, MSE and MAD should indicate the relative forecast accuracy of the models. If the OLS and the segmental beta estimates provide different information about the return on equity, then β SEG may be used to augment β OLS in achieving an improvement in predictive power (see forecast f) above).

At this point, it is useful to review the sources of prediction error in the composition of mean square error. Consider a single regression model of the type of Section 4.3,

$$R = a + b * E[R] + v, \quad (4.12)$$

where $R = R_j - R_f$ = the risk premium on security j,
 $E[R] = \beta * (R_M - R_f)$ = the predicted return from the Security Market Line,
 a and b are the population regression coefficients,
 and v represents a random error term which is orthogonal to R and E[R].

The prediction (forecast) error is defined as $e = R - E[R]$ and has variance $\sigma^2(e)$. The coefficient of determination of this regression equation is denoted by r^2 . Theil [1966] (see also

Mincer [1969]) decomposed the mean square error of the forecast¹¹ as

$$\begin{aligned}
 \text{MSE} &= E(R-E[R])^2 = E(e)^2 = [E(e)]^2 + \sigma^2(e) \\
 &= [E(e)]^2 + [\sigma^2(e) - \sigma^2(v)] + \sigma^2(v) \\
 &= [E(e)]^2 + (1-b)^2 \sigma^2(E[R]) + (1-r^2) \sigma^2(R) \\
 &= \text{bias} + \text{inefficiency} + \text{error}. \quad (4.13)
 \end{aligned}$$

The interpretation of regression equation (4.12) by equation (4.13) is illustrated graphically in Figure 4.4. Bias in the return prediction is represented by the difference between the actual mean return and the predicted mean return. An unbiased estimate has an average predicted return which is equal to the average actual return. The regression line of equation 4.12 then passes through the point

$$(x, y) = (\text{avg}(E[r]), \text{avg}(R))$$

on the 45 degree line of perfect fit. In the present study, the only unbiased estimate is one with an average predicted return equal to the average return in the multi-segment sample over the sample period.

The inefficiency of the forecast is represented by the magnitude of $\sigma^2(e)$ relative to the residual variance $\sigma^2(v)$ in regression equation (4.12). When the forecast error e is

¹¹ These equations are stated in terms of population parameters. For a sample from a population, the corresponding mean square error decomposition is:

$$\begin{aligned}
 \text{MSE} &= \sum (R-E[R])^2 \\
 &= (\text{Avg}(R) - \text{Avg}(E[R]))^2 + (1-b)^2 S^2[R] + (1-r^2) S^2 \\
 &= \text{bias} + \text{inefficiency} + \text{error},
 \end{aligned}$$

where $S^2 R$ is the sample variance of the security's risk premium $R = R_j - R_f$.

uncorrelated with the forecasted values $E[R]$, then the slope coefficient b is equal to unity, $\sigma^2(e) = \sigma^2(v)$, and the return prediction is efficient. If the forecast error is related to the predicted return, then the forecast is inefficient, the slope coefficient $b \neq 1$, and $\sigma^2(e) > \sigma^2(v)$.

Figure 4.5 gives examples of four different types of forecasts. In Figure 4.5.a, the forecast is unbiased and efficient although there exists some random estimation error. Figures 4.5.b and 4.5.c exhibit only bias and only inefficiency, respectively. Figure 4.5.d suffers from both bias and inefficiency. The alternative forecasts are compared on forecast accuracy in Section 5.4 in their unadjusted state, after adjusting for bias only, after adjusting for inefficiency only, and also after adjusting for bias and inefficiency.

Klemkosky and Martin [1975], among others, have demonstrated that historical OLS beta estimates are unbiased but inefficient. In general, historical OLS betas tend to overestimate the systematic risk of high-beta stocks and underestimate the risk of low-beta stocks. Attempts to adjust beta forecasts for this inefficiency have been presented by Blume [1971] and Vasicek [1973].

Figure 4.6 presents a typical view of the theoretical and empirically observed Security Market Line (see, for instance, Modigliani and Pogue [1974]). Explanations for the difference between the theoretical and empirical SML revolve around market imperfections such as a difference between individuals'

borrowing and lending rates (Black [1972]), the existence of differential taxation (Miller [1976] and Elton and Gruber [1978]), and so forth.

The return predictions from the alternative beta estimates in equations 4.10 and 4.11 are regressed against the actual returns ($R_j - R_f$) as in equation 4.12. The resulting slope coefficients are used to adjust the return predictions for inefficiency. Since the regression line in Figure 4.4 and equation 4.12 minimizes the sum of square errors, an adjustment is made to the return predictions to reduce the mean square error as:

$$e_j = R_j - R_f - a - (b * (\beta_j - \text{avg}(\beta_j) + \text{avg}(\beta_j)) * (R_m - R_f)). \quad (4.14)$$

The coefficient a is equal to the mean prediction error and adjusts for bias. The slope coefficient b adjusts for inefficiency by weighting the beta estimates back toward their mean. The resulting return estimates may then be compared on the residual variance v of their mean square error.

A matched pair t -test of significance between each return prediction model at the single security level indicates the relative predictive ability of the various beta estimates. For each of the 48 months in the sample period, the prediction error, prediction absolute deviation, and prediction square error are calculated and averaged over all the firms. This results in a vector of 48 observations of mean error, mean absolute deviation, and mean square error. The matched pair

t-test of significance then compares the forecast accuracy of the various return prediction models over these 48 months.

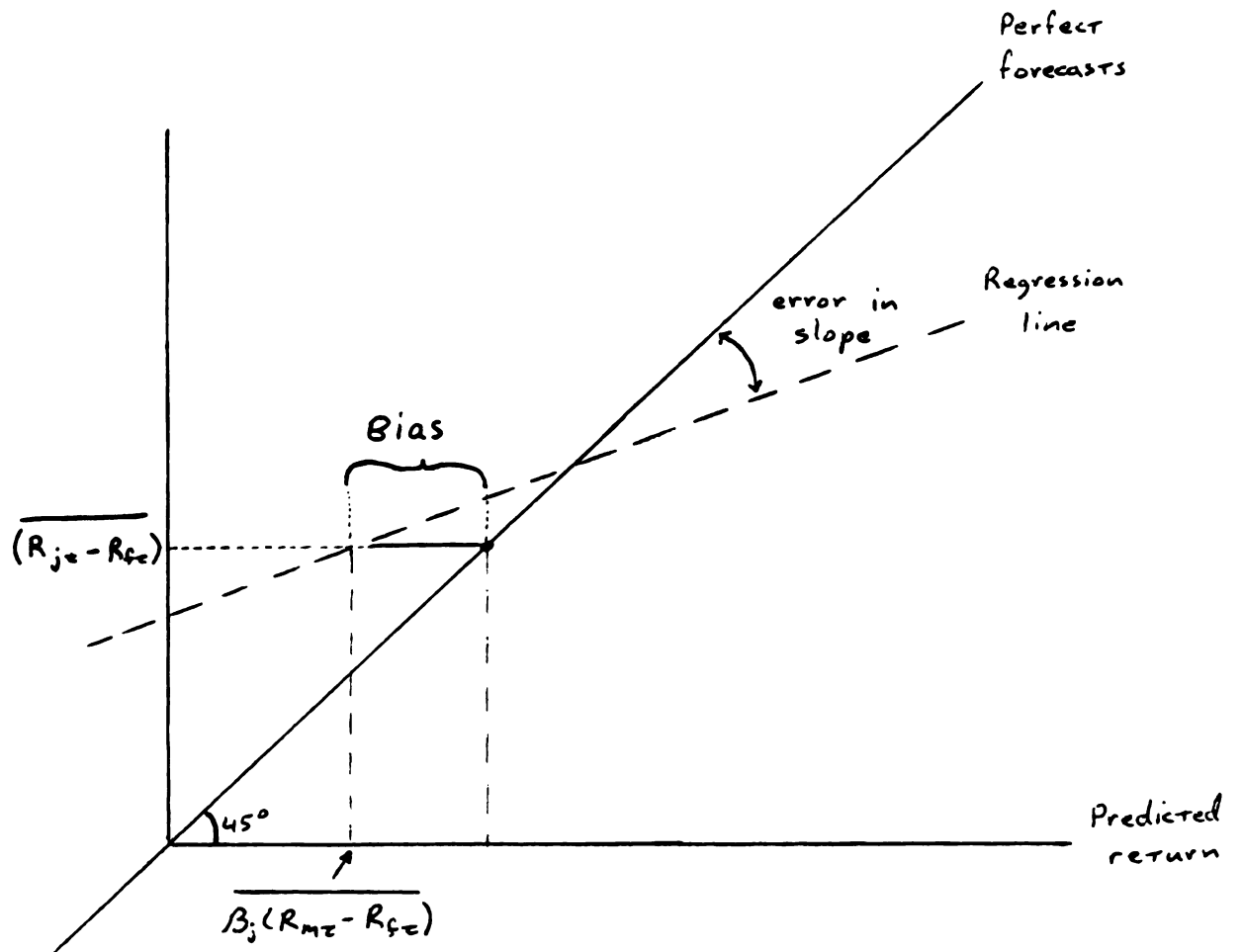
Klemkosky and Martin also investigated the composition of the MSE forecast accuracy of common stocks. There was a large amount of estimation error relative to the total MSE. In their study, the random error component accounted for between 60-94% of mean square error over the four periods studied. Aggregating securities into portfolios reduced the total MSE, primarily in the error component. Since individual security returns exhibit a great deal of firm-specific variation in return, the return predictions (4.7) through (4.11) are performed on portfolios as well as on individual firms.¹²

The sample of multi-segment firms was ranked by OLS beta and three portfolios were formed of the twenty largest beta (βHI), the twenty smallest beta (βLOW), and the twenty median beta (βMID) firms. The mean prediction errors, the mean absolute deviation of the prediction errors, and the mean square prediction errors for these three portfolios are provided in Chapter 5 to measure the predictive accuracy of the alternative return forecast models for the portfolios differing on systematic risk.

12 As Roll [1979] has pointed out, the market index portfolio is always ex post efficient. Consequently, if all the securities were combined into a single market portfolio, the predicted return would then be the actual return and the prediction error would be zero. Note that for this result to hold the securities in the sample must be the same as in the market index portfolio. In the present study, the market index is much broader than the sample of multi-segment firms.

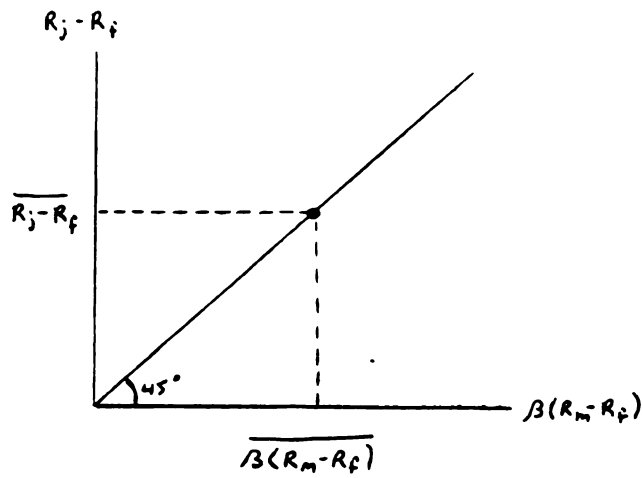
There is a possibility that the alternative return forecasts (4.7) to (4.11) may perform differently in different market environments. The 48 months in the sample period are divided into three market environments each with $(48/3) = 16$ months. In periods of average market return $(R_m - R_f)_{MID}$, the return predictions $E[RCS]$ and $E[R_m]$ should perform well for average risk stocks. For high β_{HI} and low β_{LOW} securities, the OLS and segmental beta estimates of return should outperform the market-wide forecasts (4.7) to (4.9). In periods of above $(R_m - R_f)_{HI}$ or below average $(R_m - R_f)_{LOW}$ return, the OLS and segmental forecasts which reflect the volatility of the securities relative to the market index should perform well. The relative predictive performance of the three portfolios β_{HI} , β_{MID} and β_{LOW} are examined in each of the three market environments. The results of a matched pair t-test of significance between each return prediction model at this portfolio level are also summarized.

Figure 4.4 Actual vs Predicted Return

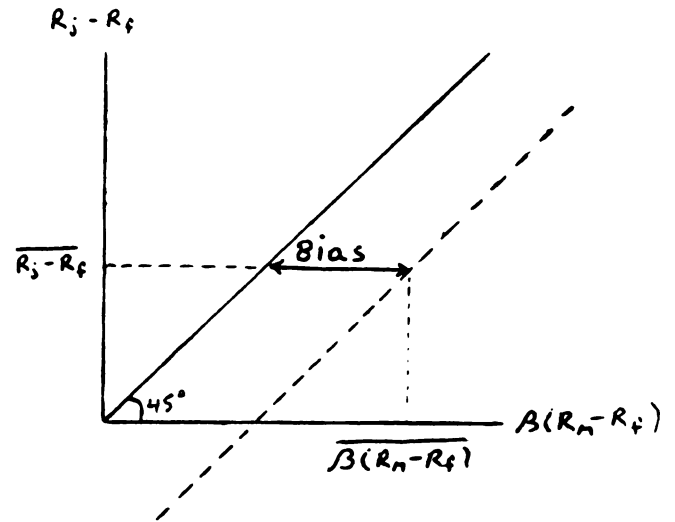


$$E[R_{j\epsilon}] - R_{f\epsilon} = \beta_j (R_{m\epsilon} - R_{f\epsilon})$$

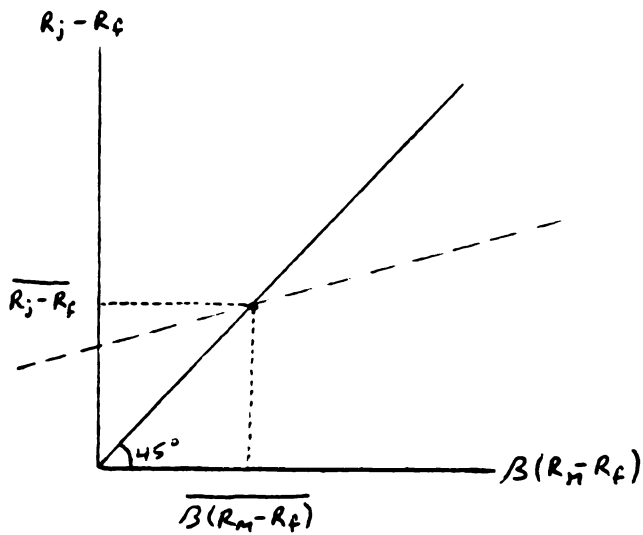
Figure 4.5 Decomposition of Mean Square Error



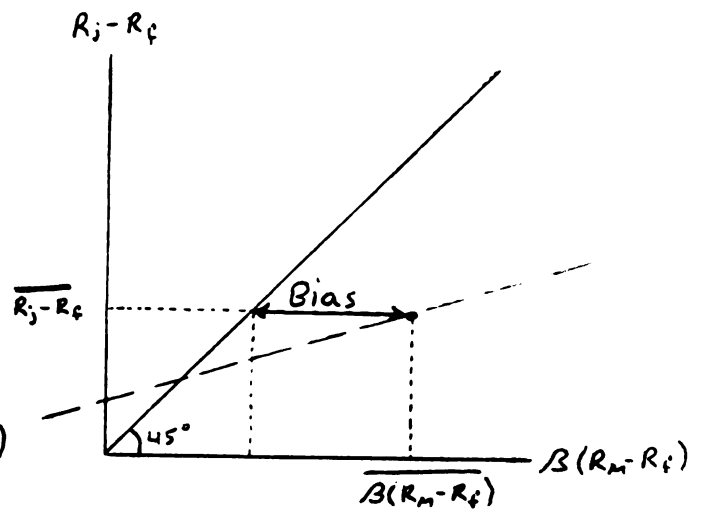
4.5.a



4.5.b

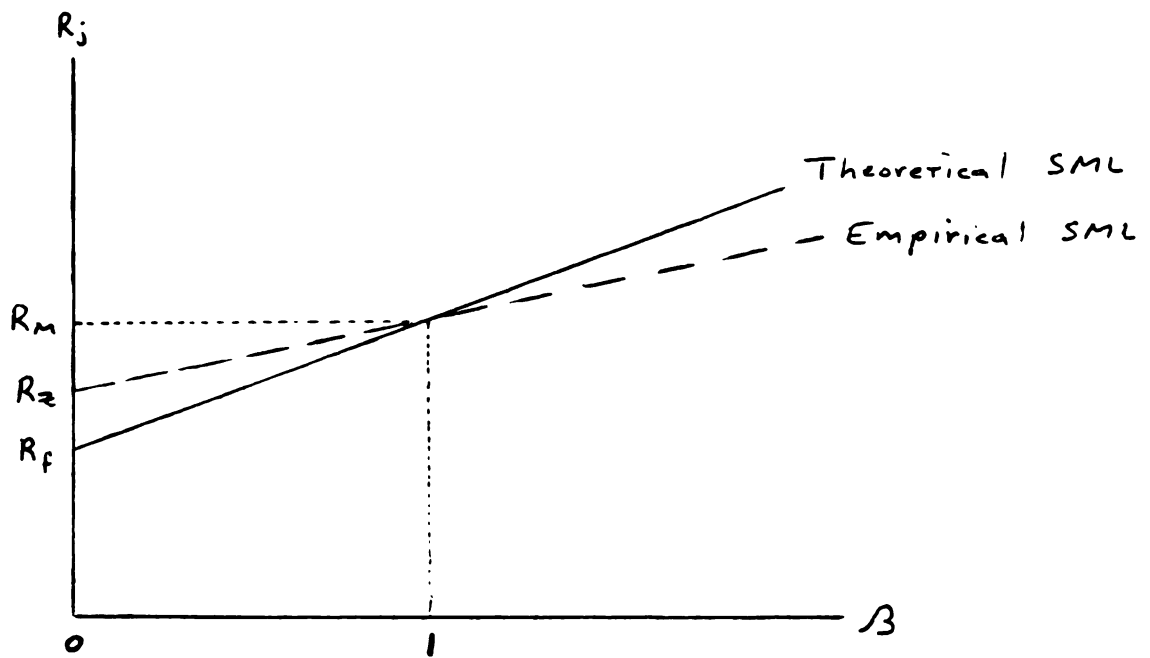


4.5.c



4.5.d

Figure 4.6 Theoretical vs Empirical Security Market Line



4.2.e Adjusting for Capital Structure and Taxes

The tests of segmental beta in Sections 4.2.a, 4.2.b, and 4.2.d are performed using several alternative estimates of the systematic risk of common stock. The various segmental beta estimates are calculated as follows:

$$1) \quad \beta_{SEG} = [\sum iX_i \cdot i\beta], \quad (4.15)$$

$$2) \quad \beta_{PSEG} = i\beta_{PSEG} \quad (4.16)$$

$$2) \quad \beta_{HAM} = IND\beta_{HAM} \cdot [1 + (1-T) \cdot (D/SL)] \quad (4.17)$$

$$3) \quad \beta_{CON} = IND\beta_{CON} \cdot [1 + (1-T) \cdot (D/SL)] - \beta_{DEBT}(1-T)(D/SL) \quad (4.18)$$

$$4) \quad \beta_{HAM}(T) = IND\beta_{HAM}(T) \cdot [1 + (1-.4) \cdot (D/SL)] \quad (4.19)$$

$$5) \quad \beta_{CON}(T) = IND\beta_{CON}(T) \cdot [1 + (1-.4) \cdot (D/SL)] - \beta_{DEBT}(1-.4)(D/SL) \quad (4.20)$$

The test of incremental explanatory power in Section 4.2.c is performed on β_{OLS} versus β_{SEG} only.

β_{SEG} is the segmental beta with no adjustment made for financial leverage. $i\beta$ is the beta of industry i where the industry pure play portfolio is composed of all single segment firms (unadjusted for leverage) in industry i . Thus, in β_{SEG} , the multi-segment firm's industry segment i is assumed to be of the same systematic risk as other firms in the industry. $i\beta_{PSEG}$ is the beta of the primary industry segment with the largest proportional sales in the company. In this case, the multi-segment firm is assumed to be of the same systematic risk as that of its primary industry segment based on sales. Note

that both β_{SEG} and β_{PSEG} make no adjustment for financial leverage.

β_{HAM} is the multi-segment counterpart of Hamada's levered beta in the presence of risk free debt and corporate taxes. The component unlevered industry segment beta estimates $i\beta_{HAM}$ explicitly adjust for financial leverage and corporate taxes in the firm's industry segment i according to:

$$i\beta_{HAM} = \beta_{SEG} / [1 + (1-T) * (D/SL)] \quad (4.21)$$

Conine's levered beta β_{CON} additionally assumes risky corporate debt. The $i\beta_{CON}$ are Conine's unlevered segmental industry betas:

$$i\beta_{CON} = [\beta_{SEG} + \beta_{DEBT}(1-T)(D/SL)] / [1 + (1-T) * (D/SL)] \quad (4.22)$$

$\beta_{HAM}(T)$ and $\beta_{CON}(T)$ are calculated the same as β_{HAM} and β_{CON} except that a tax rate of 40% is assumed for all firms in the single and multi-segment samples.

In the next chapter, these segmental beta estimates are compared on their ability to explain and/or predict the return to common stock.

Chapter 5 Empirical Results

5.1 Cross-Sectional Behavior of the Beta Estimates

Summary statistics are provided in Table 5.1 describing the cross-sectional characteristics of the beta estimates of the various multi-segment and industry firm samples. The multi-segment samples were all drawn from the 235 firms meeting the multi-segment criteria of Section 4.1.b. Firms were subsequently removed from the full sample if there were missing accounting, financial, or market data on the Uvalueline or CRSP tapes. The leverage adjusted segmental betas, for instance, could not be computed for any multi-segment firm with missing values for debt, equity, or the tax rate for a particular year. A multi-segment firm was included in the statistical tests of Section 4.2 only if the firm was in all the various multi-segment samples being used for that test.

A list of the multi-segment firms and their average betas for each of the various estimates is provided in Appendix B. The final sample included 179 multi-segment firms which had observations for all of the beta estimates during at least one month of the sample period. The industry SIC codes referenced by firms in the multi-segment sample is provided in Appendix C. The sample of single segment firms used to form industry portfolios consisted of 653 firms after the deletion of financial (SIC code 6XXX) firms.

The average tax rates for the single and multi-segment samples were 37.54% and 35.67%, respectively. The average debt ratio based on the book value of debt (total liabilities) and the market value of equity was 59.39% and 53.41% for the single and multi-segment firms, respectively.

The average OLS beta in the multi-segment sample was 1.43. By construction, the average betas of the market and of debt are 1. and 0.3, respectively. Consequently, the average beta of common stock β_{CS} is 1.3 and may be calculated as

$$\begin{aligned}\beta_M &= X_D \cdot \beta_D + X_{CS} \cdot \beta_{CS} \\ \Rightarrow \beta_{CS} &= (\beta_M - X_D \cdot \beta_D) / X_{CS} = (1 - (.3)(.3)) / (.7) \\ &= 1.3.\end{aligned}$$

The mean annual rate of return for the multi-segment sample over the four year sample period was 17.08%. Ibbotson and Singuefield's common stock total return index averaged 16.00% per year over the four year sample period.

The OLS betas (β_{OLS}), the leverage-unadjusted segmental (β_{SEG}) and primary segment betas (β_{PSEG}), and the leverage-unadjusted industry betas (β_{IND}) have almost identical mean values. This suggests that the multi-segment firms and the single segment firms comprising the industry portfolios possess approximately equal degrees of systematic risk.

Next, consider the Hamada equation for an unlevered beta:

$$\beta_U = \beta_L / [1 + (1 - T)(D/S)].$$

Theoretical unlevered betas are always less than levered betas for positive levels of debt and equity and a tax rate $0 \leq T \leq 1$.

The observed unlevered industry betas $IND\beta_{HAM}$ and $IND\beta_{CON}$ are lower than the levered industry betas as well as the levered OLS, segmental, and primary segment betas. The Hamada and Conine mean segmental betas (β_{HAM} and β_{CON}), however, are both about 0.5 above the average OLS beta of 1.43. Using β_{OLS} as a reference, both the Hamada and Conine leverage adjustments appear to have over-compensated for the financial risk of the multi-segment firm. The $\beta_{HAM}(T)$ and $\beta_{CON}(T)$ beta estimates assume a forty percent tax rate and provide a slight distributional improvement (relative to β_{OLS} and β_{SEG}) over the β_{HAM} and β_{CON} betas. The magnitude of the average segmental betas across the various methods is addressed further in Section 5.4.

The cross-sectional standard deviation of segmental beta (0.2295) is slightly less than that in the primary segment beta (0.2975) and about sixty percent of that in the OLS estimate (0.3873). The range was similarly smaller for the segmental and primary segment betas than for the OLS betas. The leverage adjustments have induced much larger standard deviations in the β_{HAM} and β_{CON} estimates, i.e., 1.0312 and 0.8669, respectively. Unlevering the industry betas $IND\beta$ does not appear to have greatly affected the variability of the unlevered estimates $IND\beta_{HAM}$, and $IND\beta_{CON}$. The Hamada adjustment on average increases the variability of beta more than does the Conine adjustment.

Pearson's product-moment correlation coefficients and Spearman's rank-order correlation coefficients between market-based (β_{OLS}) and segmental (β_{SEG}) estimates of the systematic risk of the multi-segment sample are presented in Table 5.2. Each firm's beta estimate is represented by the average beta for each of the years 1979 through 1982 and by the average beta over the entire four-year period. A scatterplot of the cross-sectional distribution of the (four-year average) OLS and segmental betas is presented in Figure 5.1.1

Table 5.3 presents Pearson's parametric product-moment correlation coefficients between the five measures of systematic risk β_{OLS} , β_{SEG} , β_{PSEG} , β_{HAM} , and β_{CON} . The average of the 48 monthly beta estimates over the four year sample period 1979-1982 was used as the measure of systematic risk for each company. The correlation coefficients depend, of course, on the particular implementations of the segmental beta that were used in this study.

The parametric coefficients require that the betas be either normally distributed or on an interval scale. Pearson's rho is an appropriate measure of correlation if the betas are viewed within the context of the CAPM. A beta of 2.0 represents twice as much exposure to market risk as a beta of 1.0, so that even if betas are asymmetrically distributed about

1 The means and standard deviations are slightly different than in the summary statistics of Table 5.1 because some of the firms in the β_{OLS} sample were not in the β_{SEG} sample and vice versa.

the mean they still lie on an interval scale.² Spearman's rank-order statistic, depending only upon an ordinal scale, is provided in Table 5.2 as a more robust and corroborating measure of association.

The OLS beta estimates are most closely correlated with the segmental and primary segment betas, neither of which have been adjusted for financial leverage. It is especially interesting that the correlation of the OLS betas with the primary segment betas is even higher than with the segmental betas. The difference is, however, slight.

While the correlations are highly significant statistically, the strength of the association is quite small.³ When the average OLS beta over the four year period

² Note that the average beta is 1.0 for equity securities only when an equity market index is used.

³ Some perspective on the magnitude of the correlation between the OLS and segmental betas can be gained by considering the optimistic scenario in which the segmental beta is equal to the true underlying beta while the OLS estimate contains an error term. Let

$$x = \beta_{SEG} = \text{true beta}$$

$$\text{and } y = \beta_{OLS} = \text{true beta} + \text{error}.$$

$$\text{Then } q_n = \hat{x}_n = x_n$$

$$\text{and } \sum_n (x_n - \hat{x}_n)^2 = 0.$$

The variance of the true beta is $\sigma^2_x = (1/N) \sum_n (x_n - \text{avg}(x))^2$. From the regression results of β_{SEG} on β_{OLS} , the error sum of squares is

$$SSE = \sum_n (y_n - q)^2 = 27.75$$

Since β_{SEG} is the true beta, the regression sum of squares is

$$\begin{aligned} SSR &= SST - SSE = \sum_n (q_n - \text{avg}(y))^2 \\ &= \sum_n (x_n - \text{avg}(x))^2 \\ &= N * \sigma^2_x. \end{aligned}$$

Again, from the regression results, $N=196$ and $\sigma^2_x = .263^2 = 0.069$. The expected regression sum of squares is then

$$\begin{aligned} E[SSR] &= N * \sigma^2_x = 196 * 0.069 = 13.52, \text{ and} \\ E[SST] &= SSE + E[SSR] = 27.75 + 13.52 = 41.27. \end{aligned}$$

for each firm is compared to the paired segmental beta, the r^2 statistic is only $r^2 = (.2131)^2 = .0454$. For the OLS and primary segment betas the $r^2 = (.2309)^2 = .053$. That is, only about 5% of the variation in the OLS beta is explained by either the segmental or the primary segment beta.

β_{SEG} is more closely associated with the leverage-adjusted segmental betas β_{HAM} and β_{CON} than with the market-based OLS beta estimates. It is also very highly correlated with the primary segment beta. The percent of the total variation in β_{SEG} explained by β_{HAM} and β_{CON} is $(.3187)^2 = 10.2\%$ and $(.3680)^2 = 13.5\%$, respectively. Since these leverage-adjusted estimates were derived from the same industry pure play portfolios as the beta estimate β_{SEG} , the higher correlation with β_{SEG} than with β_{OLS} is not surprising. Similarly, since the r^2 of the segmental beta of a single segment firm and its primary segment beta is by definition unity, the relatively high r^2 of $(.8142)^2 = .663$ between the segmental and primary segment betas is to be expected.

The expected R^2 in this idealized regression is

$$R^2 = 1 - (SSE/SST) = 1 - (27.75/41.27) = 0.33,$$

$$\text{or } R = (0.33)^{.5} = 0.57.$$

Thus, even if the segmental beta is the true underlying beta, the expected correlation coefficient is still only 0.57 because of the variation in β_{OLS} .

4 Mohr [1983] reports parametric correlation coefficients from 0.435 to 0.501 between similarly constructed line of business accounting betas and market-based betas. Klemme [1983] reports correlation coefficients from 0.13 to 0.33 between market betas and various line of business accounting betas.

The Conine adjusted betas are slightly more highly correlated with the OLS, segmental, and primary segment betas than are the Hamada adjusted betas. This provides only weak evidence that the more sophisticated Conine model, including an adjustment for risky debt, is more consistent with observed historical OLS betas than the more simplistic Hamada model. The β_{HAM} and β_{CON} estimates themselves are very highly correlated, with an $r^2 = (.9979)^2 = 99.58\%$. These estimates differ only by the adjustment for risky corporate debt, $\beta_{DEBT} * (D/S) * (1-T)$, which varies across firms due to the different tax rates and leverage ratios. Even though one of these leverage-adjusted estimates may still be a less biased and hence better estimate of the true beta, the two estimates are nevertheless based on substantially the same information.

In summary, based on the relatively small standard errors of Table 5.3, the various beta estimates are all significantly correlated at the 1% level of confidence. However, the variation in the segmental estimates explains, at most, only about 5% of the variation in the OLS estimate. The OLS beta estimates are most closely correlated with the segmental and primary segment betas, neither of which have been adjusted for financial leverage.

Figure 5.1 Standardized Scatterplot of Average β OLS and β SEG
196 Observations

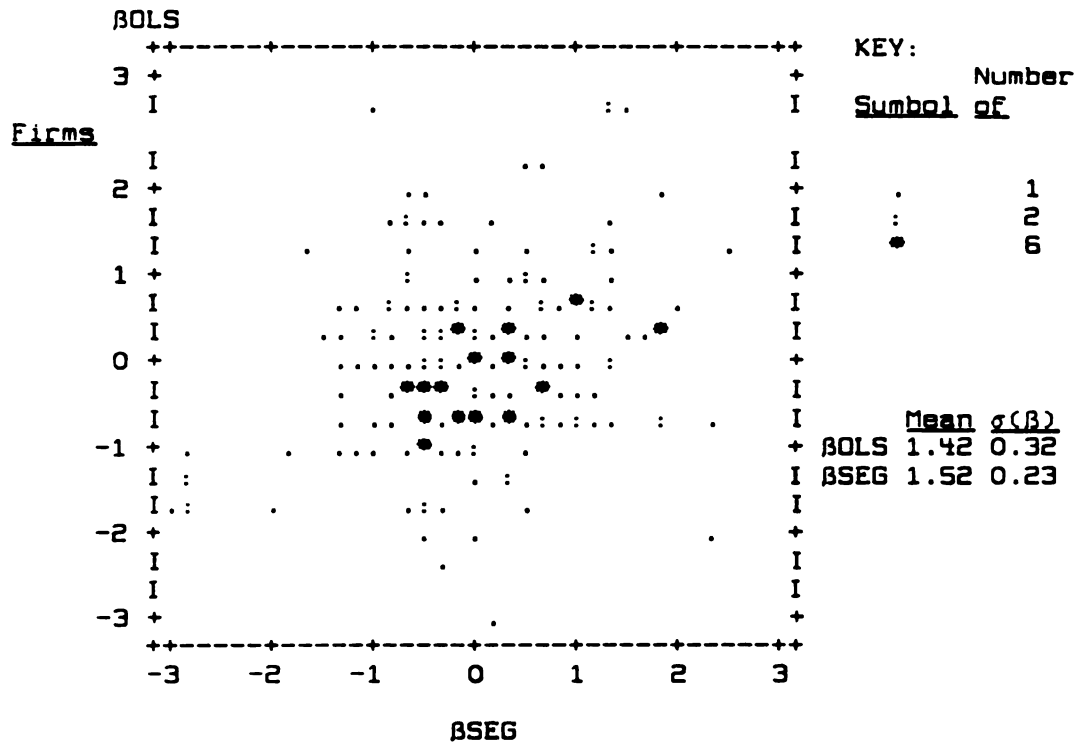


Table 5.1 Betas: Cross-Sectional Descriptive Statistics

	<u># of Firms</u>	<u>Mean</u>	<u>Standard Deviation</u>	<u>Range</u>
BOLS	201	1.4322	0.3873	0.2952 to 2.4772
BSEG	230	1.5268	0.2295	0.8184 to 2.0693
BPSEG	230	1.5215	0.2975	0.7021 to 2.2039
BHAM	234	2.1244	1.0312	0.4792 to 10.9308
BCON	234	2.0150	0.8669	0.5739 to 9.6091
BHAM(T)	234	1.9763	0.9126	0.5016 to 8.7680
BCON(T)	234	1.8681	0.7699	0.5868 to 7.7638

	<u># of Industries</u>	<u>Mean</u>	<u>Standard Deviation</u>	<u>Range</u>
INDB	95	1.5386	0.3854	0.6860 to 2.9219
INDBHAM	86	0.9122	0.4241	0.0453 to 1.7961
INDBCON	86	1.0348	0.3665	0.3335 to 1.8490
INDBHAM(T)	86	0.8909	0.4264	0.0559 to 1.7786
INDBCON(T)	86	1.0180	0.3685	0.3412 to 1.8278

Table 5.2 Cross-Sectional Correlation: OLS vs. Segmental Beta

(significance in parentheses)

<u>Avg of Year</u>	<u># of Cases</u>	<u>Nonparametric Spearman's</u>	<u>Parametric Pearson's</u>
1979	151	.3188 (.001)	.3406 (.001)
1980	193	.1435 (.024)	.2117 (.003)
1981	196	.2123 (.002)	.1943 (.006)
1982	197	.2801 (.001)	.2570 (.001)
Average of 1979-1982	198	.1454 (.002)	.2170 (.002)

Table 5.3 Cross-Sectional Correlation: average betas 1979-1982
 (significance in parentheses)

Pearson's rho

	β_{OLS}	β_{SEG}	β_{PSEG}	β_{HAM}	β_{CON}	$\beta_{HAM(T)}$
	----	----	----	----	----	----
β_{SEG}	.2131 (.002)	-				
β_{PSEG}	.2309 (.001)	.8142 (.001)	-			
β_{HAM}	.1704 (.015)	.3187 (.001)	.3123 (.001)	-		
β_{CON}	.1809 (.010)	.3680 (.001)	.3566 (.001)	.9979 (.001)	-	
$\beta_{HAM(T)}$	.1294 (.068)	.3687 (.001)	.9700 (.001)	.3625 (.001)	.9687 (.001)	-
$\beta_{CON(T)}$	.1420 (.045)	.4187 (.001)	.9716 (.001)	.4070 (.001)	.9661 (.001)	.9978 (.001)

5.2 Intertemporal Behavior of the Beta Estimates

The standard deviation of beta over the 48 monthly observations was calculated for each firm in the single and multi-segment firm samples. These intertemporal standard deviations were then averaged across all the firms in each sample. Table 5.4 presents the summary statistics.

A potential advantage of the segmental betas is that they may be more responsive to changes in the financing and investment of the firm. As the proportion of sales in a particular division changes, for instance, the segmental beta reflects this change in the operations of the firm. Likewise, the levered betas automatically adjust to any change in the proportion of debt in the capitalization of the firm. Consequently, some variability in the segmental betas is to be expected.

The intertemporal behavior of the segmental beta estimates exhibits much less variability than either the OLS estimates or the leverage-adjusted segmental estimates. The lower standard deviation in BSEG is at least partially due to the portfolio effects of aggregating single-segment firms in the formation of the industry portfolios and of aggregating segments in the multi-segment firm sample.

The Conine and Hamada leverage adjustments again caused a greater variability in levered beta. The increase over the segmental beta was proportionally less than in the

cross-sectional standard deviations. The Conine beta estimates again exhibited more stability than did the Hamada estimates, and the adjustments calculated using average tax rates exhibited more stability than the adjustments using annual tax rates. These results are consistent with the cross-sectional summary statistics.

Table 5.4 Betas: Intertemporal Descriptive Statistics

	<u># of</u> <u>Firms</u>	<u>Mean</u>	<u>Standard</u> <u>Deviation</u>
β_{OLS}	201	1.4322	0.2214
β_{SEG}	230	1.5268	0.1258
β_{HAM}	234	2.1244	0.3462
β_{CON}	234	2.0150	0.3018
β_{PSEG}	86	1.5215	0.1736
$\beta_{HAM}(T)$	234	1.9763	0.3049
$\beta_{CON}(T)$	234	1.8681	0.2702
$IND\beta$	95	1.5386	0.1842
$IND\beta_{HAM}$	86	0.9122	0.1405
$IND\beta_{CON}$	86	1.0348	0.1329
$IND\beta_{HAM}(T)$	86	0.8909	0.1331
$IND\beta_{CON}(T)$	86	1.0180	0.1277

5.3 The Incremental Explanatory Power of β SEG and β OLS

The multiple regression results of Equation (4.1) are presented in Tables 5.5 and 5.6. Table 5.5 presents the multiple regression results for the pooled sample including up to 196 firms and 48 months.⁵ Because of missing data, only 8737 observations were used in this regression. Table 5.6 provides the multiple regression results for the first twelve months of the sample period.

The relatively low cross-sectional correlation between β OLS and β SEG (of Section 5.1) may allow a qualified interpretation of the coefficients a and b in the multiple regression Equation (4.1). If β SEG and β OLS are uncorrelated, then the slope coefficients are unbiased and the significance of the slope coefficients can be evaluated relative to their standard errors. Since the regressors are only somewhat linearly related through the beta estimates, some guarded statements about the magnitude and significance of the coefficients a and b may be possible. The relatively low correlation may also allow the two beta estimates to contribute unique information about the systematic risk of common stock.

⁵ Pooling cross-sectional and time series data may be inappropriate in this regression application because of the high serial correlation within the beta estimates for each firm. The standard errors around the slope coefficients are fairly narrow, however. The relatively low degree of serial correlation in the regressors apparently has not caused too severe of an impact on the regression results.

In the single regressions of Table 5.5, the β OLS and β SEG independent variables explain 24.991% and 24.797%, respectively, of the variation in the dependent variable $R_j - R_f$. The r^2 for the regression combining both independent variables is only 0.25594, so the multiple regression explains 25.594% of the variability in the risk premium $R_j - R_f$. The incremental r^2 added to the multiple regression by the OLS and segmental beta is only 0.572% and 0.603%, respectively. The partial F statistics are highly significant because of the high precision in the regression results due to the 8737 observations. The increase in r^2 , however, represents less than a three percent increase when adding the second variable to the regression equation.

This result is both an encouragement and a disappointment. The results indicate that segmental and OLS beta contain nearly the same information in explaining the return to common stock. Augmenting an OLS beta with a segmental beta as in Equation (4.12) of Section 4.2 is unlikely to produce better return forecasts than when using either of the betas alone. On the other hand, segmental beta possesses several properties which may recommend it over β OLS. First, it exhibits greater intertemporal stability as demonstrated in Section 5.2. And since segmental beta is based upon the average systematic risk of the multi-segment firm's component industries, β SEG is more adaptable to rapid changes in the

investment mix of the firm.⁶ The computations involved in BSEG are, however, considerably more complex than those associated with BOLS.

The performance of the OLS and segmental beta estimates in explaining the return to common stock in various market environments was also examined. Table 5.6 presents the single and multiple regression results cross-sectionally for each of the first twelve months of the sample period. For each month, in the first stage regression, the independent variable with the highest r^2 was entered into a single variable regression model. Then, in the second stage, the remaining independent variable was entered into a multiple regression model and the partial F statistic was examined.

Unfortunately, the r^2 and F statistics for these cross-sectional samples exhibited little stability. The small number of observations and the large unsystematic or random component in the security returns conspired to lend little precision to the regression estimates. Results were similarly inconclusive when performing the regression on individual firms across time.

⁶ The characteristics of the Hamada and Conine financial leverage adjustments are examined in the next section.

Table 5.5 Multiple Regression: Pooled NxT Sample

$$R_j - R_f = \alpha + b_1 * \beta_{OLS} * (R_m - R_f) + b_2 * \beta_{SEG} * (R_m - R_f) + u$$

Correlation:	(Rj-Rf)	$\beta_{OLS} * (R_m - R_f)$	$\beta_{SEG} * (R_m - R_f)$
(Rj-Rf)	1.000	.500	.500
$\beta_{OLS} * (R_m - R_f)$	.500	1.000	.954
$\beta_{SEG} * (R_m - R_f)$	.500	.954	1.000

Single regression with $\beta_{OLS} * (R_m - R_f)$ only:

$$\alpha = 0.00471 \quad \beta_1 = 0.78885$$

Standard error (0.00090) (0.01462)

$$r^2 = 0.24991 \quad F = 2910.26 \quad \text{Significance of } F = 0.0000$$

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	1	20.64531	20.64531
Residual	8735	61.96581	0.00709

Single regression with $\beta_{SEG} * (R_m - R_f)$ only:

$$\alpha = 0.00446 \quad b_2 = 0.77065$$

Standard error (0.00092) (0.01450)

$$r^2 = 0.24797 \quad F = 2823.8 \quad \text{Significance of } F = 0.0000$$

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	1	20.55920	20.55920
Residual	8564	62.35187	0.00728

Multiple regression: both $\beta_{SEG} * (R_m - R_f)$ and $\beta_{OLS} * (R_m - R_f)$ entered

$$\alpha = 0.00458 \quad b_1 = 0.39849 \quad b_2 = 0.39643$$

Standard error (0.00092) (0.04863) (0.04711)

$$r^2 = 0.25594 \quad F = 1502.16 \quad \text{Significance of } F = 0.0000$$

Analysis of Variance:

	DF	Sum of Squares	Mean Square
Regression	2	21.14359	10.57180
Residual	8734	61.46753	.00704

Partial F statistics:

Variable in the equation	Variable to be added	r^2 change	Partial F	Significance
$\beta_{OLS} * (R_m - R_f)$	$\beta_{SEG} * (R_m - R_f)$	.00603	70.80074	0.0000
$\beta_{SEG} * (R_m - R_f)$	$\beta_{OLS} * (R_m - R_f)$	.00572	67.15999	0.0000

TABLE 5.6 Multiple Regression: Results by month

$$R_j - R_f = \alpha + b_1 * \beta_{OLS} * (R_m - R_f) + b_2 * \beta_{SEG} * (R_m - R_f) + u$$

For each month, the first line represents the first variable entered and the second line represents the last variable entered. Standard errors of the slope coefficients are in parentheses under the variables as they are entered.

Month	N	OLS vs SEG Corr	Slope Coefficients		r^2	F		F Change
			OLS (se)	SEG (se)		E	Signif	
1	150	0.328	-.516 (.403)		0.010	1.64	0.20	
			-.390 (.427)	-.847 (.942)	0.016	1.22	0.29	0.370
2	150	0.329		1.464 (.531)	0.048	7.59	0.00	
			0.329 (.256)	1.227 (.561)	0.059	4.63	0.01	0.201
3	150	0.333	1.562 (.323)		0.136	23.3	0.00	
			1.430 (.342)	0.865 (.748)	0.144	12.3	0.00	0.249
4	150	0.336		-1.18 (2.42)	0.001	0.23	0.62	
			0.270 (1.21)	-1.14 (2.59)	0.001	0.14	0.86	0.824
5	150	0.349	0.886 (.687)		0.011	1.66	0.19	
			1.223 (.731)	-2.08 (1.57)	0.022	1.71	0.18	0.186
6	150	0.346		-.671 (.722)	0.005	0.86	0.35	
			-.109 (.358)	-.589 (.773)	0.006	0.47	0.62	0.760
7	150	0.343		9.336 (8.67)	0.007	1.15	0.28	
			-4.69 (4.35)	12.74 (9.23)	0.015	1.15	0.31	0.283
8	151	0.323		0.752 (.736)	0.007	1.04	0.30	
			-.083 (.357)	0.811 (.780)	0.007	0.54	0.58	0.815
9	151	0.338	2.098 (.856)		0.038	6.00	0.01	
			2.054 (.913)	0.277 (1.96)	0.038	2.99	0.05	0.887

TABLE 5.6 Multiple Regression: Results by month (continued)

<u>Month</u>	<u>N</u>	<u>OLS vs SEG Corr</u>	<u>Slope Coefficients</u>		<u>r²</u>	<u>F</u>	<u>Signif</u>	<u>F Change</u> <u>Signif</u>
			<u>OLS</u> <u>(se)</u>	<u>SEG</u> <u>(se)</u>				
10	151	0.308	0.341 (.103)		0.068	11.0	0.00	
			0.373 (.108)	-.224 (.236)	0.074	5.95	0.00	0.344
11	151	0.356	0.346 (.272)		0.010	1.61	0.20	
			0.512 (.290)	-.868 (.540)	0.027	2.10	0.12	0.110
12	151	0.319		5.221 (4.19)	0.010	1.55	0.21	
			2.011 (2.37)	4.022 (4.42)	0.015	1.13	0.32	0.397
avg	1st var				0.029	4.81	0.20	
	2nd var				0.035	2.87	0.28	0.452

5.4 The Predictive Power of the Beta Estimates

If the Capital Asset Pricing Model holds, then a forecast of the return to security j at time t is

$$E[R_{jt}] = R_{ft} + \beta_j * (R_{mt} - R_{ft}) \quad (5.1)$$

and the prediction error is

$$\begin{aligned} e_{jt} &= R_{jt} - E[R_{jt}] \\ &= R_{jt} - R_{ft} - \beta_j * (R_{mt} - R_{ft}). \end{aligned} \quad (5.2)$$

An ideal beta estimate should produce security return predictions which are unbiased ($E[e_{jt}] = 0$) and efficient (minimum variance $\sigma^2(e)$). The forecast accuracy of the return predictions is analyzed with three statistics. The mean errors (ME) provide a measure of the average prediction bias over the sample period. The mean absolute deviations (MAD) and mean square errors (MSE) measure the dispersion of the return forecasts around the actual returns and hence provide a measure of the forecast accuracy of the estimates.

The return predictions are predictions only in a very restricted sense. The beta estimates β_j at time t are based upon publicly available information from previous periods (months $t-60$ to $t-1$). The return forecasts, however, are based upon the actual market return R_{mt} and the actual T-Bill rate R_{ft} . Consequently, no investor in the market could form return forecasts in this fashion.

The tests of forecast accuracy focus on the performance of the return estimates relative to the market risk premium. The

forecasts are based upon firm-specific information available at time t and market-wide events which are unknown until the end of period t . The tests of forecast accuracy thus focus on firm-specific factors. If one beta estimate leads to better return forecasts, then its prediction should exhibit a smaller mean square error. It is in this restricted sense that the various return prediction models are tested.

5.4.a The Research Design

The Security Market Line captures market risk since well-diversified investors price market or nondiversifiable risk in the marketplace. The prediction errors of individual firm returns suffer from large nonsystematic or firm-specific return behavior that is not captured in the Security Market Line. Some of this firm-specific behavior can be eliminated by forming portfolios of securities and then performing the statistical tests on the portfolio return prediction errors.

Figure 5.2 provides an overview of the research methodology as applied to the portfolio return predictions. Prediction errors were analyzed for the entire multi-segment firm sample over all 48 months. The return predictions were made using the time t market return and risk-free rate. The sample of multi-segment firms was then ranked by OLS beta and three portfolios were formed of the twenty largest beta (β_{HI}), the twenty smallest beta (β_{LOW}), and the twenty median beta

(BMID) firms. The forecast accuracy results for the three portfolios differing in market risk, along with the individual firm results, are presented in Table 5.7. Since the alternative beta estimates may perform differently in different market environments, the portfolio and sample return predictions are also examined in periods of high, average, and low market return performance (as measured by the ex-post market risk premium $(R_m - R_f)$).

Figure 5.3 outlines the methodology applied to the individual security predictions. Adjustments are performed at the single security level in an attempt to reduce the forecast error. The prediction models unadjusted for bias or inefficiency are analyzed on mean error, mean absolute deviation, and mean square error. Adjustments are subsequently made to increase the efficiency of the return estimate and then to reduce the bias of the return estimate. Finally, both adjustments are performed simultaneously. To perform these adjustments, the return predictions from each of the beta estimates were regressed against the actual return premiums

$$R_j - R_f = a + b[\beta_j(R_m - R_f)] + e$$

to attain an estimate of the slope coefficient b . (The results of these regressions appear in Table 5.19.)

The mean unadjusted errors (ME), mean absolute deviations (MAD), and the mean square errors (MSE) from equation (5.2) for the sample of multi-segment firms are provided in Table 5.11. The effects of adjusting for bias and inefficiency in these

forecasts are examined in Tables 5.12 through 5.14. The results of the matched pair t-test of significance between the various return prediction models at the single security level are summarized in Table 5.15 through Table 5.18.

5.4.b The Empirical Results

The mean errors measure the bias of the estimates over the sample period. The naive prediction of the risk-free rate was in all cases the most biased. The standard errors are too large, however, to state with precision that one prediction method is superior to another in minimizing bias.

Across the high, median, and low beta portfolios of Tables 5.7 through 5.10, the results were consistent with the individual firm mean prediction errors. The naive risk-free predictions consistently exhibited larger bias than any of the other return predictions; yet, based on the standard errors, the mean errors of this naive model are no more significantly different from zero than those associated with the other prediction methods.

The mean error of the naive prediction $E[R_j] - R_f$ has a positive expected value:

$$\begin{aligned} E[e_j] &= R_j - E[R_j] \\ &= R_j - R_f > 0 \end{aligned}$$

for $E[RCS] > R[RF]$. This return prediction on average underestimates the return to common stock. The Security Market

Line return predictions using OLS and segmental beta estimates and the market index predictions $E[R_j] = R_m$ and $E[R_j] = RCS$ exhibit predominantly positive mean error and hence also underestimate the average return on the multi-segment portfolios.

One reason for the positive mean errors of the market index prediction R_m and the equity index prediction RCS is that the value weighted Ibbotson and Sinquefeld common stock index RCS returned 16.00% per year on average while the multi-segment sample has an equal weighted average annual return of 17.08% over the sample period. Consequently, the market index predictions are less than the actual returns on the sample.

A second reason for the positive mean errors across the return prediction models arises in the calculation of the mean error. The mean error calculation places an equal weight on each firm's prediction error and is therefore equivalent to taking an equal weighted average of the sample's prediction errors. The Ibbotson and Sinquefeld common stock index⁷ used in the calculation of the market return R_m , however, is a market value weighted index. And, over the sample period, small capitalization stocks performed much better than large capitalization issues. While Ibbotson and Sinquefeld's common stock index returned an annual average of 16.00% over the sample period, their small capitalization stock index

⁷ Ibbotson and Sinquefeld use the value weighted S&P 500 as their index of the average return to common stock.

(representing the smallest quintile of stocks on the NYSE) returned 30.8%.⁸ Consequently, an equal weighted index on the period will show a larger annual return than a comparable value weighted index. Combined with the persistent bull market in small capitalization stocks over the sample period, the mean error calculation consistently gives positive results.

The high beta portfolio had by far the largest mean error for every return prediction method. The low beta portfolio had a slightly smaller mean error than the median risk portfolio, but, based on the standard errors, the difference is generally not significant. This further suggests that the return predictions based on the value weighted market index RCS (and RM composed of RCS and RDEBT) consistently underestimate the actual return for the average stock in the sample.

The mean error of the common stock return prediction based on β CS and the OLS, segmental, and primary segment predictions were approximately the same. The Hamada and Conine predictions had slightly smaller mean errors. In all cases, however, the standard errors are relatively large and the mean errors are not significantly different from zero.

The mean absolute deviation and mean square error for $\beta=1$, $\beta=1.43$, β OLS and β SEG are perhaps most interesting for the portfolio results of Tables 5.7 to 5.10. Predicting a market

⁸ The CRSP value weighted stock index returned 16.99% on average over the period 1979 through 1982. The equal weighted index returned 24.82% over the same period. The average annual rate of return on 30-day T-bills was 11.7% from 1979 through 1982.

return ($\beta=1$) is similar to selecting a low beta equity portfolio since the market is composed of both debt and equity. This prediction performed relatively well for the low beta portfolio and not so well for the high beta portfolio. As the systematic risk of the firm diverges from the mean, the simple return prediction of the average market or equity return performs less satisfactorily than a firm-specific return estimate. Across all three market environments of Tables 5.8 through 5.10 (and summarized in Table 5.7), the segmental beta forecasts proved to be superior for the high beta portfolio BHI. For low beta firms the OLS beta performed best, while the segmental beta forecasts and the equity return predictions performed comparably. Primary segment beta β_{PSEG} performed similarly, but not quite as well, to segmental beta in forecast accuracy. The average equity return prediction based on β_{CS} performed best for the firms of average systematic risk.

The various return predictions performed comparably over all three market environments. Segmental beta did least well for the low beta portfolio and better for the high beta portfolio. The equity return prediction performed best for the average risk stocks. The important categorization turned out to be across high and low risk stocks and not across alternative market environments.

An examination of the single security results over the entire sample period (Tables 5.11 through 5.18) reveals that the average market return prediction R_m , the average equity

return prediction RCS and the OLS return predictions possess the best forecast accuracy. For the unadjusted return predictions of Table 5.11 (significance levels appear in Table 5.15) the order of forecast accuracy among the methods which do not adjust for financial leverage was $\beta_M > \beta_{CS} > \beta_{OLS} > \beta_{SEG} > \beta_{PSEG}$ based on mean square error. Neither the OLS nor the segmental betas were worse than the market or equity return predictions at the 5% confidence level. All except the market return prediction R_m were better than the primary segment beta β_{PSEG} at $\alpha = .05$.

Again, looking at the mean square error statistics, the leverage adjusted segmental betas performed much worse than the segmental and OLS betas. The Hamada beta β_{HAM} even performed worse than the naive estimate of the risk free rate, though not significantly so. The leverage adjusted betas $\beta_{HAM}(T)$ and $\beta_{CON}(T)$ utilizing average tax rates performed better than the leverage adjusted segmental betas β_{HAM} and β_{CON} with annual tax rates. Also, the Conine adjustment consistently provided better forecast accuracy than the Hamada adjustment. None of the leverage adjusted betas, however, performed as well as either the β_{OLS} or β_{SEG} predictions.

The adjustments for inefficiency in the estimates (Table 5.12 and 5.16) did not noticeably improve the forecast accuracy of the OLS, segmental or primary segment betas. The leverage adjusted betas performed significantly better after adjusting the beta estimates back toward their mean. The leverage

adjusted betas still did not, however, perform as well as the betas without a leverage adjustment. Again, the Conine betas demonstrated better forecast accuracy than the Hamada betas and the levered betas using average tax rates performed better than the levered betas using actual annual tax rates.

The bias adjustment of Tables 5.13 and 5.17 added very little to the forecast ability of the models. The reason lies in the decomposition of mean square error:

$$\begin{aligned} \text{MSE} &= [(\text{Avg}(R) - \text{Avg}(E[R]))^2] + [((1-b)^2) * (\text{SE}[R]^2)] \\ &\quad + [(1-r^2) * \text{SR}^2] \\ &= \text{bias} + \text{inefficiency} + \text{error}. \end{aligned}$$

The bias component adds to MSE as the square of the mean error. Taking segmental beta as an example, the mean error in Table 5.11 of β_{SEG} is .0042. The bias added to mean square error is thus $(.0042)^2 = .00001684$, which is smaller than the four significant digits reported. The bias adjustment to mean square error is hence relatively minor for all of the return prediction models. And, relatedly, the forecast accuracy results of Tables 5.14 and 5.18 for the bias and slope adjusted return forecasts are nearly identical to the results of the slope adjusted forecasts (Tables 5.12 and 5.16). The bias adjustment again adds very little to predictive accuracy.

Figure 5.2 Research Design: Portfolios
Beta versus Market Premium

20-Firm Portfolios Ranked on β OLS

<u>Market Premium</u>	<u>βHI</u>	<u>βMID</u>	<u>βLOW</u>	<u>All Firms</u>
All months	(...)	Table 5.7	(...)	(...)
(RM-RF)HI	(...)	Table 5.8	(...)	(...)
(RM-RF)MID	(...)	Table 5.9	(...)	(...)
(RM-RF)LOW	(...)	Table 5.10	(...)	(...)

Figure 5.3 Research Design: Individual Securities
Return Predictions

<u>Forecast</u>	Mean error Mean absolute deviation Mean square error <u>Forecast Accuracy</u>	Matched Pair T-Test of <u>Significance</u>
Unadjusted	Table 5.11	Table 5.15
Slope adjusted	Table 5.12	Table 5.16
Bias adjusted	Table 5.13	Table 5.17
Slope & Bias adjusted	Table 5.14	Table 5.18

Unadjusted forecasts:

$$e_j = R_j - R_f - \beta_j (R_m - R_f)$$

Slope adjusted forecasts:

$$e_j = R_j - R_f - (\text{slope} * (\beta_j - \text{avg}(\beta_j) + \text{avg}(\beta_j)) * (R_m - R_f))$$

Bias adjusted forecasts

$$e_j = R_j - R_f - \text{bias} - \beta_j (R_m - R_f)$$

Bias and slope adjusted forecasts

$$e_j = R_j - R_f - \text{bias} - (\text{slope} * (\beta_j - \text{avg}(\beta_j) + \text{avg}(\beta_j)) * (R_m - R_f))$$

Table 5.7 Portfolio Prediction Errors: all 48 months

20-Firm portfolios β_{HI} , β_{MID} , and β_{LOW} ranked on β_{OLS} and calculated over the entire 48 month sample period.

<u>Predictor</u>	<u>β_{HI}</u>	<u>β_{MID}</u>	<u>β_{LOW}</u>	<u>All firms</u>	
$\beta=0$ (RF)	.0231	.0054	.0044	.0079	ME
	(.013)	(.009)	(.006)	(.008)	
	.1038 *	.0756 *	.0542 *	.0728 *	MAD
	(.006)	(.004)	(.002)	(.003)	
	.0196 *	.0098 *	.0052 *	.0093 *	MSE
	(.003)	(.001)	(.000)	(.001)	
$\beta=1$ (RM)	.0207	.0030	.0020	.0055	ME
	(.009)	(.005)	(.003)	(.004)	
	.0887	.0642	.0484	.0616	MAD
	(.005)	(.002)	(.002)	(.002)	
	.0155	.0072	.0043	.0069	MSE
	(.002)	(.001)	(.000)	(.000)	
$\beta=1.43$ (RCS)	.0197	.0020	.0010	.0044	.
	(.008)	(.005)	(.005)	(.004)	.
	.0860	.0639	.0528 *	.0620	.
	(.004)	(.002)	(.003)	(.002)	
	.0147	.0071 *	.0049 *	.0070	
	(.002)	(.001)	(.001)	(.000)	
β_{OLS}	.0188	.0018	.0021	.0045	
	(.008)	(.005)	(.003)	(.004)	
	.0892	.0646	.0480	.0621	
	(.004)	(.002)	(.002)	(.002)	
	.0152	.0073	.0042	.0070	
	(.002)	(.001)	(.000)	(.000)	
β_{SEG}	.0194	.0015	.0011	.0042	
	(.008)	(.005)	(.005)	(.004)	
	.0854 *	.0648	.0525 *	.0627 *	
	(.004)	(.002)	(.003)	(.002)	
	.0145	.0072	.0050 *	.0071	
	(.002)	(.001)	(.001)	(.000)	
β_{PSEG}	.0192	.0015	.0009	.0042	
	(.004)	(.002)	(.005)	(.004)	
	.0857 *	.0655 *	.0532 *	.0630 *	
	(.004)	(.002)	(.003)	(.002)	
	.0144	.0073	.0051 *	.0072	
	(.002)	(.001)	(.001)	(.000)	

β_{HAM}	.0157 (.008) .0942 * (.004) .0176 * (.002)	.0002 (.006) .0704 * (.003) .0084 * (.001)	-.0002 (.007) .0615 * (.004) .0074 * (.001)	.0024 (.006) .0718 * (.003) .0100 * (.001)
$\beta_{HAM}(T)$	.0167 (.008) .0915 (.004) .0166 * (.002)	.0006 (.006) .0681 * (.003) .0079 * (.001)	-.0001 (.007) .0605 * (.004) .0071 * (.001)	.0029 (.006) .0695 * (.003) .0092 * (.001)
β_{CON}	.0164 (.008) .0909 (.004) .0162 (.002)	.0005 (.006) .0690 * (.003) .0080 * (.001)	.0001 (.007) .0594 * (.004) .0068 * (.001)	.0027 (.006) .0694 * (.003) .0085 * (.001)
$\beta_{CON}(T)$	.0172 (.008) .0890 (.004) .0157 (.002)	.0008 (.006) .0673 * (.003) .0077 * (.001)	.0001 (.006) .0588 * (.004) .0066 * (.001)	.0031 (.005) .0677 * (.002) .0070 * (.001)

* Different from β_{OLS} at $\alpha = .05$

(Standard errors in parentheses)

Table 5.8 Portfolio Prediction Errors: (RM-RF)HI

20-Firm portfolios β HI, β MID, and β LOW ranked on BOLS
16 largest monthly returns based on (RM-RF)

<u>Predictor</u>	<u>βHI</u>	<u>βMID</u>	<u>βLOW</u>	<u>All Firms</u>	
$\beta=0$ (RF)	.1010 *	.0600 *	.0415 *	.0650 *	ME
	(.014)	(.007)	(.004)	(.007)	
	.1197 *	.0793	.0613 *	.0844 *	MAD
	(.011)	(.007)	(.004)	(.005)	
	.0240 *	.0110	.0063 *	.0130 *	MSE
	(.004)	(.002)	(.001)	(.002)	
$\beta=1$ (RM)	.0537 *	.0127 *	-.0058 *	.0177 *	ME
	(.015)	(.008)	(.007)	(.007)	
	.0967	.0651	.0533	.0697	MAD
	(.010)	(.003)	(.003)	(.005)	
	.0171	.0071	.0533	.0091	MSE
	(.003)	(.001)	(.000)	(.001)	
$\beta=1.43$ (RCS)	.0333 *	-.0076	-.0261 *	-.0026	.
	(.016)	(.009)	(.009)	(.008)	.
	.0936	.0661	.0605	.0716	.
	(.0047)	(.004)	(.005)	(.004)	
	.0159	.0071 *	.0059	.0092	
	(.003)	(.001)	(.001)	(.001)	
BOLS	-.0030	-.0067	.0039	-.0032	
	(.019)	(.009)	(.006)	(.009)	
	.1000	.0674	.0528	.0719	
	(.008)	(.004)	(.010)	(.004)	
	.0169	.0075	.0047	.0093	
	(.003)	(.001)	(.000)	(.001)	
β SEG	.0255 *	-.0128 *	-.0210 *	-.0051 *	
	(.016)	(.009)	(.008)	(.009)	
	.0932	.0682	.0614 *	.0726	
	(.008)	(.005)	(.005)	(.004)	
	.0155	.0076	.0061 *	.0093	
	(.003)	(.001)	(.001)	(.001)	
β PSEG	.0229 *	-.0136 *	-.0221 *	-.0064 *	
	(.016)	(.010)	(.008)	(.009)	
	.0933	.0690	.0625 *	.0734	
	(.008)	(.005)	(.005)	(.004)	
	.0153	.0077	.0064 *	.0094	
	(.003)	(.001)	(.001)	(.001)	

BHAM	-.0161 *	-.0347 *	-.0459 *	-.0333 *
	(.017)	(.011)	(.011)	(.011)
	.1091 *	.0778 *	.0757 *	.0860 *
	(.008)	(.006)	(.008)	(.007)
	.0213 *	.0098 *	.0102 *	.0133 *
	(.003)	(.001)	(.002)	(.002)
BHAM(T)	-.0057	-.0269 *	-.0433 *	-.0265 *
	(.017)	(.010)	(.011)	(.010)
	.1041	.0734 *	.0097 *	.0824 *
	(.008)	(.006)	(.008)	(.006)
	.0197	.0087 *	.0097 *	.0123 *
	(.003)	(.001)	(.002)	(.002)
BCON	-.0081	-.0305 *	-.0409 *	-.0278 *
	(.017)	(.010)	(.010)	(.011)
	.1039	.0755 *	.0725 *	.0825 *
	(.008)	(.006)	(.007)	(.006)
	.0189	.0091 *	.0092 *	.0120 *
	(.003)	(.001)	(.002)	(.002)
BCON(T)	.0001	-.0244 *	-.0391 *	-.0225 *
	(.016)	(.009)	(.010)	(.010)
	.1002	.0721 *	-.0391 *	.0798 *
	(.008)	(.006)	(.008)	(.006)
	.0180	.0084 *	.0089 *	.0113 *
	(.003)	(.001)	(.002)	(.002)

* Different from β OLS at $\alpha = .05$

(Standard errors in parentheses)

Table 5.9 Portfolio Prediction Errors: (RM-RF)MID

20-Firm portfolios BHI, BMID, and BLOW ranked on BOLS
16 middle monthly returns based on (RM-RF)

<u>Predictor</u>	<u>BHI</u>	<u>BMID</u>	<u>BLOW</u>	<u>All Firms</u>	
$\beta=0$ (RF)	-.0199 *	-.0215 *	.0155 *	-.0190 *	ME
	(.025)	(.016)	(.010)	(.016)	
	.1059	.0791	.0555 *	.0791	MAD
	(.012)	(.008)	(.004)	(.007)	
	.0191	.0104	.0059 *	.0115	MSE
	(.004)	(.002)	(.001)	(.002)	
$\beta=1$ (RM)	.0049 *	.0033 *	.0093 *	.0058 *	ME
	(.008)	(.004)	(.004)	(.009)	
	.0867	.0627	.0492	.0654	MAD
	(.008)	(.004)	(.004)	(.004)	
	.0140	.0071	.0049	.0084	MSE
	(.003)	(.001)	(.001)	(.001)	
$\beta=1.4$ (RCS)	.0156 *	.0140	.0200 *	.0165	.
	(.016)	(.007)	(.008)	(.007)	.
	.0818	.0616	.0547 *	.0654	.
	(.008)	(.004)	(.005)	(.004)	
	.0130	.0068	.0056	.0083	
	(.003)	(.001)	(.001)	(.001)	
BOLS	.0373	.0135	.0037	.0174	
	(.013)	(.007)	(.006)	(.007)	
	.0844	.0618	.0481	.0643	
	(.008)	(.004)	(.004)	(.004)	
	.0133	.0070	.0057	.0082	
	(.003)	(.001)	(.001)	(.001)	
β SEG	.0219 *	.0168 *	.0178 *	.0182 *	
	(.014)	(.007)	(.008)	(.007)	
	.0808	.0625	.0537 *	.0651	
	(.008)	(.004)	(.004)	(.004)	
	.0126	.0070	.0057	.0083	
	(.003)	(.001)	(.001)	(.001)	
β PSEG	.0219 *	.0168 *	.0178 *	.0186 *	
	(.014)	(.007)	(.008)	(.007)	
	.0808	.0636 *	.0545 *	.0658	
	(.008)	(.004)	(.004)	(.004)	
	.0126	.0071	.0059	.0084	
	(.003)	(.001)	(.001)	(.001)	

β_{HAM}	.0388 (.013)	.0270 * (.008)	.0307 * (.012)	.0313 * (.008)
	.0901 (.007)	.0694 * (.004)	.0652 * (.007)	.0741 * (.004)
	.0158 (.003)	.0082 * (.001)	.0086 * (.001)	.0105 * (.001)
$\beta_{HAM}(T)$	.0345 (.013)	.0231 * (.007)	.0291 * (.011)	.0282 * (.008)
	.0871 (.007)	.0670 * (.004)	.0641 * (.007)	.0722 * (.004)
	.0144 (.003)	.0077 * (.001)	.0082 * (.001)	.0099 * (.001)
β_{CON}	.0354 (.013)	.0251 * (.008)	.0279 * (.011)	.0288 * (.008)
	.0862 (.007)	.0677 * (.004)	.0626 * (.006)	.0716 * (.004)
	.0143 (.002)	.0078 * (.001)	.0079 * (.002)	.0098 * (.001)
$\beta_{CON}(T)$	.0320 (.013)	.0220 * (.007)	.0269 * (.011)	.0264 * (.007)
	.0839 (.007)	.0660 * (.004)	.0620 * (.006)	.0702 * (.004)
	.0135 (.003)	.0075 (.001)	.0077 * (.002)	.0094 * (.001)

* Different from BOLS at $\alpha = .05$

(Standard errors in parentheses)

Table 5.10 Portfolio Prediction Errors: (RM-RF)LOW

20-Firm portfolios BHI, BMID, and BLOW ranked on BOLS
16 smallest monthly returns based on (RM-RF)

<u>Predictor</u>	<u>BHI</u>	<u>BMID</u>	<u>BLOW</u>	<u>All Firms</u>	
$\beta=0$ (RF)	-.0116 *	-.0223 *	-.0128 *	-.0160 *	ME
	(.010)	(.010)	(.005)	(.007)	
	.0857	.0686	.0457 *	.0657	MAD
	(.005)	(.005)	(.002)	(.003)	
	.0157	.0081	.0033 *	.0088	MSE
	(.006)	(.001)	(.000)	(.002)	
$\beta=1$ (RM)	.0037 *	-.0071 *	.0025 *	-.0007	ME
	(.005)	(.009)	(.004)	(.006)	
	.0827	.0649	.0428	.0625	MAD
	(.005)	(.004)	(.003)	(.003)	
	.0152	.0073	.0031	.0083	MSE
	(.006)	(.001)	(.000)	(.002)	
$\beta=1.4$ (RCS)	.0102 *	-.0005 *	.0090 *	.0059	.
	(.008)	(.009)	(.004)	(.005)	.
	.0827	.0639 *	.0431	.0622	.
	(.005)	(.004)	(.003)	(.003)	
	.0152	.0072 *	.0032	.0082	
	(.006)	(.001)	(.000)	(.002)	
BOLS	.0220	-.0014	-.0014	.0057	
	(.008)	(.009)	(.004)	(.006)	
	.0832	.0645	.0431	.0626	
	(.006)	(.004)	(.003)	(.003)	
	.0155	.0073	.0031	.0083	
	(.006)	(.001)	(.000)	(.002)	
BSEG	.0122 *	.0009 *	.0069 *	.0062 *	
	(.008)	(.009)	(.004)	(.006)	
	.0825	.0638	.0425	.0620 *	
	(.005)	(.004)	(.003)	(.003)	
	.0152	.0072 *	.0031	.0082 *	
	(.006)	(.001)	(.000)	(.002)	
BPSEG	.0128 *	.0013 *	.0071 *	.0066 *	
	(.008)	(.009)	(.004)	(.006)	
	.0830	.0639	.0427	.0622	
	(.005)	(.004)	(.003)	(.003)	
	.0153	.0071 *	.0031	.0082 *	
	(.006)	(.001)	(.000)	(.002)	

β_{HAM}	.0245 *	.0083 *	.0148 *	.0151 *
	(.008)	(.008)	(.004)	(.005)
	.0834	.0639	.0437	.0627
	(.006)	(.004)	(.003)	(.003)
	.0157	.0072	.0033	.0084
	(.006)	(.001)	(.000)	(.002)
$\beta_{HAM(T)}$	.0213	.0057 *	.0138 *	.0129 *
	(.008)	(.008)	(.004)	(.005)
	.0834	.0638	.0634	.0626
	(.006)	(.004)	(.003)	(.003)
	.0156	.0072	.0033	.0084
	(.006)	(.001)	(.000)	(.002)
β_{CON}	.0221	.0068 *	.0131 *	.0134 *
	(.008)	(.008)	(.004)	(.005)
	.0827	.0638	.0432	.0623
	(.006)	(.004)	(.003)	(.003)
	.0155	.0072	.0033	.0084
	(.006)	(.001)	(.000)	(.002)
$\beta_{CON(T)}$	.0196	.0048 *	.0125 *	.0116 *
	(.008)	(.008)	(.004)	(.005)
	.0830	.0637	.0431	.0623
	(.006)	(.004)	(.003)	(.003)
	.0155	.0071	.0033	.0083
	(.006)	(.001)	(.000)	(.002)

* Different from β_{OLS} at $\alpha = .05$

(Standard errors in parentheses)

Table 5.11 Return Prediction Errors: Unadjusted

	<u>ME</u>	<u>MAD</u>	<u>MSE</u>
BRF = 0	.0079 (.008)	.0728 (.003)	.0093 (.001)
BM = 1	.0055 (.004)	.0616 (.002)	.0069 (.000)
BCS = 1.43	.0044 (.004)	.0620 (.002)	.0070 (.000)
BOLS	.0045 (.004)	.0621 (.002)	.0070 (.000)
BSEG	.0042 (.004)	.0627 (.002)	.0071 (.000)
BPSEG	.0042 (.004)	.0630 (.002)	.0072 (.000)
BHAM	.0024 (.006)	.0718 (.003)	.0100 (.001)
BHAM(T)	.0029 (.006)	.0695 (.003)	.0092 (.001)
BCON	.0027 (.006)	.0694 (.003)	.0091 (.001)
BCON(T)	.0031 (.005)	.0677 (.002)	.0085 (.000)

Table 5.12 Return Prediction Errors: Slope Adjusted

	<u>ME</u>	<u>MAD</u>	<u>MSE</u>
$\beta_{RF} = 0$	.0079 (.008)	.0728 (.003)	.0093 (.001)
$\beta_M = 1$	.0055 (.004)	.0616 (.002)	.0069 (.000)
$\beta_{CS} = 1.43$	.0044 (.004)	.0620 (.002)	.0070 (.000)
β_{OLS}	.0045 (.004)	.0618 (.002)	.0070 (.000)
β_{SEG}	.0042 (.004)	.0626 (.002)	.0071 (.000)
β_{PSEG}	.0042 (.004)	.0626 (.002)	.0071 (.000)
β_{HAM}	.0026 (.006)	.0691 (.003)	.0086 (.001)
$\beta_{HAM(T)}$	.0030 (.006)	.0670 (.003)	.0081 (.001)
β_{CON}	.0029 (.006)	.0675 (.003)	.0082 (.001)
$\beta_{CON(T)}$	.0032 (.006)	.0660 (.002)	.0079 (.001)

Table 5.13 Return Prediction Errors: Bias Adjusted

	<u>ME</u>	<u>MAD</u>	<u>MSE</u>
BRF - 0	.0000 (.008)	.0728 (.003)	.0093 (.001)
BM - 1	.0000 (.004)	.0617 (.002)	.0069 (.000)
BCS - 1.43	.0000 (.004)	.0621 (.002)	.0069 (.000)
BOLS	.0006 (.004)	.0621 (.002)	.0070 (.000)
BSEG	.0005 (.004)	.0628 (.002)	.0071 (.000)
BPSEG	.0006 (.004)	.0630 (.002)	.0071 (.000)
BHAM	.0006 (.006)	.0718 (.003)	.0100 (.001)
BHAM(T)	.0005 (.006)	.0695 (.003)	.0091 (.001)
BCON	.0006 (.006)	.0694 (.003)	.0091 (.001)
BCON(T)	.0005 (.005)	.0677 (.002)	.0085 (.000)

Table 5.14 Return Prediction Errors: Slope & Bias Adjusted

	<u>ME</u>	<u>MAD</u>	<u>MSE</u>
$\beta_{RF} = 0$	.0000 (.008)	.0728 (.003)	.0093 (.001)
$\beta_M = 1$	.0000 (.004)	.0617 (.002)	.0069 (.000)
$\beta_{CS} = 1.43$	.0000 (.004)	.0621 (.002)	.0069 (.000)
β_{OLS}	.0000 (.004)	.0618 (.002)	.0069 (.000)
β_{SEG}	.0000 (.004)	.0626 (.002)	.0071 (.000)
β_{PSEG}	.0000 (.004)	.0627 (.002)	.0071 (.000)
β_{HAM}	.0000 (.006)	.0691 (.003)	.0086 (.001)
$\beta_{HAM}(T)$	.0000 (.006)	.0671 (.003)	.0081 (.001)
β_{CON}	.0000 (.006)	.0675 (.003)	.0079 (.001)
$\beta_{CON}(T)$	.0000 (.005)	.0661 (.002)	.0069 (.000)

**Table 5.15 Matched Pair T-Test of Significance:
Unadjusted Forecasts**

In each cell, three significance values are given. From top to bottom, they are:

mean error (ME),
mean absolute deviation (MAD),
and mean square error (MSE).

	RF	Rm	Rcs	β OLS	β SEG	β PSEG	β HAM	β HAM(T)	β CON
	----	----	----	----	----	----	----	----	----
Rm	.690 .000 .000	-	-	-	-	-	-	-	-
Rcs	.690 .000 .001	.690 .562 .901	-	-	-	-	-	-	-
β OLS	.696 .000 .001	.717 .544 .604	.849 .759 .245	-	-	-	-	-	-
β SEG	.691 .001 .001	.698 .241 .397	.800 .061 .064	.636 .028 .223	-	-	-	-	-
β PSEG	.687 .001 .001	.685 .155 .267	.763 .019 .023	.564 .005 .050	.688 .005 .009	-	-	-	-
β HAM	.664 .744 .386	.642 .000 .001	.614 .000 .000	.601 .000 .000	.596 .000 .000	.609 .000 .000	-	-	-
β HAM(T)	.670 .250 .796	.650 .000 .001	.623 .000 .000	.602 .000 .000	.596 .000 .000	.613 .000 .000	.614 .000 .001	-	-
β CON	.668 .254 .728	.648 .000 .001	.620 .000 .000	.604 .000 .000	.597 .000 .000	.613 .000 .000	.592 .000 .000	.697 .563 .204	-
β CON(T)	.673 .081 .220	.657 .001 .002	.632 .000 .000	.605 .000 .000	.598 .000 .000	.619 .000 .000	.602 .000 .001	.587 .000 .000	.614 .000 .001

**Table 5.16 Matched Pair T-Test of Significance:
Slope Adjusted Forecasts**

In each cell, three significance values are given. From top to bottom, they are:

mean error (ME),
mean absolute deviation (MAD),
and mean square error (MSE).

	Rf	Rm	Rcs	BOLS	BSEG	BPSEG	BHAM	BHAM(T)	BCON
	----	----	----	----	----	----	----	----	----
Rm	.690 .000 .000	-	-	-	-	-	-	-	-
Rcs	.690 .000 .001	.690 .562 .901	-	-	-	-	-	-	-
BOLS	.695 .000 .001	.710 .808 .917	.841 .361 .991	-	-	-	-	-	-
BSEG	.691 .001 .001	.695 .292 .487	.767 .071 .084	.647 .003 .026	-	-	-	-	-
BPSEG	.687 .001 .001	.685 .250 .416	.734 .043 .050	.589 .001 .015	.742 .122 .080	-	-	-	-
BHAM	.678 .226 .280	.667 .001 .004	.654 .000 .001	.645 .000 .000	.646 .000 .001	.656 .000 .001	-	-	-
BHAM(T)	.680 .055 .070	.669 .003 .007	.653 .000 .001	.641 .000 .000	.640 .000 .001	.654 .000 .001	.663 .000 .001	-	-
BCON	.679 .081 .096	.668 .003 .007	.653 .000 .001	.642 .000 .001	.641 .000 .001	.654 .000 .001	.664 .000 .000	.674 .005 .029	-
BCON(T)	.681 .027 .031	.671 .008 .013	.654 .000 .001	.638 .000 .001	.637 .000 .001	.654 .000 .001	.659 .000 .000	.655 .000 .000	.657 .000 .001

**Table 5.17 Matched Pair T-Test of Significance:
Bias Adjusted Forecasts**

In each cell, three significance values are given. From top to bottom, they are:

mean error (ME),
mean absolute deviation (MAD),
and mean square error (MSE).

	RF	Rm	Rcs	β OLS	β SEG	β PSEG	β HAM	β HAM(T)	β CON
	----	----	----	----	----	----	----	----	----
Rm	.999 .000 .000	-	-	-	-	-	-	-	-
Rcs	.995 .001 .001	.980 .659 .852	-	-	-	-	-	-	-
β OLS	.993 .001 .002	.976 .633 .591	.984 .783 .259	-	-	-	-	-	-
β SEG	.995 .002 .003	.984 .307 .391	1.000 .076 .069	.986 .031 .202	-	-	-	-	-
β PSEG	.999 .002 .003	.994 .213 .268	.958 .027 .025	.930 .006 .045	.668 .008 .008	-	-	-	-
β HAM	1.000 .738 .392	.999 .000 .001	.990 .000 .000	.988 .000 .000	.988 .000 .000	.998 .000 .000	-	-	-
β HAM(T)	.999 .273 .873	.996 .000 .001	.990 .000 .000	.988 .000 .000	.988 .000 .000	.998 .000 .000	.988 .000 .001	-	-
β CON	.995 .279 .808	.990 .001 .001	.998 .000 .000	1.000 .000 .000	.997 .000 .000	.986 .000 .000	.926 .000 .000	.905 .585 .208	-
β CON(T)	.995 .099 .296	.988 .001 .002	.996 .000 .000	1.000 .000 .000	.995 .000 .000	.979 .000 .000	.964 .000 .001	.913 .000 .000	.996 .000 .001

**Table 5.18 Matched Pair T-Test of Significance:
Slope & Bias Adjusted Forecasts**

In each cell, three significance values are given. From top to bottom, they are:

mean error (ME),
mean absolute deviation (MAD),
and mean square error (MSE).

	RF	Rm	Rcs	β OLS	β SEG	β PSEG	β HAM	β HAM(T)	β CON
	----	----	----	----	----	----	----	----	----
Rm	.999 .000 .000	-	-	-	-	-	-	-	-
Rcs	.995 .001 .001	.980 .659 .852	-	-	-	-	-	-	-
β OLS	.995 .001 .001	.982 .911 .901	.986 .312 .922	-	-	-	-	-	-
β SEG	.996 .002 .002	.986 .362 .471	.990 .087 .089	.998 .003 .019	-	-	-	-	-
β PSEG	.998 .002 .002	.993 .323 .402	.959 .060 .052	.963 .002 .010	.738 .212 .066	-	-	-	-
β HAM	.985 .254 .374	.970 .002 .004	.964 .000 .001	.963 .000 .000	.956 .000 .000	.951 .000 .000	-	-	-
β HAM(T)	.988 .073 .113	.975 .005 .007	.970 .000 .001	.958 .000 .000	.961 .000 .000	.953 .000 .000	.945 .000 .001	-	-
β CON	.984 .102 .149	.968 .005 .007	.959 .000 .001	.958 .000 .001	.948 .000 .001	.941 .000 .001	.992 .006 .000	.853 .000 .027	-
β CON(T)	.988 .036 .054	.973 .011 .014	.966 .000 .001	.964 .000 .001	.952 .000 .001	.943 .000 .001	.962 .000 .000	1.000 .000 .000	.936 .000 .001

Table 5.19 Bias and Slope Adjustments

$$e_j = R_j - R_f - \text{bias} - (\text{slope} * (\beta_j - \text{avg}(\beta_j) + \text{avg}(\beta_j)) * (R_m - R_f))$$

Slope coefficients (inefficiency adjustment) were obtained from the regression:

$$R_j - R_f = \text{intercept} + \text{slope } \beta_j * (R_m - R_f)$$

where beta β_j is as below.

Bias is computed as the average actual monthly return ($R_j - R_f$) minus the average predicted return $\beta_j * (R_m - R_f)$.

<u>Beta</u>	<u>Bias</u>	<u>Slope</u>
$\beta = 0$ (RF)	-.0079	*
$\beta = 1$ (Rm)	-.0055	*
$\beta = 1.43$ (RCS)	-.0044	*
β_{OLS}	-.0045	.7932
β_{SEG}	-.0042	.7620
β_{PSEG}	-.0042	.7524
β_{HAM}	-.0026	.4541
$\beta_{HAM}(T)$	-.0030	.5010
β_{CON}	-.0029	.5048
$\beta_{CON}(T)$	-.0032	.5465

- * These forecasts are constants for any given month and do not vary across firms. They do vary across months as the market risk premium ($R_m - R_f$) varies.

Chapter 6 Summary and Discussion

The evidence of Chapter 5 is consistent with the following:

- i) Segmental and OLS beta estimates are very similar in character,
- ii) Primary segment betas provide much the same information as segmental and OLS betas,
- iii) The Conine adjustment for financial leverage provides better estimates of systematic risk than the Hamada adjustment in this application,
- iv) Average tax rates provide more realistic levered betas in this application than tax rates which change annually,
- v) Neither the Hamada nor the Conine beta estimates performed at the level of the segmental and OLS beta estimates.
- vi) The use of mean square prediction error for the comparison of alternative estimates of systematic risk is most useful during periods of above or below average market performance.

Each of these conclusions, along with any implications and qualifications, is discussed in the remainder of this chapter.

6.1 Summary of the Empirical Results

The evidence of section 5.3 indicates that historical ordinary least squares betas (β_{OLS}) and segmental betas (β_{SEG}) contribute much the same information in explaining the returns to common stock. Further support of this conclusion is provided by their significant cross-sectional correlation (section 5.1) and by their comparable performance in predicting security returns (section 5.4). Segmental beta is no more biased than β_{OLS} and has an almost identical relationship to equity return. The conclusion that segmental beta is very similar in nature to the OLS beta is strongly supported by the evidence and is a fundamental result of this study.

Segmental beta additionally exhibits much greater stability than OLS beta over time. Section 5.2 demonstrated that the standard deviation of β_{SEG} is about half of the standard deviation of β_{OLS} . Segmental beta is thus an alternative estimate of the systematic risk of a multi-segment firm which possesses much the same explanatory and predictive power as β_{OLS} yet exhibits greater intertemporal stability.

Primary segment beta (β_{PSEG}) performed nearly as well as β_{SEG} in the predictive tests of section 5.4. Much of the information provided by segmental and OLS beta is captured when using only the primary segment beta. β_{PSEG} also enjoys greater stability than β_{OLS} , though not as great as β_{SEG} .

The Conine adjustment for financial leverage consistently performed better in predictive accuracy than the Hamada adjustment. The Conine adjustment might be expected to perform better since the Hamada betas overestimate the systematic risk of equity to a greater degree than the Conine betas. That is, the average Hamada and Conine betas were 2.12 and 2.01, respectively, while the average OLS beta of the multi-segment sample was only 1.43. But the Conine adjustment continued its predictive superiority over the Hamada adjustment even after correcting both sets of return predictions for this bias. The Conine betas required a smaller adjustment for inefficiency than the Hamada betas and also exhibited smaller forecast errors after adjusting for both bias and inefficiency.

The variability of the annual tax rates in the Conine and Hamada adjustments to financial leverage severely impaired the predictive ability of these models. The leverage adjustments using a constant average tax rate had consistently better predictive accuracy than the adjustments using annually changing rates. This was apparent even after adjusting for bias and inefficiency and was true for both the Hamada and Conine estimates. This result is not surprising since the leverage adjustments are based on perpetual cash flow models while observed tax rates exhibit great variability.

Neither the Hamada nor the Conine leverage-adjusted betas performed as well in predicting security returns as the OLS and segmental betas. This was true for the leverage-adjusted betas

BHAM and BCON using annual tax rates as well as the $\beta\text{HAM}(T)$ and $\beta\text{CON}(T)$ betas using an average tax rate. Apparently, there are still significant factors in the market's adjustment for financial leverage which have not been captured in the Hamada and Conine equations. In the present application, better return predictions were obtained when the financial leverage adjustments were ignored entirely. The segmental beta estimates, which assumed the same degree of financial leverage at the multi-segment firm and industry levels, provided much closer approximations to βSEG than the estimates BHAM, $\beta\text{HAM}(T)$, BCON and $\beta\text{CON}(T)$ which explicitly adjusted for financial leverage. The existing leverage adjustments are either sufficiently misspecified or too poorly implemented to enhance the beta estimation process.

In the development of the financial leverage adjustments to systematic risk, the assumption of perpetual cash flows is clearly specious. Including personal taxes in the leverage equations may serve to reduce the misspecification and improve the forecast accuracy. However, the existence of heterogeneous personal tax rates and tax liabilities makes this a difficult factor to examine empirically. Bankruptcy and agency costs are also omitted from the current application because they are again very difficult to quantify. Although the leverage adjustments may prove fruitful in other settings, their performance is not encouraging in the present application.

One additional point concerning the tests of predictive accuracy requires mention. The large amount of random behavior in the return distributions of common stock and their low correlation with the market index means that predicting security returns is a very inexact procedure. Simply predicting the average return to common stock ($\beta_{CS}=1.43$) yields forecasts which are as good as the predictive accuracy of the firm-specific estimates β_{SEG} and β_{OLS} . This was true for average risk stocks β_{MID} during periods of above, average, and below average market returns. As the systematic risk of a firm diverges from the average, however, the segmental and OLS beta estimates may perform better than a simple estimate of the market return.

6.2 Suggestions for Future Research

Segmental beta β_{SEG} are a useful alternative measure of the systematic risk of common stocks. The relative stability of segmental beta and its close correspondence with the OLS estimate recommend β_{SEG} when OLS estimates are either inappropriate or unavailable. This is especially true in situations where the multi-segment firm has recently undergone a change in its investment mix. Major acquisitions, mergers, or divestitures make OLS beta estimates inappropriate; yet such changes pose no threat to the more adaptable segmental beta estimates. In such situations, the segmental estimate can be immediately adjusted to reflect the new investment mix of the firm.

Moreover, the predictive tests of section 5.4 provide a means of comparing the OLS and segmental beta estimates in such circumstances of asset mix changes. By examining the period immediately after an acquisition or divestiture, the estimates may be compared in terms of bias, inefficiency, and overall forecast accuracy. The estimates may be compared both to each other and to their own pre-merger (or pre-divestiture) levels.

The systematic risk adjustments for financial leverage do not promise the same potential in the present application. Stock repurchase announcements and large stock or debt offerings create an immediate and important impact on the systematic risk of equity. Yet, the existing adjustments to

beta for financial leverage are only rough approximations. There may be significant omitted variables and measurement errors, as well as possible misspecification of the functional form of the relationship between unlevered and levered beta. Nevertheless, the levered betas may provide a valuable adjustment to systematic risk estimates. This avenue of research is perhaps most promising when combined with Bayesian adjustments to the absolute and relative level of the levered betas.

Initial tests of the theory of financial leverage should isolate the financing from the investment effects. This study has demonstrated that segmental betas utilizing industry information are a valuable alternative to historical OLS betas. The results of the financial leverage adjustments were not nearly so conclusive. One obstacle to the examination of the leverage adjustments is that the leverage adjustments were performed on the segmental betas, thus compounding the effect of the financing and investment of the firm. For the leverage adjustments to be proven accurate and/or useful, they should first be analyzed without the segmental beta adjustment for the asset mix of the multi-segment firm. Once the financing effects are isolated, then they may be applied to segmental beta in a more productive fashion.

Appendix A

Pooling Cross-sectional and Time Series Observations:

A Statistical Note

Consider the general regression model

$$y_{it} = b_{1it} X_{1it} + \dots + b_{Kit} X_{Kit} + e_{it},$$

where $i=1,2,\dots,N$ refers to a cross-sectional observation on an individual (in the present context, an individual firm), $t=1,2,\dots,T$ refers to a given time period, and there are K independent variables. Thus y_{it} is the observation of the dependent variable for firm i at time t . Typically, $X_{1it} = 1$, so that each regression equation contains a constant term (possibly with a coefficient of zero). This general regression model describes the pooling of cross-sectional and time series data to form a sample of $N \times T$ observations of the dependent variable y_{it} and independent variables X_{kit} , $k=1,2,\dots,K$.

The potential advantage of pooling N cross-sectional observations over T time periods is in increasing the number of observations to $N \times T$ and thereby increasing the efficiency of the coefficient estimates. Pooling of time series and cross-sectional observations in a regression is appropriate only when the regression coefficients are constant for all individuals i and over all time t . Additionally, the residuals must exhibit constant variance. If either of these conditions are violated, then the pooling technique yields biased tests of

significance [see, for instance, Beaver, Griffin, and Landsman, 1982].

Ordinary least squares estimation requires the following necessary conditions on the errors

$$e_{it} = y_{it} - b_{lit} X_{lit} - \dots - b_{Kit} X_{Kit}$$

- 1) $E[e_{it}] = 0$ mean zero errors
- 2) $E[e_{it}, e_{it+1}] = 0$ serial independence
- 3) $E[e_{it}, e_{jt}] = 0$ cross-sectional independence
- 4) $E[e_{it}, e_{jt+1}] = 0$ zero intertemporal cross covariance
- 5) $E[(e_{it})^2] = \sigma^2(e)$ homoskedastic errors

for all firms i and j and time t . In matrix notation, restrictions 2) through 5) may be expressed as

$$E[ee'] = \sigma^2(e) \text{ IN} \times \text{N} = \begin{matrix} & \sigma^2(e) & 0 & \dots & 0 \\ \sigma^2(e) & 0 & \sigma^2(e) & & \\ & 0 & \dots & & \\ & \dots & & & \sigma^2(e) \end{matrix}$$

Under these conditions, the OLS estimator $b = (X'X)^{-1}X'Y$ is unbiased, consistent as either N or T approaches infinity, and efficient. If the errors are also multivariate normal, then the usual t - and F -tests of significance hold.

If the errors e_{it} are not multi-variate normal or if some of the conditions 1) through 5) are not present, some important OLS results do not necessarily hold. In particular, the b estimates are no longer multi-variate normal, b and the residual variance estimate $\sigma^2(e)$ are no longer necessarily independent, and $[(NT-K)\sigma^2(e)]/\sigma^2(e)$ is no longer necessarily chi-square distributed with $NT-K$ degrees of freedom. Consequently, test statistics for significance of the regression coefficients b are no longer $t(NT-K)$ distributed and

tests based on the F distribution are invalid [Schmidt, 11-31].

The general model translates into a Two-Stage Least Squares (2SLS) application as

Stage 1: $[\beta_{seg}, it(Rmt-Rft)] = a_{1it} + b_{1it}[\beta_{OLS}, it(Rmt-Rft)] + U_{it}$

Stage 2: $[R_{it}-R_{ft}] = a_{2it} + b_{2it}[\beta_{OLS}, it(Rmt-Rft)] + c_{it}U_{it} + e_{it}$.

In the first stage $X_{1it} = 1$ and $X_{2it} = [\beta_{OLS}, it(Rmt-Rft)]$. In the second stage, $X_{1it} = 1$, $X_{2it} = [\beta_{OLS}, it(Rmt-Rft)]$, and $X_{3it} = U_{it}$ is the OLS residual from the first stage.

The stage 1 residual $U = Y - X\beta$ is orthogonal to $X = (R_m - R_f)\beta_{OLS}$ by construction since

$$\begin{aligned} X'U &= X'(Y - X\beta) \\ &= X'(Y - X((X'X)^{-1}X'Y)) \\ &= X'Y - (X'X)(X'X)^{-1}X'Y \\ &= X'Y - X'Y \\ &= 0. \end{aligned}$$

The independent variables $U_{it} = [\beta_{SEG}, it(Rmt-Rft)] - [\beta_{OLS}, it(Rmt-Rft)]$ and $X_{2it} = [\beta_{OLS}, it(Rmt-Rft)]$ of the second stage regression equation are then noncollinear by construction. If the errors are multivariate normal and conform to conditions 1)-5), then the coefficient c may be interpreted as the incremental explanatory power of the variable $[\beta_{SEG}(R_m - R_f)]$ beyond that explained by the independent variable $[\beta_{OLS}(R_m - R_f)]$.

Note, however, that the β_{SEG} and β_{OLS} are systematic risk estimates for each firm i from a historical OLS time series regression on the immediately preceding 60 month time interval. Adjacent monthly estimates of segmental or OLS beta

will not be independent estimates since they contain 59 common observations and are calculated over nearly the same time period. If any firm's time series of beta estimates is over- or under-estimated, then that firm's residuals in both stage 1 and stage 2 of the 2SLS procedure will exhibit serial autocorrelation as well as serial cross-correlation with other over- and under-estimated firms. As an example, consider a firm with a true beta of 1 and an OLS estimate of 2. Whenever $R_{mt} > R_{ft}$, then $E[R_{it}]$ will be over-estimated by $\beta_{OLS, it}$. This beta estimate will then exhibit serial auto and cross-correlation with other over- and under-estimated beta estimates. In this case the pooling technique yields biased estimates of the 2SLS regression coefficients and is hence inappropriate.

Cross-sectional dependence in the residuals of the second stage regression may also occur because of common economy-wide or industry factors. Such cross-sectional correlation would also serve to bias the regression coefficients and invalidate the use of a pooled sample. The use of pooled time series and cross-sectional observations thus imposes strict conditions on the regression equations.

APPENDIX B: MULTI-SEGMENT FIRM SAMPLE

	CUSIP NUMBER	COMPANY TICKER NAME	ESTIMATED BETAS						
			BOLS	BSEG	BPSEGBHAM	BHAMIBCON	BCONT		
1	800	ACF A C F INDS INC	1.42	1.61	1.58	2.35	1.72	2.20	1.70
2	2040	ARA A R A SUCS INC	1.17	1.60	1.72	2.09	2.05	2.00	1.97
3	2824	ABT ABBOTT LABS	1.21	1.73	1.32	1.59	1.56	1.61	1.58
4	17372	AG ALLEGHENY INTL INC	1.64	1.75	1.64	5.36	4.25	4.75	3.83
5	19087	ALD ALLIED CORP	1.55	1.46	1.32	2.42	2.44	2.21	2.23
6	19411	ADP ALLIED PRODS CORP DEL	0.48	1.46	1.42	3.64	3.21	3.24	2.93
7	23519	AAE AMERACE CORP	1.18	1.79	1.82	2.75	2.72	2.59	2.56
8	24843	AC AMERICAN CAN CO	0.68	1.52	1.54	3.03	2.90	2.75	2.64
9	25321	ACY AMERICAN CYANAMID CO	1.36	1.37	1.32	1.95	1.86	1.83	1.76
10	26609	AHP AMERICAN HOME PRODS CORP	1.02	1.36	1.32	1.15	1.14	1.18	1.18
11	29717	AST AMERICAN STD INC	1.54	1.48	1.45	1.75	1.24	1.72	1.31
12	31105	AME AMETEK INC	1.63	1.75	1.73	1.67	1.70	1.68	1.71
13	31141	AMA AMFAC INC	1.18	1.50	1.57	2.36	2.25	2.15	2.07
14	32037	AP AMPCO-PITTSBURGH CORP	1.44	1.53	1.53	2.44	1.98	2.26	1.89
15	32177	AD AMSTED INDS INC	1.60	1.47	1.53	1.17	0.47	1.24	0.68
16	33047	ARH ANCHOR HOCKING CORP	1.14	1.71	1.54	2.45	2.40	2.32	2.27
17	34663	AGL ANGELICA CORP	1.57	1.60	1.66	1.32	1.34	1.37	1.38
18	37411	APA APACHE CORP	1.81	1.65	1.72	1.75	1.76	1.74	1.74
19	42170	AS ARMCO INC							
20	43147	ATA ARTIRA GROUP INC	1.48	1.69	1.77	1.78	1.77	1.77	1.76
21	47483	ATH ATHLONE INDS INC	1.09	1.27	1.21	1.76	1.64	1.65	1.56
22	54595	AX AXIA CORP	1.40	1.59	1.62	1.43	1.41	1.46	1.45
23	60221	BNK BANGOR PUNTA CORP	1.91	1.43	1.49	2.35	1.60	2.18	1.58
24	66545	BNR BANNER INDS INC	1.40	1.40	1.26	2.27	1.79	2.09	1.71
25	67806	B BARNES GROUP INC	0.96	1.58	1.82	1.94	1.91	1.87	1.84
26	68887	BAR BARRY WRIGHT CORP	1.63	1.70	1.97	1.44	1.16	1.49	1.27
27	77851	BHW BELL & HOWELL CO	1.71	1.68	1.67	2.64	2.59	2.47	2.42
28	89671	BIG BIG THREE INDS INC	1.41	1.52	1.57	1.46	1.45	1.47	1.46
29	99725	BOR BORG WARNER CORP	1.14	1.29	1.23	1.60	1.18	1.55	1.23
30	110097	BMY BRISTOL MYERS CO	1.34	1.43	1.32	1.22	1.21	1.24	1.23
31	124845	CBS C B S INC	1.17	1.47	1.05	1.16	1.17	1.19	1.20
32	126157	CPN CP NATL CORP	0.78	0.83	0.81	1.15	1.06	1.04	0.98
33	127055	CBT CABOT CORP	1.99	1.51	1.74	1.57	1.56	1.56	1.56
34	142339	CSL CARLISLE CORP	1.99	1.38	1.82	1.19	1.00	1.25	1.10
35	146285	CAR CARTER WALLACE INC	1.15	1.50	1.30	1.70	1.57	1.61	1.51
36	158525	CHA CHAMPION INTL CORP	1.44	1.47	1.59	2.28	2.16	2.15	2.05
37	163267	CHD CHELSEA INDS INC	1.63	1.32	1.32	2.78	2.62	2.46	2.33
38	165159	CSK CHESAPEAKE CORP VA	1.19	1.52	1.54	1.57	1.49	1.56	1.50
39	165339	CBM CHESEBROUGH PONDS INC	1.22	1.50	1.27	1.26	1.25	1.29	1.28
40	167763	CHG CHICAGO MILWAUKEE CORP	2.40	1.67	1.72	1.65	1.70	1.67	1.72
41	171106	CRO CHROMALLOY AMERN CORP	1.35	1.53	1.54	2.42	2.4	2.27	2.24
42	196864	COT COLT INDS INC DEL	1.24	1.37	1.21	1.56	1.16	1.53	1.22
43	210615	CMS CONSUMERS PWR CO	0.8	0.86	0.78	1.38	1.1	1.2	1.02
44	211452	CCC CONTINENTAL GROUP INC	0.97	1.46	1.59	2.49	2.17	2.3	2.04
45	216669	CBE COOPER INDS INC	1.43	1.73	1.57	1.68	1.72	1.68	1.72
46	219327	GLW CORNING GLASS WKS	1.4	1.83	2.18	2.1	1.96	2.05	1.94
47	224399	CR CRANE CO	1.42	1.44	1.3	2.08	1.86	1.96	1.79
48	228669	ZB CROWN ZELLERBACH CORP	1.4	1.54	1.54	2.08	1.97	1.97	1.89

49	231561	CW	CURTISS WRIGHT CORP	2.4	1.62	1.54	1.9	1.55	1.85	1.57
50	252165	DEX	DEXTER CORP	1.54	1.35	1.32	1.57	1.6	1.54	1.57
51	252741	DIA	DIAMOND SHAMROCK	1.66	1.45	1.51	1.55	1.5	1.53	1.49
52	250003	DOV	DOVER CORP							
53	261471	DRU	DRAVO CORP							
54	261597	DI	DRESSER INDS INC	1.22	1.59	1.62	1.6	1.58	1.6	1.59
55	264830	DNB	DUN & BRADSTREET CORP	1.34	1.61	1.33	0.81	0.76	0.94	0.89
56	268039	DYA	DYNAMICS CORP AMER							
57	269803	EPI	EAGLE PICKER INDS INC	1.21	1.39	1.73	1.8	1.6	1.73	1.58
58	270330	ES	EASCO CORP	1.23	1.67	1.82	2.4	2.4	2.26	2.27
59	276461	EFU	EASTERN GAS & FUEL	2.08	1.34	0.99	0.77	0.73	0.84	0.81
60	278058	ETN	EATON CORP	1.13	1.6	1.39	2.17	1.88	2.05	1.84
61	280875	EBS	EDISON BROS STORES							
62	291210	EMH	EMHART CORP VA	1.61	1.48	1.41	2.34	2.25	2.19	2.11
63	293567	ENS	ENSERCH CORP	1.18	1.31	0.97	1.45	1.42	1.44	1.41
64	296695	ESX	ESSEX CHEM CORP	1.98	1.15	1.23	2.3	2.1	2.03	1.89
65	297425	ESL	ESTERLINE CORP	2.47	1.86	1.82	1.89	1.93	1.87	1.91
66	300587	XLO	EX CELL O CORP	1.73	1.34	1.38	1.33	1.0	1.33	1.08
67	302491	FMC	F M C CORP	1.72	1.54	1.78	2.84	2.48	2.6	2.31
68	313693	FBO	FEDERAL PAPER BRD INC	1.42	1.52	1.54	2.42	2.29	2.25	2.15
69	313855	FSS	FEDERAL SIGNAL CORP	1.15	1.64	1.82	1.54	1.45	1.56	1.49
70	320891	FRM	FIRST MISS CORP	2.12	1.37	1.27	1.35	1.35	1.35	1.35
71	351586	FSP	FOX STANLEY PHOTO	1.04	1.52	1.57	1.83	1.79	1.77	1.73
72	361028	FQA	FUQUA INDS INC	1.84	1.72	1.81	4.58	4.97	4.12	4.44
73	361428	GAF	G A F CORP							
74	361448	GMT	G A T X CORP	1.56	1.68	1.73	4.19	3.51	3.72	3.18
75	369352	GCN	GENERAL CINEMA CORP	2.16	1.36	1.69	1.92	1.96	1.88	1.91
76	369604	GE	GENERAL ELEC CO	1.29	1.67	1.73	1.92	1.68	1.88	1.68
77	370064	GH	GENERAL HOST CORP	1.51	1.22	1.21	2.47	2.33	2.18	2.08
78	370334	GIS	GENERAL MLS INC	0.7	1.41	1.32	1.47	1.5	1.46	1.49
79	370838	GSX	GENERAL SIGNAL CORP							
80	371352	GY	GENERAL TIRE & RUBR	1.29	1.39	1.36	1.28	0.9	1.3	1.0
81	382388	GR	GOODRICH B F CO	1.38	1.39	1.36	3.07	2.85	2.75	2.57
82	383883	GRA	GRACE W R & CO	1.12	1.39	1.32	2.1	2.07	1.97	1.94
83	398028	G	GREYHOUND CORP	1.18	1.43	1.36	1.96	1.7	1.84	1.63
84	401370	GRD	GUARDIAN INDS CORP	1.98	1.61	1.82	1.99	1.85	1.94	1.83
85	402496	GRE	GULF RES & CHEM							
86	402784	GUL	GULTON INDS INC	1.74	1.84	1.77	2.5	2.56	2.39	2.44
87	408306	HML	HAMMERMILL PAPER CO	1.59	1.54	1.57	2.62	2.45	2.41	2.27
88	411631	HBJ	HARCOURT BRACE	1.43	1.3	1.33	2.05	2.07	1.88	1.9
89	413875	HPS	HARRIS CORP DEL	1.55	1.49	1.7	1.61	1.58	1.61	1.58
90	415864	HSC	HARSCO CORP	0.83	1.65	1.82	1.76	1.76	1.77	1.77
91	427056	HPC	HERCULES INC	1.44	1.27	1.32	1.88	1.57	1.76	1.51
92	428236	HWP	HEWLETT PACKARD CO	1.56	1.94	2.03	1.74	1.75	1.77	1.78
93	429812	HVE	HIGH VOLTAGE ENGR	2.43	1.81	1.73	1.84	1.84	1.83	1.83
94	431573	HB	HILLENBRAND INDS	1.16	1.92	1.82	1.7	1.72	1.74	1.76
95	437614	HM	HOMESTAKE MNG CO	1.39	1.63	1.51	1.44	1.4	1.46	1.42
96	438506	HON	HONEYWELL INC	1.91	1.78	1.82	2.28	1.99	2.18	1.95
97	439316	HUU	HOOVER UNUL INC	1.68	1.78	1.79	2.08	2.06	2.02	2.01
98	449268	ICX	I C INDS INC	1.62	1.67	1.82	4.62	4.61	4.09	4.08
99	450694	IU	I U INTL CORP	1.18	1.47	1.36	3.56	3.17	3.11	2.81
100	452308	ITW	ILLINOIS TOOL WKS INC	1.29	1.8	1.82	1.5	1.48	1.55	1.54
101	457659	INR	INSILCO CORP							

102	458506	ISS INTERCO INC	1.08	1.41	1.49	1.3	1.34	1.34	1.36
103	458702	IK INTERLAKE INC	1.19	1.52	1.44	2.96	2.39	2.69	2.23
104	459578	HR INTERNAT'L HARVESTER	1.46	1.33	1.23	6.12	4.72	5.09	4.08
105	459884	IGL INTERNAT'L MNRL&CHEM	1.03	1.42	1.27	1.81	1.77	1.73	1.7
106	460146	IP INTERNATIONAL PAPER	1.65	1.52	1.54	1.9	1.73	1.83	1.69
107	462470	IWG IOWA ILL GAS & ELEC	0.73	0.88	0.97	0.92	0.94	0.91	0.92
108	478160	JNJ JOHNSON & JOHNSON	1.1	1.74	1.27	1.35	1.33	1.4	1.38
109	478366	JCI JOHNSON CTLS INC	1.37	1.76	2.21	2.28	1.97	2.2	1.97
110	481196	JOY JOY MFG CO	1.47	1.63	1.7	1.62	1.65	1.62	1.65
111	484170	KAB KANEB SVCS INC	1.92	1.78	1.71	1.71	1.54	1.72	1.58
112	486026	KT KATY INDS INC	2.02	1.56	1.51	3.13	2.71	2.83	2.48
113	500440	KOL KOLLMORGEN CORP	2.12	1.82	2.13	1.87	1.79	1.86	1.8
114	500602	KOP KOPPERS INC	1.27	1.55	1.27	1.89	1.81	1.8	1.73
115	501173	KUB KUBOTA LTD	0.29	1.55	1.7	1.82	1.94	1.8	1.9
116	501566	KZ KYSOR INDL CORP DEL	1.61	1.19	1.05	1.26	1.28	1.25	1.27
117	502210	LTV L T V CORP	2.48	1.31	1.16	5.02	3.47	4.25	3.02
118	513696	LMS LAMSON & SESSIONS	1.72	1.47	1.48	2.92	2.09	2.62	1.98
119	521894	LSI LEAR SIEGLER INC	2.3	1.64	1.45	1.94	1.19	1.89	1.3
120	538021	LIT LITTON INDS INC	1.62	1.99	1.85	2.47	2.51	2.38	2.42
121	576879	MC MATSUSHITA ELEC INDL LTDO	0.59	2.05	2.18	2.61	2.79	2.53	2.68
122	577081	MAT MATTEL INC							
123	581556	MCK MCKESSON CORP	1.12	1.47	1.32	2.33	2.25	2.14	2.07
124	582562	MME MC NEIL CORP	1.26	1.66	1.66	3.46	3.3	3.14	3.01
125	585745	MES MELVILLE CORP							
126	597715	MLR MIDLAND ROSS CORP	1.27	1.67	1.73	2.31	1.99	2.19	1.94
127	604059	MMM MINNESOTA MNG & MFG CO	1.13	2.04	1.82	1.8	1.77	1.82	1.81
128	612017	MDU MONTANA DAKOTA UTILS CO	0.82	1.05	0.97	1.2	1.04	1.12	1.01
129	612085	MTP MONTANA PWR CO	0.96	0.86	0.78	0.92	0.78	0.9	0.81
130	615798	MMR MOORE MC CORMACK RES INC	1.75	1.63	1.43	2.51	2.35	2.3	2.18
131	619426	MII MORTON THIOKOL INC	1.44	1.22	1.27	1.56	1.49	1.49	1.43
132	627151	MYO MURRAY OHIO MFG CO	0.86	1.6	1.72	2.65	2.76	2.5	2.6
133	635655	DR NAT'L DISTILLERS & CHEM	1.24	1.68	1.32	1.78	1.71	1.75	1.69
134	637657	NAS NATIONAL SVC INDS INC	1.22	1.5	1.63	1.44	1.39	1.46	1.42
135	651639	NEM NEWMONT MNG CORP	1.56	1.58	1.57	1.73	1.61	1.7	1.6
136	665262	NI NORTHERN IND PUB SVC CO	0.86	0.88	0.97	0.93	1.0	0.91	0.95
137	666807	NOC NORTHROP CORP	1.81	1.65	1.45	1.86	1.39	1.83	1.46
138	667528	NWT NORTHWEST INDS INC	1.5	1.64	1.57	2.12	2.15	2.03	2.05
139	676346	OG OGDEN CORP	1.32	1.81	1.91	4.0	3.3	3.63	3.05
140	680665	OLN OLIN CORP	1.07	1.42	1.32	2.6	2.16	2.36	2.01
141	690207	OKD OVERHEAD DOOR CORP							
142	693506	PPG P P G INDS INC							
143	698822	PCT PAPERCRAFT CORP	1.6	1.39	1.5	1.34	1.39	1.36	1.39
144	701094	PH PARKER HANNIFIN CORP	1.45	1.56	1.72	1.71	1.38	1.68	1.43
145	709903	PZL PENNZOIL CO	1.38	1.53	1.51	1.6	1.53	1.59	1.53
146	713448	PEP PEPSICO INC	1.15	1.41	1.69	1.53	1.55	1.54	1.55
147	714041	PKN PERKIN ELMER CORP	1.88	1.83	1.67	1.76	1.69	1.77	1.72
148	716544	PTO PETROLANE INC	1.68	1.21	1.08	0.95	0.94	1.03	1.02
149	723645	PNA PIONEER CORP TEX	1.33	1.21	0.97	0.89	0.89	0.98	0.98
150	725701	PCO PITTSION CO	1.83	1.63	1.58	1.34	1.26	1.39	1.32
151	729110	PLY PLESSEY PLC	0.96	1.53	2.21	1.55	1.5	1.58	1.54
152	740512	PRE PREMIER INDL CORP	1.14	1.61	1.54	1.04	1.0	1.16	1.13
153	742718	PG PROCTER & GAMBLE CO	0.75	1.42	1.24	1.21	1.2	1.22	1.22
154	744448	PSR PUBLIC SVC CO COLO	0.99	0.86	0.78	0.8	0.83	0.82	0.84

155	749285	RCA R C A CORP	1.52	1.92	2.18	3.14	2.97	2.95	2.81
156	755111	RTN RAYTHEON CO	1.54	1.89	2.18	2.0	1.88	1.99	1.89
157	761753	RJR REYNOLDS R J INDS INC							
158	770519	ROF ROBERTSHAW CTLS CO							
159	774347	ROK ROCKWELL INTL CORP	1.22	1.67	1.47	2.02	1.59	1.96	1.63
160	775711	ROL ROLLINS INC							
161	776338	RON RONSON CORP	1.19	1.57	1.55	3.02	2.01	2.74	1.93
162	784015	SCM S C M CORP	2.02	1.42	1.27	2.98	2.86	2.68	2.58
163	793453	SRT ST REGIS CORP	1.42	1.49	1.54	2.05	1.91	1.95	1.84
164	806605	SGP SCHERING PLOUGH CORP	1.19	1.48	1.32	1.38	1.3	1.36	1.29
165	809367	SFZ SCOTT & FETZER CO	1.54	1.53	1.33	2.03	2.04	1.93	1.94
166	810640	SCO SCOVILL INC							
167	824348	SHW SHERWIN WILLIAMS CO	1.57	1.27	1.32	2.64	2.79	2.36	2.48
168	826622	SGN SIGNAL COS INC							
169	829302	SMF SINGER CO	1.69	1.73	1.73	5.72	5.61	5.03	4.94
170	844861	SWF SOUTHWEST FOREST INDS	2.12	1.47	1.59	3.3	3.18	2.97	2.88
171	847235	SPA SPARTON CORP							
172	848355	SY SPERRY CORP	1.79	1.8	2.09	2.99	2.69	2.81	2.57
173	851783	SMI SPRINGS INDS INC	1.36	1.39	1.47	1.38	1.19	1.4	1.25
174	854231	SXI STANDEX INTL CORP	1.19	1.83	1.77	2.26	2.26	2.18	2.18
175	854616	SWK STANLEY WKS	1.49	1.51	1.27	1.6	1.56	1.58	1.56
176	857721	STF STAUFFER CHEM CO	1.11	1.2	1.27	2.03	1.79	1.85	1.67
177	867323	SNS SUNSTRAND CORP	1.82	1.35	1.45	1.14	0.56	1.19	0.74
178	871140	SYB SYBRON CORP	1.5	1.87	2.2	2.89	2.9	2.74	2.75
179	872649	TRW T R W INC							
180	874687	TAL TALLEY INDS INC	1.16	1.92	1.82	5.08	5.11	4.56	4.58
181	880370	IGT TENNECO INC	1.24	1.38	1.42	2.01	1.92	1.89	1.81
182	883203	IXT TETRION INC	1.52	1.6	1.45	1.79	1.45	1.75	1.48
183	887224	IL TIME INC	1.24	1.38	1.33	1.71	1.67	1.65	1.62
184	892348	IRR TRACOR INC	2.46	1.82	2.21	1.94	1.77	1.92	1.79
185	894015	TNW TRANSWAY INTL CORP	1.06	1.09	1.00	0.79	0.64	0.87	0.76
186	902120	TYC TYCO LABS INC	2.24	1.93	1.78	2.83	2.8	2.67	2.65
187	902182	TYL TYLER CORP							
188	902686	UGI U G I CORP	1.04	1.22	1.14	1.82	1.72	1.71	1.63
189	902878	UMT U M C INDS INC	1.38	1.81	1.7	2.29	2.28	2.2	2.19
190	904784	UN UNILEVER N U	0.82	1.43	1.36	2.18	2.26	1.99	2.05
191	905530	UCC UNION CAMP CORP	1.29	1.44	1.54	1.5	1.45	1.51	1.46
192	905581	UK UNION CARBIDE CORP	1.09	1.49	1.32	2.63	2.32	2.39	2.15
193	906072	UCO UNION CORP	1.73	1.78	1.72	3.3	3.21	3.04	2.97
194	909660	UB UNITED BRANDS CO	2.03	1.32	1.32	4.11	4.31	3.46	3.62
195	910671	UIC UNITED INDL CORP							
196	912027	USG UNITED STS GYPSUM CO							
197	912078	USI UNITED STS INDS INC	0.94	1.65	1.72	2.47	2.53	2.35	2.39
198	913017	UTX UNITED TECHNOLOGIES	1.37	1.46	1.45	2.18	1.56	2.06	1.56
199	922204	VAR VARIAN ASSOC INC	1.51	1.92	2.04	2.73	2.64	2.61	2.53
200	929160	VMC VULCAN MATLS CO	0.66	1.36	1.25	1.47	1.45	1.46	1.44
201	934488	WLA WARNER LAMBERT CO	1.25	1.44	1.32	1.62	1.64	1.57	1.59
202	969457	WMB WILLIAMS COS	1.58	1.28	1.32	1.89	1.79	1.75	1.67
203	978165	WOM WOMETCO ENTERPRISES							
-----			-----	-----	-----	-----	-----	-----	-----
AVERAGE			1.42	1.53	1.52	2.1	1.94	1.99	1.87
STANDARD DEVIATION			0.16	0.05	0.08	0.83	0.70	0.57	0.49

APPENDIX C: SIC CODES

180

<u>SIC CODE</u>	<u># OF SINGLE-SEGMENT FIRMS IN INDUSTRY</u>	<u># OF MULTI-SEGMENT REFERENCES</u>
179	0	1
1000	9	15
1011	0	1
1020	2	
1021	2	1
1030	2	
1031	2	5
1040	5	
1041	0	4
1044	2	1
1081	0	1
1200	1	
1210	1	13
1211	0	3
1299	0	2
1300	22	15
1311	0	5
1422	0	1
1475	0	1
1500	2	
1540	1	46
1600	5	
1610	0	2
1622	0	1
1623	0	1
1629	0	1
1731	0	1
2000	35	29
2010	2	
2011	1	1
2013	0	1
2041	0	1
2046	0	1
2051	0	1
2060	5	1
2080	11	
2082	4	4
2085	3	6
2086	3	6
2100	1	2
2111	0	2
2200	19	2
2211	0	1
2241	0	1
2300	14	9
2321	0	1
2328	0	1
2431	0	1
2435	0	1
2599	0	1
2600	9	29
2611	0	1
2621	0	6
2631	0	2

2640	2	25
2641	0	1
2648	0	1
2700	14	11
2710	0	1
2711	0	1
2721	0	2
2731	0	1
2800	23	1
2810	2	27
2812	0	2
2813	0	19
2819	0	5
2820	1	30
2830	3	
2833	1	6
2834	2	18
2840	6	13
2841	0	2
2842	0	1
2844	2	12
2851	0	1
2861	0	1
2869	0	1
2873	0	1
2895	0	1
2899	0	1
2900	7	21
3000	5	6
3011	0	3
3069	0	1
3100	2	
3140	2	9
3143	0	1
3144	0	1
3200	9	
3211	0	2
3229	0	3
3240	4	2
3275	0	1
3292	0	1
3300	26	
3310	15	
3311	0	7
3312	11	11
3313	0	7
3316	0	2
3321	0	3
3325	0	1
3350	5	1
3400	20	45
3411	0	2
3423	0	1
3429	0	3
3431	0	1
3446	0	1

3448	0	1
3452	0	2
3479	0	1
3493	0	1
3494	0	3
3495	0	1
3499	0	1
3500	57	42
3519	0	2
3520	1	9
3523	0	2
3530	9	8
3531	0	2
3532	0	1
3533	5	32
3534	0	1
3540	8	10
3563	0	1
3569	0	1
3570	24	12
3572	0	2
3573	0	6
3581	0	1
3599	0	1
3600	37	41
3610	0	1
3612	0	3
3620	0	1
3630	0	1
3635	0	1
3636	0	1
3641	0	1
3651	0	1
3662	0	9
3670	14	39
3673	0	1
3679	0	3
3700	15	
3710	6	8
3711	0	2
3714	4	11
3716	0	22
3720	3	39
3721	0	2
3724	0	2
3728	0	3
3731	0	1
3732	0	1
3740	0	11
3751	0	1
3790	2	
3792	1	
3800	19	22
3822	0	1
3825	0	2
3829	0	1

3832	0	2
3841	0	2
3842	0	1
3843	0	1
3860	3	4
3861	0	2
3873	0	1
3900	11	24
3914	0	1
3940	3	5
3944	0	1
3990	5	
3993	0	1
3998	0	19
3999	5	19
4000	8	
4001	0	1
4011	0	2
4060	0	6
4200	5	8
4213	0	2
4400	1	10
4500	16	
4510	15	3
4712	0	1
4743	0	2
4800	16	
4810	10	8
4830	1	8
4833	0	1
4900	74	
4910	45	
4911	45	2
4912	0	9
4913	0	5
4920	22	21
4923	0	1
4924	0	2
4929	0	4
4931	0	5
4932	0	1
4940	2	1
5000	13	9
5081	0	1
5084	0	1
5122	0	1
5300	22	2
5311	0	1
5400	12	3
5600	7	7
5661	0	1
5800	11	
5810	11	
5812	11	10
5900	22	
5910	12	1

5984	0	1
6000	44	
6100	19	7
6120	11	
6170	0	2
6200	7	
6210	6	
6300	19	
6310	10	
6320	2	1
6330	4	
6500	10	6
6700	7	
7000	2	3
7200	2	
7213	0	1
7300	19	22
7321	0	1
7813	0	1
7832	0	1
7900	2	17
8000	8	
8060	4	14
9100	0	7
9900	1	
9913	0	24
9970	0	12
9975	0	5
9980	0	1
9990	1	92
9991	0	2

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KEY:

AER Accounting and Economic Review
AR Accounting Review
BJE Bell Journal of Economics
EC Econometrica
FAJ Financial Analysts Journal
FM Financial Management
JAE Journal of Accounting and Economics
JAL Journal of Accounting Literature
JAR Journal of Accounting Research
JASA Journal of the American Statistical Association
JEB Journal of Economics and Business
JET Journal of Economic Theory
JF Journal of Finance
JFE Journal of Financial Economics
JFQA Journal of Financial and Quantitative Analysis
JPE Journal of Political Economy

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