MULTIFACTOR RETURN MODEL BASED ON INTERIM FINANCIAL STATEMENTS

by

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(ABSTRACT)

The purpose of this research is to examine the significance of a market factor, an industry factor, a company factor and a growth factor in explaining security returns. A secondary objective is to determine if interim financial statements--the balance sheet and the income statement--provide useful information in developing the return model.

Market-related and industry-related systematic risks are constructed as surrogate measurements for the market and industry factors. The company factor is composed of one accounting return measure (profitability) and five accounting risk measures (accounting beta, operating leverage, financial leverage, dividend covariability, and cash flow beta). These variables are included as individual regressors in the return model. Also, a company index (the first principal component) is constructed and tested for its significance in the four-factor return model. The compound growth rate in total assets measures the growth of individual companies. Quarterly accounting information is used to measure these company and growth variables, and their significance provides evidence supporting the

usefulness of interim financial statements.

A multiple regression analysis is employed to develop the return model. In addition to the market factor, an industry factor, components of the company factor (dividend covariability and profitability), and a growth factor are found to contribute significantly to estimation of the return model. The use of a company index in lieu of individual company variables, however, is not recommended for developing the return model. Additionally, results indicate that the market model provides the best surrogate measure of the market factor, and Line of Business information is recommended for classifying companies into industry groups.

Major limitations of the study are (i) a self-selection bias of companies for the sample; (ii) measurement errors in interim financial statement data due to accounting allocations; (iii) seasonality of quarterly accounting information; (iv) use of average regression statistics in determining the best return model; (v) a limited number of regression models examined; and (vi) multicollinearity. These may limit the generalizability of the findings beyond the sample data and the interpretation of relationship between security return and its potential determinants.

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CHAPTER I

INTRODUCTION

MOTIVATION

Portfolio managers and security analysts are concerned with identifying profitable investments. Technical analysts believe that by studying patterns in the sequence of past prices, they will be able to predict the future price movement of a security. On the other hand, fundamentalists rely on financial statement analysis in making investment decisions, because they believe that accounting information reveals the earning power and risk attributes of individual companies.

Several empirical studies provide evidence supporting the usefulness of annual accounting information in assessing risk and return. For example, Nerlove [1968] has examined the significance of accounting variables in explaining the variation of rates of return on common stocks; Beaver, Kettler and Scholes [1970], Beaver and Manegold [1975], Eskew [1979] and many others have investigated the relationship between accounting variables and systematic risk.

Studies of quarterly accounting information, however, are limited to the examination of quarterly earnings and dividends data (e.g., Griffin [1976], Foster [1977], Aharony and Swary [1980]). Typically, these studies focus on the time-series properties of quarterly earnings and dividends, as well as their usefulness in assessing risk. This may be attributed to the high costs and difficulty in gathering other quarterly accounting information, especially balance sheet data. Balance sheet presentation is not mandatory for companies that prepare interim financial statements. In fact, it was not until recently that quarterly balance sheet data were required in the 10-Q reports filed with the Securities and Exchange Commission (SEC). As a consequence, the significance of quarterly balance sheet data in assessing risk and return has never been examined. Thus, the present study is designed to examine the role of quarterly accounting information, including both interim income statement and balance sheet information, in security analysis.

The development of the equilibrium model of capital asset pricing (Sharpe [1964], Lintner[1965a], and Mossin [1966]) has introduced new ideas into the world of investments. According to the Capital Asset Pricing Model (CAPM), an equilibrium relationship exists between risk and expected return on a security. In a market equilibrium, a security is expected to provide a return commensurate with its systematic risk. Since its introduction, systematic risk has been used extensively in evaluating security performance as well as in making portfolio decisions.

Despite its usefulness in security analysis, the "true" systematic risk of any security is unobservable. Thus, a number of techniques have been developed to provide reliable estimates of systematic risk. The market model was the first model used to estimate systematic risk. Because of the instability of this systematic risk estimate over time, and its tendency to regress towards a value of one, adjustment techniques have subsequently been developed (Blume [1971;1975], Vasicek [1973]).

Over the past two decades, the CAPM has been used extensively in market-based empirical research. Yet the critique by Roll [1977] raises doubts as to the effectiveness of the CAPM in explaining the empirical constellation of asset returns. In a subsequent study, Roll and Ross [1980] advocate the Arbitrage Pricing Theory (APT) as a more appropriate alternative to the CAPM. This latter theory assumes a linear return generating process that permits more than one factor in explaining the return on assets. Because market equilibrium must be consistent with zero arbitrage profits, it is proposed that a linear relationship must exist in every equilibrium between each asset's return and that return's response amplitudes on the common factors. In their study, Roll and Ross [1980] were successful in finding three to four return generating factors, although their constituents are not known.

On the basis of the APT, it appears appropriate to use other factors besides the market factor suggested by the CAPM in attempting to explain the return generating process of assets. The primary objective of the present study is to investigate other selected factors that may also help explain security returns. As suggested by the APT, some of these so-called return generating factors are common to all assets in the market. Other factors describe the unique characteristics of individual companies. These latter factors are also examined in the present study to see if specific company attributes are significant in explaining variation in security returns. Quarterly accounting information is used to measure these attributes, and the role of interim financial statement data in describing the return generating process of securities can be assessed accordingly.

The proposed multifactor return model, in its generic form, is presented as follows:

$$R = M + I + C + G$$

where R = return on security;

M = market factor;

I = industry factor;

C = company factor;

G = growth factor.

PURPOSE OF THE STUDY

Basically, the purpose of this study is to determine if there are factors other than the market factor that contribute significantly to explaining security returns.

In the literature, there is little objection to accepting the significance of a market factor in explaining security returns. This relationship is well documented, and the CAPM is the appropriate framework for describing the theoretical relationship. Briefly, the CAPM describes an equilibrium in the capital market where a direct linear relationship exists between security returns and systematic risk. Because of the crucial role played by systematic risk in accounting for security returns, many models have been developed to estimate systematic risk. Among them is the commonly used market model (Sharpe [1963]), which assumes a bivariate normal distribution between security return and market return. Adjustment models (mean reversion model, order bias adjustment model, Bayesian adjustment model) have received less attention in the literature; nevertheless, empirical evidence (Klemkosky and Martin [1975], Elgers [1979]) indicates that they are superior to the market model in terms of providing accurate forecasts of systematic risk. A secondary purpose of the present study is then to examine which of these estimation models provides the "best" surrogate measure of the market factor. The criterion used to evaluate these models is how well these estimates of systematic risk explain and predict security returns.

Other than the market factor, it is difficult to identify other return generating factors suggested by the APT that are common to all assets in the capital market. One fairly close estimate is an industry factor whose effect can be significant with respect to certain segments of the market. Thus, the impact of an industry factor on security returns is also examined in this study. There are, however, some problems associated with the study of an industry effect. The most obvious one is how an industry should be defined. The Bureau of Budget has established a four-digit code for classifying companies as industries. This four-digit code, called the Standard Industrial Classification (SIC) code, is inadequate in classifying companies into homogeneous groups because it does not account for companies whose operations are well diversified and subject to change over time. Consequently, some authors have advocated the use of clustering techniques (Elton and Gruber [1973], Fertuck [1975]), while others have proposed the use of the Line of Business (LOB) information provided in 10-K reports filed with the SEC (Foster [1981]). The significance of an industry effect on security returns will depend on how precise an industry is defined. Thus, another purpose of this study is to assess which of two potential definitions of industry effect best contributes to explaining the return generating process of securities.

The third factor that may be significant in explaining security returns is "the company" itself. For example, operational efficiency and effectiveness are crucial to determining how well a company performs. Strategic planning of the management is also vital to any long-term success of a company. Thus, these fundamental characteristics may somehow reflect the return generating power of a company. Accordingly, the company factor is expected to play a significant role in explaining the variation in security returns. In the literature review section, a number of company variables have been identified to represent the unique characteristics of individual companies, and these variables are selected as components of the so-called company factor.

Accounting data are used to measure these company variables (components of the company factor). In the present study, quarterly accounting information is used in lieu of annual accounting information since the former is available on a more frequent basis. This implies that the time period being studied can be shortened because interim financial statements provide more data points in computing the company variables than annual financial statements. This, in fact, is vital for reducing the averaging of economic effects in computing these company variables for the time period being studid. However, seasonality of quarterly accounting data may result in wider fluctuations in the data points, as compared to annual accounting data. The related impact on findings of the present study is not known, and should be kept in mind when interpreting the results. Nonetherless, fundamentalists are concerned about the use of interim financial statement data in evaluating security performance. Thus, another objective of this study is to provide evidence with respect to the potential use of quarterly accounting information in explaining the variation of security returns.

The earning potential of a company by and large determines how profitable a company will be in the long run. Needless to say, companies with good investment opportunities are expected to provide greater returns to investors. Thus, the impact of the earning potential, or growth, of a company on security returns is also examined in the present study.

In summary, the major purpose of this research is to determine if, in addition to the market factor, an industry factor, a company factor, and a growth factor contribute significantly to explaining security returns. Secondary purposes include an evaluation of the adjustment models used in providing systematic risk estimates, an investigation of industry classification schemes, and an exploration of the potential use of quarterly accounting information.

JUSTIFICATION FOR THE STUDY

Investors are concerned with security returns. They invest in securities with the hope of earning a fair return on the investment. Risk-averse investors would like to identify those securities that generate a constant and stable return, regardless of changes in the economy. Risk-seeking investors, on the other hand, would like to pick those securities that provide unexpected capital gains from time to time. In order to satisfy both such ivestor type, financial analysts and theorists have tried to uncover the return generating process of securities. For example, technical analysts look at the historical movement of security returns to predicting future returns, whereas fundamentalists concentrate on financial statement data when forecasting the return on a security. Additionally, theorists have devoted much time and effort to developing models and theories that best describe the return generating process of securities. Empirical researchers, in contrast, gather observations from the capital market in order to investigate the underlying factors that determine the return on a security. It is clear that extensive efforts have been devoted to studying variations in security returns, but the significant findings have not been presented in an organized fashion.

This study summarizes and combines the various theoretical and empirical works on the issue, with the hope of developing a return model that can adequately explain the variation in security returns and provide an accurate prediction of security returns. This research should be able to identify the significant determinants of security returns and provide a useful tool to investors in making their investment decisions.

There are two areas of this research that distinguish it from similar studies. First, interim financial statement data are used to compute the company and growth variables. Although, many studies have examined the impact of quarterly earnings and dividends on return as well as risk, quarterly balance sheet data have not been examined in such studies. This is because quarterly balance sheet data were not available until the early 1970's and then it was time-consuming to gather this information from the financial statements of a company. Quarterly balance sheet data are now available on computer tapes, and data accessability is no longer a problem.

This study attempts to explore the use of quarterly income statement and balance sheet data in security analysis. Balance sheet data are used in the present study because they reflect certain business structures (e.g., capital structure) of a company, and are believed to be significant determinants of security returns. In addition, if quarterly accounting information is found to be useful, the high costs incurred in preparing interim financial statements can be justified. In addition, it is hoped that the results of this study will stimulate other research interests in the use of quarterly accounting information. This would extend the borders of knowledge in the accounting discipline, certainly a major objective of the profession.

Second, a new variable, the industry-related systematic risk of a company, is developed to examine the impact of an industry factor on security returns. In most studies (e.g., Nerlove [1968]), the impact of the industry factor has been examined by including an industry dummy variable when estimating the return model. This typical approach is deficient for the following reasons. First, if numerous industries are examined, a substantial number of industry dummy variables would be needed. For example, when twenty industries are included in the sample for investigation, nineteen dummy variables are required in estimating the return model. It becomes not only difficult but also tedious to interpret the significance of the numerous dummy variables. Besides, the number of industries examined has to be limited because of the increased complexity of the return model. The industry-related systematic risk variable constructed in the present study has no such deficiency. Basically, it measures the responsiveness of a company's return to that of its industry. Thus, the construction of this new variable, industry-related systematic risk, in the present study should improve the research methods for examining an industry effect.

The present study is not intended to be a direct test of any theoretical model. Rather, it attempts to investigate the return generating process of securities. Hopefully, the results of the study will provide information useful to investors in making their investment decisions.

ORGANIZATION OF THE STUDY

The purpose and justification of the present study have already been discussed. The contents of the following chapters are summarized below.

Chapter II presents a review of the relevant literature. It is divided into two major sections. The first section is a discussion of two models of capital market equilibrium, the Capital Asset Pricing Model and the Arbitrage Pricing Theory. The implications of these equilibrium models to the present study are also discussed. The second section is a description of the four factors--a market factor, an industry factor, a company factor and a growth factor--that are hypothesized to be significant determinants of security returns. The components of the company factor are also identified in this section. Theoretical and empirical evidence on these proposed return generating factors are included. This discussion serves as the groundwork for the hypothesis developed in Chapter III.

In Chapter III, the hypothesis of the study is stated. The basic hypothesis is that there exists a multifactor return model that best explains the variation in security returns. An operational definition of the instrumental variables used in constructing the return model is then presented. Finally, the data selection process and statistical methods used in the study are described.

The findings and results of this research are presented in Chapter IV. Since the analyses performed are quite extensive, the results are reported in a systematic fashion. First, the findings are categorized into four major sections depending on which classification scheme is used for grouping companies into industries. Second, within each classification scheme, statistics for each alternative estimate of market-related systematic risk are presented. Third, for each alternative estimate of market-related systematic risk, regression statistics of the estimated regression models are reported and evaluated. This hierarchical approach is used in order to facilitate the determination of the "best" return model. The final section summarizes the results of the previous analyses to enable the reader to recognize the significance of the findings and their influence on security analysis.

The last chapter presents the conclusions of this research project. Limitations with respect to the research methodology as well as the statistical methodology are discussed. Finally, a word about this project's implications for future resarch are given.

CHAPTER II

LITERATURE REVIEW

The literature review is divided into two main sections. The first section presents two methods of describing equilibrium in the capital markets--the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT), which provide the groundwork for developing the multifactor return model. The second section presents factors that are potential determinants of security returns. These return generating factors include a market factor, an industry factor, a company factor, and a growth factor.

Prior to a review of the relevant literature, it is enlightening to clarify certain terminology that is used in this paper. Systematic risk employed by the CAPM for each company is the <u>market-related systematic risk</u>, which represents the responsiveness of a security's return to that of the market. This risk definition is differentiated from the <u>industry-related systematic risk</u>, which measures the responsiveness of a security's return to that of its industry.

MODELS OF EQUILIBRIUM IN THE CAPITAL MARKET

An analysis of general equilibrium conditions in the capital markets allows determination of "the relevant measure of risk for any asset and the relationship between expected return and risk for any asset."[1] The analysis also enables assessment of the prices and returns of risky securities when markets are in equilibrium. This information is especially useful in deciding which securities should be included when forming the most desirable portfolio.

The first general equilibrium model, the Capital Asset Pricing Model (Sharpe [1964], Lintner [1965a], and Mossin [1966]) is based on the assumption that the expected return of any asset is linearly related to its market-related systematic risk when markets are in equilibrium. Since its development, the Capital Asset Pricing Model has been used extensively in market-based empirical research. Recently, however, doubts have arisen concerning the model's effectiveness in explaining the empirical constellation of asset returns. A new approach, the Arbitrage Pricing Theory, was proposed in Ross [1976] and Roll and Ross [1980] as a more appropriate alternative to the Capital Asset Pricing Model. The basic premise of the Arbitrage Pricing Theory is that there are several factors

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1 Elton, Edwin J. , and Martin J. Gruber. Modern Portfolio Theory and Investment Analysis, John Wiley & Sons, New York, 1981, p. 274.

that are significant in explaining asset returns, assuming that the return generating process is linear.

These two approaches to general equilibrium theory have different perspectives on the return generating process of securities. The fundamentals of these two models, as well as their implications to the research thesis, are presented in the following sections.

Capital Asset Pricing Model (CAPM)

ASSUMPTIONS

The Capital Asset Pricing Model (CAPM) was developed under the following stringent set of assumptions:[2]

1. the capital markets are perfectly competitive;
2. there are no transaction costs;
3. there is no personal income tax;
4. assets are infinitely divisible;
5. all assets are marketable;
6. there are unlimited short sales;
7. there are unlimited borrowing and lending at the risk free rate of interest;

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[2] Ibid. pp. 275-276.

8. investors seek to maximize their expected utility which is a function of the expected values and standard deviations of the returns on their portfolios; and

9. investors have homogeneous expectations with respect to the mean and variance of asset returns over a single period.

Some of the assumptions appear to be objectionable because they do not represent a realistic view of the capital markets. The usefulness of a model, however, may not always be determined by how realistic its assumptions are, but rather it may sometimes be determined by how well it predicts the phenomenon it purports to describe. Therfore, the CAPM should be evaluated not on the basis of its assumptions, but by examining the relationship between the predictions of the model and the observed real world phenomena. Empirical studies on the appropriateness of the CAPM in describing asset returns are numerous, and some of the more important findings are discussed in later sections.

SUGGESTED HYPOTHESES FOR EMPIRICAL TESTING

According to the CAPM, an equilibrium relationship exists between risk and expected return from a security. In market equilibrium, a security is expected to provide a return commensurate with its market-related systematic risk. The model can be written as:

$$E(R_i) = R_f + \beta_i^m \, [E(R_m) - R_f],$$

where $E(R_i)$ = expected return on security i;

$E(R_m)$ = expected return on the market;

R_f = risk free rate of interest;

β_i^m = market-related systematic risk of security i.

The model itself suggests a number of testable hypotheses. The first is that higher risk (market-related systematic risk, β_i^m) should be associated with a higher level of return. The second is that return is linearly related to market-related systematic risk. The third is that there should be no added return for nonmarket risk. These hypotheses have been tested in numerous empirical studies. The results of some are summarized in the following section.

EMPIRICAL TESTS AND FINDINGS

Most of the early empirical tests of the CAPM involved the use of a time-series (first pass) regression to estimate the market-related systematic risk, and a cross-sectional (second pass) regression to test the hypotheses suggested by the model. The first pass regression is of the form:

$$R_{it} = \alpha_i^m + \beta_i^m R_{mt} + e_{it}, \; t = 1, 2, \ldots, T$$

where R_{it} = return on security i in period t;

R_{mt} = return on the market in period t;

e_{it} = residual term of linear relationship;

α_i^m = intercept of linear relationship;

β_i^m = slope of linear relationship, which is an estimate of the market-related systematic risk of security i;

T = number of periods.

The second pass regression is then performed on a sample of securities in the form specified below:

$$R_i = a_1 + a_2 \beta_i^m + a_3 S_{ei}^2 + \varepsilon_i, \quad i = 1, 2, \ldots, N$$

where R_i = mean return on security i;

β_i^m = estimate of market-related systematic risk of security i from first pass regression;

S_{ei}^2 = residual variance from first pass regression;

ε_i = residual term of linear relationship;

a_1, a_2, a_3 = regression coefficients of linear relationship;

N = number of securities in sample.

Theoretically, a_1 should be equal to R_f; a_2 should be equal to $E(R_m) - R_f$; and a_3 should be equal to zero. Empirical results (Lintner [1965b], Douglas [1968]) seem to violate the hypothesized CAPM, since a_1 is larger than any reasonable estimate of R_f; a_2, although statistically significant, has a value slightly lower than $E(R_m) - R_f$; and a_3 is statistically different from zero. In a classic article, Miller and Scholes [1972] have shown that the bias in the coefficients is a result of the sampling error in estimating market-related systematic risk for the second pass regression. In their study, Miller and Scholes also found that return distributions are positively skewed. Furthermore, they show that if there is skewness, the second pass (cross-sectional) regression will show an association between residual risk (S_{ei}^2) and return, even though there is no such association. Therefore, it is inappropriate to regard the results of the previous studies (Lintner [1965b], Douglas [1968]) as evidence against the CAPM.

In order to alleviate these statistical problems, Black, Jensen and Scholes [1972] employed a portfolio approach to test the CAPM empirically. Their approach presumes that errors in measuring market-related systematic risk are random. These errors should cancel out, such that aggregate error should be very small when estimating market-related systematic risk for portfolios. Black, Jensen and Scholes find evidence in support of the two-factor CAPM (or the so-called zero-Beta version of the CAPM), which has the following form:

$$E(R_i) = E(R_z) + \beta_i^m [E(R_m) - E(R_z)],$$

where $E(R_i)$ = expected return on security i;

$E(R_m)$ = expected return on the market;

$E(R_z)$ = expected return on the zero-beta portfolio;

β_i^m = market-related systematic risk of security i.

In a later study, Fama and MacBeth [1973] used the portfolio approach suggested by Black et al., and tested the following cross-sectional model for each month t:

$$R_{it} = \gamma_{0t} + \gamma_{1t}\,\beta_i^m + \gamma_{2t}\,\beta_i^{m\,2} + \gamma_{3t}\,S_{ei} + \eta_{it},\ i = 1, 2, \ldots N$$

where R_{it} = return on security i in month t;

β_i^m = market-related systematic risk of security i;

S_{ei} = standard deviation of residual from time-series regression of security i's return on market return;

η_{it} = residual term of linear relationship;

γ_{jt} = regression coefficient of linear relationship, and $j = 0, 1, 2, 3$;

N = number of securities in sample.

Fama and MacBeth estimated γ_{0t}, γ_{1t}, γ_{2t}, γ_{3t}, and η_{it} for each month over the period January 1935 to June 1968. The average value of γ_{jt} (denoted by γ_j) can be tested to see if it is significantly different from zero. The results indicate that γ_0 is generally greater than R_f; γ_1 is significantly greater than zero, although it is generally less than R_m - R_f; and both γ_2 and γ_3 are not statistically different from zero. This evidence supports the CAPM, and leads to the conclusion that a positive relationship exists between expected return and market-related systematic risk. In addition, no added return exists for nonmarket risk. The average values of γ_{0t} and γ_{1t} again imply that the two-factor model is more consistent with equilibrium conditions than the one-factor CAPM.

In summary, empirical evidence supports the hypothesis that there is a positive, linear relationship between expected return and market-related systematic risk. The significance of residual risk, however, has not yet been determined.

ROLL'S CRITIQUE

Despite these efforts in testing the CAPM, Roll [1977] argues that the tests so far provide little evidence for or against the CAPM. Roll proposes that there is only one testable hypothesis associated with the CAPM, namely that "the market portfolio is mean-variance efficient." He also states that other implications of the model--the best known being the linearity relationship between expected return and market-related systematic risk--are not independently testable. In addition, Roll shows that the return on any asset is an exact linear function of market-related systematic risk if the latter is computed using any efficient portfolio. Conversely, if the portfolio used to compute market-related systematic risk is not efficient, then no exact linear relationship exists between return and market-related systematic risk. Furthermore, Roll argues that the CAPM is not testable unless the exact composition of the market portfolio is known and used in the tests. Thus, the so-called empirical tests of the CAPM so far have only addressed the question whether the market proxy chosen is efficient or not. Finally, Roll concludes that (a) no correct and unambiguous test of the theory has appeared in the literature; and (b) there is practically no possibility that such a test can be constructed in the future.[3] These critiques raise concerns with respect to the appropriateness of the CAPM in describing return behavior of the actual capital markets, despite its theoretical soundness.

Arbitrage Pricing Theory (APT)

DERIVATION OF ARBITRAGE PRICING THEORY

Ross [1976] and Roll and Ross [1980] advocate the Arbitrage Pricing Theory (APT) as a more appropriate alternative to the CAPM. The theory assumes a linear return generating process and allows more than one factor in generating asset returns. In general, if asset returns are assumed to be generated by k basic factors, then the return generating process can be described as follows:

$$r_i = E_i + b_{i1}\,\delta_1 + b_{i2}\,\delta_2 + \dots + b_{ik}\,\delta_k + e_i,$$

where r_i = return on asset i;

E_i = mean return on asset i;

δ_j = mean value of the j^{th} return generating factor common to all assets in the market;

b_{ij} = a coefficient measuring the effect of the j^{th} return

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[3] Roll, Richard. "A Critique of the Asset Pricing Theory's Tests - Part I: On Past and Potential Testability of the Theory," Journal of Financial Economics, March 1977, p. 129.

[4] Roll, Richard, and Stephen Ross. "An Empirical Investigation of the Arbitrage Pricing Theory," Journal of Finance, December 1980, pp. 1076-1079.

generating factor on the return from asset i;

e_i = random noise.

Basically, any market equilibrium must be consistent with no arbitrage profits. Consequently, the expected return on an "arbitrage" portfolio must be zero, since an "arbitrage" portfolio is one that bears no risk and involves zero net investment. An algebraic consequence of this statement is that the expected return on any security i must be a linear combination of the b_{ij} terms. Therefore, in algebraic terms, there exist k+1 weights, $\lambda_0, \lambda_1, \lambda_2, \ldots, \lambda_k$, such that

$$E_i = \lambda_0 + \lambda_1 b_{i1} + \lambda_2 b_{i2} + \ldots + \lambda_k b_{ik}, \text{ for all i.}$$

If there is a riskless asset with return E_0, then $b_{ij} = 0$ for all j, and

$$E_0 = \lambda_0;$$

hence the equilibrium return model can be written as

$$E_i - E_0 = \lambda_1 b_{i1} + \lambda_2 b_{i2} + \ldots + \lambda_k b_{ik}, \text{ for all i.}$$

By forming a portfolio with unit systematic risk on the j^{th} factor and no risk on the other factors, where E^j is the mean return on such a portfolio, λ_j ($\lambda_j = E^j - E_0$) can then be interpreted as the excess return on portfolios with only systematic factor j risk. Each λ_j can be determined in a similar fashion. Thus the equilibrium model, as defined by the APT, is

$$E_i - E_0 = (E^1 - E_0)\, b_{i1} + (E^2 - E_0)\, b_{i2} + \ldots (E^k - E_0)\, b_{ik}.$$

The advantage of the APT, as suggested by Roll and Ross, is that the market portfolio plays no special role in the model. This implies testability of the theory, as compared to the CAPM. In fact, k well-diversified portfolios could be constructed to approximate the k factors that are proposed to be better than any single market index.

EMPIRICAL TESTS AND FINDINGS

Contrary to the CAPM, empirical studies on the APT are limited. Long before the development of the theory, the possibility of multiple return generating factors was recognized. King [1966] was among the earliest to find that an industry effect is significant in explaining stock prices, in addition to the market effect. Brennan [1971] decomposed the residuals from a market model regression, and from his findings concludes that "the true return generating process must be represented by at least a two factor model rather than by the single factor diagonal model."[5] Roll and Ross [1980] used factor analysis to determine the number of factors that should be included in describing the return generating process of securities. Three to four factors were found to be significant in affecting the return generating process. The composition of these factors, however, is unknown. Cho, Elton and Gruber [1984] extended Roll and Ross's study on

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[5] Brennan, M. J. "Capital Asset Pricing and the Structure of Security Returns," Unpublished manuscript, University of British Columbia, May 1971, p. 30.

simulated return data. In the latter study, historical beta and Wilshire beta[6] were used separately in the zero-beta CAPM to simulate daily return data of the sample securities. The conclusion for the simulated return data was that "there were fewer factors identified as generating returns and fewer factors required to explain equilibrium returns than the numbers corresponding to actual data."[7] In fact, three factors were found to be sufficient in explaining the return generating process of the simulated data.

The tests of the APT reported by Roll and Ross are subject to several limitations, as suggested by Dhrymes, Friend and Gultekin [1984]. The major criticisms on the research methodology are that[8] (i) it is generally not permissible to carry out tests on whether a given "risk factor is priced"; this is a result inherent in the structure of standard factor analytic models, unless one is prepared a priori to specify that in the "true" structure certain factor loadings are known; (ii) factor analyzing

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6 Historical beta is estimated by regressing daily security returns on daily value-weighted market returns. Wilshire beta, on the other hand, is determined by such factors as historical beta, a set of fundamental factors, and industry membership.

7 Cho, D. Chinhyung, Edwin J. Elton, and Martin J. Gruber. "On the Robustness of the Roll and Ross Arbitrage Pricing Theory," Journal of Financial and Quantitativf Analysis, March 1984, p. 2.

8 Dhrymes, Phoebus J., Irwin Friend, and N. Bulent Gultekin. "A Critical Reexamination of the Empirical Evidence on the Arbitrage Pricing Theory," Journal of Finance, June 1984, p. 324.

small groups of securities is not equivalent to factor analyzing a group of securities sufficiently large for the APT model to hold; and (iii) as one increases the size of the security groups to which the APT/factor analytic procedures are applied, the number of "factors" determined increases. This implies that factor analysis is not an appropriate tool for testing the APT.

In another study, Pari [1980] used the portfolio approach to test the APT, and in general, the results, support a four-factor version of the APT. Another crucial finding of Pari's study is that industry portfolios can be constructed to describe the return generating process of securities, although the economic affiliations among companies within some industry clusters are not strong. Therefore, despite the limitations on the use of factor analysis in empirically testing APT, the results reported by Pari are in support of a multifactor return model. Furthermore, Chen [1983] compares the evidence on the APT and the CAPM, and concludes that the APT performs well in explaining the process generating security returns. The evidence provided by Chen also indicates that estimated expected returns depend on estimated factor loadings, and variables such as the variance of a security's return and company size do not contribute additional explanatory power to that of the factor loadings.

Implications

Regardless of Roll's criticisms, the so-called empirical tests of the CAPM (Black, Jensen, and Scholes [1972], Fama and MacBeth [1973]) provide evidence in support of the proposition that a positive, linear relationship exists between expected return and market-related systematic risk. Other empirical evidence (Brenner [1971], Roll and Ross [1980], Pari [1980] Cho, Elton and Gruber [1984]), however, indicates that there are at least three to four factors that are significant in generating security returns. Furthermore, APT provides a theoretical basis for advocating the existence of a multifactor return model at market equilibrium. All these developments lead to greater concern, as well as research interest in testing the appropriateness of a multifactor return model.

The present study attempts to examine if factors other than market-related systematic risk play significant roles in explaining security returns. It is necessary to make it clear, however, that the intent of this study is not to test the CAPM or APT directly. Rather, it seeks to determine what other factors also help explain the return on securities; such factors do not necessarily represent factors that are common to all assets in the capital market. That is why factors specific to individual companies, such as a company factor and a growth factor, are included in determining the multifactor return model. Quarterly accounting information is used in constructing the company factor as well as the growth factor. This is based on the belief that quarterly accounting data (which are more frequently available than annual accounting data) provide better residual risk measures for individual companies, since more data observations are available for constructing the variables for a given period.

RETURN GENERATING FACTORS

A survey of the literature suggests that four factors can be significant in describing security returns. They are a market factor, an industry factor, a company factor, and a growth factor. In general, the market factor affects all assets in the capital market, while the industry factor affects only specific (industrial) segments of the market. The company factor, on the other hand, describes the fundamental characteristics of the individual company, which in itself is unique in nature. Finally, the growth factor reflects both the influence of general economic conditions on the individual company and the company's earnings potential in the future. Each of these factors is described in detail in the following sections.

Market Factor

EMPIRICAL SIGNIFICANCE

It is a generally accepted view that some ideal "market portfolio" cannot be identified. As a remedy, empirical researchers turn to readily available proxies of the market portfolio. Regardless of which proxy is chosen, research findings indicate that the average explanatory power of the market return with respect to security returns is within a range of 20 to 40 percent (Melicher [1974], Fama [1976], Livingston [1977], Foster [1978]). This evidence has two implications: first, because of the relatively large degree of explanation, the market factor is a significant factor in determining security returns; and second, because of the large proportion of unexplained variation in security returns, the omission of other return generating factors from the market model can be crucial.

Factor analytic methods, in addition to the market model, have been used to determine how well the market factor explains security returns. King [1966] was among the pioneers who used factor analysis to study stock price behavior. Based on his findings,[9] he concluded that the typical stock has about half its variance explained by an element of price change that affects the whole market. King's findings were supported by Meyers [1973]; however, Meyers found that the percentage of variation in stock prices explained by the market factor tends to decline over time. Livingston [1977] criticizes the use of factor analytic methods in extracting the market factor. He found that factor analysis is sample sensitive, and

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[9] King, Benjamin F. "Market and Industry Factors in Stock Price Behavior," Journal of Business, January 1966, p. 151.

its solutions seem to put more variance into their market factor and less into the residuals.[10] This results in an upward bias when factor analysis is used to determine the explanatory power of the market factor on security returns. Using the market model as a basis for isolating the market effect, Livingston found that the market factor explains only 25 percent of the variance of security returns on the average, rather than 50 percent.

Regardless of the methodology used, these empirical findings lead to the conclusion that there is a market factor that plays an important role in explaining variation in security returns.

MARKET-RELATED SYSTEMATIC RISK AND ITS ESTIMATION

Stock prices tend to move together in response to economic, political, or other events. This observation has led to the development of the market model (Sharpe [1963]), which is based on the assumption of a linear relationship between a security's return and the market return, if their joint distribution is bivariate normal. Since then, the market model has been used extensively in financial research, especially for estimating the market-related systematic risk of securities.

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[10] Livingston, Miles. "Industry Movements of Common Stocks," Journal of Finance, March 1977, p. 865.

According to the CAPM, a security's return is dependent on its market-related systematic risk, which measures its riskiness relative to that of the market. Empirical findings (Black, Jensen, and Scholes [1972], Fama and MacBeth [1973]) are consistent with this theoretical hypothesis. As a matter of fact, a positive linear relationship has been found to exist between a security's return and its market-related systematic risk.

The use of market-related systematic risk in the financial community is extensive. Security analysts use this risk measure to evaluate security performance as well as to identify securities that are potential candidates for inclusion in a portfolio. Its use in reducing uncertainty is so crucial that several models have been developed to provide future forecasts of market-related systematic risk. The most commonly known models include the market model (Sharpe [1963]), the mean reversion model (Blume [1971]), the order bias adjustment model (Blume [1975]), and the Bayesian adjustment model (Vasicek [1973]).

MARKET MODEL: The market model (Sharpe [1963]) is the most commonly used model for estimating the market-related systematic risk of a company. The basic assumption of the market model is that the joint distribution between a security's return and the market return is bivariate normal. According to the market model, the market-related systematic risk of a company can be estimated by regressing time-series observations of security returns on observations of the market return over the same period. The regression coefficient for the market return is then an estimate of the market-related systematic risk. Like any regression coefficients, this estimate is subject to error. Moreover, the situation is further complicated by the fact that the market-related systematic risk is not stationary over time. This is due to the fact that the market-related systematic risk changes as the fundamental characteristics of the firm change. As a consequence, adjustment techniques have been developed to reduce the error associated with measuring the true market-related systematic risk and the possibility of its shift over time.

The estimate of market-related systematic risk for any stock is partly a function of the true underlying market-related systematic risk and partly a function of sampling error. If a very high estimate of the market-related systematic risk for a security is computed, there is an increased probability that a positive sampling error exists. In contrast, if a very low estimate of the market-related systematic risk is computed, there is an increased chance that a negative sampling error exists. This scenario is supported by empirical evidence. Blume [1975] found that the estimate of market-related systematic risk, on the average, tends to converge towards the value of one in successive periods. Some adjustment techniques, presented below, have attempted to capture this tendency of market-related systematic risk estimate to regress towards the value of one.

MEAN REVERSION MODEL: Blume [1971] advocated a method of correction for the tendency of market-related systematic risk estimates to regress toward the value of one. He asserted that the rate of regression towards the value of one is stationary over time. If that assumption holds, the method of correction is to regress the estimated values of market-related systematic risk in one period on the values estimated in a previous period and to use this estimated relationship to modify the assessment of the future. In his study, Blume found that this adjustment method improves the accuracy of the estimate of market-related systematic risk of a company for a future period. In brief, this "Mean Reversion model" proposed by Blume provides a systematic approach for adjusting the market-related systematic risk estimate of any company for the tendency of these estimates to revert towards the mean--that is, the value of one. A mathematical description of the model will be presented in later sections.

ORDER BIAS ADJUSTMENT MODEL: In a later study, Blume [1975] argued that when estimating market-related systematic risk for a portfolio of securities, risk estimates other than the value of one are biased. When estimates of portfolio market-related systematic risk are less than one, the true portfolio market-related systematic risk is understated; conversely, estimates of portfolio market-related systematic risk greater than one tend to overestimate the true value. He argued that this phenomenon is a consequence of order bias. In his study, Blume proposed a model for adjusting this order bias. In principle, the "Order Bias Adjustment model" defines a procedure for adjusting the market-related systematic risk estimate for any company depending on its distance from the mean, i.e., the value of one and the precision of its estimate. In fact, Blume found that the order bias adjustment model is important but is less important than mean reversion in explaining the time series behavior of the market-related systematic risk estimates.

BAYESIAN ADJUSTMENT MODEL: Estimates of market-related systematic risk for different companies are associated with different sampling errors. It is obvious that the larger the sampling error, the greater the chance of large differences from the average. Consequently, the greater the sampling error, the larger the adjustment has to be. Vasicek [1973] suggested an adjustment technique that accounts for such cases. He suggested a Bayesian procedure for adjusting estimates of market-related systematic risk to minimize misestimation errors. This Bayesian adjustment model incorporates the prior distributional information for market-related systematic risk estimates in addition to the sample information.

SYNTHESIS

The above mentioned models have been evaluated on the basis of their forecasting accuracy. Klemkosky and Martin [1975] found that both the Blume and Bayesian adjustment techniques led to more accurate forecasts of future market-related systematic risk than did the unadjusted market-related systematic risk determined by the market model. One deficiency of such an approach is that the criterion for evaluation--the "true" market-related systematic risk of the future--is unobservable. This implies that the results reported by Klemkosky and Martin should be interpreted with caution. A more appropriate approach in evaluating these models is to examine their explanatory power and ability to predict security returns. This approach is superior to that of Klemkosky and Martin because security return is a readily observable criterion with no measurement error, and it is of major concern to security analysts in evaluating security performance and making portfolio decisions.

In summary, the literature provides both theoretical and empirical support that the market factor has a special role in describing the return generating process of securities. In the present study, market-related systematic risk is used to reflect the effect of market conditions on each security's return. Since the "true" market-related systematic risk is unobservable, its estimate will be used as an instrumental variable in developing the multifactor return model. As has been discussed previously, four models (the market model, the mean reversion model, the order bias adjustment model, the Bayesian adjustment model) are available to provide estimates of market-related systematic risk. These alternative estimates are examined individually to determine their explanatory power and ability to predict security returns.

Industry Factor

EMPIRICAL SIGNIFICANCE

Brown and Ball [1967] investigated the degree of association between the earnings of a firm, the earnings of other firms in their respective industries, and the earnings of all firms in the economy. The principle result of the study[11] is that industry and market indexes provide information about the earnings of the firm. The industry index was found to explain an additional 10 to 15 percent of the variability of earnings above that of the market index. In a recent study by Foster [1981], the impact of a firm's earnings releases on the stock prices of other firms in its industry is examined. For firms that have a larger percentage of their revenues in the same line of business as the earnings release firm, the impact of the intra-industry information is more significant. Based on the empirical findings of these studies, it can be concluded that earnings are responsive to industry conditions.

The effect of industry membership on stock prices and security returns has also been investigated in other empirical works (e.g., King [1966], Meyers [1973], Livingston [1977]). The findings and significance

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[11] Brown, Philip, and Ray Ball. "Some Preliminary Findings on the Association Between the Earnings of a Firm, Its Industry, and the Economy," Journal of Accounting Research, Supplement 1967, p. 65.

of these studies are presented in the following sections.

Factor analysis has been used in a number of studies to investigate the existence of both a market factor and an industry factor. King [1966] concluded that the average proportion of variance of stock prices due to industry effects is about 10 percent, but these particular findings were challenged by Meyers [1973]. Meyers agreed that industry relationships represent an important source of interdependence among securities, but their effect is considerably less important than is suggested by King [1966]. In contrast, Livingston [1977] found that approximately 18 percent of the total variance of security returns is explained by residual industry effects, and these effects are approximately three-quarters the size of the market effect.[12] Nerlove [1968] used a different approach to examine the significance of industry factors in explaining the differences among rates of return on common stocks. He found that the use of industry dummy variables improves the explanatory power of the regression models on rates of return of common stocks by an average of 10 percent. Unfortunately, empirical findings on the relative significance of an industry effect on security returns are somewhat inconclusive.

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[12] Ibid. p. 873.

INDUSTRY-RELATED SYSTEMATIC RISK

Fabozzi and Francis [1979] suggested that future inquiries into the determinants of market-related systematic risk of securities should be adjusted for industry effect.[13] In their study, the inclusion of industry dummy variables improves the explanation of market-related systematic risk by a significant 16 percent. It may thus be concluded that the market-related systematic risk of any company is significantly affected by industry-related factors

In order to determine if industry-related factors are significant in explaining security returns, however, it is necessary to separate the effect of the industry from that of the market. Thus, a surrogate for measuring the industry effect has been developed for the present study in such a way as to account for the market effect. The industry-related systematic risk, which represents the responsiveness of a security's return to that of its industry, is used as a surrogate measure of the industry effect. The approach used in constructing the industry-related systematic risk of a company will be described in later sections.

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[13] Fabozzi, Frank J., and Jack Clark Francis. "Industry Effects and the Determinants of Beta," Quarterly Review of Economics and Business, Autumn 1979, p. 72.

SUMMARY

In summary, several empirical studies (King [1966], Brown and Ball [1967], Livingston [1977], Foster [1981]) indicate that an industry factor plays a role in determining earnings, stock prices and security returns. The importance of the industry factor varies from study to study, however. This may be attributed to differences in methodology, as well as differences in defining an industry. It is, therefore, interesting to examine the contribution of the industry factor toward determining security returns. In addition, the surrogate for industry effect must be constructed in such a way as to account for the market effect, as suggested by Fabozzi and Francis [1979].

Company Factor

There is general agreement that both the market and industry factors are major determinants of security returns. A third factor has also been identified in the literature, and may contribute to explaining the return generating process of securities. This factor captures the fundamental characteristics of each individual company.

EMPIRICAL SIGNIFICANCE

Nerlove [1968] is among the earliest who looked into the company itself to identify factors affecting differences among rates of return on common stocks. The results are consistent with the following hypothesis:[14]

> Rates of return on investments in different common stocks differ in some measure because of differences in riskiness, but much more importantly because of substantial disequilibrium in the capital market. Not only is external capital severely rationed, but investors in stocks share the imperfect recognition of profitable expansion with other suppliers of capital. Dim perception of opportunities which appear to be especially prevalent in rapidly expanding firms is responsible for lower prices initially. As, however, the great profitability of internal investment is realized, prices rise resulting in substantial capital gains. Over long periods of time, firms with considerable internal investment potential, which they realize through high retention of earnings, pay out high or increased dividends which contribute importantly to a high rate of return on investments in the common stock of such firms. Retained earnings, however, coupled with profitable opportunities for investing them, remain the most important single source of high rates of returns on investments in individual common stocks.

Nerlove [1968] presumes that both the riskiness and investment opportunities for a company are reflected in financial statement variables. Leverage is found to be positively associated with the rate of return. The most important variables explaining the differences among rates of return appear to be growth in sales and retention of earnings. Dividends are also significant, but the coefficient for dividends is only about one-eighth of the coefficient for retained earnings in the regression model. The set of company variables chosen are rate of growth of sales, rate

[14] Nerlove, Marc. "Factors Affecting Differences Among Rates of Return on Investments in Individual Common Stocks," Review of Economics and Statistics, August 1968, p.313.

of growth of earnings, retained earnings per dollar of total assets, dividends per dollar of total assets, reciprocal of leverage, inventory turnover, share turnover, and gross plant per dollar of total assets. On the average, these variables explained about 42 percent of the variance in rates of return. As indicated earlier, the inclusion of industry dummy variables by Nerlove increases the percentage of explained variance by another 10 percent.

Simkowitz and Logue [1973] concluded that in addition to the market factor, financial data of companies are also important in explaining security returns. They investigated the drug and oil industries under the assumption that returns on securities are jointly and simultaneously determined. When variables reflecting profitability, dividend policy, and debt policy of a company were included in the regression, the statistical significance of the market factor was for the most part destroyed, but the explanatory power of the model improved by about 10 percent. Therefore, the importance of the market factor as an explanatory variable for security returns virtually disappears. This implies that corporate financial characteristics do not only comprise unsystematic risk,[15] but the market factor can be also viewed as a surrogate for some real variables of the company.

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[15] Simkowitz, Michael A., and Dennis E. Logue. "The Interdependent Structure of Security Returns," Journal of Financial and Quantitative Analysis, March 1973, p. 264.

Lee and Zumwalt [1981] extended Simkowitz and Logue's [1973] study by investigating the significance of corporate financial variables for 35 industries classified according to two-digit Standard Industrial Classification (SIC) codes. Measures of profitability, leverage, and dividend policy were included in the CAPM. The profitability variable proved to be significant for most companies, whereas the dividend policy variable was significant for the least number of cases. In general, the results suggest that accounting profitability measures have a significant impact on security returns. Nevertheless, because different accounting methods (e.g. LIFO, FIFO, straight-line depreciation, accelerated depreciation etc.) are used in various industries, different accounting profitability measures should be used by security analysts in analyzing rates of return on securities in those different industries.

THEORETICAL BASIS

The choice of company variables in the above studies is primarily based on researcher intuition. There is a lack of theoretical justification for including these company variables in the CAPM. In an earlier study, Rosenberg and McKibben [1973] attempted to justify the use of company variables in explaining security returns. Their model showed that market-related systematic risk is a function of company variables. Since the rate of return on securites is associated with its market-related systematic risk, it implies that company variables will also play a part in determining security returns. No direct empirical evidence concerning the contribution of company variables toward explaining security returns is provided. Nevertheless, the findings support the proposition that company variables are useful in predicting market-related systematic risk.

In addition, Rosenberg [1974] demonstrated that "there are highly significant extra-market components of covariance among security returns; moreover, these risk components are such that the loadings of individual security returns on the factors are determined by observable characteristics of the firm: income statement and balance sheet data [emphasis added], industry membership, and historical behavior of returns on the security."[16] Unfortunately, the income statement and balance sheet data to which he refers were not defined specifically in the study.

COMPONENTS OF THE COMPANY FACTOR

The motivation of researchers in examining the significance of company variables to explain security returns cannot be ignored. This is attributable to their belief that there exists a company factor that is significant in determining the return generating process of securities, although the composition of this company factor is still unknown. (Ner-

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[16] Rosenberg, Barr. "Extra-Market Components of Covariance in Security Returns," Journal of Financial of Quantitative Analysis, March 1974, p. 263.

love [1968], Simkowitz and Logue [1973], Lee and Zumwalt [1981])

The determination of which financial variables are essential to defining the company factor is a difficult task, however. Financial statements can provide as many financial variables as are desired. Ratios of these financial variables can be grouped into eight basic factors:[17] (1) return on investment, (2) cash position, (3) inventory intensiveness, (4) capital intensiveness, (5) receivable intensiveness, (6) short-term liquidity, (7) debt structure, and (8) cash flow from operations.[18] These eight factors include measures of profitability (return on investment), operating leverage (capital intensiveness), financial leverage (debt structure), liquidity (cash position, inventory intensiveness, receivable intensiveness, and short-term liquidity), and cash flow from operations of a company. For the present study, the choice of which of these measures to include as components of the company factor has been based on a study of the following literature.

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[17] Gombola, Michael J., and J. Edward Ketz. "A Note on Cash Flow and Classification Patterns of Financial Ratios," The Accounting Review, January 1983, p. 110.

[18] In an earlier study by Pinches, Mingo and Caruthers [1973], only seven factors were identified, excluding the cash flow from operations. The difference in results of the two studies is attributed to a more exact measure of cash flow by Gombola and Ketz [1983].

PROFITABILITY: In general, profitability measures the operating efficiency of a company. The calculation of profitability, however, can be very subjective in nature, involving the professional judgement of accountants in computing the net income of a company. The Financial Accounting Standards Board has issued Statements of Accounting Standards to serve as guidelines when preparing financial statements. Nevertheless, accountants are still left with some choice among alternative accounting methods, all of which are generally accepted accounting principles.

Despite their subjective nature, profitability ratios such as gross profit margin, net profit margin, return on assets, return on stockholders' equity, remain powerful tools for both management and investors in evaluating the performance of a company. Furthermore, empirical results (Simkowitz and Logue [1973], Lee and Zumwalt [1981]) indicate that profitability measures are significant in explaining the return generating process of securities. These findings are consistent with the notion that if a company is efficient in using the resources provided by investors, investors should earn a greater rate of return by investing in the company's operation rather than other less efficient operations.

Therefore, a positive relationship is expected to exist between a company's profitability and the return of its securities. In the present study, profitability is included as a component of the company factor, which is hypothesized to be significant in determining the return generating process of securities.

OPERATING LEVERAGE: Operating leverage is tied to a company's cost structure. It arises from operational costs that are fixed regardless of the sales volume. With fixed costs, the percentage change in profits associated with a change in sales volume is greater than the percentage change in sales volume. This phenomenon is known as operating leverage.

Operating leverage is one component of the overall business risk of a company. The principal source of risk faced by a company is the uncertainty in both sales demand and costs of production. It is possible that as a result of fluctuations in sales demand, the sales revenues generated will not be adequate to cover the fixed costs incurred in production. Thus, companies with high fixed costs have greater leverage and face a greater risk in operations as compared to companies whose committed fixed costs are less substantial. In brief, operating leverage magnifies the impact of uncertainties in both sales demand and production costs on the variability of profits.

A number of studies (Percival [1974], Lev [1974], Hill and Stone [1980], Gahlon [1981]) have shown that a theoretical relationship exists between the market-related systematic risk and the operating leverage of a company. Empirical evidence (Mandelker and Rhee [1984]) is supportive of the above theory. As suggested by Rosenberg and McKibben [1973], company variables can be significant in explaining security returns if they are determinants of market-related systematic risk. Furthermore, Choi [1982] concludes that unsystematic operating risk has a greater effect on capital asset pricing and rate of return on common stock than does unsystematic financial risk. Thus, it is appropriate to include operating leverage as a potential determinant of security returns in developing the multifactor return model.

LIQUIDITY: Measures of liquidity are used to judge the ability of a company to meet its short-term obligations. The cash solvency of a company is dependent on its ability to convert non-cash assets into cash in the event of adversities. It is obvious that the impact of insolvency can be disastrous at times, but its impact on security returns may not be significant.

Nerlove [1968] was unsuccessful in finding a significant inverse relationship between liquidity measures and rate of return on common stocks. In general, no theoretical or empirical work can be found to support a significant relationship between liquidity and return, or liquidity and market-related systematic risk. Possibly as a consequence, studies by Simkowitz and Logue [1973], and Lee and Zumwalt [1981] ignore the liquidity factor in defining the multifactor return model. Thus, despite its usefulness in predicting the cash solvency of a company, liquidity measures will not be included as potential determinants of security returns in the present study.

FINANCIAL LEVERAGE: Financial leverage is a subject that has been discussed extensively in the literature. Modiglianli and Miller (MM) [1958] advocated that, in a perfect capital market, the market value of a company is independent of its capital structure. MM's leverage irrelevance proposition has been validated under an increasingly relaxed set of assumptions using a variety of equilibrium approaches (Hamade [1969], Stiglitz [1969,1974]).

Under United States Tax Law, interest expense is deductible, and it creates a tax shield for companies that raise their capital through debt issues. This situation led MM [1963, 1965] to conclude that the optimal capital structure for a company should be 100 percent debt if the company decides to take advantage of this tax shield. But their proposition is inconsistent with what is observed in the capital markets. Empirical evidence (Scott and Martin [1975], Ferri and Jones [1979]) indicates that the capital structure of a company is also correlated with its industry class, size and operating leverage.

The association of high bankruptcy costs with increased leverage is the basic argument against MM's leverage irrelevance proposition in a perfect capital market as well as their leverage dominance proposition in a world of corporate taxes. Other market imperfections, such as imperfect information (Heinkel [1982]), agency costs (Jensen and Meckling [1976], Myers [1977]), and the clientele effect (Kim, Lewellen, and McConnell [1979], Grier and Strebel [1983]) have also been suggested as having significant influence on the capital structure of a company. Since the capital market operating at present is less than perfect, an optimal capital stucture (less than 100 percent debt), at which market values are maximized, does exist for companies.

The rate of return of a company is dependent on its change in market value over the investment horizon. Because market value is affected by capital structure, it can be asserted that a company's rate of return is also dependent on its capital structure. In fact, empirical studies (Nerlove [1968]), Simkowitz and Logue [1973]) indicate a significant association between financial leverage and rate of return on common stocks.

This discussion has examined the impact of capital structure on return from the "market value" perspective. The same impact can also be examined from the "systematic risk" perspective, as discussed in the following sections.

Raising capital in the form of debt requires fixed interest payments made by the company to the creditors. This commitment leads to the so-called financial leverage phenomenon. In general, financial leverage involves the use of funds obtained at a fixed cost in the hope of increasing the return to common stockholders. If the leverage is positive, the company has earned more on the assets purchased with the funds than the fixed cost of their use. Accordingly, the return to common stockholders increases. On the other hand, if the leverage is negative, the company pays more for its funds than it earns on their their utilization, thereby increasing the likelihood of bankruptcy. Hence, a company's capital structure also constitutes part of its business risk. In general, investors expect a higher return from companies with a high debt structure in order to compensate for the high risk involved.

Furthermore, a positive relationship is purported to exist between market-related systematic risk and financial leverage (Hamada [1972], Bowman [1979], Hill and Stone [1980]). This hypothesis is supported empirically in many studies (Logue and Merville [1972], Bildersee [1975], Ben-zion and Shalit [1975], Fabozzi and Francis [1979], Bowman [1980], Elgers [1980]). Some studies, however, do not support the hypothesis that a positive relationship exists between market-related systematic risk and financial leverage (Beaver, Kettler and Scholes [1970], Melicher [1974], Eskew [1979]), and the sign of the regression coefficient is found to be unstable over time (Breen and Lerner [1973]). One possible explanation for such inconsistencies may be attributed to the specification of the leverage variable (book value vs. market value). Finance theorists advocate the use of market values of debt and equity in defining the financial leverage (or more exactly, the debt-to-equity ratio) of a company. Because of problems in determining the market value of debt, the book value of debt has been used to examine the relationship between market-related systematic risk and financial leverage. Moreover, different definitions of debt have been used in different studies, and may account for such inconsistent findings. In any event, the existing theoretical models (Hamada [1972], Rubinstein [1973], Bowman [1979], Hill and Stone [1980]) suggest that financial leverage should be considered as a significant determinant of market-related systematic risk.

As suggested by Rosenberg and McKibben [1973], company variables that are significant determinants of market-related systematic risk are also potential determinants of security returns. As a consequence, financial leverage is also included as another component of the company factor in developing the multifactor return model.

CASH FLOW FROM OPERATIONS: In capital budgeting, there is a greater emphasis on the use of cash flows than on accounting income. The reason is that accounting income is determined on an accrual basis, which ignores the timing of cash flows in and out of a company. Timing of cash flows, however, is very important because cash is an essential ingredient in smoothly running a business operation. Besides, the discounted value of actual cash flows determines the rate of return on an investment project.

If cash flows are tied to the return on an investment project, it can also be demonstrated that cash flow from operations determines the return on a security. The relationship can be described as follows:[19]

> Investors' return for a period may be computed as the stock market price at the end of the period, plus dividends paid during the period, less the stock market price at the beginning of the period (adjusted for stock splits, rights issues, and similar special events). A rate of return for the period may be computed by dividing the return by the price at the start of the period. The current stock market price of an equity security incorporates the market estimates of the discounted amount of future cash distributions from the enterprise to investors and future stock market prices. Since distributions from the enterprise to present and future investors ultimately depend on the cash flow of the enterprise, the market's assessment of future cash distributions must necessarily entail an assessment by the market as to the amounts, timing, and uncertainty of enterprise cash flows. As a consequence, the stock market price for an equity security may be regarded, at least in part, as a market estimate of the discounted amount of expected future cash flows of the enterprise. Those estimates of cash flows are commonly based on the enterprise's past performance, its present financial position, its liquidity and financial flexibility, and other information available to those who make investment decisions. As a consequence, there is a link--often complex and indirect--between an investor's rate of return on an investment in an enterprise and the enterprise's cash flows.

In addition to this "complex and indirect" relationship between cash flows and return to investors (i.e., return on securities), cash flows have also been shown to be theoretically related to the market-related systematic risk of a company (Pettit and Westerfield [1972], Myers and Turnbull [1977]). Based on these attributes of cash flows, it is appro-

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[19] Financial Accounting Standards Board. Exposure Draft: Reporting Income, Cash Flows and Financial Position of Business Enterpriese, Financial Accounting Standards Board, Connecticut, 1981, pp. 2-3.

priate to include cash flow from operations as another component of the company factor.

The articles reviewed so far have indicated that profitability, operating leverage, financial leverage and cash flow from operations are major components of the company factor, and they are expected to help explain the return generating process of securities. There are, however, other components of the company factor that have been the subject of extensive investigation in the last twenty years that are not covered in these articles. They are the accounting beta and dividend policy of a company. These company variables may affect secruity returns, as discussed in the following sections.

ACCOUNTING BETA: Accounting beta was first introduced by Beaver, Kettler and Scholes [1970] (BKS), when they examined the association between certain accounting risk measures and the market-related systematic risk of companies. In their study, BKS found that earnings variability, rather than accounting beta, has the strongest association with market-related systematic risk, and further that this variable is significant in predicting market-related systematic risk. Gonedes [1973], on the other hand, concluded that a statistically significant relationship exists between market-based and accounting-based estimates of market-related systematic risk if the accounting-based estimates are derived from first differences in income numbers.

In order to reconcile his findings with those of BKS, Gonedes argued that the significant association between market-related systematic risk and the accounting beta is a "spurious correlation", arising because market prices were used by BKS to scale the income numbers. In response to this criticism, Beaver and Manegold [1975] investigated the association between market-related systematic risk and the accounting beta, using a variety of alternative measures for income. Their conclusion was that a statistically significant correlation exists between market-related systematic risk and accounting beta. In a later study, Eskew [1979] found that earnings variability is significant in predicting market-related systematic risk, but accounting beta is not. On the other hand, Bildersee [1975] and Elgers [1980] provided evidence on the significance of accounting beta in predicting market-related systematic risk.

These mixed results of the relative significance of accounting beta and earnings variability in determining market-related systematic risk are also documented in the theoretical work by Thompson [1976]. Thompson showed that a theoretical relationship exists between market-related systematic risk and three company-related risk measures: the earnings beta (or accounting beta), the dividends beta, and the earnings multiple beta. His model is substantiated by empirical findings which indicate that the covariance form of earnings (i.e., accounting beta) can better explain a security's market-related systematic risk than its mean and variance forms. Moreover, Bowman [1979] also shows that a theoretical relationship exists between a company's market-related systematic risk and its accounting beta. In spite of the inconsistencies in empirical findings, there is a sound theoretical basis for suggesting an association between a company's market-related systematic risk and its accounting beta.

As suggested by Rosenberg and McKibben [1973], company variables that are significant determinants of market-related systematic risk are also potential determinants of security returns. It is thus necessary to include accounting beta as another potential determinant of security returns, since this company variable is a significant determinant of the company's market-related systematic risk.

DIVIDEND POLICY: The landmark study on dividend policy by MM [1961] advocates that in a perfect capital market, given the investment decisions of the company, the dividend payout policy that it chooses to follow has no effect on either the current price of its stock or the total return to its stockholders. Gordon [1963], however, argued that because investors are risk-averse, the receipt of dividends will resolve investors' perceptions of uncertainties and dividend payouts by companies should have an influence on stock prices.

Debates over the relevance of dividend policy on security prices and returns have continued since the early sixties. The basic argument for the relevance of dividend policy is the hypothesis of "information content of dividends." This hypothesis is based on the assumption that dividends have an effect on stock prices because they communicate information to investors about the profitability of the company. Watts [1973] found that the information content of dividends can only be trivial because the return from monopolistic possession of the information does not exceed transaction costs.[20] Others (Pettit [1972], Griffin [1976], Laub [1976], Pettit [1976], Aharony and Swary [1980], Kalay [1980], Kwan [1980], Wooldridge [1982], Divecha and Morse [1983]) have found that dividend announcements convey not only substantial information to investors about the earning potential of the company but also other information as well. Thus, the hypothesis of information content of dividends is supported. In fact, MM [1961] admitted the possibility that the announcement of dividends may affect security prices. They contended, however, that security prices are determined by expectation of earnings. Dividends are merely a reflection of the earning potential of a company and do not themselves determine value. Moreover, empirical findings concerning the information content of dividends are not inconsistent with the irrelevance proposition.

Black and Scholes [1974], in support of MM's argument, reported that there is no significant difference in returns between high dividend yield

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[20] Watts, Ross. "The Information Content of Dividends," Journal of Business, April 1973, p. 211.

stock and low dividend yield stock. But, in a later study, Litzenberger and Ramaswamy [1982] found a positive, nonlinear relationship between common stock returns and expected dividend yield. It appears inconclusive, at this stage, as to whether dividends are determinants of security returns.

Because of the differential tax treatments of dividends and capital gains, one would expect a bias in favor of the lower-taxed capital gains as opposed to dividends. On the other hand, current dividends are preferred to capital gains because of the uncertainty and transaction costs involved in realizing the capital gains. Consequently, different investors may have different preferences between dividends and capital gains. MM [1961] suggest that "such [a] corporation would tend to attract to itself a 'clientele' consisting of those preferring its particular payout ratio, but one clientele would be entirely as good as another in terms of the valuation it would imply for the firm."[21] Empirical evidence on such a clientele effect is limited. Elton and Gruber [1970] provide positive evidence with respect to the clientele effect. Two other studies (Lewellen, Stanley, Lease and Schlarbaum [1978], Hess [1982]), however, provide little evidence in support of the clientele effect. Hess [1982] concludes that dividends are proxies for changes in expected returns of common

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[21] Miller, Merton H., and Franco Modigliani. "Dividend Policy, Growth, and the Valuation of Shares," Journal of Business, October 1961, p. 429.

stock, which further suggests a significant association between dividends and security returns.

As noted earlier, MM do not believe that dividends determine market values of companies despite their information content and clientele effect. Nevertheless, the existence of a significant relationship between dividend yield and security returns (Nerlove [1968], Litzenberger and Ramaswamy [1982], Hess [1982]) cannot be neglected. In spite of MM's dividends irrelevance proposition, it seems likely that dividends have an indirect impact on security returns. In fact, the return on a security is defined as the sum of its dividend yield and capital gains over the investment horizon. Thus, the effect of dividend policy on security returns should not be ignored.

Bowman [1979] has indicated that no theoretical (or direct) relationship exists between a company's market-related systematic risk and its dividends. Contrary to Bowman's conclusion, Thompson [1976] finds a theoretical relationship between market-related systematic risk and dividend beta, which is also substantiated empirically in his study. Other empirical evidence has shown that a significant negative relationship exists between market-related systematic risk and dividends (BKS [1970], Breen and Lerner [1973], Ben-zion and Shalit [1975], Griffin [1976], Fabozzi and Francis [1979], Elger [1980]). These findings suggest that dividend payout may have resolved investors' perceptions about the risk and uncertainty associated with realizing returns. Therefore, dividend policy is also included in the present study as another component of company factor in determining security returns.

SUMMARY

In summary, the company factor used in this dissertation will include measures of profitability as well as certain accounting risk measures--accounting beta, operating leverage, financial leverage, cash flow from operations and the dividend policy of the company. The operational definitions of these company variables are described in later sections.

Growth Factor

EMPIRICAL SIGNIFICANCE

Previous sections have identified three potential return generating factors, including the market factor, the industry factor, and the company factor. A fourth factor has been suggested by Farrell [1974]. In his study, Farrell found that when companies are classified on the basis of whether they have growth, cyclical, or stable return characteristics, he was better able to explain security returns. The effect of growth on security returns has also been tested empirically by Nerlove [1968]. In his study, Nerlove constructed two growth variables in explaining the variation of return on common stocks. These two variables are the rate of growth of net sales and the rate of growth of earnings available for common stockholders. Nerlove proposed that investors might expect a higher rate of returns on rapidly growing firms if it is assumed that rapid expansion ultimately proves profitable, and increased profitability is not offset by increased risk due to rapid growth. The results of Nerlove's study indicate that these growth variables are significant and have a positive impact on return on common stock. This conclusion suggests that a growth factor may also be significant in explaining the return on securities.

In addition to these empirical results on the direct relationship between growth and security returns, growth is shown to have an inverse relationship with market-related systematic risk (Myers [1976], Myers and Turnbull [1977]). That is, increasing growth rate will decrease market-related systematic risk, which, in turn will lead to a decrease in security returns. Senbet and Thompson [1982], on the other hand, show that[22] "the way in which β [market-related systematic risk] and g [growth] are related depends on the way in which the response of cash flows to unanticipated change in the economy changes with g (growth)." In fact,

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22 Senbet, Lamma, and Howard E. Thompson. "Growth and Risk," Journal of Financial and Quantitative Analysis, September 1982, p. 340.

the relationship between growth and market-related systematic risk can be positive at times.

Despite the controversial relationship between growth and market-related systematic risk, growth is found to have a significant positive impact on security returns (Nerlove [1968]). Thus it is appropriate to include the growth factor as a potential determinant of security returns in the present study. The growth factor reflects both a company's potential for making an above-cost-of-capital return on its internal resources as well as the impact of general economic conditions on a security's return. In a recessive economy, the growth of companies is expected to slow down and investors expect a lower return on their investments. On the other hand, in a booming economy, the more successful companies are expected to have better opportunities, and a higher rate of return is expected. Thus, growth not only is a potential determinant of security returns but also provides information with respect to a company's performance relative to that of the market as a whole.

Conclusion

In conclusion, it is hypothesized that a multifactor return model, which includes a market factor (market-related systematic risk), an industry factor (industry-related systematic risk), a company factor (accounting beta, operating leverage, financial leverage, dividend policy, cash flow from operations, and profitability), and a growth factor of a company will explain the variance of security returns better than the single-factor CAPM model.

Mathematically, the proposed return model can be expressed as follows:

$$R_i = a_0 + a_1\,\beta_i^m + a_2\,\beta_i^I + a_3\,C_i + a_4\,G_i,$$

where R_i = return on security i;

β_i^m = market-related systematic risk of security i;

β_i^I = industry-related systematic risk of security i;

C_i = fundamental characteristics of security i, which include accounting beta, operating leverage, financial leverage, dividend policy, cash flow from operations, and profitability;

G_i = growth of security i;

a_j = regression coefficients of linear model, and j = 0, 1, 2, 3, 4.

The proposed return model includes factors that are common to most, if not all assets in the capital market--the market factor and the industry factor. It also includes factors that are unique to each individual asset--the company factor and the growth factor.

The common factors are determined by measuring the responsiveness of the security's return to that of the market (or its industry). The unique factors, on the other hand, reflect the fundamental characteristics of the individual company. In the present study, quarterly accounting data are used to measure these characteristics of an individual company because quarterly accounting data are available more frequently than annual accounting data for a specific company. If the company factor is found to be significant in explaining and predicting security returns, this would enhance the use of quarterly accounting information in security analysis and portfolio management.

The operational definitions of these factors and the research methodology employed for this research are presented in full detail in the following chapter.

CHAPTER III

METHODOLOGY

The primary objective of the present study is to determine what factors are significant in describing the return generating process of securities. Four factors were identified, in the literature review, as potential determinants of security returns. They are a market factor, an industry factor, a company factor, and a growth factor. Quarterly accounting information is used in defining the components of the company factor as well as the growth factor. Components of the company factor can be classified into two basic groups. The first includes the profitability measure of the company; the second describes the risk attributes of the company. Thus, a secondary objective of the present study is to determine if quarterly accounting information can be useful in developing the multifactor return model.

This chapter is divided into four sections. First, the hypothesis to be tested in the present study is stated. Second, the definitions of the instrumental variables used in developing the multifactor return model are presented. Third, the sample selection process is given; and fourth, the statistical methods used for analysis are described.

HYPOTHESIS

According to the CAPM, the market-related systematic risk is the sole determinant of security returns. This proposition is challenged by the APT, which is based on the assumption that several factors are significant in describing the return generating process of securities. As discussed previously, this study does not purport to test the appropriateness of these two equilibrium models in the capital markets. Rather, it examines factors, in addition to the market-related systematic risk, to determine if they also contribute significantly to explaining and predicting security returns. These return generating factors do not necessarily represent factors that are common to all assets in the capital markets, as defined in APT. For example, one of the factors being examined may be significant to certain segments of the capital markets, while the others are unique to each individual company.

In addition to the market-related systematic risk suggested by the CAPM, three other factors have been identified that contribute significantly to explaining security returns. They are (i) the industry factor, (ii) the company factor, and (iii) the growth factor. A multifactor return model may be more appropriate in describing the return generating process of securities than the CAPM. This proposition will be tested in terms of the following null hypothesis:

HYPOTHESIS: The addition to the return model of an industry factor, a company factor, and a growth factor does not significantly improve the explanatory power or predictive ability of that model.

As noted in the hypothesis, the present study is interested in evaluating both the explanatory power and predictive ability of the estimated return model. In general, explanatory power refers to how well the model explains variation in security returns. In most market studies, predictive ability refers to the accuracy of the model in providing forecasts, on the basis of currently available information. In the present study, the term "predictive ability" is interpreted in a different manner.

In auditing , analytical review procedures are commonly used in testing the reasonableness of a reported financial statement item. When applying these procedures, the auditor uses historical data to estimate the regression model. The current data of the regressors are then used to obtain a "predicted value" of the financial statement item. This "predicted value" is then compared to the actual response to determine if the reported item is reasonable. This scenario in auditing describes the term "predictive ability" (or prediction) used in the present study. In brief, historical data are used to estimate the multifactor return model; and current data of the regressors are used to provide a "predicted value" of security return for the current period. This predicted security return is the basis for determining how well the model predicts.

OPERATING VARIABLES

Prior to discussing the choice and definition of operating variables, a word on the time period under investigation is appropriate.

The period being studied runs from January 1976 to December 1982. This period is subdivided into four overlapping four-year periods. Period I--from January 1976 to December 1979; Period II--from January 1977 to December 1980; Period III--from January 1978 to December 1981; and Period IV--from January 1979 to December 1982. The use of four overlapping periods facilitates the comparison of empirical results over time, and is essential for cross-sectional studies if generalizability of research findings from one period to another is desired.

As discussed previously, market-related systematic risk is used as a surrogate measurement for the effect of capital markets on security returns (the market factor). Four alternative estimates of market-related systematic risk (the market model, the mean reversion model, the order bias adjustment model, the Bayesian adjustment model) are used in the study to determine if their role in determining security returns differs from one another. These estimates of market-related systematic risk depend on information for both the current period and prior periods. For example, the mean reversion model requires information from one and two previous periods (T-2 and T-1) in order to estimate the market-related systematic risk of the current period (T). Thus, the data on market return and security returns were collected for ninety-six months prior to January 1976. Referring to the example of the mean reversion model, this means that if period T covers from January 1976 to December 1979, then period T-1 will start from January 1972 and run to December 1975, and period T-2 will start from January 1968 and run to December 1971. Therefore, companies in the sample should have return data for the period January 1968 to December 1982. However, only interim financial statement data for the period of January 1976 to December 1982 were required for the analysis.

Fiscal quarters were used as the basis for identifying the time dimension of accounting data. For companies whose fiscal year ends during the first five months of a year (e.g., May 1978), the accounting data are deemed to be associated with the earlier fiscal year (e.g., 1977); in contrast, fiscal year ends for companies during the last seven months of a year (e.g., September 1978) are deemed to be associated with the next fiscal year (e.g., 1978). This convention is adopted by the Standard and Poor's Compustat Service in preparing the quarterly accounting data tape. This procedure serves to increase the sample size and includes as many industries as possible for analysis. This decision, again, enhances the generalizability of the research findings.

Various operating variables for each period T are defined and discussed in detail in the following sections.

Estimates of Market-Related Systematic Risk

MARKET MODEL

The market model requires a bivariate normal distribution between the security return and the market return. An ordinary least squares (OLS) regression is used to estimate the market-related systematic risk for each company i. The regression model is of the form:

$$R_{it} = \alpha_i^m + \beta_i^m R_{mt} + e_{it}, \quad t = 1, 2, 3, \ldots, 48$$

where R_{it} = return on security i in month t, and

$$R_{it} = \frac{d_{it} + p_{it} - p_{it-1}}{p_{it-1}},$$

d_{it} = dividend of security i in month t;

p_{it} = price of security i at end of month t;

R_{mt} = return on the market in month t, (the Standard and Poor's 500 Composite Index was used as the proxy for market return);

e_{it} = residual term of linear relationship;

α_i^m = intercept of linear relationship;

β_i^m = slope of linear relationship, which is the OLS estimate of the market-related systematic risk for company i.

MEAN REVERSION MODEL

The mean reversion model provides a systematic way to adjust the OLS estimate of market-related systematic risk for the observed tendency of all OLS estimates to revert towards the value of one. The mean reversion adjusted estimate of the market-related systematic risk for each company i in period T, $\beta_{i,T}^m(MR)$, can be obtained from the following expression:

$$\beta_{i,T}^m(MR) - 1 = r\ (\beta_{i,T-1}^m - 1),$$

where $\beta_{i,T-1}^m$ = the OLS estimate of the market-related systematic risk of company i in period T-1;

r = mean reversion coefficient estimated using OLS estimates of market-related systematic risk from periods T-1 and T-2, that is,

$$r = \frac{\sum_{i=1}^{N}(\beta^m_{i,T-1} - \overline{\beta^m_{T-1}})(\beta^m_{i,T-2} - \overline{\beta^m_{T-2}})}{\sum_{i=1}^{N}(\beta^m_{i,T-2} - \overline{\beta^m_{T-2}})^2};$$

$\overline{\beta^m_{T-1}}$ = the sample mean, across firms, of the OLS estimates of market-related systematic risk in period T-1;

$\overline{\beta^m_{T-2}}$ = the sample mean, across firms, of the OLS estimates of market-related systematic risk in period T-2.

ORDER BIAS ADJUSTMENT MODEL

The order bias adjustment model provides a procedure for adjusting the OLS estimate of market-related systematic risk, depending on its distance from the value of one and the precision of its estimate. The order bias adjusted estimate of the market-related systematic risk for company i in period T, $\beta^m_{i,T}(OB)$, is given by

$$\beta^m_{i,T}(OB) - 1 = c_i \; (\beta^m_{i,T-1} - 1),$$

where $\beta^m_{i,T-1}$ = the OLS estimate of the market-related systematic risk of company i in period T-1;

$$c_i = \frac{s_i^2(\hat{\beta}^m_{i,T-1})}{s^2(\hat{\beta}^m_{i,T-1})};$$

$s_i^2(\hat{\beta}^m_{i,T-1})$ = variance of the OLS estimate of market-related systematic risk for company i in period T-1;

$s^2(\hat{\beta}^m_{i,T-1})$ = the sample variance, across firms, of the OLS estimate of market-related systematic risk in period T-1.

BAYESIAN ADJUSTMENT MODEL

The Bayesian adjustment model provides a procedure for adjusting OLS estimates of market-related systematic risk to minimize misestimation loss. The adjustment incorporates prior distributional information of the OLS estimate of market-related systematic risk for each company. The Bayesian adjusted estimate of market-related systematic risk for company i in period T, $\beta^m_{i,T}(BA)$, is determined by the following expression:

$$\beta^m_{i,T}(BA) = \frac{\left[\overline{\beta^m_{T-1}} \;/\; s'^2(\hat{\beta}^m_{i,T-1})\right] - \left[\beta^m_{i,T-1} \;/\; s_i^2(\hat{\beta}^m_{i,T-1})\right]}{\left[1 \;/\; s'^2(\hat{\beta}^m_{i,T-1})\right] - \left[1 \;/\; s_i^2(\hat{\beta}^m_{i,T-1})\right]},$$

where $\overline{\beta^m_{T-1}}$ = the sample mean, across firms, of the OLS estimate of market-related systematic risk in period T-1;

$\beta^{m}_{i,T-1}$ = OLS estimate of market-related systematic risk of company i in period T-1;

$s^{2}_{i}(\hat{\beta}^{m}_{i,T-1})$ = variance of OLS estimate of market-related systematic risk of company i in period T-1;

$s'^{2}(\hat{\beta}^{m}_{i,T-1})$ = difference between the sample variance across firms of the OLS esitmate of market-related systematic risk in period T-1 and the mean across firms of the variance of OLS estimates.

Estimates of Industry-Related Systematic Risk

The literature suggests that industry membership may be a significant determinant of security returns. In this study, the effect of industry on security returns (the industry factor) is measured in terms of the responsiveness of a security's return to that of its industry. This is referred to as the industry-related systematic risk, β^{I}_{i}, which is different from the market-related systematic risk, β^{m}_{i}, as discussed in the previous sections.

Prior to defining the industry-related systematic risk operationally, it is necessary to discuss the industry classification scheme that was used in this study. Standard Industrial Classification (SIC) codes are four-digit indexes based on the principal end product of the company. The codes are defined in such a way that when the right-most digit is removed, the companies are aggregated into broader but still similar groups; for example, the two-digit SIC code has a broader aggregation level than the four-digit SIC code. Many studies (King [1966], Farrell [1974], Bildersee [1975], Fabozzi and Francis [1979], and Lee and Zumwalt [1981]) have used the two-digit SIC code to segregate industries. The popularity of the two-digit code can be attributed to its ready availability and ease of application.

In his study, Fertuck [1975] attempted to determine which level of aggregation (1-, 2-, 3-digit) of the SIC code is more appropriate in describing industry effects. He concludes that the industry effect on security returns, though trivial in some industries, can be as large as one-third of the market effect in others. In any case, the industry index has to be at the three-digit level to be useful. The use of one- and two-digit SIC codes explains less than 3 percent of the variance in security returns. In fact, little support can be found for the use of two-digit SIC codes in defining industry. [23]

Foster [1981] proposes the use of Homogeneous Line of Business (LOB) classifications in defining industry, instead of using SIC codes. He lists several limitations to the use of SIC industry definitions, primari-

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[23] Fertuck, Leonard. "A Test of Industry Indices Based on SIC Codes," Journal of Financial and Quantitative Analysis, December 1975, p. 847.

ly based on (i) the level of aggregation at which some SIC industries are defined, and (ii) the diversification strategies adopted by many companies. [24] Because of these limitations, Foster concludes that the LOB information, which can be obtained from 10-K reports filed with the Securities and Exchange Commission (SEC), should be used in defining industry. The criterion used by Foster to classify companies within a particular industry is that they derive at least 50 percent of their revenues from that industry's line of business.

Elton and Gruber [1971] have suggest the use of a clustering technique to classify companies into homogeneous groups. They suggested the use of different criteria for the clustering procedure, with the choice of criteria dependent on the objective of the classification. In their study, Elton and Gruber [1971] conclude that their clustering technique, based on the earnings-growth patterns of companies, leads to better estimates of earnings per share than a grouping based on SIC codes. On the other hand, Fertuck's [1975] findings do not support the clustering technique. He notes that clustering by similarity of past residuals of security returns, for example, does not create a more useful industry definition, despite the poor performance of the SIC code in defining industry. Research evidence with respect to the use of clustering tech-

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[24] Foster, George. "Intra-industry Information Transfers Associated with Earnings Releases," Journal of Accounting and Economics, September 1981, p. 206.

niques in defining industries is somewhat inconclusive. Thus, this technique is not used in the present study to classify companies into homogeneous industry-related groups.

In the present study, four different approaches are used to classify companies into industry groups. The literature indicates that the SIC code is the most commonly used basis for defining industry. Accordingly, both the two-digit and three-digit SIC codes are used to group companies into industries. On the basis of Fertuck's [1975] findings, it was expected that three-digit SIC code would outperform two-digit SIC code in explaining the variance of security returns.

The LOB information, as recommended by Foster [1981], was also used for industry classification. The LOB information in the 10-K reports was examined to see which product line generates the largest amount of sales revenues to the company. This major line of business was then compared to the primary SIC code of the company in deciding whether the company should be included in its primary SIC industry group. Again, both the two- and three-digit codes were used to classify companies on the basis of the LOB information.

Industries were segregated on the basis of each classification scheme, and a return index for each resulting industry was developed. The industry return is computed as the geometric mean of the returns on all companies in that industry (as recommended by Latane, Tuttle, and Jones [1975]).[25] Mathematically, the return on industry I in month t, R_{It}, is given as:

$$R_{It} = \sqrt[N_I]{\prod_{i=1}^{N_I} (1 + R_{it})} - 1$$

where R_{it} = return on security i in month t, where i is a member of industry I;

R_{It} = return on industry I in month t;

N_I = number of companies in industry I.

Because industry return is related to market return, R_{It} is not appropriate "as is" for constructing the industry-related systematic risk for each company. A two-step regression approach[26] is used to develop an industry-related systematic risk estimate for each company. First, the return (R_{It}) on industry I is regressed on the market return (R_{mt}) to obtain a residual return of the industry (e_{It}). This represents the por-

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[25] Latane, Tuttle, and Jones [1975] (<u>Security Analysis and Portfolio Management</u>, Second Edition, The Ronald Press Company, New York, 1975, pp. 565-567) suggest that the use of geometric mean takes into account risk as well as return. Thus, the return index for any industry I will be constructed on the basis of the geometric mean, rather than arithmethic mean, of the return of all companies in that particular industry.

[26] In the article "Some Preliminary Findings on the Association Between Earnings of a Firm, Its Industry, and the Economy" (<u>Journal of Accounting Research</u>, Supplement 1967, pp. 55-80.), Brown and Ball used this methodology to construct the earnings index for an industry in studying the association between the earnings of a firm, its industry, and the economy.

tion of R_{It} that is statistically independent of the market return. Then, for each company i in industry I, its return (R_{it}) is regressed on the residual return of industry I (e_{It}) to obtain the industry-related systematic risk (β_i^I), which is the regression coefficient of the model. In summary, the approach can be described in terms of the following regression models:

(1) $$R_{It} = c_0 + c_1 R_{mt} + e_{It};\ t = 1, 2, 3, \ldots, 48$$

(2) $$R_{it} = \alpha_i^I + \beta_i^I e_{It} + e'_{it};\ t = 1, 2, 3, \ldots, 48$$

where R_{it} = return on security i in month t, and i is a member of industry I;

R_{It} = return on industry I in month t;

R_{mt} = return on the market in month t;

e_{It} = residual return on industry I that is uncorrelated with the market return;

c_0, c_1 = intercept and slope of linear relationship (1);

α_i^I = intercept of linear relationship (2);

β_i^I = slope of linear relationship (2), and measures the industry-related systematic risk of security i with respect to industry I;

e'_{it} = residual term of linear relationship (2).

Estimates of the Company Factor

Six accounting variables (accounting beta, operating leverage, financial leverage, dividend covariability, cash flow beta, and profitability) are expected to account for the fundamental characteristics of a company. The company factor, a function of these variables, may be a significant determinant of security returns. Two alternative functions were used to include these accounting variables in the multifactor return model. First, the accounting variables were tested for their significant contributions to explaining security returns. Second, principal component analysis was used to construct a single index from the accounting variables; the resulting principal component (a linear combination of the variables) represents the unique characteristics of a company. Both approaches have weaknesses. Because of the intercorrelations among accounting variables, the first approach has to deal with the problem of multicollinearity. Although multicollinearity can be avoided in the second approach, there is a possible loss of information when a single index is used to represent the company. In this study, the first approach was examined in detail, and the second approach was only investigated to the extent that it significantly influenced the development of the return model.

These six accounting variables can be divided into two basic groups. The first group measures specific risk attributes of a company, and are referred to as accounting risk measures (accounting beta, operating leverage, financial leverage, dividend covariability, and cash flow beta) in this paper. The second group, on the other hand, measures the accounting return (profitability) of each company.

ACCOUNTING RISK MEASURES

Five accounting risk measures were included in this study to determine their significance in explaining and predicting security returns. Theoretical and empirical evidence suggest that these accounting risk measures are significantly associated with a company's market-related systematic risk. Some of these accounting risk measures (e.g. accounting beta and cash flow beta) reflect the covariation of the company with that of the market. Other accounting risk measures (e.g. operating leverage and financial leverage) reflect the business risks that are faced by companies in their normal operations.

For each four-year period (1976-79, 1977-80, 1978-81, and 1979-82), these accounting risk measures are computed from sixteen quarterly accounting observations for each company.

Accounting Beta, $ABETA_i$: The accounting beta, $ABETA_i$, of company i for each period is defined as the covariance of its earnings-price ratio with that of the market (BKS [1970]), and is given by:

$$ABETA_i = \frac{\sum_{q=1}^{16}(E_q / P_{q-1} - \overline{E/P})(M_q - \bar{M})}{\sum_{q=1}^{16}(M_q - \bar{M})^2},$$

where E_q = earnings per share in quarter q;

P_{q-1} = price per share at the end of quarter q-1;

$\overline{E/P}$ = mean across quarters of earnings-price ratio for the 16-quarter period, that is, $[\Sigma(E_q / P_{q-1})] / 16$;

M_q = earnings-price ratio of the market, which is the quarterly average earnings-price ratio of all companies in the sample;

$\bar{M}$ = mean across quarters of earnings-price ratios of the market for the 16-quarter period, that is, $\Sigma M_q / 16$.

Operating Leverage, $GMDOL_i$: Percival [1974][27] and Lev [1974][28] write that the operating leverage of a company can be measured in terms of the contribution margin or the variable costs of production. The major problem with this approach is that the contribution margin and the variable costs of production cannot be determined directly from the financial statements, and measurement errors can be significant when estimation methods are used. Thus, this approach was not used in the present study

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[27] Percival, John R. "Operating Leverage and Risk," Journal of Business Research, April 1974, pp. 223-227.

[28] Lev, Baruch. "On the Association Between Operating Leverage and Risk," :hp|.us Journal of Financial and Quantitative Analysis, September 1974, pp. 627-638.

to define operating leverage. Hill and Stone [1980] state that "operating risk is generally associated with the uncertainty of operating results, especially operating earnings";[29] therefore, it is more appropriate to use the degree of operating leverage in measuring operating leverage. This is because the degree of operating leverage reflects the uncertainty of operating results, and measures the responsiveness of profitability to sales volatility. One problem associated with the use of degree of operating leverage as an instrumental variable is that its value could be extremely large when there is a very small percentage change in sales. One measure to overcome such a problem is to use the geometric mean of the degree of operating leverage over the 16-quarter period. In addition, the geometric mean incorporates any risks that are related to the operating leverage of a company in each quarter.

The degree of operating leverage, DOL_{iq}, for each company i for each quarter q is given by:

$$DOL_{iq} = \sum_{q=1}^{16} \frac{(EBIT_q - EBIT_{q-1}) / EBIT_{q-1}}{(S_q - S_{q-1}) / S_{q-1}} ,$$

[29] Hill, Ned C. and Bernell K. Stone. "Accounting Betas, Systematic Risk, Operating Risk, and Financial Leverage: a Risk Composite Approach to the Determinants of Systematic Risk," Journal of Financial and Quantitative Analysis, September 1980, p. 600.

where $EBIT_q$ = earnings before interest and taxes for quarter q;

S_q = sales for quarter q.

Therefore, the geometric mean of the degree of operating leverage, $GMDOL_i$, for each company i for each period is given by:

$$GMDOL_i = \sqrt{\prod_{q=1}^{16} DOL_{iq}}.$$

Financial Leverage, LEV_i: The debt-to-equity ratio is a commonly used measure of the financial leverage of a company. Theoretically, market values should be used in defining the debt-to-equity ratio. Because of the difficulty in determining the market value of debt, its book value has been used in various studies to measure the financial leverage of companies (e.g., BKS [1970], Logue and Merville [1972], Breen and Lerner[1973], Ben-zion and Shalit [1975], Eskew [1979]). On the other hand, Bowman [1980] provides a detailed description of how to approximate the market value of debt. In his study, the importance of a market-value measurement of debt in assessing leverage was investigated by examining its association with market-related systematic risk. The results indicate "that accounting measures of debt were statistically indistinguishable from market-value measures." [30]

Considering the costs and benefits associated with determining the market value of debt, the book value of debt, together with the market-value of common equity, was used in assessing the financial leverage of a company. Debt, in this context, includes not only the total liabilities of a company but also its preferred stock. Preferred stock is included in determining debt because it is very similar to bonds in nature. First, both bondholders and preferred stockholders have priority over common stockholders in asset distributions of the company. Second, most preferred stockholders do not have voting rights over company policies, and this is the case for most bondholders. Besides, the present study examines the impact of return generating factors on return on common equity. Thus, the inclusion of preferred stock in determining debt seems appropriate.

The ratio of book value of debt to market value of common equity was used to measure the financial leverage of each company, such that the average financial leverage, LEV_i, for company i for each period is given by:

$$LEV_i = \frac{1}{16} \sum_{q=1}^{16} \left[\frac{TA_q - CE(bk)_q}{CE(mkt)_q} \right],$$

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[30] Bowman, Robert G. "The Importance of a Market-value Measurement of Debt in Assessing Leverage," Journal of Accounting Research, Spring 1980, p. 253.

where TA_q = total assets at end of quarter q;

$CE(bk)_q$ = book value of common equity at end of quarter q;

$CE(MKT)_q$ = market value of common equity at end of quarter q.

Dividends Covariability, $DIVCO_i$: The literature on the information content of dividends (e.g., Aharony and Swary [1980], Divecha and Morse [1983]) suggests that an abnormal return on securities is associated with a change in dividends between the current and previous periods. That is to say, an increase in dividends is associated with a positive abnormal return, and a decrease in dividends is associated with a negative return, after the date dividends are announced. These relations suggest that it is the change in dividend payout between any two consecutive periods that may have an impact on the return of the company.

In this study, the impact of dividends is measured by the covariability of dividend payout and net income available to common stockholders for each period. The dividend covariability, $DIVCO_i$, for company i for each period is given by:

$$DIVCO_i = \frac{\sum_{q=1}^{16}(DIV_q - \overline{DIV})(NICE_q - \overline{NICE})}{[\sum_{q=1}^{16}(DIV_q - \overline{DIV})^2 \sum_{q=1}^{16}(NICE_q - \overline{NICE})^2]^{\frac{1}{2}}},$$

where DIV_q = common dividends in quarter q;

$\overline{DIV}$ = average of common dividends in the 16-quarter period;

$NICE_q$ = net income available to common stockholders in quarter q;

$\overline{NICE}$ = average of net income available to common stockholders in the 16-quarter period.

Cash Flow Beta, $CFBETA_i$: Net income plus depreciation has generally been used to approximate cash flow from operations. Gombola and Ketz [1981] [31] suggest that adjustment of accruals and deferrals should also be included in computing cash flow from operations. It is argued that since accounting income is the result of applying the matching principle, cash flow from operations for any quarter should equal working capital from operations adjusted for changes in current assets less current liabilities (except cash).

Pettit and Westerfield [1972] show that a theoretical relationship exists between the market-related systematic risk of a company and its cash flow beta. Cash flow beta, which measures the relative riskiness of a company's cash flow with respect to that of the market, was used in the present study to examine its impact on security returns. The cash flow

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[31] A detailed description on the computation of cash flow from operations is included in "A Note on Cash Flow and Classification Patterns of Financial Ratios" by Gombola and Ketz (The Accounting Review, January 1983, pp. 105-114).

beta, $CFBETA_i$, of company i for each period can be expressed as:

$$CFBETA_i = \frac{\sum_{q=1}^{16}(CF_q - \overline{CF})(MCF_q - \overline{MCF})}{\sum_{q=1}^{16}(MCF_q - \overline{MCF})^2},$$

where CF_q = cash flow from operations in quarter q;

$\overline{CF}$ = mean across quarters of cash flow from operations for the 16-quarter period;

MCF_q = cash flow of the market, which is the average of cash flow from operations of all companies in the sample;

$\overline{MCF}$ = mean across quarters of cash flow of the market for the 16-quarter period.

ACCOUNTING RETURN MEASURE

In general, accounting return is measured by the return on investment (profitability). Return is usually defined as earnings before interest and taxes (EBIT), net income (NI), or net income plus depreciation (NIPD). On the other hand, total assets (TA), net worth (NW), and common equity (CEq) have generally been used in defining the level of investments for a company. Simkowitz and Logue [1973] and Lee and Zumwalt [1981] define profitability to be "quarterly retained profits (excluding taxes, i.e., retained earnings plus interest and preferred dividends) divided by total assets and then summed over the current and three preceding quarters." [32]

In Lee and Zumwalt [1981], the impact on security returns of six profitability measures is investigated. They conclude that "different profitability measures should be used by security analysts or investors to determine the equity rates of return for different industries. In general, however, it appears that EBIT/TA and the NI/CEq provide the most consistent results."[33] As a result, they determine EBIT/TA to be the best profitability measure in terms of explaining security returns. For each period, then, the profitability of each company i, π_i, is defined as the ratio of total earnings before interest and taxes for the sixteen quarters to the average total assets; that is,

$$\pi_i = \frac{\sum_{q=1}^{16} EBIT_q}{\left(\sum_{q=1}^{16} TA_q\right) / 16},$$

where $EBIT_q$ = earnings before interest and taxes in quarter q;

TA_q = total assets at end of quarter q.

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[32] Simkowitz, Michael A., and Dennis E. Logue. "The Interdependent Structure of Security Returns," Journal of Financial and Quantitative Analysis, March 1973, p. 263.

[33] Lee, Cheng Few, and J. Kenton Zumwalt. "Association Between Alternative Accounting Profitability Measures and Security Returns," Journal of Financial and Quantitative Analysis, March 1981, p. 82-83.

Estimate of the Growth Factor

Growth in sales, growth in earnings, and growth in assets have all been used to represent the growth of a company in empirical studies. Basically, growth refers to a company's opportunities to earn an above-normal rate of return on its investments. An exact measure of growth would require detailed analysis of the investment projects undertaken by a company. This approach is not possible because companies do not release such information. Thus a surrogate measure for growth was developed for the present study.

Seasonality has significant impact on the quarterly sales and earnings of most companies. In this case, the use of raw sales and earnings in defining the growth potential of a company would be subject to biases and errors. Thus, the geometric mean of the compound growth rate in total assets was used to measure the growth, G_i, of company i in each 16-quarter period because total assets of a company rarely fluctuate substantially from one quarter to another. The compound growth rate for each quarter q is defined as:

1 + quarterly percentage change in total assets = $1 + G_{iq}$;

that is,

$$1 + G_{iq} = 1 + \frac{TA_q - TA_{q-1}}{TA_{q-1}} = \frac{TA_q}{TA_{q-1}}.$$

Therefore,

$$G_i = \text{growth of company } i \text{ assets over a period of } n \text{ quarters,}$$

$$= \text{geometric mean of compound growth rate} - 1,$$

$$= \sqrt[n]{\prod_{q=1}^{n} (1 + G_{iq})} - 1,$$

$$= \sqrt[n]{\prod_{q=1}^{n} \frac{TA_q}{TA_{q-1}}} - 1,$$

$$= \sqrt[n]{\frac{TA_n}{TA_0}} - 1.$$

For $n = 16$,

$$G_i = \sqrt[16]{\frac{TA_{16}}{TA_0}} - 1,$$

where TA_{16} = total assets at end of 16th quarter in period T;

TA_0 = total assets at beginning of 1st quarter in period T.

DATA SELECTION

Companies on both the New York Stock Exchange (NYSE) and American Stock Exchange (AMX) were included in the present study. In general, NYSE companies have total assets of at least $16 million each while AMX companies have total assets of at least $4 million each. The reason for including companies on both exchanges is to reduce the bias of company size on the findings. Moreover, this approach also improves the generalizability of the results to a greater set of assets in the capital markets.

Two types of data are required to develop the multifactor return model. First, monthly return data for the sample companies and market portfolio are required to determine their market-related and industry-related systematic risks. Second, quarterly financial statement data are required to determine profitability, accounting risk measures, and growth of the companies. The Standard and Poor's Compustat Service has provided these data files on tapes; these files are the major source of data collection for this study. The sample selection process is described in the following sections.

Monthly Return Data

Monthly return data for 1093 companies, over the period of January

1968 to December 1982, were obtained from the Compustat Price-Dividends-Earnings (PDE) tape. The Standard & Poor's 500 Composite Index, which serves as the market proxy, was also accessed from the PDE tape for the same period. These market and company return data were then used to compute alternative estimates of market-related systematic risk, in accordance with the definitions provided in the previous sections.

As indicated earlier, an industry return index must be estimated in order to compute the company's industry-related systematic risk. Some industries are dominated by only a few companies. In these cases, the industry return index would be strongly influenced by these dominating companies. This influence, in turn, suggests that the industry-related systematic risk for these dominating companies would be biased. One way to alleviate this problem is to exclude those industries with only a few companies from the sample. The criterion of "at least 10 companies within each industry" was chosen so that a greater number of companies and industries could be included in the study, and so that only a minor bias would result from estimating the industry return index.

The return index for each industry depends not only on the number of companies within that particular industry, but also on how the industry is defined. In the present study, companies are grouped into industries based on the following classification schemes: (i) the two-digit SIC code, (ii) the three-digit SIC code, (iii) the two-digit LOB code, and

(iv) the three-digit LOB code. For the last two classification schemes, companies are classified into industries on the basis of the Line of Business (LOB) information provided in the 10-K reports. The product line accounting for the largest percent of sales determines the two- or three-digit LOB code for the company.

The primary two- and three-digit SIC codes for the companies were obtained from Dun's Business Rankings. The two- and three-digit LOB codes, on the other hand, can be determined by analyzing the 10-K reports. However, the Standard and Poor's Compustat Service has provided this information in its industrial files. An industry classification number (DNUM) is assigned to companies, and conforms as nearly as possible to the Bureau of Budget SIC Codes. Individual companies are assigned a four-digit DNUM (similar to the four-digit SIC code) according to the product line breakdown provided in the 10-K reports. The DNUM is assigned in such a way that it corresponds to the product line that generates the largest amount of sales revenues to the company. This implies that the DNUM codes assigned by the Standard and Poor's Compustat Service correspond to the LOB codes that are used in the present study. Thus, the two- and three-digit LOB codes for the companies were also obtained from the Compustat PDE Tape.

Because of these differences in industry definition, not all 1093 companies were used to construct the return index for each individual industry. A breakdown of companies into industries (Appendix A) indicates that the return index for each industry is dependent on its size. For example in the "petroleum refining" classification (2900), only 12 companies contribute to the determination of the industry return index, whereas in the classification "machinery except electrical" (3500), a relatively large number of companies contributes to the industry return index.

Interim Financial Statement Data

Monthly return data facilitate the determination of market-related and industry-related systematic risks. Not all 1093 companies have their interim financial statement data ready for analysis, however. The reason is that required disclosures in interim financial reporting are not as extensive as those required in annual financial reporting. In fact, Accounting Principles Board (APB) Opinion No. 28 states that only the following minimum data need to be reported: as a minimum:[34]

1. sales or gross revenues, provision for income taxes, extraordinary items (including related income tax effects), cumulative effect of a change in accounting principles or practices, and net income;

2. primary and fully diluted earnings per share data for each period presented, determined in accordance with the provisions of APB Opinion No. 15, Earnings Per Share;

3. seasonal revenue, costs, or expenses;

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[34] Accounting Principles Board, APB Opinion No. 28 - Interim Financial Reporting, American Institute of Certified Public Accountants, New York, May 1973, ¶30.

4. significant changes in estimates or provisions for income taxes;

5. disposal of a segment of a business and extraordinary, unusual or infrequently occurring items;

6. contingent items;

7. changes in accounting principles or estimates; and

8. significant changes in financial position.

These required disclosures summarize the results of operations of a company for an interim period. The preparation of financial statements, such as the balance sheet, income statement, and statement of changes in financial position for the interim periods, however, is not mandatory. This limits the type of quarterly accounting data that are available for empirical studies. The Securities and Exchange Commission (SEC) requires publicly traded companies to file 10-Q reports, which comprise an important source of quarterly accounting data. Nonetheless, only 390 companies (of the total 1093 companies) were found to have all interim financial statement data required by the present study. This may lead to the so-called survivorship bias, which results from such a limited data base.

Interim financial statement data were obtained from the Compustat II Tape, and the 390 companies with complete data were used to develop the multifactor return model. Similar breakdowns of these companies into industries are presented in Appendix B.

STATISTICAL ANALYSIS

Multiple linear regression was the major statistical tool used to analyze the data. It was applied to determine which linear model best explains and predicts security returns.

In brief, the objective of the statistical analysis is to determine if the instrumental variables significantly contribute to explaining and predicting security returns. These variables, again, include market-related systematic risk, industry-related systematic risk, accounting risk measures (accounting beta, degree of operating leverage, financial leverage, dividend covariability, and cash flow beta), a profitability measure, and growth in total assets.

Determination of Return Model

A regression analysis was performed to determine which instrumental variables should be included in the return model.

Stepwise regression has been used in many empirical studies (BKS [1970], Eskew [1979], Elgers [1980]) for model selection. The selection process of stepwise regression is based on certain predetermined criteria, such as the F statistic, the maximum or minimum improvement in the coefficient of determination.

There are several deficiencies with such an approach. First, the criterion chosen may not be appropriate with respect to the discipline being studied. Second, the use of different criteria in stepwise regression may result in different models, and the analyst has little control over the selection process. Third, none of the procedures (backward elimination, forward selection, and stepwise) guarantees that the "best" subset regression model of any size will be identified. In fact, different models can be derived from these different procedures. Fourth, a few of the regressor variables will be eliminated from the model. Yet, there is no assurance that these eliminated variables do not contribute at all to explaining variation in the dependent variable. These variables, if included in the model, may improve the applicability of the model to a wider population. Fifth, a simple model determined by stepwise regression does not eliminate all the possibilities of multicollinearity among the regressors. In fact, intercorrelations between the regressors affect the order of entry into, or the removal of a variable from, the model. Based on these potential problems, stepwise regression is not used in the present study to develop the "best" return model.

In this study, a number of statistical criteria were used in selecting the "best" return model. These statistics are conceptually appealing, and provide information with respect to the explanatory power and predictive ability of the regression model. An examination of these statistics to determine the "best" return model is preferred to stepwise regression because the former method provides more information about the performance of the estimated model. In addition, the former approach allows evaluation of the predictive ability of the estimated model, whereas the criteria (F statistic and coefficient of determination) used by stepwise regression in model selection is related to the model's explanatory power only. Therefore, by examining the statistics for all models estimated, it is possible to determine which model provides the best explanation and prediction of security returns. The statistics employed in the present study include:

1. F statistic, which describes the overall significance of the regression model;
2. the coefficient of determination, R^2, which is the proportion of variation of the dependent variable explained by the regressor variables;
3. the adjusted coefficient of determination, R_a^2, which is the proportion of variation of the dependent variable explained by the regressor variables, adjusted for degrees of freedom;
4. the residual mean square, S_{e^2}, which measures the standard error of the regression model;
5. Mallow's C_p statistic, which measures the total error of the regression model, and is defined as the sum of the variance of prediction and the total squared bias of prediction; and
6. the Prediction Error Sum of Squares, PRESS, which measures the squared

error of prediction.

Models exhibiting significant F statistic; high R^2 and R_a^2; and low S_{e^2}, C_p statistic and PRESS were considered as having good explanatory power and predictive ability.

In addition to the above statistical criteria, other measures were used in determining the validity and predictive ability of the return models. There are three measures of forecast error: mean forecast error (MFE), mean absolute forecast error (MAFE), and mean square forecast error (MSFE). These measures were constructed to provide additional information to select the "best" return model. The basis of this approach is that the estimated return models of period I were used to predict security returns of periods II, III, and IV, and the estimated return models of period II were used to predict security returns of periods III and IV, and so forth. The model with the smallest MFE, MAFE, and MSFE would be regarded as the best return model in terms of predictive ability.

Mathematically,

$$\text{MFE} = \sum_{N,K}(R_{i,T} - \hat{R}_{i,T}) \;/\; NK,$$

$$\text{MAFE} = \sum_{N,K}|R_{i,T} - \hat{R}_{i,T}| \;/\; NK,$$

$$\text{MSFE} = \sum_{N,K}(R_{i,T} - \hat{R}_{i,T})^2 \;/\; NK,$$

where $R_{i,T}$ = realized return on security i in period T;

$\hat{R}_{i,T}$ = predicted return on security i in period T;

K = total number of periods (T = I , II, III, IV) in which security returns are forecast;

N = total number of companies.

The criteria used in selecting the "best" return model was described in the previous sections. In general, S_{e^2}; R^2; and R_a^2 are used in determining the goodness of fit of the model to the data and the explanatory power of the regression model. Mallow's C_p statistic and PRESS, on the other hand, are used in examining the ability of the model to predict security returns. MFE, MAFE, and MSFE are supplementary measures used for evaluating the ability of the model in providing accurate predictions. Prior to discussing the actual analysis performed, the proposed return model is expressed again as follows:

$$R_i = a_0 + a_1 \beta_i^m + a_2 \beta_i^I + a_3 C_i + a_4 G_i, \quad i = 1, 2, 3, \ldots, N$$

where R_i = return on security i, and

$$R_i = \prod_{t=1}^{48}(1 + R_{it}) - 1;$$

R_{it} = return on security i in month t;

β_i^m = market-related systematic risk of security i;

β_i^I = industry-related systematic risk of security i;

C_i = fundamental characteristics of security i which includes accounting beta, operating leverage, financial leverage, dividend covariability, cash flow beta, and profitability;

G_i = growth of security i;

a_j = regression coefficients of linear model, and $j = 1, 2, 3, 4$.

This return model can be expanded by including all the accounting risk measures and the profitability measure being tested as significant determinants of security returns in the regression model. Mathematically, the expanded return model is of the form presented as follows:

$$R_i = b_0 + b_1 \beta_i^m + b_2 \beta_i^I + b_3 \, ABETA_i + b_4 \, GMDOL_i + b_5 \, LEV_i + b_6 \, DIVCO_i + b_7 \, CFBETA_i + b_8 \, PROFIT_i + b_9 \, GR_i,$$

and $i = 1, 2, \ldots, N$

where R_i = return on security i, and

$$R_i = \prod_{t=1}^{48}(1 + R_{it}) - 1;$$

R_{it} = return on security i in month t;

β_i^m = market-related systematic risk of security i;

β_i^I = industry-related systematic risk of security i;

$ABETA_i$ = accounting beta of security i;

$GMDOL_i$ = operating leverage of security i;

LEV_i = financial leverage of security i;

$DIVCO_i$ = dividend covariability of security i;

$CFBETA_i$ = cash flow beta of security i;

$PROFIT_i$ = return on average assets of security i;

GR_i = compound growth in total assets of security i;

b_j = regression coefficients of linear model,

and $j = 0, 1, 2, \ldots, 9$.

This expanded return model will be referred to as the <u>full model</u> in the rest of the paper. The full model includes all the instrumental variables as regressors of security returns. In multiple regression analysis, the selection of the "best" model always starts with the full model, and this approach is used in the present study to decide which variables are significant in explaining and predicting security returns.

A regression analysis of the full model was performed for each of the four-year test periods covering from January 1976 to December 1982. In addition, since there are four alternative estimates of market-related systematic risk, regression analysis was also performed for each of these estimates. By examining the full model for each period and for each estimate of market-related systematic risk, it is possible to determine which market-related systematic risk estimate is the "best" in terms of explaining and predicting security returns. The results of such an analysis are reported in a later chapter.

Inspection of the significance of the regression coefficients of the full model, b_j, provides guidelines for determining which regressor variables should be included in the model. A numb er of submodels were estimated and examined. The above-mentioned statistical criteria were also used to determine which of these submodels provides the "best" explanation and prediction of security returns. As a consequence of this model selection process, the "best" return model was defined. The results are again reported in a later chapter.

As was discussed previously, two approaches can be used to determine the significance of the company factor. The first approach is to include all the company variables in the regression model. The second approach is to construct a company index on the basis of these company variables, and regard the company index as an independent variable of the return model. The analysis used in the first approach was discussed in the previous section. For the second approach, a principal component analysis was first performed on the company variables, and the first principal component was extracted to represent a "company index". Then, a regression model was developed for the following independent variables: market-related systematic risk, industry-related systematic risk, company index (the first principal component of company variables), and compound growth in total assets of a company. This regression model was then compared with the "best" model determined from the first approach. These results enable us to determine if a company index can replace certain company variables in explaining and predicting security returns.

Four schemes were used to group companies into industries. This grouping implies that the industry-related systematic risk of a company can be determined in four different ways, depending on how industry is defined. In order to determine which industry definition is better, the above analysis was performed separately under each classification scheme.

It was anticipated that the results would provide additional evidence with respect to which industry definition is more useful in terms of explaining and predicting security returns.

The experimental analyses were described briefly in previous sections. A more detailed presentation is included in the following chapter, along with a report of the results and findings of the present study.

CHAPTER IV

ANALYSES AND RESULTS

Four alternative estimates of market-related systematic risk (the market model, the mean reversion model, the order bias adjustment model, and the Bayesian adjustment model) are used separately to examine the impact of the market factor on security returns. The reason for such an approach is that the "true" market-related systematic risk is unobservable, which implies that "forecast accuracy" is not a meaningful criterion for deciding which model is most appropriate in estimating market-related systematic risk. A better approach is to examine how well these estimates help explain and predict security returns. In the present study, a regression analysis was performed on each of these alternative estimates separately in order to develop a multifactor return model. This analysis will provide additional evidence about the usefulness of these estimation models.

Also examined is the impact of an industry factor on security returns. Four schemes (two-digit SIC code, three-digit SIC code, two-digit LOB code, three-digit LOB code) are used to classify companies into homogeneous industry-related groups. Empirical evidence supports the use of three-digit codes (Fertuck [1975]) and Line of Business information (Foster [1981]) in studying industry effects; nonetheless, the use of two-digit SIC codes in research is predominant. The results can differ significantly depending on which industry classification scheme is used. In fact, the impact of an industry factor on security returns can only be meaningfully examined if the classification scheme employed is appropriate. By applying four independent industry classification schemes, the findings of this study provide additional evidence with respect to which scheme is most appropriate when an industry effect is examined.

Two approaches are used to investigate the impact of individual company variables on the return model. In the first approach, all company variables are included as independent variables in the regression model. In the second approach, the individual company variables are replaced by a company index variable, which is the first principal component of the company variables. The second approach is included in the study to determine if there exists an index that incorporates the fundamental characteristics of a company. In addition, it is possible to determine if such a company index might play a significant role in explaining and predicting security returns. This issue should be of special interest to accounting professionals who, as a group, would like to know if the accounting information they provide summarizes the financial attributes of a company. If it does, the benefits of accounting information to its users are verified. Thus, both approaches were adopted in the present study to develop the multifactor return model.

The discussion so far has described thirty-two alternative ways of developing the multifactor return model employed in the present study: 4 estimates of market-related systematic risk X 4 industry classification schemes X 2 approaches in treating company variables. This approach could prove very complicated to the reader if systematic procedures are not used to report the findings and results. Consequently, the results will be reported in the following manner.

The findings are organized on the basis of the industry classification scheme. Within each scheme, correlation statistics, regression statistics of the full model, submodels, and the four-factor model are reported for each alternative estimate of market-related systematic risk, and the "best" return model is then labeled. Based on these statistics, it is also possible to determine which estimate of market-related systematic risk is most appropriate in developing the multifactor return model. After presenting the results for the four industry classification schemes, a summary of the statistical findings is reported. In this manner, the most appropriate estimate of market-related systematic risk, and the most appropriate industry classification scheme, as well as the "best" return model, are developed in a systematic fashion.

STATISTICAL FINDINGS AND RESULTS

Prior to discussing the statistical results of the study, it is necessary to recall some of the abbreviations from Chapter III:

- β_i^m(OLS) stands for the estimate of market-related systematic risk from the market model;
- β_i^m(MR) stands for the estimate of market-related systematic risk from the mean reversion model;
- β_i^m(OB) stands for the estimate of market-related systematic risk from the order bias adjustment model;
- β_i^m(BA) stands for the estimate of market-related systematic risk from the Bayesian adjustment model;
- β_i^I stands for the estimate of industry-related systematic risk;
- ABETA stands for accounting beta;
- GMDOL stands for operating leverage;
- LEV stands for financial leverage;
- DIVCO stands for dividend covariability;
- CFBETA stands for cash flow beta;
- PROFIT stands for profitability;
- GR stands for growth in total assets;
- COFAC stands for company index; and
- RETURN stands for security return.

In Chapter III, it was noted that there are 390 companies whose returns and financial statement data are available for analysis. A smaller number of companies was actually included in the analysis, however. There are two reasons for this. First, in the process of estimating the return model, outliers[35] were discovered. The outliers constitute about 10 percent of the original sample, and were deleted [36] from the sample in order to obtain more reliable results. Although this procedure improves the model's explantion of security return, the procedure may limit the generalizability of the models beyond the sample being examined. A breakdown of the sample companies and outliers, on the basis of industry classification schemes, is included in Appendix C.

Second, the three-digit code is a more restrictive classification scheme than the two-digit code. Consequently, companies grouped under the same industry by the two-digit code may not necessarily be included in the same industry by the three-digit code. As a result, there are fewer companies within each three-digit industry. In order to reduce the biases from company dominance of an industry, three-digit industries containing fewer than ten companies are excluded from the sample. Consequently, for the three-digit SIC and LOB classification schemes, a much smaller sample is used in the analysis. The difference in sample size may limit the comparability of the return models across industry classification schemes.

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[35] Outliers are extreme observations which are data points that are not typical of the rest of the data. In the present study, outliers were discovered when inspecting the statistical properties of each variable, and these outliers were found to affect the specification of the regression model.

[36] The method used to delete outliers from the sample involves constructing an upper and lower boundary for all variables. For example, the upper boundary for accounting beta is +20, and its lower boundary is -20, which is approximately three standard deviations from the mean. A different boundary is used for different variables, but in general, the cutoff point is approximately three standard deviations from the mean.

Most of the statistics are presented along with the discussion. Some statistics (e.g, summary statistics of independent and dependent variables, correlation statistics among independent variables, and summary statistics of four-factor models), however, are included in the Appendix.

Industry Classification - Two-Digit SIC Code

The sample consists of 347 companies whose industry composition is presented in Appendix C. Although four different methods are used to provide estimates of market-related systematic risk, the correlation statistics, as given in Table 1, indicate that these estimates are strongly associated. The association is positive and significant in most cases, except for period IV, where the associations between β_i^m(OLS) and β_i^m(MR), and β_i^m(OLS) and β_i^m(OB) are not significant at the 0.05 level. The significant associations are expected as β_i^m(MR), β_i^m(OB), and β_i^m(BA) are adjustments from the ordinary least squares estimate of market-related systematic risk from the market model.

There are some interesting findings related to the correlation between security return and its determinants. Inspection of the correlation statistics reported in Table 2 reveals that β_i^m(OLS) is the only estimate of market-related systematic risk that demonstrates a consistent, significant positive association with security returns at the 0.01 level. It appears that the market model provides a more appropriate

Table 1: Correlation Statistics Between Alternative Estimates

of Market-Related Systematic Risk

Industry Classification: Two-Digit SIC Code

Period I (1976 - 79)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)
β_i^m(OLS) * **		0.450 (0.001)	0.446 (0.001)	0.417 (0.001)
β_i^m(MR)	0.274 (0.001)		0.844 (0.001)	0.957 (0.001)
β_i^m(OB)	0.238 (0.001)	0.815 (0.001)		0.671 (0.001)
β_i^m(BA)	0.282 (0.001)	0.962 (0.001)	0.644 (0.001)	

Period II (1977 - 80)

Period III (1978 - 81)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)
β_i^m(OLS) * **		0.225 (0.001)	0.186 (0.001)	0.240 (0.001)
β_i^m(MR)	0.085 (0.115)		0.809 (0.001)	0.940 (0.001)
β_i^m(OB)	0.363 (0.500)	0.820 (0.001)		0.583 (0.001)
β_i^m(BA)	0.121 (0.001)	0.944 (0.001)	0.603 (0.001)	

Period IV (1979 - 82)

* product moment correlation coefficient

** level of significance

Table 2: Correlation Statistics Between Security

Return and Regressor Variables

Industry Classification: Two-Digit SIC Code

	Period I (1976-78)	Period II (1977-79)	Period III (1978-80)	Period IV (1979-82)
β_i^m(OLS) *	0.202	0.330	0.258	0.144
**	(0.001)	(0.001)	(0.001)	(0.007)
β_i^m(MR)	0.040	0.061	0.037	0.116
	(0.459)	(0.261)	(0.499)	(0.031)
β_i^m(OB)	0.062	0.054	0.001	0.122
	(0.251)	(0.319)	(0.982)	(0.023)
β_i^m(BA)	0.042	0.077	0.071	0.103
	(0.431)	(0.151)	(0.187)	(0.055)
β_i^I	0.298	0.204	0.168	0.205
	(0.001)	(0.001)	(0.002)	(0.001)
ABETA	0.260	0.104	-0.100	-0.285
	(0.001)	(0.054)	(0.062)	(0.001)
GMDOL	-0.103	-0.300	-0.272	-0.049
	(0.056)	(0.001)	(0.001)	(0.362)
LEV	0.257	-0.157	-0.220	-0.230
	(0.634)	(0.004)	(0.001)	(0.001)
DIVCO	0.178	0.249	0.273	0.197
	(0.001)	(0.001)	(0.001)	(0.001)
CFBETA	-0.156	-0.140	-0.017	0.744
	(0.004)	(0.009)	(0.749)	(0.167)
PROFIT	0.250	0.405	0.442	0.531
	(0.001)	(0.001)	(0.001)	(0.001)
GR	0.341	0.500	0.483	0.441
	(0.001)	(0.001)	(0.001)	(0.001)
Company Index	0.149	-0.347	-0.399	-0.394
	(0.005)	(0.001)	(0.001)	(0.001)

* product moment correlation coefficient

** level of significance

estimate of market-related systematic risk since it exhibits the strongest association with security return. This conclusion agrees with the earlier statement made above (see p. 5), which states that "forecast accuracy of market-related systematic risk" cannot be a meaningful criterion for evaluating the performance of these estimation models (the market model, the mean reversion model, the order bias adjustment model, the Bayesian adjustment model), and that the findings of Klemkosky and Martin [1975][37] should be interpreted with reservation. The reason is that "the criterion for assessing predictive efficiency must be related to the object for which a prediction is desired,"[38] and in this case, security return is a more desirable object of prediction as compared to the forecast of market-related systematic risk. Furthermore, a significant positive association (at a level of 0.01) is found between industry-related systematic risk and security returns across all four periods. This situation implies that the industry factor also contributes significantly to security returns.

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[37] In the article "The Adjustment of Beta Forecasts" (Journal of Finance, September 1975, pp. 1123-1128), Klemkosky and Martin investigated the forecasting accuracy of the market model, the mean reversion model, the order bias adjustment model, and the Bayesian adjustment model. They found that both Blume's and Bayesian's adjustment models provide better future forecasts of market-related systematic risk than the unadjusted ordinary least squares estimate of the market model.

[38] Revsine, Lawrence. "Predictive Ability, Market Prices and Operating Flows," The Accounting Review, July 1971, p. 489.

For the six company variables, the associations between dividend covariability and security returns, and between profitability and security returns are positive and significant at the 0.01 level across all test periods.

The positive association between dividend covariability and security returns can be interpreted in the following manner. Dividend covariability measures the correlation between dividends paid to common stockholders and income available to common stockholders. A high positive value of dividend covariability implies that dividend payout is closely tied to the income level of the company. If the income is high, more dividends are distributed, and vice versa. This relationship implies that dividend payout can fluctuate substantially from one period to another, depending on the income of the company. Risk-averse investors, therefore, would require a higher return from companies that do not adopt a stable dividend policy. Consequently, a positive association found between dividend covariability and security returns is consistent with the proposition that investors in the capital market are rather conservative, and prefer a stable stream of dividend income to uncertain capital gains in the future.

Security return is also positively associated with the accounting return measure (profitability). This finding is exciting from the accountant's perspective. The subjective determination of accounting income has long been debated by economists and accountants. Economists substantially doubt about the usefulness of accounting income because accounting income is an artificial construct[39] which does not reflect the economic income of a company. The present study has found a positive association between accounting return (profitability) and security return, thus providing positive evidence that accounting income can provide useful information in determining security returns. These findings could enhance investors' confidence in using quarterly accounting information in security analysis and in making portfolio decisions.

The associations between operating leverage, financial leverage, cash flow beta and security returns are negative and significant at the 0.01 level in some periods. These company variables purport to measure specific risk attributes of the individual company. A significant negative association between these accounting risk measures and security returns implies that investors, as a group, are conservative, and do not expect higher returns on the securities to compensate for nonmarket (business) risks of each individual company.

The most interesting finding about the company variables is that accounting beta has a significant positive association (at a level of 0.01) with security return in period I, but a significant negative associ-

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[39] Revsine, Lawrence. Replacement Cost Accounting, Prentice Hall, New Jersey, 1973, p.125.

ation (at a level of 0.01) in period IV. The literature reviewed in Chapter II was consistent in advocating a positive relationship between accounting beta and market-related systematic risk, and a positive relationship between market-related systematic risk and security return. Theoretically, one would expect a positive association between accounting beta and security return because the accounting beta is presumably a risk measure of the company. This, however, is not necessarily true from the statistical point of view. In statistics, it has been shown that[40] for any random variables A, B, and C, if A is positively associated with B, and B is positively associated with C, then A may be negatively associated with C if the relationship between A and B, or B and C, is weak. Thus, the significant negative association found in period IV may be attributed to the weak associations between accounting beta and market-related systematic risk, and market-related systematic risk and security return. Since the association changes gradually over time, it implies that time may play a rather significant role in interpreting relationships among financial variables. That is, the general economic conditions in a specific time period may affect the importance and statistical significance of any relationship among financial variables.

Finally, as anticipated a significant positive association (at a lev-

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[40] Draper, N. R., and H. Smith. Applied Regression Analysis, John Wiley & Sons, Inc., New York, 1966. pp. 285-295.

el of 0.01) was found to exist between growth and security return. Because growth reflects the earning potential of a company, companies that have better growth opportunites are likely to earn greater returns.

The correlation statistics indicate that a relationship does exist between security return and its potential determinants. Consequently, a multiple regression analysis was used to estimate the multifactor return model. The regression statistics of the full model, submodels, and four-factor model for each alternative estimate of market-related systematic risk are presented in the following sections.

REGRESSION ANALYSIS - MARKET MODEL

Summary statistics of the full model for the four test periods are presented in Table 3. The full model explains about 40 percent of the variation in security returns, on the average. From the t statistics (or more specifically, the partial t statistics),[41] it can be concluded that the regression coefficients of industry-related systematic risk, dividend

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[41] In multiple regression, the coefficient of regressor j represents the expected change in the response (or dependent variable) per unit change in regressor j when all the remaining regressor variables are held constant. For this reason, the coefficients are often called partial regression coefficients. Consequently, the test for the significance of any regressor is a partial t test because the regression coefficient estimated for regressor j depends on all the other regressor variables that are in the model.

Table 3: Summary Statistics of Full Model

Market-Related Systematic Risk - Market Model

Industry Classification: Two-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.124	-0.121	-0.067	-0.073
(t-value)	(-3.894)**	(-4.049)**	(-2.660)**	(-3.103)**
Regression Coefficients:				
β_i^M (10^{-2})	0.126	0.651	0.286	-0.022
(t-value)	(0.913)	(4.358)**	(2.306)*	(-0.161)
β_i^I (10^{-2})	0.764	0.528	0.400	0.487
(t-value)	(5.737)**	(4.023)**	(3.348)**	(4.309)**
ABETA (10^{-2})	0.177	0.013	-0.010	-0.411
(t-value)	(4.411)**	(0.849)	(-0.535)	(-4.556)**
GMDOL (10^{-3})	0.152	-0.324	-0.057	0.928
(t-value)	(0.668)	(-1.503)	(-0.307)	(5.207)**
LEV (10^{-2})	1.500	0.171	0.093	0.247
(t-value)	(2.896)**	(0.339)	(0.216)	(0.547)
DIVCO (10^{-2})	0.314	0.428	0.545	0.473
(t-value)	(4.663)**	(4.266)**	(4.000)**	(3.293)**
CFBETA (10^{-2})	-0.136	-0.156	-0.032	0.024
(t-value)	(-2.749)**	(-3.437)**	(-0.968)	(0.879)
PROFIT (10^{-1})	0.119	0.093	0.097	0.196
(t-value)	(4.199)**	(3.335)**	(3.997)**	(7.718)**
GR	0.173	0.207	0.152	0.103
(t-value)	(4.931)**	(5.834)**	(5.130)**	(3.453)**
F-statistic	21.424	27.839	20.748	30.318
S_{e^2} (10^{-1})	0.110	0.108	0.091	0.096
R^2	0.364	0.426	0.357	0.447
R_a^2	0.344	0.411	0.339	0.433
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.436	0.422	0.303	0.336
MFE (10^{-2})	0.059	0.356	0.552	-
MAFE (10^{-2})	0.963	0.926	0.950	-
MSFE (10^{-3})	0.158	0.141	0.141	-

* significant at the 0.05 level

** significant at the 0.01 level

covariability, profitability, and growth are positive and significant at the 0.01 level across all four periods. This relationship suggests that the industry factor, specific components of the company factor (dividend covariability and profitability), and the growth factor contribute significantly to explaining security returns. These instrumental variables should be included in further regression analyses when developing other submodels. Furthermore, the regression coefficient of market-related systematic risk is positive and significant at the 0.01 level in periods II and III. The impact of market factor on security returns thus appears to be inconsistent over time; nonetheless, it is included in further regression analyses, because the objective of this study is to determine if the other factors contribute signficantly to explaining security returns, in addition to that of the single-factor CAPM model. Therefore, the market factor is also included in developing the multifactor return model.

A number of submodels have been estimated to determine if other components of the company factor (accounting beta, operating leverage, financial leverage, and cash flow beta) should be excluded from the return model. Because of their significance in explaining security returns (as indicated by the partial t values in Table 3), the following independent variables -- β_i^m(OLS), β_i^I, DIVCO, PROFIT, GR -- must be included in further regression analyses. Therefore, the submodels to be examined in the present study have included these five variables together with any combination of the remaining four company variables (ABETA, GMDOL, LEV, CFBETA). The fifteen submodels, in their functional forms, are given as follows:[42]

1. RETURN = $f(\beta_i^m(OLS)$, β_i^I, ABETA, GMDOL, LEV, DIVCO, PROFIT, GR)
2. RETURN = $f(\beta_i^m(OLS)$, β_i^I, ABETA, GMDOL, DIVCO, CFBETA, PROFIT, GR)
3. RETURN = $f(\beta_i^m(OLS)$, β_i^I, ABETA, LEV, DIVCO, CFBETA, PROFIT, GR)
4. RETURN = $f(\beta_i^m(OLS)$, β_i^I, GMDOL, LEV, DIVCO, CFBETA, PROFIT, GR)
5. RETURN = $f(\beta_i^m(OLS)$, β_i^I, ABETA, GMDOL, DIVCO, PROFIT, GR)
6. RETURN = $f(\beta_i^m(OLS)$, β_i^I, ABETA, LEV, DIVCO, PROFIT, GR)
7. RETURN = $f(\beta_i^m(OLS)$, β_i^I, ABETA, DIVCO, CFBETA, PROFIT, GR)
8. RETURN = $f(\beta_i^m(OLS)$, β_i^I, GMDOL, LEV, DIVCO, PROFIT, GR)
9. RETURN = $f(\beta_i^m(OLS)$, β_i^I, GMDOL, DIVCO, CFBETA, PROFIT, GR)
10. RETURN = $f(\beta_i^m(OLS)$, β_i^I, LEV, DIVCO, CFBETA, PROFIT, GR)
11. RETURN = $f(\beta_i^m(OLS)$, β_i^I, ABETA, DIVCO, PROFIT, GR)
12. RETURN = $f(\beta_i^m(OLS)$, β_i^I, GMDOL, DIVCO, PROFIT, GR)
13. RETURN = $f(\beta_i^m(OLS)$, β_i^I, LEV, DIVCO, PROFIT, GR)
14. RETURN = $f(\beta_i^m(OLS)$, β_i^I, DIVCO, CFBETA, PROFIT, GR)
15. RETURN = $f(\beta_i^m(OLS)$, β_i^I, DIVCO, PROFIT, GR)

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[42] These fifteen submodels were estimated for all other combinations of industry classification schemes and market-related sytematic risk estimates (e.g., three-digit SIC code and estimate of market-related systematic risk from order bias adjustment model). The analysis is restricted to these fifteen submodels to facilitate comparison across alternative estimates of market-related systematic risk and industry classification schemes.

These submodels are compared with the full model to determine which is the "best" return model in terms of its explanation and prediction of security returns. The criteria employed in the selection process include residual mean square, S_{e^2}; coefficient of determination, R^2; adjusted coefficient of determination, R_a^2; Mallow's C_p statistic; prediction error sum of squares, PRESS; mean forecast error, MFE; mean absolute forecast error, MAFE; and mean square forecast error, MSFE. When these criteria are examined, no single model emerges as the best in all these measures. In fact, there is no substantial difference in these measures among the estimated models. Thus, the selection of the "best" return model involves tradeoffs among these statistical criteria. In addition, the subjective judgement of the author also plays an important role in making the decision.[43]

The average statistics, that is, a simple average of the statistics across the four test periods, of the models are presented in Table 4. In general, the full model is the "best" in terms of explaining the variation in security returns (R^2 = 0.398), and its R_a^2 (0.381) is the second best among all the models examined. Submodel 2, on the other hand, has a relatively superior ability in predicting security returns, as indicated by the low forecast errors.

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[43] A detailed description of the subjective judgement (or decision process) involved in determining the "best" return model is presented in Appendix H.

Table 4: Average Statistics of Regression Models

Market-Related Systematic Risk - Market Model

Industry Classification: Two-Digit SIC Code

	S_{e^2} (10^{-1})	R^2	R^2_a	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.101	0.398	0.381	10.000	0.374	0.497	0.946	0.146
Submodel 1	0.102	0.389	0.374	13.269	0.377	0.344	0.933	0.141
Submodel 2	0.102	0.394	0.380	10.212	0.374	0.325	0.941	0.143
Submodel 3	0.102	0.386	0.371	15.478	0.379	0.337	0.944	0.145
Submodel 4	0.103	0.380	0.365	18.306	0.370	0.340	0.917	0.134
Submodel 5	0.102	0.384	0.372	13.649	0.378	0.317	0.930	0.140
Submodel 6	0.103	0.377	0.364	18.106	0.383	0.328	0.934	0.142
Submodel 7	0.102	0.381	0.368	15.934	0.355	0.324	0.942	0.143
Submodel 8	0.103	0.371	0.383	23.939	0.386	0.329	0.907	0.131
Submodel 9	0.103	0.377	0.364	17.775	0.381	0.333	0.918	0.134
Submodel 10	0.104	0.368	0.355	23.566	0.387	0.332	0.917	0.134
Submodel 11	0.103	0.372	0.361	19.691	0.383	0.323	0.929	0.139
Submodel 12	0.104	0.370	0.356	21.234	0.385	0.327	0.906	0.130
Submodel 13	0.105	0.359	0.348	26.535	0.391	0.325	0.906	0.130
Submodel 14	0.104	0.364	0.353	23.432	0.386	0.332	0.917	0.133
Submodel 15	0.104	0.356	0.346	26.553	0.390	0.326	0.905	0.130
Four-Factor	0.108	0.310	0.301	5.000	0.415	0.259	0.926	0.138

The regression statistics indicate that no single "best" return model can be identified when individual company variables are included as regressors in the model. The analysis now proceeds to estimating the four-factor model to see if such a model would be preferable in explaining the variation in security returns.

In developing the four-factor model, a principal component analysis was performed to construct a company index that was used as an independent variable in the model. The first principal component, or the company index, explains about 35 percent of the variation in the company variables (ABETA, GMDOL, LEV, DIVCO, CFBETA, PROFIT). The average statistics, as given in Table 4, indicate that the explanatory power of the four-factor model (R^2 = 0.310) is substantially less than that of the full model. Moreover, there is little improvement in its ability to predict security returns, as indicated by a high PRESS statistic of 0.415. Thus, it appears that the loss of information in the company index outweighs its simplicity in model specification.

In summary, when the major concern is the prediction of security returns, submodel 2 is preferred to the full model (as indicated by the forecast errors), which has the greatest explanatory power of security returns.

REGRESSION ANALYSIS - MEAN REVERSION MODEL

In general, the full model explains about 39 percent of the variation in security returns. The Student's t statistics for the variables in the full model (Table 5) indicate that industry-related systematic risk, dividend covariability, profitability, and growth are significant determinants of security returns across all four periods. Market-related systematic risk, β_i^m(MR), on the other hand, is significant at the 0.01 level in period IV only, suggesting that β_i^m(MR) may not have adequately captured the impact of the market factor on security returns, as compared to β_i^m(OLS).

From the average statistics presented in Table 6, no definite statement can be made with respect to which is the "best" return model. In general, the full model explains the largest proportion of variation in security returns (R^2 = 0.393; R_a^2 = 0.377). Submodel 2, on the other hand, is relatively superior in terms of its ability to predict security returns, as evidenced by the low forecast errors. The use of a company index in the return model reduces its explanatory power (compared to the full model) by approximately 10 percent. Furthermore, the ability of the four-factor model to predict security returns is poor, as indicated by its high PRESS statistic of 0.421. Once again, the evidence shows that the use of a company index in place of the individual company variables in determining the return model is not appropriate.

Table 5: Summary Statistics of Full Model

Market-Related Systematic Risk - Mean Reversion Model

Industry Classification: Two-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.093	-0.068	-0.053	-0.127
(t-value)	(-2.537)*	(-1.952)	(-1.683)	(-5.106)**
Regression Coefficients:				
β_i^m (10^{-2})	-0.185	-0.055	0.041	0.450
(t-value)	(-0.953)	(-0.323)	(0.212)	(3.716)**
β_i^I (10^{-2})	0.867	0.699	0.483	0.349
(t-value)	(6.869)**	(5.001)**	(3.961)**	(2.997)**
ABETA (10^{-2})	0.174	0.020	-0.008	-0.420
(t-value)	(4.296)**	(1.250)	(-0.405)	(-4.748)**
GMDOL (10^{-3})	0.092	-0.366	-0.088	0.983
(t-value)	(0.403)	(-1.638)	(-0.473)	(5.635)**
LEV (10^{-2})	1.500	0.227	0.100	0.288
(t-value)	(2.888)**	(0.440)	(0.231)	(0.652)
DIVCO (10^{-2})	0.305	0.441	0.544	0.470
(t-value)	(4.521)**	(4.284)**	(3.957)**	(3.349)**
CFBETA (10^{-2})	-0.140	-0.179	-0.036	0.027
(t-value)	(-2.830)**	(-3.840)**	(-1.091)	(1.006)
PROFIT (10^{-1})	0.119	0.097	0.097	0.203
(t-value)	(4.185)**	(3.374)**	(3.934)**	(8.134)**
GR	0.171	0.215	0.165	0.108
(t-value)	(4.877)**	(6.020)**	(5.584)**	(3.836)**
F-statistic	21.437	24.376	19.852	33.089
S_{e^2} (10^{-1})	0.110	0.111	0.092	0.094
R^2	0.364	0.394	0.347	0.469
R_a^2	0.347	0.378	0.329	0.455
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.435	0.446	0.307	0.322
MFE (10^{-2})	-0.078	0.368	0.536	-
MAFE (10^{-2})	0.969	0.899	0.938	-
MSFE (10^{-3})	0.160	0.133	0.138	-

* significant at the 0.05 level

** significant at the 0.01 level

Table 6: Average Statistics of Regression Models

Market-Related Systematic Risk - Mean Reversion Model

Industry Classification: Two-Digit SIC Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.102	0.393	0.377	10.000	0.377	0.562	0.935	0.143
Submodel 1	0.103	0.382	0.367	14.238	0.382	0.330	0.922	0.138
Submodel 2	0.102	0.389	0.374	10.253	0.377	0.324	0.932	0.141
Submodel 3	0.103	0.379	0.365	16.691	0.384	0.333	0.934	0.142
Submodel 4	0.103	0.375	0.357	18.679	0.386	0.318	0.909	0.132
Submodel 5	0.103	0.377	0.364	14.730	0.382	0.326	0.917	0.135
Submodel 6	0.104	0.368	0.355	23.436	0.388	0.605	0.920	0.137
Submodel 7	0.103	0.375	0.362	17.168	0.384	0.330	0.931	0.140
Submodel 8	0.104	0.363	0.350	22.882	0.392	0.311	0.895	0.127
Submodel 9	0.103	0.372	0.361	18.342	0.385	0.318	0.909	0.131
Submodel 10	0.104	0.361	0.348	24.898	0.392	0.323	0.908	0.131
Submodel 11	0.104	0.363	0.351	21.350	0.389	0.332	0.915	0.135
Submodel 12	0.104	0.360	0.374	22.739	0.390	0.311	0.894	0.126
Submodel 13	0.105	0.351	0.339	28.858	0.396	0.315	0.893	0.126
Submodel 14	0.104	0.358	0.347	24.735	0.391	0.322	0.908	0.131
Submodel 15	0.105	0.347	0.338	28.883	0.396	0.315	0.893	0.126
Four-Factor	0.107	0.299	0.291	5.000	0.421	0.251	0.919	0.136

In summary, the regression results associated with $\beta_i^m(MR)$ are very similar to those of $\beta_i^m(OLS)$, except that $\beta_i^m(MR)$ is significant at the 0.01 level in period IV, whereas $\beta_i^m(OLS)$ is significant at the 0.01 level in periods II and III.

REGRESSION ANALYSIS - ORDER BIAS ADJUSTMENT MODEL

The statistics of the full model (Table 7) indicate that about 40 percent of the variation in security returns is accounted for by the regressor variables. The regression coefficients of industry-related systematic risk, dividend covariability, profitability, and growth are positive and significant at the 0.01 level in all four periods. This confirms the earlier findings that the industry factor, specific components of the company factor (dividend covariability and profitability), and the growth factor are significant determinants of security returns. The impact of the market factor on security returns is found to be significant at the 0.01 level only in period IV.

Average statistics of the estimated models (Table 8) indicate that the explanation of the full model on security returns is the "best" (R^2 = 0.393; R_a^2 = 0.377), and submodel 2 is slightly preferred to other models in terms of its ability to predict security returns, as indicated by the low forecast errors of the model. The four-factor model explains about 30 percent of the variation in security returns, on the average. Its predic-

Table 7: Summary Statistics of Full Model

Market-Related Systematic Risk - Order Bias Adjustment Model

Industry Classification: Two-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.105	-0.079	-0.051	-0.098
(t-value)	(-3.206)**	(-2.476)*	(-1.992)*	(-4.469)**
Regression Coefficients:				
β_i^m (10^{-2})	-0.088	0.037	0.026	0.250
(t-value)	(-0.645)	(0.278)	(0.286)	(3.161)**
β_i^I (10^{-2})	0.855	0.669	0.480	0.355
(t-value)	(6.709)**	(4.809)**	(3.970)**	(3.002)**
ABETA (10^{-2})	0.176	0.020	-0.008	-0.417
(t-value)	(4.370)**	(1.239)	(-0.422)	(-4.694)**
GMDOL (10^{-3})	0.121	-0.354	-0.091	0.918
(t-value)	(0.534)	(-1.597)	(-0.488)	(5.251)**
LEV (10^{-2})	1.508	0.237	0.102	0.269
(t-value)	(2.911)**	(0.458)	(0.236)	(0.604)
DIVCO (10^{-2})	0.305	0.443	0.545	0.469
(t-value)	(4.524)**	(4.300)**	(3.962)**	(3.324)**
CFBETA (10^{-2})	-0.139	-0.177	-0.036	0.029
(t-value)	(-2.813)**	(-3.788)**	(-1.087)	(1.072)
PROFIT (10^{-1})	0.119	0.098	0.097	0.200
(t-value)	(4.188)**	(3.428)**	(3.937)**	(7.983)**
GR	0.173	0.216	0.165	0.107
(t-value)	(4.912)**	(6.038)**	(5.590)**	(3.784)**
F-statistic	21.351	24.371	19.858	32.321
S_e^2 (10^{-1})	0.110	0.111	0.092	0.099
R^2	0.363	0.394	0.347	0.463
R_a^2	0.346	0.378	0.329	0.449
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.436	0.448	0.309	0.327
MFE (10^{-2})	-0.084	0.371	0.540	-
MAFE (10^{-2})	0.971	0.896	0.939	-
MSFE (10^{-3})	0.160	0.132	0.138	-

* significant at the 0.05 level

** significant at the 0.01 level

Table 8: Average Statistics of Regression Models

Market-Related Systematic Risk - Order Bias Adjustment Model

Industry Classification: Two-Digit SIC Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.103	0.391	0.375	10.000	0.379	0.584	0.939	0.143
Submodel 1	0.104	0.380	0.365	14.148	0.383	0.332	0.922	0.138
Submodel 2	0.102	0.387	0.373	10.250	0.380	0.328	0.932	0.141
Submodel 3	0.103	0.379	0.364	15.661	0.385	0.337	0.934	0.142
Submodel 4	0.103	0.373	0.358	18.710	0.388	0.319	0.908	0.131
Submodel 5	0.103	0.375	0.363	12.137	0.384	0.329	0.917	0.135
Submodel 6	0.104	0.368	0.355	19.588	0.389	0.338	0.921	0.137
Submodel 7	0.103	0.374	0.361	16.140	0.385	0.335	0.931	0.140
Submodel 8	0.104	0.362	0.348	22.798	0.393	0.310	0.894	0.127
Submodel 9	0.104	0.372	0.357	18.648	0.387	0.318	0.908	0.131
Submodel 10	0.104	0.361	0.348	24.031	0.393	0.359	0.907	0.130
Submodel 11	0.104	0.363	0.352	20.272	0.365	0.336	0.916	0.135
Submodel 12	0.104	0.358	0.347	22.681	0.392	0.310	0.894	0.126
Submodel 13	0.105	0.350	0.338	27.909	0.397	0.314	0.893	0.126
Submodel 14	0.104	0.357	0.346	23.902	0.392	0.322	0.906	0.130
Submodel 15	0.105	0.347	0.337	27.966	0.397	0.313	0.892	0.126
Four-Factor	0.109	0.299	0.291	5.000	0.421	0.253	0.914	0.134

tion of security returns offers no substantial improvement over that of other models. The findings suggest that the inclusion of company variables in the regression model on an individual basis will provide better results.

In summary, the use of β_i^m(MR) or β_i^m(OB) in estimating return models produces almost identical results. This may be due to the similarity of the two methods in providing adjusted estimates of market-related systematic risk.

REGRESSION ANALYSIS - BAYESIAN ADJUSTMENT MODEL

For β_i^m(BA), the average proportion of variation in security returns explained by the full model is 39.3 percent over the four test periods (Table 9). As was anticipated, industry-related systematic risk, dividend covariability, profitability, and growth continue to make significant contributions (at the 0.01 level) toward explaining security returns in all four periods. The regression coefficient of market-related systematic risk, however, is significant at the 0.01 level only in period IV. This is consistent with the previous findings in which the impact of market factor on security returns is not as significant as the other three factors--the industry factor, the company factor, and the growth factor.

Average statistics for the estimated models (Table 10) again demon-

Table 9: Summary Statistics of Full Model

Market-Related Systematic Risk - Bayesian Adjustment Model

Industry Classification: Two-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.082	-0.065	-0.057	-0.138
(t-value)	(-2.026)*	(-1.692)	(-1.751)	(-4.942)**
Regression Coefficients:				
β_i^m (10^{-2})	-0.269	-0.082	0.079	0.498
(t-value)	(-1.146)	(-0.398)	(0.392)	(3.357)**
β_i^I (10^{-2})	0.874	0.702	0.477	0.384
(t-value)	(6.975)**	(5.056)**	(3.956)**	(3.351)**
ABETA (10^{-2})	0.173	0.020	-0.007	-0.417
(t-value)	(4.278)**	(1.247)	(-0.395)	(-4.702)**
GMDOL (10^{-3})	0.076	-0.372	-0.084	0.995
(t-value)	(0.330)	(-1.653)	(-0.444)	(5.667)**
LEV (10^{-2})	1.503	0.232	0.101	0.261
(t-value)	(2.908)**	(0.449)	(0.232)	(0.588)
DIVCO (10^{-2})	0.305	0.442	0.544	0.471
(t-value)	(4.535)**	(4.289)**	(3.960)**	(3.348)**
CFBETA (10^{-2})	-0.141	-0.180	-0.036	0.026
(t-value)	(-2.850)**	(-3.848)**	(-1.085)	(0.961)
PROFIT (10^{-1})	0.119	0.097	0.097	0.202
(t-value)	(4.205)**	(3.382)**	(3.941)**	(8.091)**
GR	0.171	0.215	0.165	0.104
(t-value)	(4.875)**	(6.021)**	(5.599)**	(3.694)**
F-statistic	21.508	24.386	19.870	32.578
S_e^2(10^{-1})	0.110	0.111	0.092	0.095
R^2	0.365	0.394	0.347	0.465
R_a^2	0.348	0.378	0.329	0.451
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.434	0.445	0.307	0.324
MFE (10^{-2})	-0.074	0.367	0.535	-
MAFE (10^{-2})	0.969	0.899	0.936	-
MSFE (10^{-3})	0.160	0.134	0.137	-

* significant at the 0.05 level

** significant at the 0.01 level

Table 10: Average Statistics of Regression Models

Market-Related Systematic Risk - Bayesian Adjustment Model

Industry Classification: Two-Digit SIC Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.102	0.392	0.376	10.000	0.377	0.547	0.935	0.143
Submodel 1	0.103	0.381	0.366	14.506	0.382	0.327	0.921	0.138
Submodel 2	0.102	0.388	0.374	10.263	0.377	0.321	0.932	0.141
Submodel 3	0.103	0.378	0.363	16.790	0.384	0.329	0.934	0.142
Submodel 4	0.103	0.374	0.359	18.530	0.386	0.317	0.908	0.132
Submodel 5	0.103	0.376	0.363	14.729	0.382	0.324	0.916	0.135
Submodel 6	0.104	0.367	0.354	18.281	0.388	0.333	0.918	0.137
Submodel 7	0.103	0.374	0.361	17.243	0.384	0.327	0.930	0.140
Submodel 8	0.104	0.363	0.350	22.761	0.391	0.311	0.894	0.127
Submodel 9	0.103	0.371	0.358	15.804	0.385	0.317	0.909	0.131
Submodel 10	0.104	0.362	0.348	24.809	0.391	0.323	0.907	0.131
Submodel 11	0.104	0.362	0.351	21.436	0.389	0.330	0.915	0.134
Submodel 12	0.104	0.359	0.348	22.897	0.390	0.310	0.893	0.126
Submodel 13	0.105	0.350	0.338	28.819	0.396	0.315	0.892	0.126
Submodel 14	0.104	0.357	0.346	24.663	0.391	0.322	0.907	0.130
Submodel 15	0.105	0.347	0.337	28.835	0.396	0.314	0.892	0.126
Four-Factor	0.108	0.299	0.290	5.000	0.421	0.249	0.919	0.136

strate that the full model explains the largest proportion of variation in security returns ($R^2 = 0.391$; $R_a^2 = 0.373$), and submodel 2 is slightly superior in predicting security returns. The four-factor model still exhibits poor explanatory power (about 30 percent, on average), and gives relatively poor predictions of the security returns, as evidenced by the high PRESS statistic.

In summary, the results of the regression analysis using $\beta_i^m(BA)$ are very similar to those of $\beta_i^m(MR)$ and $\beta_i^m(OB)$. The full model provides the "best" explanation of security returns, whereas submodel 2 provides a relatively superior prediction of security returns in terms of the forecast errors.

SYNTHESIS

Regardless of which estimate of market-related systematic risk is used to construct the return model, industry-related systematic risk, dividend covariability, profitability, and growth contribute significantly to the determination of security returns across all test periods examined. These results suggest that the impact of industry factor on security returns should not be taken lightly. In addition, certain attributes of a company, such as its dividend policy, profitability, and growth potential, also play an important role in determining security returns. It is interesting to note that the role of the market factor, as compared to the industry, company and growth factors, is a less significant determinant of security returns than the literature suggests. This observation may be attributed to the significant association between market-related and industry-related systematic risks, and/or to sample-specific attributes.

According to Fabozzi and Francis [1979], the impact of the industry factor on market-related systematic risk cannot be ignored. Thus the current study has attempted to construct industry-related systematic risk in such a manner that it is statistically independent of the market return structure. The correlation statistics, shown in Table 11, however, indicate a failure to accomplish this. It appears that the operating environment within any industry is so strongly influenced by the market that it is impossible to segregate industry effect from that of the market. Thus, this strong association between market and industry may account for the insignificance of market-related systematic risk in determining the return model. Another possible explanation relates to Simkowitz and Logue's [1973][44] conclusion that the market factor is a surrogate for some real variables of the company. That is to say, the impact of the market factor on security returns may be partially reflected in the significance of some company variables, namely dividend covariability, profitability,

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[44] Simkowitz, Michael A. and Dennis E. Logue. "The Interdependent Structure of Security Returns," Journal of Financial and Quantitative Analysis, March 1973, p. 264.

Table 11: Correlation Statistics Between

Market- and Industry-Related Systematic Risk

Industry Classification: Two-Digit SIC Code

	Period I (1976-78)	Period II (1977-79)	Period III (1978-80)	Period IV (1979-82)
β_i^m(OLS) *	0.532	0.294	0.352	0.100
**	(0.001)	(0.001)	(0.001)	(0.064)
β_i^m(MR)	0.369	0.398	0.369	0.310
	(0.001)	(0.001)	(0.001)	(0.001)
β_i^m(OB)	0.421	0.396	0.358	0.364
	(0.001)	(0.001)	(0.001)	(0.001)
β_i^m(BA)	0.341	0.379	0.342	0.252
	(0.001)	(0.001)	(0.001)	(0.001)

* product moment correlation coefficient

** level of significance

and growth in total assets.

Other company variables, such as accounting beta, operating leverage, financial leverage, and cash flow beta, play an inconsistent role in explaining security returns. The impact of accounting beta on security returns is positive and significant in period I, but negative and significant in period IV. Such inconsistent results may occur because the association between accounting beta and market-related systematic risk is not as strong and consistent as the literature suggests. Alternatively, the use of quarterly accounting information may have distorted the relationship between accounting beta and security return. Or, multicollinearity[45] among regressor variables may have led to a significant negative coefficient of accounting beta in period IV. The answers to these questions will not be addressed in the present study. Further research may lead to an explanation of the cause of such an inconsistent relationship between accounting beta and security returns.

Operating leverage and financial leverage mutually describe the

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[45] When multicollinearity is present, interpretating the significance of regression coefficients may be misleading because multicollinearity will inflate both the absolute magnitude of the regression coefficients and their standard errors. Besides, the impact (positive or negative) of a regressor on the response variable cannot be determined by the sign of its coefficient when multicollinearity is present. Thus, the sign of the product moment correlation coefficient between security return and its regressors is also considered in interpreting such relationship throughout the rest of the paper.

business risk of a company. The regression coefficient of operating leverage is positive and significant in period IV, and for financial leverage, it is positive and significant in period I. This positive relationship is proposed in the literature but the insignificant results in periods II, III and IV suggest that the market, as a whole, does not generally demand higher returns to compensate for the higher business risk involved. The evidence provides partial support for the portfolio theory that business risks are diversifiable, and no additional returns are required for these residual risks. The regression coefficient of cash flow beta is negative and significant in periods I and II, however. This is consistent with the correlation statistics that the product moment correlation coefficients between cash flow beta and security returns are negative and significant in preiods I and II. These results imply that investors, as a group, have responded negatively to the variation of a company's cash flows with that of the market. The reason for such behavior is either that investors are conservative, or that they are not very concerned about cash flows as long as a company is operating profitably. Such negative findings raise questions about whether cash flow beta actually measures what it purports to measure, and this point may be answered through further research on the issue.

From the average statistics of the 68 models (4 full models, 60 submodels, and 4 four-factor models) examined, β_i^m(OLS) appears to outperform other alternative estimates of market-related systematic risk both in explaining and predicting security returns. The full model explains the largest proportion of variation in security returns (about 40 percent, on the average), whereas the four-factor model provides the least powerful explanation (about 30 percent, on the average). These results are consistent consistent with the principle that the greater the number of independent variables included in a regression model, the better its explanatory power. The full model also outperforms the four-factor model in predicting security returns.[46] The forecast errors, on the other hand, show that the four-factor model is slightly superior, though difference is not substantial. Thus, it can be concluded that the use of a company index, in place of the individual company variables, does not improve the explanation of security returns. Despite the significant association among some of the company variables (Appendix F), it appears that the loss of information related to the use of a company index outweighs the problem

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[46] Mallow's Cp statistic is not relevant in this case because its value always equals one plus the number of independent variables included in the full model. That is, the Cp value of the multifactor model is always 10, whereas for the four-factor model, its Cp value always equals 5. Thus, this statement is based solely on the PRESS statistics.

[47] When strong multicollinearity is present, the least squares method will generally produce poor estimates of the individual model parameters. This does not imply that the explanatory power of the model is poor, or that the fitted model is a poor predictor. In fact, if predictions are confined to regions of the x-space (i.e., within relevant boundaries of the regressor variables) where the multicollinearity holds approximately, the fitted model can produce satisfactory predictions. (see Montgomery and Peck [1981], Introduction to Applied Regression Statistics, pp. 291-296).

of multicollinearity [47] in determining the return model.

Finally, based on the average statistics, it is concluded that the full model is the "best" in terms of its explanation of security returns. Submodel 2, on the other hand, is relatively superior in terms of its ability to predict security returns. Again, it is necessary to note that subjective judgement[48] plays an important role in deciding which is the "best" return model, since there is no substantial difference in the statistics among the models examined.

Industry Classification - Three-Digit SIC Code

The number of companies included in the analysis under the three-digit SIC code classification is 175. The reduced sample size is a direct consequence of employing a more restrictive scheme, three-digit versus two-digit codes, in grouping companies into industries. The classification of the sample companies into three-digit SIC industries is shown in Appendix C.

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[48] There is no ambiguity in determining which model best explains variation in security returns. The decision with respect to which model best predicts security returns, however, involves tradeoffs, since no single model is superior in all five predictive criteria (Cp, PRESS, MFE, MAFE, MSFE). In determining which is the "best" return model, it is desirable to ensure that the selected model is acceptable both in terms of its explanatory power and ability to predict security returns.

Correlation statistics in Table 12 indicate a significant positive association among the four alternative estimates of market-related systematic risk, except that the association between β_i^m(OLS) and β_i^m(OB) is not significant at the 0.05 level in period IV. The results are expected, because β_i^m(MR), β_i^m(OB), and β_i^m(BA) are adjustments of β_i^m(OLS).

There are several interesting findings with respect to the correlation between security return and its potential determinants (refer to Table 13). Among the four alternative estimates of market-related systematic risk, β_i^m(OLS) is the one that demonstrates consistent, significant positive association (at a level of 0.01) with security returns across all four test periods. For the other estimates, significant positive associations (at a level of 0.05) exist in some periods, but not in others. These simple statistics imply that β_i^m(OLS) will play a more important role than other estimates in determining the return model. Moreover, the association between industry-related systematic risk and security returns is positive and significant at the 0.05 level across all four periods. It appears that the use of three-digit SIC code has weakened the association between industry-related systematic risk and security returns, as compared to the two-digit SIC code (Table 1 versus Table 13). The statistics, however, should be interpreted with more caution. Sample size has a strong impact on the level of significance an association exhibits. In general, the larger the sample size, the more likely that a statistically significant association will be found. Since the sample size (347

Table 12: Correlation Statistics Between Alternative Estimates of Market-Related Systematic Risk

Industry Classification: Three-Digit SIC Code

Period I (1976 - 79)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)
β_i^m(OLS) *		0.462	0.477	0.419
**		(0.001)	(0.001)	(0.001)
β_i^m(MR)	0.324		0.845	0.956
	(0.001)		(0.001)	(0.001)
β_i^m(OB)	0.271	0.802		0.667
	(0.001)	(0.001)		(0.001)
β_i^m(BA)	0.330	0.957	0.609	
	(0.001)	(0.001)	(0.001)	

Period II (1977 - 80)

Period III (1978 - 81)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)
β_i^m(OLS) *		0.275	0.219	0.292
**		(0.002)	(0.004)	(0.001)
β_i^m(MR)	0.148		0.798	0.935
	(0.050)		(0.001)	(0.001)
β_i^m(OB)	0.098	0.820		0.553
	(0.198)	(0.001)		(0.001)
β_i^m(BA)	0.185	0.935	0.580	
	(0.014)	(0.001)	(0.001)	

Period IV (1979 - 82)

* product moment correlation coefficient

** level of significance

Table 13: Correlation Statistics Between Security Return and Regressor Variables

Industry Classification: Three-Digit SIC Code

	Period I (1976-78)	Period II (1977-79)	Period III (1978-80)	Period IV (1979-82)
β_i^m (OLS) *	0.314	0.457	0.356	0.209
**	(0.001)	(0.001)	(0.001)	(0.007)
β_i^m (MR)	0.156	0.161	0.110	0.155
	(0.040)	(0.033)	(0.147)	(0.040)
β_i^m (OB)	0.189	0.115	0.022	0.140
	(0.012)	(0.131)	(0.766)	(0.066)
β_i^m (BA)	0.127	0.176	0.165	0.149
	(0.094)	(0.020)	(0.029)	(0.049)
β_i^I	0.339	0.197	0.164	0.201
	(0.001)	(0.009)	(0.031)	(0.008)
ABETA	0.228	0.086	-0.080	-0.206
	(0.002)	(0.260)	(0.294)	(0.006)
GMDOL	-0.006	-0.229	-0.264	0.091
	(0.933)	(0.002)	(0.001)	(0.230)
LEV	0.053	-0.120	-0.132	-0.121
	(0.487)	(0.113)	(0.082)	(0.110)
DIVCO	0.167	0.245	0.269	0.197
	(0.027)	(0.001)	(0.001)	(0.009)
CFBETA	-0.173	-0.167	-0.021	0.056
	(0.022)	(0.027)	(0.782)	(0.465)
PROFIT	0.170	0.370	0.475	0.540
	(0.025)	(0.001)	(0.001)	(0.001)
GR	0.234	0.451	0.440	0.396
	(0.002)	(0.001)	(0.001)	(0.001)
Company Index	-0.102	-0.355	-0.411	-0.367
	(0.152)	(0.001)	(0.001)	(0.001)

* product moment correlation coefficient

** level of significance

companies) for the two-digit SIC industry classification is substantially greater than that of the three-digit SIC classification (175 companies), it is more likely that significant association between industry-related systematic risk and security returns would be found for the two-digit classification. It is thus inappropriate to compare, at least at this stage, the two industry classification schemes solely on the basis of the correlation statistics.

For the company variables, there exists a significant positive association between dividend covariablity and security returns (at a level of 0.05) as well as between profitability and security returns (at a level of 0.01), across all four periods. On the other hand, note the significant negative associations (at a level of 0.10) between certain company variables (operating leverage, financial leverage, cash flow beta) and security returns in some periods. The association of accounting beta with security returns is positive and significant at the 0.01 level in period I, but negative and significant at the 0.01 level in period IV. These correlation statistics are similar to those that were found for the two-digit industry classification. Finally, the product moment correlation coefficients between growth and security returns are positive and significant at the 0.01 level across all test periods (see pp. 112-114 for a detailed discussion on implications of the findings).

Statistical descriptions of the regression models, for each alternative estimate of market-related systematic risk, are presented in the following sections.

REGRESSION ANALYSIS - MARKET MODEL

Statistics of the full model (Table 14) indicate that market-related systematic risk is significant at the 0.01 level in periods II and III, while industry-related systematic risk is significant at the 0.01 level in periods I and IV. It appears that the roles played by the market factor and industry factor in determining security returns have been collaborative. That is, these two factors work together in explaining the variation in security returns. Table 15 discloses a strong association between market-related and industry-related systematic risks, thus contributing a possible explanation. When two independent variables are strongly associated, either of them may indicate significance in estimating the regression model. For the company variables, dividend covariability and profitability contribute significantly at a level of 0.05 to explaining security returns for all test periods, as indicated in Table 14. The regression coefficient of the growth variable is positive and significant at the 0.05 level in periods I and II only. It seems that there exists no definite set of independent variables that should be included for further regression analyses. Therefore, taking into account the results of the previous analyses, it was decided that the same set of submodels, fifteen altogether, would be estimated and examined during the

Table 14: Summary Statistics of Full Model

Market-Related Systematic Risk - Market Model

Industry Classification: Three-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.103	-0.148	-0.157	-0.159
(t-value)	(-2.276)*	(-3.466)**	(-4.463)**	(-4.665)**
Regression Coefficients:				
β_i^m (10^{-2})	0.334	1.090	0.662	0.281
(t-value)	(1.549)	(5.494)**	(4.018)**	(1.338)**
β_i^I (10^{-2})	0.687	0.333	0.249	0.362
(t-value)	(3.412)**	(1.893)	(1.584)	(2.378)*
ABETA (10^{-2})	0.138	-0.006	-0.030	-0.439
(t-value)	(2.247)*	(-0.254)	(-1.145)	(-3.158)**
GMDOL (10^{-3})	0.156	-0.234	-0.070	0.985
(t-value)	(0.470)	(-0.721)	(-0.262)	(3.876)**
LEV (10^{-2})	0.920	0.659	0.183	0.197
(t-value)	(1.144)	(0.829)	(2.734)**	(2.571)*
DIVCO (10^{-2})	0.313	0.407	0.637	0.592
(t-value)	(3.589)**	(3.324)**	(3.543)**	(2.740)**
CFBETA (10^{-2})	-0.123	-0.127	-0.019	0.021
(t-value)	(-2.216)*	(-2.442)*	(-0.500)	(0.607)
PROFIT (10^{-1})	0.106	0.111	0.198	0.278
(t-value)	(2.332)*	(2.455)*	(4.887)**	(7.226)**
GR	0.119	0.171	0.081	0.063
(t-value)	(2.500)*	(3.783)**	(1.845)	(1.296)
F-statistic	8.912	15.492	14.091	16.860
S_e^2(10^{-1})	0.114	0.104	0.088	0.097
R^2	0.327	0.458	0.435	0.479
R_a^2	0.290	0.428	0.404	0.451
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.246	0.203	0.151	0.182
MFE (10^{-2})	-0.016	0.194	0.507	-
MAFE (10^{-2})	0.908	0.903	0.906	-
MSFE (10^{-3})	0.139	0.134	0.135	-

* significant at the 0.05 level

** significant at the 0.01 level

Table 15: Correlation Statistics Between

Market- and Industry-Related Systematic Risk

Industry Classification: Three-Digit SIC Code

	Period I (1976-78)	Period II (1977-79)	Period III (1978-80)	Period IV (1979-82)
β_i^m(OLS) *	0.620	0.344	0.393	0.174
**	(0.001)	(0.001)	(0.001)	(0.022)
β_i^m(MR)	0.422	0.450	0.434	0.390
	(0.001)	(0.001)	(0.001)	(0.001)
β_i^m(OB)	0.496	0.428	0.384	0.410
	(0.001)	(0.001)	(0.001)	(0.001)
β_i^m(BA)	0.373	0.418	0.400	0.307
	(0.001)	(0.001)	(0.001)	(0.001)

* product moment correlation coefficient

** level of significance

process of selecting the "best" return model. This approach makes the analyses more manageable, and the comparison across industry classification schemes is also feasible and meaningful.

There is no substantial difference in the average statistics of the full model and submodels, as indicated in Table 16. The full model explains about 42 percent of the variation in security returns, on the average. Needless to say, it is the "best" in terms of explanatory power (R^2 = 0.424; R_a^2 = 0.393). Furthermore, the full model is also relatively superior in its ability to predict security returns, as indicated by the low PRESS statistic of 0.195. In this case, there does exist one model that is the "best" in terms of the selective criteria used in the present study.

The first principal component explains approximately 35 percent of the variation in the company variables. It is used as an independent variable--the company index--in estimating the four-factor return model. The average statistics indicate that the four-factor model is only able to explain about 29 percent of the variation in security returns. This is much worse than the explanatory power of the full model, a difference of 13 percent. Furthermore, the ability of the four-factor model to predict security returns (PRESS = 0.221) is not any better than that of the full model. Thus it may be concluded that the loss of information in the four-factor model is substantial, and the full model is the "best" return

Table 16: Average Statistics of Regression Models

Market-Related Systematic Risk - Market Model

Industry Classification: Three-Digit SIC Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.101	0.424	0.393	10.000	0.195	0.239	0.907	0.136
Submodel 1	0.101	0.414	0.386	10.775	0.196	0.251	0.889	0.131
Submodel 2	0.101	0.411	0.383	12.020	0.196	0.248	0.912	0.136
Submodel 3	0.101	0.412	0.383	11.958	0.197	0.253	0.902	0.134
Submodel 4	0.102	0.410	0.382	12.099	0.196	0.497	0.891	0.129
Submodel 5	0.102	0.400	0.375	12.935	0.197	0.242	0.902	0.134
Submodel 6	0.102	0.402	0.377	12.666	0.197	0.244	0.860	0.132
Submodel 7	0.103	0.394	0.343	15.378	0.199	0.244	0.917	0.138
Submodel 8	0.102	0.400	0.375	12.097	0.196	0.265	0.882	0.127
Submodel 9	0.102	0.397	0.372	13.924	0.196	0.269	0.840	0.132
Submodel 10	0.102	0.398	0.373	13.876	0.197	0.268	0.894	0.129
Submodel 11	0.103	0.383	0.361	16.213	0.200	0.245	0.904	0.135
Submodel 12	0.103	0.387	0.365	14.769	0.197	0.266	0.892	0.129
Submodel 13	0.103	0.388	0.367	14.506	0.197	0.265	0.881	0.126
Submodel 14	0.103	0.381	0.359	16.960	0.199	0.266	0.903	0.132
Submodel 15	0.104	0.371	0.353	17.723	0.200	0.263	0.891	0.129
Four-Factor	0.110	0.290	0.273	5.000	0.221	0.202	0.921	0.137

model in terms of both its explanation and its prediction of security returns.

REGRESSION ANALYSIS - MEAN REVERSION MODEL

The full model explains about 38.5 percent of the variation in security returns, on the average. Statistics of the full model (Table 17) indicate that the regression coefficient of market-related systematic risk is not significantly different from zero at the 0.05 level in all test periods. On the other hand, the industry factor, specific components of the company factor (dividend covariability and profitability), and the growth factor contribute significantly at a level of 0.05 to explaining security returns for at least three of the four test periods. These findings are consistent with the previous observation that the impact of the market factor and industry factor on security returns may be collaborative, and the market factor may be a surrogate measure of some fundamental characteristics of the individual company.

The same set of submodels has been examined to determine which is the "best" return model. The average statistics (Table 18) indicate that the full model explains the largest proportion of variation in security returns ($R^2 = 0.385$; $R_a^2 = 0.351$), and its ability to predict security returns, as indicated by the PRESS statistic, is also relatively better than the other submodels examined. The four-factor model explains only 25 percent of the variation in security returns, and there is no substantial

Table 17: Summary Statistics of Full Model

Market-Related Systematic Risk - Mean Reversion Model

Industry Classification: Three-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.081	-0.075	-0.112	-0.174
(t-value)	(-1.589)	(-1.466)	(-2.531)*	(-4.933)**
Regression Coefficients:				
β_i^m (10^{-2})	-0.032	-0.005	-0.003	0.350
(t-value)	(-0.102)	(-0.020)	(-0.010)	(1.938)
β_i^I (10^{-2})	0.877	0.651	0.482	0.266
(t-value)	(4.681)**	(3.241)**	(2.856)**	(1.634)
ABETA (10^{-2})	0.151	0.010	-0.022	-0.447
(t-value)	(2.430)*	(0.405)	(-0.818)	(-3.240)**
GMDOL (10^{-3})	0.108	-0.244	-0.107	0.945
(t-value)	(0.321)	(-0.687)	(-0.380)	(3.752)**
LEV (10^{-2})	1.043	0.571	0.157	0.205
(t-value)	(1.294)	(0.660)	(2.200)*	(2.703)**
DIVCO (10^{-2})	0.301	0.446	0.602	0.499
(t-value)	(3.446)**	(3.348)**	(3.189)**	(2.310)*
CFBETA (10^{-2})	-0.124	-0.157	-0.029	0.022
(t-value)	(-2.127)*	(-2.783)**	(-0.751)	(0.636)
PROFIT (10^{-1})	0.115	0.115	0.189	0.281
(t-value)	(2.514)*	(2.334)*	(4.887)**	(7.352)**
GR	0.115	0.192	0.124	0.086
(t-value)	(2.395)*	(3.971)**	(2.780)**	(1.925)
F-statistic	8.523	10.262	11.202	17.275
S_e^2(10^{-1})	0.115	0.113	0.092	0.097
R^2	0.317	0.359	0.379	0.485
R_a^2	0.280	0.324	0.345	0.457
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.248	0.244	0.167	0.179
MFE (10^{-2})	-0.093	0.221	0.493	-
MAFE (10^{-2})	0.946	0.863	0.909	-
MSFE (10^{-3})	0.149	0.124	0.133	-

* significant at the 0.05 level

** significant at the 0.01 level

Table 18: Average Statistics of Regression Models

Market-Related Systematic Risk - Mean Reversion Model

Industry Classification: Three-Digit SIC Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.104	0.385	0.351	10.000	0.209	0.269	0.906	0.135
Submodel 1	0.105	0.372	0.341	11.309	0.210	0.273	0.887	0.130
Submodel 2	0.105	0.372	0.342	11.564	0.209	0.273	0.917	0.138
Submodel 3	0.105	0.372	0.343	11.699	0.210	0.272	0.904	0.135
Submodel 4	0.105	0.370	0.339	12.309	0.210	0.242	0.890	0.128
Submodel 5	0.106	0.359	0.332	13.013	0.210	0.278	0.897	0.133
Submodel 6	0.106	0.360	0.333	12.933	0.211	0.277	0.885	0.129
Submodel 7	0.106	0.356	0.329	14.647	0.212	0.276	0.917	0.137
Submodel 8	0.106	0.357	0.330	13.552	0.211	0.247	0.872	0.123
Submodel 9	0.106	0.332	0.330	13.794	0.210	0.244	0.902	0.130
Submodel 10	0.106	0.359	0.332	13.678	0.211	0.248	0.888	0.127
Submodel 11	0.107	0.343	0.319	16.009	0.213	0.281	0.897	0.133
Submodel 12	0.107	0.344	0.321	15.190	0.211	0.249	0.883	0.126
Submodel 13	0.106	0.346	0.323	14.845	0.212	0.253	0.869	0.122
Submodel 14	0.107	0.342	0.319	16.431	0.213	0.249	0.901	0.130
Submodel 15	0.107	0.330	0.310	17.743	0.214	0.254	0.882	0.126
Four-Factor	0.113	0.248	0.230	5.000	0.232	0.220	0.915	0.136

improvement in its ability to predict security returns. Therefore, it can be concluded that the full model is the "best" return model according to the criteria used in the present study.

REGRESSION ANALYSIS - ORDER BIAS ADJUSTMENT MODEL

On the average, 38 percent of the variation in security returns is explained by the full model. The regression statistics of the full model (Table 19) are very similar to those observed when $\beta_i^m(MR)$ was used as the surrogate of market factor. Once again, the regression coefficient of market-related systematic risk is not significantly different from zero at the 0.05 level for any of the test periods. The regression coefficient of industry-related systematic risk remains positive and significant at the 0.05 level for three of the four test periods. Dividend covariability, profitability, and growth are found to contribute significantly at a level of 0.05 to explaining security returns in all four periods. This provides additional evidence that the industry factor, the company factor, and the growth factor each play a more crucial role than the market factor in explaining security returns. This is consistent with the earlier observation that the significance of the market factor may have been captured by other factors, as reflected in the t statistics of the model.

An examination of the average statistics of the full model and the

Table 19: Summary Statistics of Full Model

Market-Related Systematic Risk - Order Bias Adjustment Model

Industry Classification: Three-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.082	-0.076	-0.112	-0.153
(t-value)	(-1.796)	(-1.599)	(-3.048)**	(-4.924)**
Regression Coefficients:				
β_i^m (10^{-2})	-0.023	0.002	-0.000	0.187
(t-value)	(-0.102)	(0.009)	(-0.004)	(1.790)
β_i^I (10^{-2})	0.878	0.649	0.481	0.273
(t-value)	(4.626)**	(3.288)**	(2.936)**	(1.669)
ABETA (10^{-2})	0.152	0.010	-0.022	-0.457
(t-value)	(2.475)*	(0.401)	(-0.817)	(-3.302)**
GMDOL (10^{-3})	0.111	-0.244	-0.106	0.900
(t-value)	(1.295)	(-0.688)	(-0.381)	(3.540)**
LEV (10^{-2})	1.044	0.572	0.157	0.210
(t-value)	(1.295)	(0.659)	(2.192)*	(2.750)**
DIVCO (10^{-2})	0.301	0.446	0.602	0.528
(t-value)	(3.444)**	(3.354)**	(3.199)**	(2.458)*
CFBETA (10^{-2})	-0.124	-0.157	-0.029	0.025
(t-value)	(-2.127)*	(-2.787)**	(-0.750)	(0.720)
PROFIT (10^{-1})	0.115	0.157	0.189	0.279
(t-value)	(2.517)*	(2.330)*	(4.875)**	(7.288)**
GR	0.115	0.195	0.124	0.091
(t-value)	(2.393)*	(3.969)**	(2.787)**	(2.022)*
F-statistic	8.523	10.262	11.202	17.158
S_e^2(10^{-1})	0.115	0.113	0.092	0.097
R^2	0.317	0.359	0.379	0.483
R_a^2	0.280	0.324	0.355	0.455
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.249	0.248	0.175	0.181
MFE (10^{-2})	-0.093	0.221	0.493	-
MAFE (10^{-2})	0.947	0.863	0.908	-
MSFE (10^{-3})	0.149	0.124	0.132	-

* significant at the 0.05 level

** significant at the 0.01 level

fifteen submodels (Table 20) leads to the conclusion that the full model provides the most appropriate specification in explaining and predicting security returns. The full model provides the "best" explanation (R^2 = 0.384; R_a^2 = 0.355) and prediction of security returns (PRESS = 0.188). Statistics of the four-factor model indicate that there is a loss of 14 percent in its explanatory power as compared to the full model, and its prediction of security returns is never the best among all models examined. Therefore, the full model is the "best" return model among the set of models examined.

REGRESSION ANALYSIS - BAYESIAN ADJUSTMENT MODEL

The full model explains about 38 percent of the variation in security returns, on the average. Its regression statistics (Table 21) indicate that the coefficient of market-related systematic risk is not significantly different from zero at the 0.05 level for any of the four test periods. Industry-related systematic risk, however, has a significant positive impact (at a level of 0.05) in determining security returns in three of the four periods. The two company variables, dividend covariability and profitability, continue to play an important role in the determination of security returns in all periods. The regression coefficient of growth, however, is positive and significant at the 0.05 level in only three of the four test periods.

Table 20: Average Statistics of Regression Models

Market-Related Systematic Risk - Order Bias Adjustment Model

Industry Classification: Three-Digit SIC Code

	S_e^2 (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.104	0.384	0.355	10.000	0.188	0.269	0.906	0.135
Submodel 1	0.105	0.371	0.341	11.343	0.213	0.271	0.887	0.130
Submodel 2	0.105	0.372	0.341	11.619	0.213	0.272	0.917	0.138
Submodel 3	0.105	0.374	0.344	11.340	0.213	0.273	0.905	0.134
Submodel 4	0.105	0.369	0.338	12.463	0.214	0.243	0.890	0.128
Submodel 5	0.106	0.358	0.331	13.354	0.214	0.275	0.897	0.133
Submodel 6	0.105	0.361	0.334	12.594	0.214	0.308	0.885	0.129
Submodel 7	0.106	0.357	0.330	14.313	0.215	0.276	0.917	0.138
Submodel 8	0.106	0.356	0.329	11.751	0.215	0.313	0.871	0.123
Submodel 9	0.106	0.356	0.329	13.990	0.214	0.244	0.901	0.130
Submodel 10	0.106	0.359	0.332	13.519	0.214	0.251	0.888	0.127
Submodel 11	0.107	0.343	0.320	15.714	0.216	0.278	0.897	0.133
Submodel 12	0.107	0.343	0.319	15.648	0.215	0.247	0.883	0.126
Submodel 13	0.106	0.346	0.323	14.697	0.215	0.254	0.869	0.122
Submodel 14	0.107	0.342	0.319	16.306	0.216	0.257	0.900	0.130
Submodel 15	0.107	0.330	0.310	17.626	0.217	0.253	0.882	0.126
Four-Factor	0.113	0.248	0.230	5.000	0.237	0.214	0.915	0.136

Table 21: Summary Statistics of Full Model

Market-Related Systematic Risk - Bayesian Adjustment Model

Industry Classification: Three-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.073	-0.080	-0.122	-0.182
(t-value)	(-1.267)	(-1.444)	(-2.641)**	(-4.603)**
Regression Coefficients:				
β_i^m (10^{-2})	-0.111	0.044	0.102	0.386
(t-value)	(-0.300)	(0.144)	(0.334)	(1.730)
β_i^I (10^{-2})	0.893	0.638	0.459	0.304
(t-value)	(4.850)**	(3.218)**	(2.761)**	(1.920)
ABETA (10^{-2})	0.148	0.010	-0.021	-0.442
(t-value)	(2.377)*	(0.408)	(-0.777)	(-3.190)**
GMDOL (10^{-3})	0.098	-0.237	-0.098	0.969
(t-value)	(0.292)	(-0.665)	(-0.348)	(3.837)**
LEV (10^{-2})	1.042	0.570	0.158	0.201
(t-value)	(1.292)	(0.659)	(2.213)*	(2.637)**
DIVCO (10^{-2})	0.301	0.444	0.596	0.505
(t-value)	(3.442)**	(3.331)**	(3.155)**	(2.333)*
CFBETA (10^{-2})	-0.125	-0.156	-0.030	0.020
(t-value)	(-2.139)*	(-2.761)**	(-0.759)	(0.583)
PROFIT (10^{-1})	0.116	0.115	0.190	0.281
(t-value)	(2.536)*	(2.341)*	(4.921)**	(7.315)**
GR	0.115	0.195	0.123	0.083
(t-value)	(2.399)*	(3.962)**	(2.739)*	(1.843)
F-statistic	8.536	10.265	11.222	17.113
S_e (10^{-1})	0.115	0.113	0.092	0.097
R^2	0.318	0.359	0.380	0.483
R_a^2	0.281	0.324	0.346	0.455
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.247	0.243	0.166	0.179
MFE (10^{-2})	-0.088	0.223	0.478	-
MAFE (10^{-2})	0.946	0.861	0.900	-
MSFE (10^{-3})	0.149	0.123	0.130	-

* significant at the 0.05 level

** significant at the 0.01 level

A comparison of the full model with the submodels (Table 22) indicates that the full model not only explains the largest proportion of variation in security returns (R^2 = 0.384; and R_a^2 = 0.353), but also provides the "best" prediction of security returns (PRESS = 0.208). The explanatory power of the four-factor model is substantially less than that of the full model (a difference of 12 percent), and its prediction of security returns is not impressive when compared to the other models examined. Thus, it is appropriate to state that the full model exhibits the "best" explanation and prediction of security returns.

SYNTHESIS

For the sixteen full models examined (4 periods X 4 alternative estimates of market-related systematic risk), the regression coefficient of market-related systematic risk is not significantly different from zero at the 0.05 level in fourteen cases (β_i^m(OLS) is significant at the 0.05 level only in periods II and III). This means that in 87.5 percent of the cases, the market factor did not contribute significantly to explaining security returns. This is in contradiction with the literature. The most plausible explanation is that the market factor is strongly related to other return generating factors (e.g, industry factor) that its impact on security returns is captured and reflected in the significance of these factors. This issue is worth exploring because it is commonly believed that security return is determined by market risk only (see references on

Table 22: Average Statistics of Regression Models

Market-Related Systematic Risk - Bayesian Adjustment Model

Industry Classification: Three-Digit SIC Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.104	0.384	0.353	10.000	0.208	0.263	0.903	0.134
Submodel 1	0.105	0.371	0.341	11.278	0.209	0.269	0.884	0.129
Submodel 2	0.105	0.372	0.342	11.714	0.209	0.265	0.913	0.136
Submodel 3	0.105	0.372	0.342	11.843	0.210	0.266	0.901	0.143
Submodel 4	0.105	0.370	0.339	12.149	0.209	0.235	0.887	0.127
Submodel 5	0.106	0.359	0.332	12.905	0.210	0.272	0.894	0.132
Submodel 6	0.106	0.359	0.333	13.051	0.211	0.271	0.882	0.128
Submodel 7	0.106	0.356	0.329	14.711	0.212	0.269	0.913	0.136
Submodel 8	0.106	0.357	0.330	11.783	0.210	0.241	0.869	0.122
Submodel 9	0.106	0.358	0.331	13.561	0.210	0.236	0.899	0.129
Submodel 10	0.106	0.359	0.332	13.639	0.208	0.241	0.885	0.126
Submodel 11	0.107	0.317	0.319	16.020	0.213	0.274	0.894	0.132
Submodel 12	0.106	0.344	0.321	14.943	0.211	0.241	0.880	0.125
Submodel 13	0.106	0.346	0.323	14.800	0.211	0.246	0.866	0.121
Submodel 14	0.107	0.343	0.319	16.317	0.212	0.240	0.898	0.129
Submodel 15	0.107	0.330	0.310	17.627	0.213	0.246	0.880	0.125
Four-Factor	0.113	0.263	0.230	5.000	0.234	0.213	0.911	0.135

CAPM). Another possible explanation is the presence of multicollinearity which may cause an insignificance of a regressor variable in the model. The regression coefficient of industry-related systematic risk, however, is positive and significant at the 0.05 level in 68.75 percent of the cases. This strongly suggests that industry effect should not be ignored in evaluating security performance.

Two components of the company factor (dividend covariability and profitability) demonstrate consistent relationships with security returns. The regression coefficients of these two company variables are positive and significant at the 0.05 level in all models and across all periods examined. This implies that the dividend policy of a company has an influence on investors' beliefs with respect to the return generating power of the individual company. Furthermore, investors, as a group, evaluate companies with stable dividend policy more favorably (Van Horne [1980]). The significance of the accounting return measure (profitability) in determining security returns contributes to security analysts' reliance on quarterly accounting information when evaluating the performance of securities and portfolios.

The other components of the company factor (accounting beta, operating leverage, financial leverage, and cash flow beta) do not exhibit consistent relationships with security returns. The regression coefficient of accounting beta is positive and significant in period I, but negative and significant in period IV. Furthermore, although they are not always significantly different from zero, the regression coefficients indicate that the impact of operating leverage and financial leverage on security returns is positive, whereas for cash flow beta, the impact is in the opposite direction. In any case, the significance of these company variables in determining security returns is not consistent over time. This suggests that the market, as a whole, may not give serious attention to these risk attributes of a company when evaluating security performance.

The growth factor is one of the significant determinants of security returns, and its regression coefficient is positive and significant in 75 percent of the cases. This implies that the earning potential of a company can provide important information to investors in security analysis and in making portfolio decisions.

The average statistics of the models examined so far indicate that β_i^m(OLS) is a better surrogate of the market factor both in explaining and predicting security returns than β_i^m(MR), β_i^m(OB), and β_i^m(BA). When three-digit SIC codes are used for industry classification, it is possible to determine which is the "best" return model. Here, it is clear that the full model is the "best" in terms of its explanation and prediction of the security returns. In fact, the full model explains an additional 13 percent (on the average) of the variation in security returns when compared to the four-factor model. Besides its poor explanatory power, the four-factor model has relatively poor efficiency in predicting security returns. This is indicated by the predictive criteria (especially the PRESS statistics) used in the present study. Thus, the use of a company index in the four-factor model is not recommended, despite the high correlation among some of the company variables (Appendix F).

In summary, when three-digit SIC codes are used for industry classification, the results herein indicate that the market factor is not a significant determinant of security returns. On the other hand, the industry factor, components of the company factor (specifically, dividend covariability and profitability), and the growth factor all contribute significantly to explaining return on securities. Furthermore, a model can be identified which provides the "best" explanation and prediction of security returns and this is the full model.

Industry Classification - Two-Digit LOB Code

The statistical results on the use of SIC codes, both the two- and three-digit codes, in classifying companies into homogeneous groups were presented in the previous sections. A discussion on the the use of Line of Business information in industry classification is presented in the following sections.

Altogether 352 companies are included in the sample when two-digit LOB codes are used for grouping companies into related industries. The industry classification of these companies is shown in Appendix C.

The correlation statistics in Table 23 show strong associations among the four alternative estimates of market-related systematic risk. The associations are positive and significant at the 0.05 level except for the associations between β_i^m(OLS) and β_i^m(MR), and β_i^m(OLS) and β_i^m(OB) in period IV. These statistics agree with those found in the other industry classification schemes. The results are anticipated as β_i^m(MR), β_i^m(OB), and β_i^m(BA) are adjustments of the OLS estimate of market-related systematic risk from the market model.

The correlation statistics reported in Table 24 contain some interesting findings with respect to the relationship between security return and its determinants. The product moment correlation coefficients between β_i^m(OLS) and security returns are positive and significant at the 0.01 level across all test periods. The other estimates (β_i^m(MR), β_i^m(OB), and β_i^m(BA)) are also positively associated with security returns, and are significant at the 0.05 level in period IV. There is no clear evidence as to which estimate is a more appropriate surrogate of the market factor. Nevertheless, β_i^m(OLS) is preferred because its association with security returns persists across the four periods examined. A positive association also exists between industry-related systematic risk and security returns, and significant at the 0.01 level in all periods.

Table 23: Correlation Statistics Between Alternative Estimates of Market-Related Systematic Risk

Industry Classification: Two-Digit LOB Code

Period I (1976 - 79)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)
β_i^m(OLS) * **		0.435 (0.001)	0.429 (0.001)	0.406 (0.001)
β_i^m(MR)	0.287 (0.001)		0.845 (0.001)	0.958 (0.001)
β_i^m(OB)	0.253 (0.001)	0.817 (0.001)		0.676 (0.001)
β_i^m(BA)	0.293 (0.001)	0.963 (0.001)	0.648 (0.001)	

Period II (1977 - 80)

Period III (1978 - 81)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)
β_i^m(OLS) * **		0.238 (0.001)	0.202 (0.001)	0.250 (0.001)
β_i^m(MR)	0.097 (0.070)		0.811 (0.001)	0.940 (0.001)
β_i^m(OB)	0.049 (0.357)	0.822 (0.001)		0.585 (0.001)
β_i^m(BA)	0.132 (0.001)	0.944 (0.001)	0.607 (0.001)	

Period IV (1979 - 82)

* product moment correlation coefficient

** level of significance

Table 24: Correlation Statistics Between Security Return and Regressor Variables

Industry Classification: Two-Digit LOB Code

	Period I (1976-78)	Period II (1977-79)	Period III (1978-80)	Period IV (1979-82)
β_i^m(OLS) *	0.204	0.337	0.265	0.154
**	(0.001)	(0.001)	(0.001)	(0.004)
β_i^m(MR)	0.038	0.071	0.060	0.138
	(0.474)	(0.183)	(0.265)	(0.010)
β_i^m(OB)	0.060	0.062	0.020	0.135
	(0.261)	(0.241)	(0.708)	(0.012)
β_i^m(BA)	0.042	0.087	0.091	0.126
	(0.437)	(0.102)	(0.087)	(0.018)
β_i^I	0.292	0.206	0.170	0.214
	(0.001)	(0.001)	(0.001)	(0.001)
ABETA	0.262	0.111	-0.084	-0.271
	(0.001)	(0.038)	(0.116)	(0.001)
GMDOL	-0.099	-0.291	-0.262	-0.050
	(0.063)	(0.001)	(0.001)	(0.348)
LEV	0.025	-0.159	-0.224	-0.235
	(0.642)	(0.003)	(0.001)	(0.001)
DIVCO	0.176	0.244	0.264	0.190
	(0.001)	(0.001)	(0.001)	(0.001)
CFBETA	-0.157	-0.142	-0.160	0.079
	(0.003)	(0.008)	(0.765)	(0.142)
PROFIT	0.250	0.410	0.457	0.540
	(0.001)	(0.001)	(0.001)	(0.001)
GR	0.342	0.494	0.480	0.444
	(0.001)	(0.001)	(0.001)	(0.001)
Company Index	0.151	-0.350	-0.399	-0.392
	(0.152)	(0.001)	(0.001)	(0.001)

* product moment correlation coefficient

** level of significance

This implies that the industry factor may also play a significant role in

determining security returns. For the company variables, significant positive associations (at a level of 0.01) are found between dividend covariability and security returns, and between profitability and security returns. These findings are consistent with those reported in the other two cases. Accordingly, one would expect these two components of the company factor continue to play a significant role in the process of developing the "best" return model. The associations between other company variables (operating leverage, financial leverage, and cash flow beta) and security returns are negative and significant at the 0.01 level for at least two of the four test periods. These negative associations suggest that either these company variables do not capture the specific risk attributes of a company, or that investors, as a group, are conservative in evaluating these business risks of an individual company. The implications might be substantiated by more extensive research on the issue. For accounting beta, the association with security returns remains positive and significant at the 0.01 level in period I, but negative and significant at the 0.01 level in period IV. The possible causes for such findings have already been presented (see pp. 112-114).

Finally, growth in total assets is positively associated with security returns, with the correlation being significant at the 0.01 level in all four periods. This agrees with our earlier observations that the earning potential (or growth) of a company is a significant determinant of its return.

The statistics of the regression models, for each alternative estimate of market-related systematic risk, are presented in the following sections.

REGRESSION ANALYSIS - MARKET MODEL

The results resemble those obtained when the two-digit SIC code was used for industry classification. Statisitics of the full model, as given in Table 25, indicate that the regression coefficients of industry-related systematic risk, dividend covariability, profitability, and growth are significantly different from zero at the 0.01 level in all test periods. Market-related systematic risk, on the other hand, is significant at the 0.05 level in periods II and III. This agrees with the earlier findings that the role of the market factor in explaining security returns may not be as important as the other factors. As before, these five variables (β_i^m(OLS), β_i^I, DIVCO, PROFIT, and GR) will be included in further regression analyses in which a set of fifteen submodels is examined to determine the "best" return model.

Note that in Table 26, the full model explains about 40 percent of the variation in security returns, on the average. The average statistics

Table 25: Summary Statistics of Full Model

Market-Related Systematic Risk - Market Model

Industry Classification: Two-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.117	-0.123	-0.075	-0.077
(t-value)	(-3.743)**	(-4.192)**	(-3.029)**	(-3.358)**
Regression Coefficients:				
β_i^m (10^{-2})	0.101	0.648	0.293	-0.001
(t-value)	(0.749)	(4.432)**	(2.395)*	(-0.004)
β_i^I (10^{-2})	0.728	0.530	0.405	0.490
(t-value)	(5.588)**	(4.067)**	(3.377)**	(4.386)**
ABETA (10^{-2})	0.177	0.015	-0.007	-0.387
(t-value)	(4.426)**	(1.010)	(-0.393)	(-4.402)**
GMDOL (10^{-3})	1.660	-0.291	-0.015	0.943
(t-value)	(0.737)	(-1.364)	(-0.080)	(5.315)**
LEV (10^{-3})	1.500	0.153	0.104	0.234
(t-value)	(2.903)**	(0.304)	(0.240)	(0.521)
DIVCO (10^{-2})	0.316	0.430	0.538	0.467
(t-value)	(4.706)**	(4.310)**	(3.937)**	(3.272)**
CFBETA (10^{-2})	-0.140	-0.158	-0.031	0.024
(t-value)	(-2.838)**	(-3.483)**	(-0.945)	(0.881)
PROFIT (10^{-1})	0.116	0.098	0.109	0.199
(t-value)	(4.165)**	(3.600)**	(4.562)**	(8.037)**
GR	0.175	0.198	0.146	0.1011
(t-value)	(5.019)**	(5.755)**	(4.926)**	(3.420)**
F-statistic	21.335	28.226	21.474	31.474
S_{e^2}(10^{-1})	0.110	0.108	0.092	0.096
R^2	0.306	0.426	0.361	0.453
R_a^2	0.343	0.411	0.344	0.439
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.440	0.427	0.312	0.339
MFE (10^{-2})	-0.060	0.354	0.556	-
MAFE (10^{-2})	0.963	0.925	0.945	-
MSFE (10^{-3})	0.158	0.140	0.139	-

* significant at the 0.05 level

** significant at the 0.01 level

Table 26: Average Statistics of Regression Models

Market-Related Systematic Risk - Market Model

Industry Classification: Two-Digit LOB Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.101	0.397	0.384	10.000	0.379	0.323	0.944	0.145
Submodel 1	0.102	0.390	0.376	13.462	0.383	0.332	0.931	0.140
Submodel 2	0.102	0.395	0.381	10.211	0.379	0.327	0.939	0.142
Submodel 3	0.102	0.387	0.373	15.664	0.385	0.338	0.942	0.144
Submodel 4	0.103	0.382	0.368	18.033	0.387	0.339	0.914	0.133
Submodel 5	0.102	0.386	0.373	13.844	0.383	0.319	0.927	0.139
Submodel 6	0.103	0.378	0.363	18.956	0.388	0.328	0.932	0.141
Submodel 7	0.103	0.383	0.370	16.133	0.385	0.325	0.940	0.143
Submodel 8	0.103	0.373	0.360	21.284	0.391	0.324	0.904	0.130
Submodel 9	0.103	0.379	0.366	12.867	0.386	0.331	0.915	0.133
Submodel 10	0.104	0.373	0.357	19.321	0.392	0.329	0.914	0.133
Submodel 11	0.103	0.373	0.362	19.592	0.388	0.325	0.927	0.138
Submodel 12	0.103	0.369	0.358	21.157	0.390	0.325	0.903	0.129
Submodel 13	0.104	0.361	0.350	26.578	0.396	0.323	0.903	0.129
Submodel 14	0.104	0.367	0.356	23.271	0.391	0.330	0.914	0.132
Submodel 15	0.104	0.358	0.349	26.606	0.395	0.323	0.902	0.129
Four-Factor	0.108	0.309	0.301	5.000	0.421	0.255	0.924	0.140

of the estimated models indicate that the full model provides the maximum explanation of security returns ($R^2 = 0.397$; $R_a^2 = 0.384$). Submodel 2, on the other hand, has a relatively superior prediction of security returns, as indicated by MAFE and MSFE. A company index (the first principal component) was constructed for estimating the four-factor model. The index explains an average of 35 percent of the variation in the company variables. The average explanatory power of this four-factpr model is about 31 percent, and its ability to predict security returns is not substantially different from the other models examined. Thus, it may be concluded that when prediction is of major concern, submodel 2 is preferred to the full model, which has the "best" explanation of security returns.

REGRESSION ANALYSIS - MEAN REVERSION MODEL

The full model explains about 40 percent of the variation in security returns, on the average. Similar to the previous analysis, the statistics of the full model, as given in Table 27, indicate that industry-related systematic risk, dividend covariability, profitability, and growth contribute significantly at a level of 0.01 to explaining security returns in all four test periods. The regression coefficient of market-related systematic risk is significantly different from zero at the 0.01 level only in period IV. The other return generating factors--the industry factor, the company factor and the growth factor--have demonstrated greater importance in determining security returns than the market factor.

Table 27: Summary Statistics of Full Model

Market-Related Systematic Risk - Mean Reversion Model

Industry Classification: Two-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.092	-0.076	-0.069	-0.128
(t-value)	(-2.553)*	(-2.228)*	(-2.233)*	(-5.356)**
Regression Coefficients:				
β_i^m (10^{-2})	-0.152	-0.027	0.110	0.459
(t-value)	(-0.811)	(-0.163)	(0.574)	(3.890)**
β_i^I (10^{-2})	0.811	0.702	0.479	0.341
(t-value)	(6.707)**	(5.069)**	(3.919)**	(2.951)**
ABETA (10^{-2})	0.174	0.023	-0.004	-0.404
(t-value)	(4.327)**	(1.447)	(-0.227)	(-4.698)**
GMDOL (10^{-3})	1.218	-0.217	-0.035	0.992
(t-value)	(0.536)	(-1.444)	(-0.186)	(5.723)**
LEV (10^{-3})	1.502	0.217	0.116	0.281
(t-value)	(2.907)**	(0.421)	(0.267)	(0.640)
DIVCO (10^{-2})	0.308	0.441	0.536	0.471
(t-value)	(4.587)**	(4.296)**	(3.889)**	(3.389)**
CFBETA (10^{-2})	-0.143	-0.180	-0.035	0.027
(t-value)	(-2.902)**	(-3.860)**	(-1.057)	(0.994)
PROFIT (10^{-1})	0.117	0.105	0.110	0.203
(t-value)	(4.200)**	(3.746)**	(4.562)**	(8.367)**
GR	0.174	0.209	0.161	0.109
(t-value)	(4.968)**	(5.908)**	(5.422)**	(3.909)**
F-statistic	21.371	24.634	22.549	34.548
S_e^2 (10^{-1})	0.110	0.111	0.093	0.094
R^2	0.360	0.393	0.351	0.476
R_a^2	0.343	0.377	0.334	0.462
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.440	0.451	0.316	0.324
MFE (10^{-2})	-0.074	0.371	0.530	-
MAFE (10^{-2})	0.968	0.899	0.927	-
MSFE (10^{-3})	0.159	0.133	0.134	-

* significant at the 0.05 level

** significant at the 0.01 level

It is not surprising to find that the full model has the best explanatory power among all models examined (R^2 = 0.395; R_a^2 =0.379) (Table 28). However, there are no substantial differences in the predictive criteria among the sixteen models. Generally speaking, submodel 2 exhibits a relatively superior prediction of security returns (as indicated by the forecast errors), compared to the other models examined. The average statistics suggest a substantial loss in explanatory power of the four-factor model. Its explanatory power is approximately 75 percent of that of the full model, and its ability to predict security returns is not impressive (PRESS = 0.428). Thus, the four-factor model is not recommended for use in explaining the variation in security returns.

REGRESSION ANALYSIS - ORDER BIAS ADJUSTMENT MODEL

Similar to the analysis with β_i^m(MR), the regression coefficient of market-related systematic risk is only significantly different from zero at the 0.01 level in period IV only (Table 29). The other factors, which include industry-related systematic risk, dividend covariability, profitability, and growth, contribute significantly at a level of 0.01 in explaining the return on securities in all of the test periods.

The average explanatory power of the full model is about 39.3 percent (Table 30). It is the best of the sixteen models examined. None of the these models can be described as the "best" based on the predictive crite-

Table 28: Average Statistics of Regression Models

Market-Related Systematic Risk - Mean Reversion Model

Industry Classification: Two-Digit LOB Code

	S_{e^2} (10^{-1})	R^2	R^2_a	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.102	0.395	0.379	10.000	0.382	0.325	0.931	0.141
Submodel 1	0.103	0.383	0.369	14.356	0.387	0.327	0.917	0.136
Submodel 2	0.102	0.390	0.376	10.277	0.382	0.321	0.928	0.139
Submodel 3	0.103	0.381	0.367	16.788	0.389	0.330	0.931	0.141
Submodel 4	0.103	0.376	0.362	18.734	0.288	0.317	0.904	0.130
Submodel 5	0.103	0.379	0.366	14.847	0.381	0.324	0.912	0.134
Submodel 6	0.104	0.370	0.357	18.155	0.393	0.332	0.916	0.135
Submodel 7	0.103	0.376	0.364	17.297	0.389	0.327	0.927	0.139
Submodel 8	0.104	0.365	0.352	23.064	0.396	0.309	0.889	0.125
Submodel 9	0.103	0.373	0.361	15.369	0.390	0.316	0.904	0.129
Submodel 10	0.104	0.364	0.351	21.683	0.397	0.316	0.903	0.129
Submodel 11	0.104	0.365	0.354	21.622	0.394	0.329	0.911	0.133
Submodel 12	0.104	0.362	0.350	22.942	0.395	0.309	0.888	0.124
Submodel 13	0.105	0.353	0.341	28.469	0.401	0.312	0.887	0.124
Submodel 14	0.104	0.360	0.349	24.036	0.396	0.319	0.903	0.129
Submodel 15	0.105	0.349	0.340	29.114	0.401	0.311	0.888	0.124
Four-Factor	0.109	0.299	0.291	5.000	0.428	0.277	0.915	0.134

Table 29: Summary Statistics of Full Model

Market-Related Systematic Risk - Order Bias Adjustment Model

Industry Classification: Two-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.103	-0.085	-0.062	-0.100
(t-value)	(-3.166)**	(-2.701)**	(-2.451)*	(-5.209)**
Regression Coefficients:				
β_i^m (10^{-2})	-0.064	0.050	0.047	0.255
(t-value)	(-0.480)	(0.380)	(0.528)	(3.305)**
β_i^I (10^{-2})	0.798	0.675	0.483	0.351
(t-value)	(6.546)**	(4.888)**	(3.976)**	(2.989)**
ABETA (10^{-2})	0.177	0.022	-0.005	-0.399
(t-value)	(4.396)**	(1.423)	(-0.261)	(-4.609)**
GMDOL (10^{-3})	1.452	-0.312	-0.043	0.928
(t-value)	(0.645)	(-1.420)	(-0.228)	(5.337)**
LEV (10^{-3})	1.512	0.224	0.116	0.266
(t-value)	(2.926)**	(0.435)	(0.266)	(0.602)
DIVCO (10^{-2})	0.369	0.443	0.537	0.469
(t-value)	(4.596)**	(4.318)**	(3.896)**	(3.357)**
CFBETA (10^{-2})	-0.142	-0.178	-0.035	0.030
(t-value)	(-2.884)**	(-3.819)**	(-1.053)	(1.081)
PROFIT (10^{-1})	0.117	0.106	0.110	0.202
(t-value)	(4.193)**	(3.775)**	(4.561)**	(8.264)**
GR	0.175	0.210	0.161	0.107
(t-value)	(5.001)**	(5.935)**	(5.416)**	(3.837)**
F-statistic	21.297	24.655	20.541	33.693
S_e^2(10^{-1})	0.110	0.111	0.093	0.095
R^2	0.359	0.394	0.351	0.470
R_a^2	0.342	0.378	0.334	0.456
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.441	0.452	0.318	0.328
MFE (10^{-2})	-0.080	0.372	0.543	-
MAFE (10^{-2})	0.968	0.896	0.932	-
MSFE (10^{-3})	0.159	0.132	0.136	-

* significant at the 0.05 level

** significant at the 0.01 level

Table 30: Average Statistics of Regression Models

Market-Related Systematic Risk - Order Bias Adjustment Model

Industry Classification: Two-Digit LOB Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.102	0.393	0.377	10.000	0.384	0.331	0.932	0.142
Submodel 1	0.103	0.382	0.367	14.295	0.389	0.332	0.921	0.136
Submodel 2	0.102	0.386	0.374	10.292	0.384	0.328	0.929	0.139
Submodel 3	0.103	0.381	0.366	15.742	0.390	0.594	0.932	0.141
Submodel 4	0.103	0.375	0.362	18.664	0.393	0.320	0.904	0.130
Submodel 5	0.103	0.377	0.364	14.985	0.389	0.329	0.913	0.134
Submodel 6	0.104	0.370	0.357	19.822	0.394	0.337	0.918	0.136
Submodel 7	0.103	0.376	0.363	16.266	0.390	0.333	0.928	0.139
Submodel 8	0.104	0.363	0.350	22.904	0.398	0.311	0.890	0.125
Submodel 9	0.103	0.371	0.359	15.944	0.392	0.317	0.904	0.129
Submodel 10	0.104	0.363	0.350	20.741	0.398	0.322	0.903	0.129
Submodel 11	0.104	0.365	0.354	23.056	0.395	0.334	0.912	0.134
Submodel 12	0.104	0.360	0.349	22.803	0.397	0.310	0.889	0.124
Submodel 13	0.105	0.352	0.341	28.040	0.402	0.312	0.888	0.124
Submodel 14	0.104	0.360	0.348	23.596	0.398	0.321	0.903	0.129
Submodel 15	0.105	0.349	0.339	28.140	0.402	0.311	0.888	0.124
Four-Factor	0.109	0.299	0.291	5.000	0.429	0.247	0.912	0.133

ria employed in the present study. One can merely suggest that submodel 2 is slightly preferred in its prediction of security returns, as indicated by the low forecast errors. The four-factor model, on the other hand, explains about 30 percent of the variation in security returns, and its prediction of security returns (as reflected in the high PRESS statistic of 0.429) is inferior to the other models examined. Furthermore, there are no substantial differences in the forecast errors between the four-factor model and other models. Thus, the analysis indicates that the full model provides the best explanation of security returns, and that submodel 2 is preferred in terms of its ability to predict security returns.

REGRESSION ANALYSIS - BAYESIAN ADJUSTMENT MODEL

The full model explains about 39 percent of the variation in security returns, on the average. The t statistics (Table 31) indicate that the following variables--industry-related systematic risk, dividend covariability, profitability, and growth--continue to demonstrate their significant roles in determining security returns. The regression coefficient of market-related systematic risk, however, is significantly different from zero at the 0.05 level only in period IV. This agrees with the earlier proposition that the lack of significance of the market factor in determining the return model is attributed to its strong association with the industry factor, and that the market factor is a surrogate of certain

Table 31: Summary Statistics of Full Model

Market-Related Systematic Risk - Bayesian Adjustment Model

Industry Classification: Two-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.082	-0.074	-0.073	-0.140
(t-value)	(-2.049)*	(-1.969)*	(-2.280)*	(-5.209)**
Regression Coefficients:				
β_i^m (10^{-2})	-0.234	-0.047	0.147	0.511
(t-value)	(-1.022)	(-0.233)	(0.731)	(3.519)**
β_i^I (10^{-2})	0.819	0.705	0.475	0.379
(t-value)	(6.802)**	(5.127)**	(3.938)**	(3.327)**
ABETA (10^{-2})	0.173	0.023	-0.004	-0.400
(t-value)	(4.307)**	(1.446)	(-0.204)	(-4.626)**
GMDOL (10^{-3})	1.064	-0.324	-0.029	0.105
(t-value)	(0.465)	(-1.454)	(-0.156)	(5.762)**
LEV (10^{-3})	1.507	0.219	0.112	0.250
(t-value)	(2.922)**	(0.426)	(0.257)	(0.567)
DIVCO (10^{-2})	0.308	0.441	0.535	0.469
(t-value)	(4.095)**	(4.299)**	(3.890)**	(3.364)**
CFBETA (10^{-2})	-0.144	-0.180	-0.035	0.026
(t-value)	(-2.921)**	(-3.865)**	(-1.051)	(0.943)
PROFIT (10^{-1})	0.117	0.105	0.110	0.203
(t-value)	(4.219)**	(3.749)**	(4.562)**	(8.339)**
GR	0.173	0.209	0.160	0.105
(t-value)	(4.963)**	(5.909)**	(5.426)**	(3.752)**
F-statistic	21.438	24.639	20.584	33.990
S_e^2(10^{-1})	0.110	0.111	0.093	0.094
R^2	0.361	0.393	0.351	0.472
R_a^2	0.344	0.377	0.334	0.458
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.439	0.450	0.316	0.326
MFE (10^{-2})	-0.070	0.371	0.527	-
MAFE (10^{-2})	0.968	0.899	0.925	-
MSFE (10^{-3})	0.159	0.133	0.133	-

* significant at the 0.05 level

** significant at the 0.01 level

real variables of a company.

An examination of the average statistics, as given in Table 32, indicates that the full model continues to provide the best explanation of security returns ($R^2 = 0.394$; $R_a^2 = 0.378$). It appears that submodel 2 is slightly preferred to the other models in terms of its ability to predict security returns, as indicated by the low forecast errors. The explanatory power of the four-factor model is less than that of the full model by a difference of about 10 percent, on the average. Furthermore, its prediction of security returns is not substantially different from the other models examined. Thus, the full model is the best in terms of explanatory power, whereas submodel 2 is preferred in terms of its ability to predict security returns.

SYNTHESIS

Regardless of the estimate of market-related systematic risk used to determine the return model, the regression coefficients of industry-related systematic risk, dividend covariability, profitability and growth are significantly different from zero in all models across all test periods. This implies that the industry factor, specific components of the company factor (dividend covariability and profitability), and the growth factor are significant determinants of security returns. Furthermore, the regression statistics indicate that the impact of the market

Table 32: Average Statistics of Regression Models

Market-Related Systematic Risk - Bayesian Adjustment Model

Industry Classification: Two-Digit LOB Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.102	0.394	0.378	10.000	0.382	0.322	0.931	0.141
Submodel 1	0.103	0.382	0.368	14.366	0.387	0.325	0.917	0.136
Submodel 2	0.102	0.390	0.375	10.276	0.382	0.299	0.927	0.139
Submodel 3	0.103	0.380	0.366	16.887	0.389	0.327	0.930	0.141
Submodel 4	0.103	0.376	0.361	18.520	0.391	0.316	0.903	0.130
Submodel 5	0.103	0.378	0.365	14.852	0.388	0.322	0.912	0.133
Submodel 6	0.104	0.369	0.329	21.022	0.394	0.330	0.916	0.135
Submodel 7	0.103	0.375	0.363	17.376	0.389	0.324	0.927	0.138
Submodel 8	0.104	0.365	0.352	22.873	0.396	0.309	0.888	0.125
Submodel 9	0.103	0.373	0.360	15.937	0.390	0.316	0.903	0.129
Submodel 10	0.104	0.363	0.350	21.753	0.396	0.320	0.901	0.129
Submodel 11	0.104	0.364	0.353	21.708	0.394	0.327	0.911	0.133
Submodel 12	0.104	0.361	0.350	22.771	0.395	0.308	0.888	0.124
Submodel 13	0.105	0.352	0.341	28.924	0.401	0.312	0.887	0.124
Submodel 14	0.104	0.360	0.349	25.026	0.396	0.319	0.903	0.166
Submodel 15	0.105	0.349	0.339	29.004	0.401	0.477	0.887	0.124
Four-Factor	0.109	0.298	0.290	5.000	0.428	0.242	0.916	0.134

factor on security returns may not be as significant as the literature suggests. This again may be attributed to the strong association (Table 33) between market-related and industry-related systematic risks, and the likelihood that the market factor has incorporated some of the real characteristics (e.g, dividend policy and earnings potential) of each individual company.

None of the other components of the company factor (accounting beta, operating leverage, financial leverage, and cash flow beta) exhibit a consistent impact on security returns across all periods examined. For example, the regression coefficient of accounting beta is positive and significant in period I, but negative and significant in period IV. Moreover, the regression coefficient of operating leverage is positive and significant in period IV, whereas, that of financial leverage is positive and significant in period I. The lack of significance of these two variables in three of the four test periods suggests that investors may not have given serious considerations to these measures of risk in security analysis. Cash flow beta, on the other hand, exhibits negative and significant impact on security returns in periods I and II. This implies investors as a group may have responded conservatively to the variation of a company's cash flows with respect to those of the market.

Average statistics of the 68 models examined (4 full models, 60 submodels, 4 four-factor models) indicate that β_i^m(OLS) is the best of the

Table 33: Correlation Statistics Between

Market- and Industry-Related Systematic Risk

Industry Classification: Two-Digit LOB Code

	Period I (1976-78)	Period II (1977-79)	Period III (1978-80)	Period IV (1979-82)
β_i^m(OLS) *	0.538	0.305	0.365	0.104
**	(0.001)	(0.001)	(0.001)	(0.052)
β_i^m(MR)	0.343	0.397	0.375	0.325
	(0.001)	(0.001)	(0.001)	(0.001)
β_i^m(OB)	0.397	0.401	0.366	0.373
	(0.001)	(0.001)	(0.001)	(0.001)
β_i^m(BA)	0.322	0.378	0.346	0.267
	(0.001)	(0.001)	(0.001)	(0.001)

* product moment correlation coefficient

** level of significance

four alternative surrogates of the market-factor in explaining and predicting security returns. Results indicate that the full model, in all cases, provides the most explanation of security returns. Nonetheless, submodel 2 has subjective appeal when prediction of security returns is the major concern. The use of a company index with a four-factor model is not recommended because the explanatory power of the four-factor model is approximately 75 percent of the full model, and there is no strong evidence that its prediction of security returns is superior to the other models examined. Therefore, it is better to include company variables individually when estimating the return model than to use a company index.

In summary, the full model provides the best explanation of security returns, and submodel 2 is relatively superior in terms of its ability to predict security returns.

Industry Classification - Three-Digit LOB Code

The sample is made up of 199 companies. A breakdown of the sample companies into industries is presented in Appendix C.

As exhibited in Table 34, significant postive associations (at a level of 0.01) exist among the four alternative estimates of market-related systematic risk. This is because $\beta_i^m(MR)$, $\beta_i^m(OB)$, and $\beta_i^m(BA)$ are adjustments from $\beta_i^m(OLS)$.

Table 34: Correlation Statistics Between Alternative Estimates of Market-Related Systematic Risk

Industry Classification: Three-Digit LOB Code

Period I (1976 - 79)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)
β_i^m(OLS) * **		0.423 (0.001)	0.492 (0.001)	0.361 (0.001)
β_i^m(MR)	0.366 (0.001)		0.852 (0.001)	0.967 (0.001)
β_i^m(OB)	0.318 (0.001)	0.793 (0.001)		0.705 (0.001)
β_i^m(BA)	0.352 (0.001)	0.962 (0.001)	0.793 (0.001)	

Period II (1977 - 80)

Period III (1978 - 81)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)
β_i^m(OLS) * **		0.307 (0.001)	0.249 (0.001)	0.309 (0.001)
β_i^m(MR)	0.193 (0.007)		0.794 (0.001)	0.939 (0.001)
β_i^m(OB)	0.110 (0.123)	0.804 (0.001)		0.557 (0.001)
β_i^m(BA)	0.234 (0.001)	0.934 (0.001)	0.564 (0.001)	

Period IV (1979 - 82)

* product moment correlation coefficient

** level of significance

An examination of the correlation statistics in Table 35 reveals a significant association (at a level of 0.05) between market-related systematic risk and security returns. Among the four alternative estimates, β_i^m(OLS) exhibits a significant positive association (at a level of 0.01) with security returns in all test periods, whereas, for the other estimates, the association is significant at the 0.05 level for at least two of the four periods examined. These findings differ from the previous cases when different classification schemes were used. In the previous cases, the evidence showed β_i^m(OLS) to be a better surrogate of the market factor than the other estimates. There is, however, no convincing evidence to choose one of the four estimates of market-related systematic risk over the other three in this case. The results also indicate a significant positive association (at a level of 0.01) between industry-related systematic risk and security returns in all test periods. Thus, it appears that both the market factor and industry factor may be significant determinants of security returns, when the three-digit LOB code is used for classification.

For two components of the company factor, dividend covariability and profitability, the product moment correlation coefficients are significantly different from zero at the 0.01 level for all test periods, and their associations with security returns are positive. This implies that investors, as a group, prefer companies with relatively high profits and stable dividend policies. Also implied is that the accounting return mea-

Table 35: Correlation Statistics Between Security Return and Regressor Variables
Industry Classification: Three-Digit LOB Code

	Period I (1976-78)	Period II (1977-79)	Period III (1978-80)	Period IV (1979-82)
β_i^m(OLS) *	0.301	0.440	0.369	0.207
**	(0.001)	(0.001)	(0.001)	(0.003)
β_i^m(MR)	0.132	0.194	0.109	0.165
	(0.063)	(0.006)	(0.125)	(0.020)
β_i^m(OB)	0.148	0.140	0.055	0.154
	(0.038)	(0.048)	(0.125)	(0.029)
β_i^m(BA)	0.125	0.211	0.146	0.151
	(0.080)	(0.003)	(0.040)	(0.029)
β_i^I	0.322	0.209	0.211	0.274
	(0.001)	(0.003)	(0.003)	(0.001)
ABETA	0.249	0.106	-0.044	-0.238
	(0.001)	(0.137)	(0.536)	(0.001)
GMDOL	-0.073	-0.269	-0.279	-0.042
	(0.309)	(0.001)	(0.001)	(0.558)
LEV	0.016	-0.191	-0.205	-0.197
	(0.818)	(0.007)	(0.004)	(0.005)
DIVCO	0.164	0.247	0.304	0.252
	(0.020)	(0.001)	(0.001)	(0.001)
CFBETA	-0.166	-0.167	-0.070	0.028
	(0.019)	(0.018)	(0.323)	(0.699)
PROFIT	0.219	0.421	0.493	0.549
	(0.002)	(0.001)	(0.001)	(0.001)
GR	0.333	0.512	0.485	0.396
	(0.001)	(0.001)	(0.001)	(0.001)
Company Index	-0.031	-0.292	-0.373	-0.309
	(0.687)	(0.001)	(0.001)	(0.001)

* product moment correlation coefficient

** level of significance

sure (profitability) provides relevant information in evaluating security performance. For operating leverage, financial leverage, and cash flow beta, the associations with security returns are negative and significant at the 0.05 level for at least two of the four test periods. On the other hand, the association between accounting beta and security returns is positive and significant at the 0.01 level in period I, but negative and significant at the 0.01 level in period IV. These findings do not agree with the literature examined so far. Since the association has not been persistent over time, one might suspect that investors do not use these risk attributes when evaluating security returns. Alternatively, these so-called accounting risk measures may not capture the risk characterisitics of individual companies.

Finally, a significant positive association (at a level of 0.01) is found to exist between growth and security returns. This implies that the growth factor may also play a role in explaining the variation in security returns.

Statistical analyses of the regression models, for each alternative estimate of market-related systematic risk, are presented in the following sections.

REGRESSION ANALYSIS - MARKET MODEL

Summary statistics of the full model, as given in Table 36, indicate that the regression coefficient of market-related systematic risk is significantly different from zero at the 0.01 level for two of the four test periods. Industry-related systematic risk, on the other hand, is found to be significant at the 0.05 level in all four periods. Two components of the company factor (dividend covariability and profitability) also contribute significantly, at a level of 0.01, to explaining security returns in all test periods. The growth factor, is significant at the 0.05 level for three of the four test periods. These statistics indicate that these factors (a market factor, an industry factor, a company factor, and a growth factor) all help explain security returns. It appears that the industry factor and the growth factor are most crucial. Consequently, these variables (β_i^m(OLS), β_i^I, DIVCO, PROFIT, and GR) were included in further regression analyses.

The average explanatory power of the full model is 45 percent. In period II, the coefficient of determination is 0.496 which indicates that almost half of the variation in security returns is explained by the full model. Examination of the average statistics (Table 37) leads to the conclusion that the full model provides the best explanation of security returns (R^2 = 0.454; R_a^2 = 0.428), and submodel 2 is preferred when prediction (as indicated by MAFE and MSFE) is the major concern. The

Table 36: Summary Statistics of Full Model

Market-Related Systematic Risk - Market Model

Industry Classification: Three-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.147	-0.161	-0.126	-0.125
(t-value)	(-3.305)**	(-4.088)**	(-3.991)**	(-3.985)**
Regression Coefficients:				
β_i^m (10^{-2})	0.309	0.995	0.585	0.222
(t-value)	(1.838)	(5.275)**	(3.709)**	(1.132)
β_i^I (10^{-2})	0.749	0.375	0.369	0.557
(t-value)	(3.749)**	(2.184)*	(2.317)*	(3.831)**
ABETA (10^{-2})	0.163	0.012	-0.004	-0.479
(t-value)	(2.947)**	(0.621)	(-0.180)	(-3.880)**
GMDOL (10^{-3})	0.118	-0.226	-0.140	0.856
(t-value)	(0.367)	(-0.734)	(-0.581)	(3.571)**
LEV (10^{-2})	0.143	0.056	0.102	0.095
(t-value)	(1.756)	(0.775)	(1.659)	(1.392)
DIVCO (10^{-2})	0.345	0.430	0.682	0.626
(t-value)	(3.891)**	(3.725)**	(4.039)**	(3.259)**
CFBETA (10^{-2})	-0.121	-0.153	-0.053	0.006
(t-value)	(-1.993)*	(-3.022)**	(-1.531)	(0.189)
PROFIT (10^{-1})	0.100	0.117	0.154	0.229
(t-value)	(2.336)*	(2.943)**	(4.712)**	(6.538)**
GR	0.209	0.210	0.115	0.086
(t-value)	(4.305)**	(4.732)**	(2.772)**	(1.924)
F-statistic	12.835	20.694	17.529	20.059
S_e^2 (10^{-1})	0.113	0.102	0.086	0.095
R^2	0.379	0.496	0.455	0.489
R_a^2	0.350	0.472	0.429	0.464
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.271	0.219	0.163	0.194
MFE (10^{-2})	0.055	0.338	0.557	-
MAFE (10^{-2})	0.939	0.902	0.940	-
MSFE (10^{-3})	0.143	0.139	0.139	-

* significant at the 0.05 level

** significant at the 0.01 level

Table 37: Average Statistics of Regression Models

Market-Related Systematic Risk - Market Model

Industry Classification: Three-Digit LOB Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.099	0.454	0.428	10.000	0.211	0.316	0.934	0.140
Submodel 1	0.100	0.443	0.420	11.869	0.213	0.316	0.919	0.134
Submodel 2	0.099	0.448	0.425	10.093	0.211	0.329	0.932	0.138
Submodel 3	0.100	0.445	0.422	11.441	0.212	0.325	0.930	0.138
Submodel 4	0.100	0.437	0.413	14.039	0.214	0.340	0.909	0.130
Submodel 5	0.100	0.437	0.416	12.080	0.213	0.310	0.920	0.135
Submodel 6	0.103	0.409	0.413	13.300	0.216	0.305	0.920	0.135
Submodel 7	0.100	0.437	0.419	12.167	0.213	0.317	0.935	0.139
Submodel 8	0.101	0.426	0.405	15.842	0.217	0.339	0.899	0.128
Submodel 9	0.100	0.432	0.411	13.708	0.214	0.353	0.913	0.131
Submodel 10	0.101	0.427	0.406	15.542	0.215	0.351	0.909	0.130
Submodel 11	0.101	0.426	0.408	14.155	0.215	0.306	0.920	0.133
Submodel 12	0.101	0.421	0.402	15.621	0.216	0.341	0.900	0.127
Submodel 13	0.102	0.416	0.398	17.321	0.217	0.338	0.897	0.127
Submodel 14	0.101	0.421	0.403	15.750	0.215	0.349	0.911	0.130
Submodel 15	0.102	0.410	0.395	17.660	0.217	0.337	0.898	0.127
Four-Factor	0.107	0.365	0.327	5.000	0.238	0.215	0.907	0.131

four-factor model was also developed to see if a company index, in place of the individual company variables, would improve explanation and prediction of security returns. This company index (the first principal component) explains about 36 percent of the variation in company variables, on the average. The use of a company index reduces the explanatory power of the model by about 9 percent, as compared to the full model. In addition, its ability to predict security returns is not at all impressive.

In summary, it is concluded that the explantory power of the full model is the best, and submodel 2 is slightly superior in terms of the predictive criteria employed in the present study.

REGRESSION ANALYSIS - MEAN REVERSION MODEL

The full model explains about 43 percent of the variation in security returns. The Student's t statistics related to the coefficients of the full model (Table 38) indicate that industry-related systematic risk, dividend covariability, profitability and growth contribute significantly, at a level of 0.01, to determining the return model in all periods. The regression coefficient of market-related systematic risk, however, is found to be significantly different from zero at the 0.05 level in period IV only. It appears that the impact of the industry factor, company factor and growth factor have dominated those of the market factor.

Table 38: Summary Statistics of Full Model

Market-Related Systematic Risk - Mean Reversion Model

Industry Classification: Three-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.142	-0.126	-0.113	-0.146
(t-value)	(-2.732)**	(-2.654)**	(-2.695)**	(-4.420)**
Regression Coefficients:				
β_i^m (10^{-2})	0.309	0.338	0.241	0.354
(t-value)	(0.716)	(1.407)	(0.892)	(2.032)*
β_i^I (10^{-2})	0.900	0.580	0.546	0.463
(t-value)	(4.924)**	(3.110)**	(3.345)**	(2.997)**
ABETA (10^{-2})	0.182	0.023	0.002	-0.492
(t-value)	(3.327)**	(1.096)	(0.072)	(-4.028)**
GMDOL (10^{-3})	0.092	-0.187	-0.139	0.814
(t-value)	(0.284)	(-0.569)	(-0.557)	(3.424)**
LEV (10^{-2})	0.152	0.025	0.072	0.011
(t-value)	(1.845)	(0.327)	(1.130)	(1.618)
DIVCO (10^{-2})	0.341	0.469	0.666	0.571
(t-value)	(3.810)**	(3.823)**	(3.815)**	(3.010)**
CFBETA (10^{-2})	-0.123	-0.166	-0.059	0.005
(t-value)	(-2.000)*	(-3.045)**	(-1.667)	(0.160)
PROFIT (10^{-1})	0.102	0.114	0.149	0.233
(t-value)	(2.359)*	(2.682)**	(4.392)**	(6.690)**
GR	0.208	0.239	0.149	0.107
(t-value)	(4.243)**	(5.088)**	(3.583)**	(2.614)**
F-statistic	12.331	15.724	15.066	20.673
S_e^2(10^{-1})	0.114	0.108	0.089	0.094
R^2	0.370	0.428	0.418	0.494
R_a^2	0.340	0.401	0.390	0.472
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.273	0.249	0.174	0.191
MFE (10^{-2})	-0.048	0.374	0.508	-
MAFE (10^{-2})	0.964	0.876	0.915	-
MSFE (10^{-3})	0.152	0.125	0.130	-

* significant at the 0.05 level

** significant at the 0.01 level

The average statistics of the models examined are presented in Table 39. The full model provides the best explanation of security returns (R^2 = 0.427; R_a^2 = 0.400). Based on the predictive criteria used in this study, especially the forecast errors, it appears that submodel 2 appears to be better in predicting security returns. The explanatory power of the four-factor model is substantially less than that of the full model. The difference is 12 percent, on the average. In addition, there is no improvement in the ability of the four-factor model to predict security returns, as compared to the other models. Therefore, the use of a company index is not recommended in developing the return model.

REGRESSION ANALYSIS - ORDER BIAS ADJUSTMENT MODEL

The full model explains about 43 percent of the variation in security returns. Similar to the previous case, the t statistics of full model coefficients (Table 40) indicate that the industry factor, components of the company factor (dividend covariability and profitability), and the growth factor are significant at the 0.01 level in determining the return model in all periods. The regression coefficient of market-related systematic risk, however, is not significantly different from zero at the 0.05 level in any of the four periods. The minor influence of the market factor may be attributed to its strong association with the industry factor. Furthermore, the impact of the market factor on security returns may have been overshadowed by the significance of other variables, such as

Table 39: Average Statistics of Regression Models

Market-Related Systematic Risk - Mean Reversion Model

Industry Classification: Three-Digit LOB Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.101	0.427	0.400	10.000	0.221	0.309	0.955	0.135
Submodel 1	0.102	0.415	0.390	12.019	0.223	0.314	0.906	0.131
Submodel 2	0.102	0.422	0.398	9.851	0.221	0.306	0.918	0.134
Submodel 3	0.102	0.419	0.395	11.110	0.222	0.313	0.918	0.134
Submodel 4	0.103	0.407	0.382	14.978	0.226	0.308	0.890	0.124
Submodel 5	0.103	0.409	0.387	11.983	0.223	0.311	0.904	0.130
Submodel 6	0.103	0.407	0.385	13.107	0.224	0.317	0.905	0.130
Submodel 7	0.102	0.411	0.390	11.724	0.223	0.311	0.918	0.134
Submodel 8	0.104	0.394	0.372	17.039	0.228	0.294	0.877	0.120
Submodel 9	0.103	0.403	0.381	14.294	0.225	0.312	0.892	0.124
Submodel 10	0.103	0.399	0.377	16.040	0.226	0.305	0.889	0.123
Submodel 11	0.103	0.399	0.380	13.848	0.225	0.315	0.904	0.130
Submodel 12	0.104	0.390	0.371	16.452	0.227	0.298	0.878	0.120
Submodel 13	0.104	0.386	0.367	18.086	0.231	0.294	0.876	0.119
Submodel 14	0.103	0.393	0.374	16.006	0.211	0.310	0.891	0.124
Submodel 15	0.105	0.380	0.389	18.172	0.229	0.296	0.877	0.120
Four-Factor	0.110	0.311	0.297	5.000	0.249	0.232	0.888	0.125

Table 40: Summary Statistics of Full Model

Market-Related Systematic Risk - Order Bias Adjustment Model

Industry Classification: Three-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.139	-0.111	-0.097	-0.123
(t-value)	(-2.935)**	(-2.599)**	(-2.936)**	(-4.302)**
Regression Coefficients:				
β_i^m (10^{-2})	0.206	0.239	0.093	0.174
(t-value)	(0.876)	(1.339)	(0.803)	(1.666)
β_i^I (10^{-2})	0.879	0.584	0.555	0.483
(t-value)	(4.705)**	(3.126)**	(3.432)**	(3.110)**
ABETA (10^{-2})	0.182	0.023	0.001	-0.494
(t-value)	(3.259)**	(1.086)	(0.034)	(-4.029)**
GMDOL (10^{-3})	0.051	-0.247	-0.155	0.771
(t-value)	(0.158)	(-0.753)	(-0.625)	(3.189)**
LEV (10^{-2})	0.158	0.033	0.072	0.011
(t-value)	(1.906)	(0.430)	(1.137)	(1.627)
DIVCO (10^{-2})	0.342	0.472	0.668	0.578
(t-value)	(3.828)**	(3.851)**	(3.827)**	(3.040)**
CFBETA (10^{-2})	-0.124	-0.173	-0.060	0.005
(t-value)	(-2.028)*	(-3.192)**	(-1.687)	(0.146)
PROFIT (10^{-1})	0.104	0.115	0.149	0.231
(t-value)	(2.408)**	(2.718)**	(4.388)**	(6.630)**
GR	0.206	0.239	0.150	0.107
(t-value)	(4.215)**	(5.072)**	(3.587)**	(2.610)**
F-statistic	12.376	15.688	15.038	10.381
S_e (10^{-1})	0.135	0.108	0.089	0.095
R^2	0.371	0.428	0.417	0.493
R_a^2	0.341	0.400	0.390	0.468
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.275	0.250	0.176	0.193
MFE (10^{-2})	-0.052	0.348	0.535	-
MAFE (10^{-2})	0.966	0.875	0.925	-
MSFE (10^{-3})	0.152	0.125	0.133	-

* significant at the 0.05 level

** significant at the 0.01 level

dividend covariability, profitability, and growth.

The full model provides the best explanation of security returns in terms of both R^2 and R_a^2 (Table 41). Once again, submodel 2 appears to be relatively superior to the other models in terms of its ability to predict security returns, as indicated by the Mallow's C_p statistic and the forecast errors. The explanatory power of the four-factor model is only 73 percent of that of the full model, but its ability to predict security returns is slightly better than the full model and submodel 2 in terms of the forecast errors. Therefore, when prediction is the major concern, submodel 2 and the four-factor model (which exhibits low explanation) is preferred to the full model which provides the "best" explanation of security returns.

REGRESSION ANALYSIS - BAYESIAN ADJUSTMENT MODEL

The average explanatory power of the full model is about 43 percent. An examination of the summary statistics of the full model, as given in Table 42, indicates that the regression coefficients of industry-related systematic risk, dividend covariability, profitability, and growth are significantly different from zero at the 0.05 level in all test periods. The impact of the market-factor on security returns is significant at the 0.05 level in period IV only. These findings are very similar to those in the previous cases, and the impact of market factor on security returns does not appear to be as significant as the literature suggests.

Table 41: Average Statistics of Regression Models

Market-Related Systematic Risk - Order Bias Adjustment Model

Industry Classification: Three-Digit LOB Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.101	0.427	0.399	10.000	0.223	0.311	0.922	0.136
Submodel 1	0.102	0.413	0.389	12.292	0.225	0.313	0.910	0.132
Submodel 2	0.102	0.421	0.396	9.939	0.223	0.305	0.922	0.135
Submodel 3	0.102	0.419	0.395	10.788	0.223	0.315	0.922	0.136
Submodel 4	0.103	0.406	0.381	15.007	0.228	0.307	0.893	0.125
Submodel 5	0.103	0.407	0.385	12.355	0.226	0.307	0.907	0.131
Submodel 6	0.103	0.406	0.384	13.067	0.225	0.316	0.908	0.131
Submodel 7	0.102	0.413	0.389	11.486	0.224	0.310	0.922	0.135
Submodel 8	0.104	0.393	0.370	17.316	0.230	0.291	0.880	0.121
Submodel 9	0.103	0.402	0.380	14.376	0.227	0.310	0.895	0.126
Submodel 10	0.103	0.398	0.376	16.265	0.228	0.308	0.892	0.125
Submodel 11	0.103	0.397	0.378	13.890	0.226	0.312	0.906	0.130
Submodel 12	0.104	0.388	0.369	16.792	0.229	0.294	0.880	0.121
Submodel 13	0.104	0.385	0.366	18.048	0.230	0.292	0.879	0.121
Submodel 14	0.104	0.392	0.373	15.793	0.227	0.309	0.894	0.125
Submodel 15	0.105	0.379	0.363	18.198	0.230	0.293	0.879	0.121
Four-Factor	0.110	0.310	0.296	5.000	0.251	0.225	0.889	0.126

Table 42: Summary Statistics of Full Model

Market-Related Systematic Risk - Bayesian Adjustment Model

Industry Classification: Three-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-1})	-0.144	-0.140	-0.125	-0.158
(t-value)	(-2.468)*	(-2.671)**	(-2.810)**	(-4.235)**
Regression Coefficients:				
β_i^m (10^{-2})	0.203	0.428	0.332	0.417
(t-value)	(0.581)	(1.482)	(1.160)	(1.973)*
β_i^I (10^{-2})	0.913	0.587	0.539	0.490
(t-value)	(5.048)**	(3.198)**	(3.369)**	(3.261)**
ABETA (10^{-2})	0.181	0.024	0.003	-0.488
(t-value)	(3.209)**	(1.124)	(0.112)	(-3.995)**
GMDOL (10^{-3})	0.101	-0.156	-0.123	0.850
(t-value)	(0.308)	(-0.473)	(-0.492)	(3.577)**
LEV (10^{-2})	0.149	0.019	0.070	0.010
(t-value)	(1.812)	(0.243)	(1.109)	(1.491)
DIVCO (10^{-2})	0.339	0.468	0.670	0.578
(t-value)	(3.795)**	(3.821)**	(3.844)**	(3.046)**
CFBETA (10^{-2})	-0.123	-0.163	-0.058	0.006
(t-value)	(-1.989)*	(-2.967)**	(-1.637)	(0.179)
PROFIT (10^{-1})	0.101	0.112	0.148	0.232
(t-value)	(2.355)*	(2.654)**	(4.391)**	(6.666)**
GR	0.208	0.239	0.149	0.104
(t-value)	(4.237)**	(5.091)**	(3.573)**	(2.544)*
F-statistic	12.301	15.765	15.171	20.622
S_e^2(10^{-1})	0.114	0.108	0.089	0.094
R^2	0.369	0.429	0.418	0.496
R_a^2	0.339	0.402	0.392	0.471
C_p Statistic	10.000	10.000	10.000	10.000
PRESS (10^{-1})	0.273	0.248	0.173	0.191
MFE (10^{-2})	-0.046	0.379	0.500	-
MAFE (10^{-2})	0.963	0.877	0.911	-
MSFE (10^{-3})	0.151	0.125	0.129	-

* significant at the 0.05 level

** significant at the 0.01 level

From the average statistics of the models examined (Table 43), it can be concluded that the full model is the "best" in terms of its explanation of security returns ($R^2 = 0.428$; $R_a^2 = 0.401$), and submodel 2 is the "best" in predicting security returns, as indicated by the low PRESS statistic of 0.220. There is substantial loss in explanatory power when the company index is used in estimating the return model. The loss is about 12 percent from that of the full model, and there is no substantial improvement in the ability of the four-factor model to predict security returns. This implies that the "best" return model should have included the company variables as individual regressors in the model. In fact, the full model is the best in terms of its explanation of security returns, and submodel 2 provides the "best" prediction of security returns.

SYNTHESIS

Regardless of the approach used to estimate market-related systematic risk, the regression coefficients of industry-related systematic risk, dividend covariability, profitability, and growth are significantly different from zero in all models and in all test periods (with the exception of the growth variable in period IV), and their impact on security returns is positive. Market-related systematic risk, on the other hand, is only significant in four of the sixteen full models examined (4 periods X 4 estimates of market related systematic risk). This suggests that the impact of the market factor in determining security returns is not as sig-

Table 43: Average Statistics of Regression Models

Market-Related Systematic Risk - Bayesian Adjustment Model

Industry Classification: Three-Digit LOB Code

	S_{e^2} (10^{-1})	R^2	R_a^2	C_p	PRESS (10^{-1})	MFE (10^{-2})	MAFE (10^{-2})	MSFE (10^{-3})
Full Model	0.101	0.428	0.401	10.000	0.221	0.308	0.917	0.315
Submodel 1	0.102	0.416	0.391	11.867	0.223	0.313	0.906	0.131
Submodel 2	0.102	0.423	0.398	9.699	0.220	0.304	0.917	0.134
Submodel 3	0.102	0.419	0.394	11.589	0.221	0.311	0.916	0.134
Submodel 4	0.103	0.408	0.383	14.882	0.225	0.307	0.890	0.124
Submodel 5	0.102	0.410	0.389	11.662	0.222	0.310	0.904	0.129
Submodel 6	0.103	0.402	0.385	13.184	0.223	0.316	0.905	0.130
Submodel 7	0.102	0.412	0.390	11.773	0.222	0.308	0.916	0.134
Submodel 8	0.104	0.395	0.373	16.818	0.227	0.287	0.877	0.120
Submodel 9	0.103	0.404	0.382	14.105	0.224	0.310	0.891	0.124
Submodel 10	0.103	0.399	0.377	16.163	0.251	0.307	0.889	0.123
Submodel 11	0.103	0.399	0.381	13.733	0.226	0.314	0.903	0.129
Submodel 12	0.104	0.391	0.372	16.121	0.226	0.297	0.878	0.120
Submodel 13	0.104	0.386	0.367	18.095	0.228	0.293	0.877	0.119
Submodel 14	0.104	0.393	0.374	16.002	0.226	0.308	0.889	0.124
Submodel 15	0.104	0.381	0.365	18.044	0.228	0.295	0.877	0.120
Four-Factor	0.110	0.312	0.298	5.000	0.249	0.231	0.888	0.126

nificant as the other return generating factors. The insignificant role played by the market factor may be attributed to its strong association with industry-related systematic risk (see Table 44). In addition, as Simkowitz and Logue [1973] have suggested, the lack of significance may be a reflection of the fact that the market factor also incorporates certain real charateristics of the company.

The other components of the company factor--accounting beta, operating leverage, financial leverage, and cash flow beta--do not exhibit consistent roles in explaining security returns across the four test periods. The impact of accounting beta on security returns is positive and significant in period I, but negative and significant in period IV. Such inconsistent findings were addressed earlier (see pp. 134). The regression coefficient of operating leverage is significantly different from zero in period IV. No significant contribution to explaining security returns in any of the four periods could be attributed to financial leverage. This evidence suggests that investors do not require a higher return as a result of these business risk attributes of a company, and supports the portfolio theory that indicates that such residual risks are diversifiable, and no added return is required. The impact of cash flow beta on security returns, on the other hand, is negative and significant in periods I and II. Once again, the implications were discussed earlier (see p. 136).

Table 44: Correlation Statistics Between

Market- and Industry-Related Systematic Risk

Industry Classification: Three-Digit SIC Code

	Period I (1976-78)	Period II (1977-79)	Period III (1978-80)	Period IV (1979-82)
β_i^m(OLS) *	0.595	0.342	0.404	0.175
**	(0.001)	(0.001)	(0.001)	(0.014)
β_i^m(MR)	0.348	0.406	0.383	0.371
	(0.001)	(0.001)	(0.001)	(0.001)
β_i^m(OB)	0.439	0.404	0.356	0.382
	(0.001)	(0.001)	(0.001)	(0.001)
β_i^m(BA)	0.309	0.371	0.347	0.302
	(0.001)	(0.001)	(0.001)	(0.001)

* product moment correlation coefficient

** level of significance

An examination of the average statistics of the 68 models estimated (4 full models, 60 submodels, 4 four-factor models) leads to the conclusion that β_i^m(OLS) is the most appropriate surrogate of the market factor both in explaining and predicting security returns. When three-digit LOB code is used for industry classification, the full model explains as much as 43 percent of the variation in security returns, on the average. The four-factor model is the least powerful in terms of explaining security returns, and its ability to predict security returns is not substantially better than that of the full model. Thus, it may be concluded that including company variables as individual regressors in the return model yields superior explanation and prediction of returns to the use of an index to represent the fundamental characteristics of a company.

Finally, the results indicate that the full model provides the best explanation of security returns. Based on the predictive criteria, no conclusion can be made with respect to which model provides the best prediction of security returns. The use of a little judgement leads to the decision that submodel 2 is preferred in terms of its prediction of security returns to the other models examined, as indicated by the relatively low forecast errors.

SIGNIFICANCE OF FINDINGS

The results of the present study provide answers to the following questions: First, which alternative estimate of market-related systematic risk is most appropriate in explaining and predicting security returns? Second, which industry classification scheme should be used in examining the effect of an industry factor on security returns? Third, is the use of a company index in developing the multifactor return model beneficial? Fourth, what are the factors that are significant in determining the multifactor return model? The findings are summarized below in an effort to address the above questions.

Alternative Estimates of Market-Related Systematic Risk

Within each industry classification scheme, 272 models were estimated (4 alternative estimates of market-related systematic risk X 17 regression models X 4 periods). Regardless of which classification scheme is used, the regression coefficient of market-related systematic risk is significant at the 0.05 level about 50 percent of the time when the market model is used to provide a surrogate measure of the market factor. When two-digit codes (SIC and LOB) are used to group companies into industries, estimates of market-related systematic risk from the other models (mean reversion model, order bias adjustment model, Bayesian adjustment model) are significant approximately 25 percent of the time; and when three-digit codes are used, less than 10 of the total 272 models indicate a significant coefficient for these estimates of market-related systematic risk. As a result, it appears that the OLS market model provides a better surrogate measure of the market factor. That is, β_i^m(OLS) is superior to the other three estimates in explaining and predicting security returns.

An examination of the average statistics indicates that when the OLS market model is used to provide a surrogate measure of the market factor, its explanation of security returns is superior to those provided by the other three models. In fact, in 66 of the 68 cases (4 industry classification schemes X 17 regression models), the use of β_i^m(OLS) as one of the regressor variables provides the greatest explanation of security returns.

Both β_i^m(OLS) and β_i^m(BA) demonstrate better performance than the other two estimates in predicting security returns. For the two statistical criteria used in the present study (Mallow's C_p statistic and PRESS), β_i^m(OLS) has the lowest value in a majority of the cases. When forecast errors are evaluated, β_i^m(BA), however, provides the most accurate prediction of security returns. As was noted earlier, there is no substantial difference in these predictive criteria, especially forecast errors,[49] among all the models examined. Thus, it may be concluded that

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[49] There is no substantial difference in the predictive criteria among all the models examined. Forecast errors, especially, should not be given much weight in deciding which model has the best ability to predict security returns because the magnitude of these forecast errors is very small (e.g., mean forecast error is in the magnitude of 10^{-2}) as compared to Mallow's Cp statistic and PRESS.

β_i^m(OLS) is preferred to β_i^m(BA) and other estimates of market-related systematic risk in terms of predicting security returns.

The findings are therefore consistent with respect to which estimation model provides the most appropriate surrogate measure of the market factor: the OLS market model provides the best estimate of market-related systematic risk when the objective is to examine the effect of a market factor on security returns.

<u>Industry Classification Scheme</u>

The impact of an industry factor on security returns is measured by the so-called industry-related systematic risk, which is developed in the present study to reflect the responsiveness of a security's return to that of its industry. The industry-related systematic risk of a company changes as the definition of an industry changes. Therefore, four industry classification schemes have been used in the analyses to determine which is the best multifactor return model.

For three of the four classification schemes--two-digit SIC code, two-digit LOB code and three-digit LOB code--the regression coefficient of β_i^I is significant at the 0.05 level for all models examined. The only exception is that for the three-digit SIC code, 23 of the 272 models examined (4 estimates of market-related systematic risk X 17 regression models

X 4 periods) have a regression coefficient of β_i^I that is not significantly different from zero at the 0.05 level. That is, in over 98 percent of all models estimated (1065 out of a total of 1088) β_i^I was found to be significant. Thus, the impact of an industry factor on security returns is significant, but further analysis is necessary in order to determine which classification scheme is the most appropriate. However, it is necessary to note that a comparison across industry classification schemes is subject to the limitation of using different samples in constructing the return model, although one is a subsample of the other.

The average statistics of the regression models can be examined in detail to determine which classification scheme is the best. When the average statistics were compared across industry classification schemes, the return models estimated under the three-digit LOB code provided the greatest explanation of security returns both in terms of both R^2 and R_a^2. Ambiguity, however, exists with respect to which classification scheme provides a better prediction of security returns. In general, return models estimated under the three-digit SIC code and three-digit LOB code have similar values in their C_p statistics. These are better than those of the other classification schemes. An examination of the PRESS statistic indicates that the three-digit LOB code is a preferable scheme of grouping companies into homogeneous groups. For the three measures of forecast error used in the present study, return models estimated under the three-digit SIC code provide a better prediction of security returns in terms of the mean forecast error (MFE) and mean absolute forecast error (MAFE), whereas three-digit LOB code is preferred when mean square forecast error (MSFE) is the predictive criterion employed. Thus, the use of three-digit codes is better than two-digit codes in determining the multifactor return model. Further, the evidence indicates that three-digit LOB code is better when the objective is to explain the variation in security returns; however, no clear-cut statement can be made with respect to which classification scheme (three-digit SIC versus three-digit LOB) is better when prediction of security returns is the major interest. Nonetheless, because forecast errors should not be weighted as heavily as the C_p and PRESS statistics (see footnote 49), the use of three-digit LOB code is recommended for constructing an industry factor for the security return model.

Company Index versus Company Variables

Six accounting variables (ABETA, GMDOL, LEV, DIVCO, CFBETA, PROFIT) were constructed to represent the fundamental characteristics of an individual company. Also, a principal component analysis was performed on these variables to provide an index for the company. This company index (the first principal component) was included as an independent variable in a separate four-factor return model. Regardless of which industry classification scheme is used, the company index explains about 35 percent of the variation in company variables, on the average.

The average statistics indicate that the four-factor model is inferior to the full model in terms of explanatory power, with a difference magnitude ranging from a low of 8 percent to a high of 14 percent, depending on the combination of the market-related systematic risk and industry classification scheme used. This substantial loss in explanatory power in the four-factor model may be attributed to its relatively small number of regressor variables. Submodel 15 [RETURN = f(β_i^m, β_i^I, DIVCO, PROFIT, GR)] has the least number of regressor variables among all the submodels examined, and it explains an additional 5 to 8 percent of the variation in security returns as compared to the four-factor model. This evidence suggests that the small number of regressor variables in the four-factor model may not totally account for its low explanatory power. Another possible reason is that the company index may not have captured the essential attributes of a company, since the first principal component explains about only 35 percent of the variation in the company variables.

In terms of the predictive criteria used in the present study, the ability of the four-factor model to predict security returns is relatively poor. Mallow's C_p statistic cannot be used for comparison purposes because its value for any "full model" always equals one plus the number of regressor variables included in the model. Consequently, the C_p statistic for the four-factor model always equals 5.000, and that for the full model is 10.000. Therefore, the decision is based on the PRESS statistic and forecast errors. Regardless of which estimate of market-related systematic risk and industry classification scheme are used, the PRESS statistic (averaged across periods) is highest for the four-factor model. The mean forecast error, on the other hand, indicates that the four-factor model is preferred in terms of its ability to predict security returns. Conversely, the other forecast errors (mean absolute forecast error and mean square forecast error) of the four-factor model are not at all superior to the other models examined. By and large, it can be stated that the four-factor model does not yield superior prediction of security returns in comparison to the other models examined.

Therefore, the use of a company index in determining the multifactor return model is not recommended. It is better to include such company variables as individual regressors in developing the return model, even though some company variables may not contribute significantly toward explaining and predicting security returns.

Multifactor Return Model

From the previous section, "Statistical Findings and Results", the evidence is clear as to which model provides the best explanation of security returns. The full model outperforms the other models in explaining the variation in security returns in all 16 different situations (4 estimates of market-related systematic risk X 4 industry classification schemes). Its average explanatory power (R^2), across periods, ranges from a low of 36 percent to a high of 45 percent.

As was indicated earlier, submodel 2 [RETURN = f(β_i^m, β_i^I, ABETA, GMDOL, DIVCO, CFBETA, PROFIT, GR)] is competitive with the full model in explaining and predicting security returns. Obviously, the full model still provides the best explanation of security returns. The explanatory power of submodel 2, on the other hand, is about 1 percent less than that of the full model. Thus, it is difficult to make a decision between the full model and submodel 2. An examination of the predictive criteria indicates that both the average C_p and PRESS statistics of the full model are less than that of submodel 2 for at least 11 of the 16 cases. The forecast errors, on the other hand, favor submodel 2. In considering all these findings, it is concluded that the full model is the "best" return model in terms of both its explanation and its ability to predict security returns.

Regression test statistics for the full model indicate that industry-related systematic risk, dividend covariability, profitability, and growth are significant determinants of security returns. In addition, when β_i^m(OLS) is used in estimating the return model, market-related systematic risk is significant in explaining security returns. Thus it can be concluded that a market factor, an industry factor, a company factor (especially, dividend covariability and profitability), and a growth factor are all significant in developing the multifactor return model.

Use of Quarterly Accounting Information

In this research, quarterly accounting information is used in measuring components of both the company factor as well as the growth factor. It is vital to relate the above results to the use of interim financial statement data in security analyses.

Generally, the impact of some company variables (ABETA, GMDOL, LEV, and CFBETA) on security returns is insignificant. One possible explanation for the findings of insignificance is attributable to the presence of multicollinearity; however, correlation statistics also indicate insignificant associations between these company variables and security returns for at least two of the four test periods. Thus, the effect of multicollinearity on significance of regressor variables may not be as serious as one might think. It is probable that the use of quarterly accounting information in measuring these variables may account for these insignificant findings. Further research is needed to explore the potential problems of using quarterly accounting information.

On the other hand, specific components of the company factor (dividend covariability and profitability) and the growth factor (compound growth in total assets) are found to contribute significantly to explaining security returns. These findings suggest that quarterly accounting information can be useful in developing a multifactor return model. More empirical studies are needed to substantiate the findings of the present study, especially with respect to the potential use of interim financial statement data in security analysis and portfolio management.

Some concluding remarks and implications of findings will be presented in the next chapter. In addition, limitations in research methodology as well as opportunities for future research are discussed in the final chapter.

CHAPTER V

CONCLUSION AND LIMITATIONS

CONCLUSIONS

Application of the CAPM is base on the implicit assumption that a linear relationship exists between security returns and their market-related systematic risk. This proposition is supported by empirical evidence (Fama and MacBeth [1973]). Other studies (e.g., King [1965], Livingston [1973], Roll and Ross [1980], Pari [1980]), however, indicate that other factors are significant determinants of the security return generating process. On the basis of these empirical works, the primary hypothesis of the present study, in its null form, is as follows:

HYPOTHESIS: The addition to the return model of an industry factor, a company factor, and a growth factor does not contribute significantly to explaining and predicting security returns.

In general, the findings of this study are that the inclusion of of these return generating factors (an industry factor, a company factor and a growth factor) significantly improves the return model's power to explain and predict security returns. The impact of these return generating factors, including the market factor, on security returns is discussed in the following sections.

Market Factor

When the market factor alone is included in the return model, its explanatory power (R^2) ranges from a low of 1 percent to a high of 20 percent, depending on the model used to provide an estimate of market-related systematic risk and the industry classification scheme being used. In general, β_i^m(OLS) outperforms other estimates in explaining generation of security returns. When more regressor variables are included in the model, the explanatory power of the model increases, as expected. The maximum explanation provided by the full model is close to 50 percent when three-digit LOB codes are used to classify companies into industries. This substantial increase in explanatory power, from 20 to 50 percent, implies that the market factor alone does not sufficiently explain the generation of security returns. Furthermore, when other variables are included in the return model, market-related systematic risk is frequently insignificant. Therefore, the impact of the market factor on security returns is not as significant as the literature suggests.

One possible explanation for such a phenomenon is that market-related and industry-related systematic risks are so strongly correlated that their impact on security returns is collaborative. Moreover, in most cases, the significance of the industry factor has overshadowed that of the market factor. In addition, as Simkowitz and Logue [1973] suggest,[50] market-related systematic risk is a surrogate for certain real variables of a company, such that its contribution may be reflected in the significance of other company variables included in the return model. Furthermore, measurement errors in computing the market-related systematic risk of a company may also diminish its significance in explaining security returns.

There is a general consensus that the ordinary least squares (OLS) estimate of market-related systematic risk tends to regress towards its overall mean, which is a value of one. As a consequence, adjustment models (mean reversion model, order bias adjustment model, Bayesian adjustment model) were developed to provide better forecasts of the market-related systematic risk of each individual company. Klemkosky and Martin [1975] found that Blume's and Vasicek's adjustment models provide better forecasts than the OLS estimate of market-related systematic risk. Similar findings were reported by Elton, Gruber and Urich [1978] and Eskew [1979]. These results could be challanged. It is understood that the "true" market-related systematic risk is unobservable. Consequently, "forecast accuracy" of market-related systematic risk cannot be assessed

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[50] Simkowitz, Michael A., and Dennis E. Logue. "The Interdependent Structure of Security Returns," Journal of Financial and Quantitative Analysis, March 1973, p. 264.

when determining which adjustment model is the best. In the present study, "explanation and prediction of security returns" is the criterion employed in evaluating the performance of these adjustment models. The latter approach is preferred because security return is both a readily available measure and of major concern to security analysts. For all return models estimated in the present study, $\beta_i^m(OLS)$ performs better than the other estimates of market-related systematic risk in explaining and predicting security returns. These results are attributed to larger estimation errors encountered in computing $\beta_i^m(MR)$, $\beta_i^m(OB)$ and $\beta_i^m(BA)$. Since there is a difference in findings between the present study and others, further research appears appropriate to determine which model provides a better surrogate of the market factor. Based on this study, the conclusion is that the market model provides a better estimate of market-related systematic risk when the objective is to explain and predict security returns.

Industry Factor

The impact of the industry factor on security returns is more consistent from one return model to another in comparison to the market factor. When industry-related systematic risk is included in the return model alone, its explanatory power (R^2) is 10 percent on the average. Its contribution to the various multiple regression models is evidenced by the regression coefficients that are significantly different from zero at the

0.05 level in over 98 percent of the models examined. Thus, there is no reason to question the significance of the industry factor in explaining security returns.

This observation is consistent with most empirical studies (King [1965], Nerlove [1968], Livingston [1973]), which report that industry-related factors play a significant role in explaining variation in stock prices and security returns. King found that the industry effect accounts for 10 percent of changes in stock prices, whereas Livingston reported an 18 percent increase after including the industry factor in explaining security returns in some industries. Furthermore, in a study by Nerlove, the use of industry dummy variables improved the explanatory power of the estimated return model by about 10 percent.

In the present study, the explanation provided by the industry factor (in addition to the market factor) ranges from a low of 1 percent to a high of 9 percent, depending on the estimate of market-related systematic risk and the industry classification scheme being used. For the 17 models (full model, 15 submodels, four-factor model) examined, the additional explanation prpvided by the industry factor ranges from a low of 1 percent to a high of 14 percent. Its improvement in explaining security returns is the greatest with respect to the four-factor model. Therefore, it is concluded that the industry factor is a significant determinant of security returns.

The three-digit LOB code should be used to group companies into industries to investigate the impact of the industry factor on security returns. This observation agrees with the results reported in the literature. For example, Fertuck [1975] concluded that the use of the three-digit code is preferred to the two-digit code when examining the effect of an industry on security returns, even though the two-digit code is commonly used in empirical studies. Also, Foster [1981] recommended the use of Line of Business (LOB) information in classifying companies into homogeneous groups. Both authors conclude that the two-digit SIC code is inadequate for studying industry effect.

In this study, the three-digit LOB code is the most reliable of the four schemes compared. One might suspect that a four-digit code would be even better. The limitation of using four-digit codes is that they are so restrictive. That is, the number of companies included in each four-digit industry is so small that it drastically limits the number of industries included in a study and in turn the generalizability of the findings. Therefore, the three-digit LOB code is submitted as the best scheme for surrogating the impact of an industry factor on security returns. It is important to note that the use of different samples across industry classification schemes may limit the interpretation of the results, although the adjusted coefficient of determination (R_a^2) has accounted for the difference in sample size from one classification scheme to another.

Company Factor

The company factor is made up of six company variables (ABETA, GMDOL, LEV, DIVCO, CFBETA, PROFIT). These company variables were selected to describe the risk attibutes and profitability of a company.

Among these six company variables, dividend covariability and profitability contribute significantly to explanation of security returns. Nerlove [1968] found that the variable "dividend to total assets" is significant in explaining the variation in security returns, even though its regression coefficient was low compared to other significant variables. Simkowitz and Logue [1973] and Lee and Zumwalt [1981] also investigated the impact of dividend policy on security returns. In their studies, the "change in dividends to book value of equity" was used as a surrogate for dividend policy. In both studies, the dividend policy was found to contribute significantly to explanating security returns, even though the impact was usually negative. Lee and Zumwalt proposed that multicollinearity among regressor variables may have caused the significant negative correlation.

In the present study, dividend covariability was used to reflect the dividend policy of a company. The findings indicate that dividend policy has a positive impact on security returns, implying that investors, as a group, prefer a stable dividends stream. These differences in findings may be attributed to the definition of dividend policy as covariability in the present study.

The accounting return measure (profitability) was found to exhibit a significant positive relationship with security returns. Such a relationship was also reported by Simkowitz and Logue, and Lee and Zumwalt. This evidence should be of interest to the accounting profession because it supports the use of quarterly accounting information in security analysis, and because accounting return is found be to a reliable surrogate for the return on a security.

The regression coefficient of accounting beta was found to be positive and significant at the 0.05 level in period I, and negative and significant at the 0.05 level in period IV. These findings are inconsistent with previously reviewed results. First, the CAPM is based on an assumed positive linear relationship between security return and market-related systematic risk. Second, Bowman [1979] demonstrated that there is a positive theoretical association between a company's market-related systematic risk and its accounting beta. Based on these theoretical works, one would hypothesize a positive relationship between security return and accounting beta. This hypothesis was rejected in test periods II, III and IV in the present study. Worse yet, a negative relationship between security returns and accounting beta was found in period IV.

There are several possible causes for such findings. First, the use of quarterly accounting information may have distorted the relationship between security return and accounting beta. This result may be attributed to the seasonality of quarterly earnings used in computing accounting beta. Second, accounting beta is one of the many determinants of market-related systematic risk. It is possible that in some periods other determinants contribute more significantly to explaining market-related systematic risk. In that event, the relationship between accounting beta and market-related systematic risk becomes insignificant, as does the relationship between accounting beta and security returns. Third, multicollinearity among the regressor variables may have resulted in a negative coefficient for accounting beta. Fourth, the definition of accounting beta is dependent on the sample; or, more specifically, the computation of the earnings-price ratio for the market is dependent on the sample. This may affect the findings of this research. These are some possible explanations for observating such an unstable relationship between accounting beta and security returns in the present study. More research is needed for a definitive conclusion about the impact of accounting beta on security returns.

Operating leverage and financial leverage constitute the business risk of a company. These company variables had a significant positive impact (at a level of 0.01) on security returns in only one of the four test periods. On the basis of theoretical works by Lev [1974], Percival

[1974], Ramada [1972], and Bowman [1979], positive relationships between market-related systematic risk and operating leverage, and financial leverage were hypothesized. Accordingly, it was anticipated that operating leverage and financial leverage would have positive impacts on security returns. The findings herein provide some support for that hypothesis; however, they are not consistent across the four test periods. This implies that business risk as measured by these variables may not be a significant determinant of security returns. Additional research on the issue is recommended, because the insignificant findings of the present study may be attributed to the use of quarterly accounting information and the operational definitions of these company variables.

Finally, cash flow beta is found to have a significant negative impact on security returns (at a level of 0.01) in test periods I and II. Intuitively, cash flow from operations should be a determinant of the return on a company, and the association should be positive. In the present study, cash flow beta was used in lieu of cash flow from operations in examining the impact on security returns. The negative relationship found between cash flow beta and security returns suggests that investors' response to the variation of a company's cash flows with that of the market is rather conservative, but nonetheless cash flow beta is also significant in explaining and predicting security returns.

In general, the components of the company factor do play an important role in describing the return generating process of securities. Among these components, the impact of dividend covariability and profitability on security returns is most crucial. Thus, it may be concluded that quarterly accounting information, especially accounting return measure is useful in security analysis. Moreover, the company variables should be included in the return model as individual regressors, because the use of a company index did not improve the explanatory power and predictive ability of the return model significantly.

Growth Factor

Nerlove [1968] found that both growth rate of sales and growth rate of earnings are significant in explaining the variation in security returns, and the impact is positive. Growth reflects the earning potential of a company, and the returns of a company with substantial growth opportunities are expected to increase with time. Furthermore, Farrell [1975] found that the classification of companies into growth, cyclical, and stable groups also improves the explanation of security returns. The findings of this study are in agreement with that of the studies cited.

Among all models examined, the regression coefficient of the growth variable is positive and significant at the 0.05 level in more than 95 percent of the cases. Thus it is concluded that the growth factor is a significant determinant of security returns.

Multifactor Return Model

The results, then, indicate that, in addition to the market factor, the industry factor, the company factor, and the growth factor contribute significantly to developing the return model.

In the previous chapter, it was concluded that the full model yields the "best" explanation and prediction of security returns. It is necessary to state again, however, that estimates of market-related systematic risk from the market model, and the three-digit LOB code should be used in determining the multifactor return model. The regression statistics of the "best" return model are repeated in Tables 45 through 48.

ASSUMPTIONS OF REGRESSION ANALYSIS

A major assumption of the present study is that the data satisfy the basic assumptions of linear regression analysis. After determining the "best" return model, residual analysis was performed to detect any violation of the basic assumptions of regression analysis. An examination of the residual plots between residuals and each independent variable indicates that the assumption of linearity, by and large, holds. In addition, no systematic pattern in these residual plots, or the plot between residuals and predicted values was found. Thus, it is concluded that the data also satisfy the assumption of homoscedasticity (that is, constant vari-

Table 45

Summary Statistics of Best Return Model

Period I (1976 - 1979)

$$\text{RETURN} = \underset{(-3.305)}{-\,0.0147} + \underset{(1.838)}{0.0037}\ \beta_i^m + \underset{(3.749)}{0.0075}\ \beta_i^I + \underset{(2.947)}{0.0016}\ \text{ABETA}$$

$$+ \underset{(0.367)}{0.0001}\ \text{GMDOL} + \underset{(1.756)}{0.0014}\ \text{LEV} + \underset{(4.305)}{0.0034}\ \text{DIVCO}$$

$$- \underset{(-1.993)}{0.0012}\ \text{CFBETA} + \underset{(2.366)}{0.0010}\ \text{PROFIT} + \underset{(4.305)}{0.2086}\ \text{GR}$$

F statistic	12.8350
standard error of regression	0.0113
coefficient of determination	0.3793
adjusted coefficient of determination	0.3498
Mallow's C_p statistic	10.0000
prediction error sum of squares	0.0271
mean forecast error	0.0006
mean absolute forecast error	0.0094
mean square forecast error	0.0001

Table 46

Summary Statistics of Best Return Model

Period II (1977 - 1980)

$$\begin{aligned}
\text{RETURN} = &- \underset{(-4.008)}{0.0161} + \underset{(5.275)}{0.0099}\ \beta_i^m + \underset{(2.185)}{0.0037}\ \beta_i^I + \underset{(0.621)}{0.0001}\ \text{ABETA} \\
&- \underset{(-0.734)}{0.0002}\ \text{GMDOL} + \underset{(0.775)}{0.0006}\ \text{LEV} + \underset{(3.725)}{0.0043}\ \text{DIVCO} \\
&- \underset{(-3.002)}{0.0015}\ \text{CFBETA} + \underset{(2.943)}{0.0017}\ \text{PROFIT} + \underset{(4.732)}{0.2104}\ \text{GR}
\end{aligned}$$

F statistic	20.6940
standard error of regressor	0.0102
coefficient of determination	0.4963
adjusted coefficient of determination	0.4724
Mallow's C_p statistic	10.0000
prediction error sum of squares	0.0249
mean forecast error	0.0037
mean absolute forecast error	0.0088
mean square forecast error	0.0001

Table 47

Summary Statistics of Best Return Model

Period III (1978 - 1981)

$$\text{RETURN} = \underset{(-3.991)}{-\,0.0126} + \underset{(3.709)}{0.0058}\,\beta_i^m + \underset{(3.317)}{0.0037}\,\beta_i^I - \underset{(-0.180)}{0.0000}\,\text{ABETA}$$

$$-\,\underset{(-0.581)}{0.0001}\,\text{GMDOL} + \underset{(1.659)}{0.0010}\,\text{LEV} + \underset{(4.039)}{0.0068}\,\text{DIVCO}$$

$$-\,\underset{(4.932)}{0.0005}\,\text{CFBETA} + \underset{(3.583)}{0.0154}\,\text{PROFIT} + 0.1147\,\text{GR}$$

F statistic	17.5290
standard error of regression	0.0086
coefficient of determination	0.4550
adjusted coefficient of determination	0.4290
Mallow's C_p statistic	10.0000
prediction error sum of squares	0.0163
mean forecast error	0.0056
mean absolute forecast error	0.0094
mean square forecast error	0.0001

Table 48

Summary Statistics of Best Return Model

Period IV (1979 - 1982)

$$\text{RETURN} = \underset{(-3.985)}{-\,0.0125} + \underset{(1.132)}{0.0022}\,\beta_i^m + \underset{(3.831)}{0.0056}\,\beta_i^I - \underset{(-3.880)}{0.0048}\,\text{ABETA}$$

$$+ \underset{(3.571)}{0.0009}\,\text{GMDOL} + \underset{(1.392)}{0.0009}\,\text{LEV} + \underset{(3.259)}{0.0063}\,\text{DIVCO}$$

$$+ \underset{(0.175)}{0.0001}\,\text{CFBETA} + \underset{(6.538)}{0.0228}\,\text{PROFIT} + \underset{(1.924)}{0.0859}\,\text{GR}$$

F statistic	20.0590
standard error of regression	0.0095
coefficient of determination	0.4885
adjusted coefficient of determination	10.0000
prediction error sum of squares	0.0194

ance among residuals). A t-test on the residuals indicates that their means are not significantly different from zero at the 0.05 level. Furthermore, a normal probability plot of the residuals indicates that the normality assumption is not violated. Therefore, the data comply with the basic assumptions of regression analysis that there exists a linear relationship between the dependent and independent variables, and the residuals are normally distributed with mean zero and constant variance.

An examination of the correlation statistics (Appendix F) indicates significant associations among some of the regressor variables, e.g., market-related and industry-related systematic risks. In addition, the diagnostics (variance inflation factor, eigenvalue, condition index, and variance proportions) indicate that market-related systematic risk, industry-related systematic risk, profitability and growth exhibit multicollinearity. As in most multiple regression analyses, the problem of multicollinearity cannot be avoided in estimating the "best" return model in the present study. Therefore, one has to be cautious when interpreting the impact and significance of individual regressor variables on the dependent variable. In fact, multicollinearity may cause some of the negative findings of the present study; however, it will not affect the explanatory power and predictive ability of the return model (see footnote 47).

LIMITATIONS

As in other market-based studies, the present study is subject to the self-selection bias of companies included in the sample. NYSE companies have total assets of at least $16 million each, while AMX companies have total assets of at least $4 million each. Thus, the sample consists only of large companies, and this may bias the results of the study. It also limits the generalizability of the research findings to all securities in the capital market. A total of 1093 companies were accessed from the Compustat PDE Tape in computing the market-related and industry-related systematic risks. The maximum number of companies included in the sample, however, is limited to 352. This is because only a limited number of companies has their interim financial statement data available on the Compustat II Tape. Consequently, data availability was a major criterion in including companies in the sample. Because of the practical difficulties and high costs in identifying a random sample from the population of securities, the results of the study must also be qualified because of this "survivorship" problem.

The problems associated with the use of quarterly accounting data must also be acknowledged. Quarterly accounting data may be considered as "a disaggregation and, in the absence of measurement error, may contain no less information than its counterpart. Unfortunately, alternative approaches to the measurement of quarterly [data&rbr. (predictive vs discrete period), seasonality and intra-year accounting allocations may more than counterbalance any potential benefit due to disaggregation." [51] That is, accounting estimations used in preparing interim financial statements tend to smooth the income streams of companies from one quarter to another, and errors in estimation can result in misleading information. Besides, financial statement data for the fourth quarter is usually a plug figure after operating results of the entire year are summarized in the annual financial statements. Furthermore, the impact of seasonality of quarterly accounting data on results of operations of companies may also affect the results of the study. These characteristics of quarterly accounting data must be recognized in interpreting the empirical findings of this research.

In the present study, both SIC codes and Line of Business information were used to classify companies into industry groups. This information was gathered as of the year 1982. One problem with the use of these industry classification schemes is that the operations of a company may change from year to year as a consequence of the diversification strategy adopted by management. Thus, an industry code may be appropriate to describe the major operations of a company in one year, but not for the next year. It

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[51] Griffin, Paul A. "The Association Between Relative Risk and Risk Estimates Derived from Quarterly Earnings and Dividends," The Accounting Review, July 1976, p. 500.

is possible that a change in industry classification code of a company from one year to the next can affect the results reported in the present study. Thus, further study should be done to determine whether such an effect is significant. Although the change in industry code may affect a relatively small number of companies in the sample, it is still important to recognize this limitation in interpreting the empirical findings reported.

There are altogether 9 regressor variables whose effects on security returns are examined in the present study. The total number of possible return models to be examined is 2^9, that is, 512. An analysis of this large number of models is basically impossible because of the costs involved. Therefore, only 16 models were developed in determining the "best" return model. As discussed in Chapter IV, these 16 models were selected on the premise that there are five statistically significant regressor variables (β_i^m, β_i^I, DIVCO, PROFIT, and GR) that should be included in the return model, and all possible combinations of the remaining four regressor variables (ABETA, GMDOL, LEV, and CFBETA) were studied to decide which should be included in constructing the "best" return model. This limited analysis may have an effect on the final choice of the "best" return model.

Finally, average statistics, across the four test periods, were used to compare the explanatory power and predictive ability of the models.

This approach ignores the possibility that a model might be the "best" in one test period but not in another. In addition, there is no significant difference in these average statistics among the models examined. Thus, the selection of the "best" return model is based on the models' average performance across the four test periods, and subjective judgement also played a role in making the final decision.

IMPLICATIONS FOR FUTURE RESEARCH

The present study provides some general conclusions about the impact of a market factor, an industry factor, a company factor, and a growth factor on security returns. Some of the findings, however, are inconsistent with the literature reviewed. Thus, more extensive studies should be conducted to provide additional evidence on the following issues.

First, the market model is found to provide the best surrogate of the market factor in explaining and predicting security returns. This contradicts the results reported in some empirical studies (Klemkosky and Martin [1975], Eskew [1979]) which found that the adjusted models provide better forecasts of market-related systematic risk than the unadjusted market model. This issue should be explored further to see if results similar to the present study can be found when different return models are constructed.

Second, the literature suggests that the market factor should exhibit a significant impact on security returns. The findings of the present study have not provided strong evidence for this proposition. This might be a consequence of the measurement errors involved in computing market-related systematic risk. In fact, the results might be different when a larger number of observations are used to compute the market-related systematic risk. Thus, it is worthwhile to see if the use of more observations will reduce these measurement errors, and provide more significant findings about the relationship between market-related systematic risk and security returns.

Third, the impact of an industry factor on security returns has long been recognized in the literature. The present study has provided supportive evidence on the issue. There are, however, problems associated with the classification of companies into industry groups. One such problem is related to the change in industry code for a company from one year to the next as a result of its diversification policy. Therefore, a thorough investigation of industry effects can only be performed if such problems are resolved. The establishment of a better scheme in classifying companies into homogeneous groups is vital for better research design.

Fourth, this research is an exploratory study on the use of quarterly accounting information in security analysis. Some of the findings related to these company attributes are interesting. For example, a negative association is found between accounting beta and security returns in test period IV. A negative association also exists between cash flow beta and security returns. These results may be attributable to multicollinearity among regressor variables. They may also result from the use of quarterly accounting information in defining these company variables operationally. Thus, it is important to further examine if quarterly accounting information provides reliable computation of these accounting risk measures. Additionally, the results of the present study should be validated by using annual accounting information to define the company variables. This would provide additional evidence with respect to the use of quarterly accounting information in security analysis, which is of major concern to the accounting profession.

Fifth, the present study has included six components of the company factor in constructing the company index, and results indicate that the four-factor model is inferior in terms of its explanatory power and ability to predict security returns. This observation may be attributed to an incomplete definition of the company factor. If more company variables were used to construct the company index, the results might have been different. Thus, another research area that might be interesting to accountants is to determine what other accounting variables should be included in constructing the company index, and what its role should be in developing the multifactor return model.

In conclusion, some limitations of the present study can be overcome by a more vigorous research design. It is hoped that the results of this study will stimulate additional research interests, especially in investigating the effect of an industry factor, and the use of quarterly accounting information in security analysis. The latter area is of special interest to accountants, who would like evidence that interim financial statements provide useful information to their readers in explaining and predicting security returns.

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APPENDIX A

Companies Used in Computing Industry-Related Systematic Risk

Distribution Based on Industry Classification Scheme

Table (i): Two-Digit SIC Code

Industry Description	Two-Digit SIC Code	Number of Companies
Metal Mining	1000	19
Oil and Gas Extraction	1300	40
Food and Kindred Products	2000	58
Textile Mill Products	2200	22
Apparel and Fabric Products	2300	23
Lumber and Wood Products	2400	17
Paper and Allied Products	2600	23
Printing and Publishing	2700	21
Chemical and Allied Products	2800	78
Petroleum Refining	2900	12
Rubber and Plastic Products	3000	28
Stone, and Concrete Products	3200	26
Primary Metal Industries	3300	52
Fabricated Metal Products	3400	43
Machinery, except Electrical	3500	78
Electical and Electronic	3600	88
Transportation Equipment	3700	54
Measuring Instruments and Misc.	3800	43
Misc. Manufacturing Industries	3900	20
Transportation By Air	4500	17
Communication	4800	20
Wholesale Trade - Durable	5000	21
Wholesale Trade - Nondurable	5100	20
General Merchandise Stores	5300	22
Food Stores	5400	24
Misc. Retail	5900	12
Credit Agencies Other Than Banks	6100	10
Business Services	7300	16

Table (ii): Three-Digit SIC Code

Industry Description	Three-Digit SIC Code	Number of Companies
Crude Petroleum and Natural Gas	1310	32
Flour and Grain Mill Products	2040	12
Beverages	2080	16
Fabric Mills, Cotton	2210	10
Men's Clothings	2320	10
Industrial Chemicals	2810	13
Biochemical Products	2830	18
Detergents and Cosmetics	2840	17
Petroleum Refining	2910	11
Tires and Inner Tubes	3010	11
Misc. Plastic Products	3070	10
Furnaces and Steel Works	3310	30
Nonferrous Products	3350	11
Fabricated Metal Products	3490	10
Machinery and Equipment	3530	15
Metalworking Machinery	3540	12
General Industrial Equipment	3560	16
Electronic Office Equipment	3570	18
Household Appliances	3630	10
Telephone and Telegraph Apparatus	3660	19
Electronic Components	3670	19
Motor Vehicles & Related Industry	3710	23
Aircraft and Related Industry	3720	22
Measuring and Controlling Devices	3820	17
Air Transportation	4510	16
Telephone Communication	4810	10
Department Stores	5310	20
Grocery Stores	5410	24

Table (iii): Two-Digit LOB Code

Industry Description	Two-Digit LOB Code	Number of Companies
Metal Mining	1000	20
Oil and Gas Extraction	1300	23
Food and Kindred Products	2000	59
Textile Mill Products	2200	22
Apparel and Fabric Products	2300	25
Lumber and Wood Products	2400	13
Paper and Allied Products	2600	28
Printing and Publishing	2700	28
Chemical and Allied Products	2800	76
Petroleum Refining	2900	30
Rubber and Plastic Products	3000	29
Stone, and Concrete Products	3200	23
Primary Metal Industries	3300	44
Fabricated Metal Products	3400	45
Machinery, except Electrical	3500	86
Electical and Electronic	3600	93
Transportation Equipment	3700	54
Measuring Instruments and Misc.	3800	33
Misc. Manufacturing Industries	3900	16
Transportation By Air	4500	16
Communication	4800	19
Electric, Gas and Sanitary Service	4900	139
Wholesale Trade - Durable	5000	26
Wholesale Trade - Nondurable	5100	20
General Merchandise Stores	5300	19
Food Stores	5400	25
Misc. Retail	5900	15
Business Services	7300	14

Table (iv): Three-Digit LOB Code

Industry Description	Three-Digit LOB Code	Number of Companies
Crude Petroleum and Natural Gas	1310	14
Food and Kindred Products	2000	15
Beverages	2080	14
Textile Mill Products	2200	15
Apparel and Other Fabric Products	2300	25
Paper and Allied Products	2600	19
Books: Publishing and Printing	2730	11
Chemical and Allied Products	2800	14
Biochemical Products	2830	17
Detergents and Cosmetics	2840	17
Petroleum Refining	2910	29
Rubber and Misc Plastic Products	3000	14
Misc. Plastic Products	3070	14
Furnaces and Steel Works	3310	28
Fabricated Metal Products	3490	10
Machinery and Equipment	3530	17
Metalworking Machinery	3540	12
General Industrial Equipment	3560	14
Electronic Office Equipment	3570	20
Telephone and Telegraph Apparatus	3660	29
Electronic Components	3670	20
Motor Vehicles & Related Industry	3710	21
Aircraft and Related Industry	3720	22
Measuring and Controlling Devices	3820	16
Air Transportation	4510	16
Natural Gas Distribution	4920	37
Electrical Appliances	5060	11
Department Stores	5310	10
Grocery Stores	5410	25

APPENDIX B.

Companies with Data Available for Analysis

Distribution Based on Industry Classification Scheme

Table (i): Two-Digit SIC Code

Industry Description	Two-Digit SIC Code	Number of Companies
Metal Mining	1000	9
Oil and Gas Extraction	1300	15
Food and Kindred Products	2000	17
Textile Mill Products	2200	12
Apparel and Fabric Products	2300	13
Lumber and Wood Products	2400	7
Paper and Allied Products	2600	10
Printing and Publishing	2700	8
Chemical and Allied Products	2800	35
Petroleum Refining	2900	4
Rubber and Plastic Products	3000	13
Stone, and Concrete Products	3200	11
Primary Metal Industries	3300	23
Fabricated Metal Products	3400	25
Machinery, except Electrical	3500	34
Electical and Electronic	3600	34
Transportation Equipment	3700	18
Measuring Instruments and Misc.	3800	17
Misc. Manufacturing Industries	3900	8
Transportation By Air	4500	13
Communication	4800	8
Wholesale Trade - Durable	5000	11
Wholesale Trade - Nondurable	5100	5
General Merchandise Stores	5300	6
Food Stores	5400	13
Misc. Retail	5900	6
Credit Agencies Other Than Banks	6100	2
Business Services	7300	7

Table (ii): Three-Digit SIC Code

Industry Description	Three-Digit SIC Code	Number of Companies
Crude Petroleum and Natural Gas	1310	13
Flour and Grain Mill Products	2040	3
Beverages	2080	2
Fabric Mills, Cotton	2210	6
Men's Clothings	2320	8
Industrial Chemicals	2810	5
Biochemical Products	2830	6
Detergents and Cosmetics	2840	8
Petroleum Refining	2910	3
Tires and Inner Tubes	3010	5
Misc. Plastic Products	3070	5
Furnaces and Steel Works	3310	15
Nonferrous Products	3350	5
Fabricated Metal Products	3490	6
Machinery and Equipment	3530	8
Metalworking Machinery	3540	5
General Industrial Equipment	3560	3
Electronic Office Equipment	3570	11
Household Appliances	3630	5
Telephone and Telegraph Apparatus	3660	9
Electronic Components	3670	8
Motor Vehicles & Related Industry	3710	9
Aircraft and Related Industry	3720	6
Measuring and Controlling Devices	3820	10
Air Transportation	4510	13
Telephone Communication	4810	3
Department Stores	5310	6
Grocery Stores	5410	13

Table (iii): Two-Digit LOB Code

Industry Description	Two-Digit LOB Code	Number of Companies
Metal Mining	1000	8
Oil and Gas Extraction	1300	8
Food and Kindred Products	2000	16
Textile Mill Products	2200	11
Apparel and Fabric Products	2300	13
Lumber and Wood Products	2400	8
Paper and Allied Products	2600	10
Printing and Publishing	2700	11
Chemical and Allied Products	2800	33
Petroleum Refining	2900	14
Rubber and Plastic Products	3000	12
Stone, and Concrete Products	3200	11
Primary Metal Industries	3300	25
Fabricated Metal Products	3400	21
Machinery, except Electrical	3500	43
Electical and Electronic	3600	37
Transportation Equipment	3700	17
Measuring Instruments and Misc.	3800	12
Misc. Manufacturing Industries	3900	5
Transportation By Air	4500	13
Communication	4800	7
Electric, Gas and Sanitary Service	4900	1
Wholesale Trade - Durable	5000	14
Wholesale Trade - Nondurable	5100	6
General Merchandise Stores	5300	7
Food Stores	5400	14
Misc. Retail	5900	7
Business Services	7300	6

Table (iv): Three-Digit LOB Code

Industry Description	Three-Digit LOB Code	Number of Companies
Crude Petroleum and Natural Gas	1310	6
Food and Kindred Products	2000	6
Beverages	2080	2
Textile Mill Products	2200	8
Apparel and Other Fabric Products	2300	13
Paper and Allied Products	2600	6
Books: Publishing and Printing	2730	4
Chemical and Allied Products	2800	5
Biochemical Products	2830	5
Detergents and Cosmetics	2840	9
Petroleum Refining	2910	14
Rubber and Misc Plastic Products	3000	7
Misc. Plastic Products	3070	5
Furnaces and Steel Works	3310	16
Fabricated Metal Products	3490	6
Machinery and Equipment	3530	11
Metalworking Machinery	3540	5
General Industrial Equipment	3560	4
Electronic Office Equipment	3570	13
Telephone and Telegraph Apparatus	3660	14
Electronic Components	3670	8
Motor Vehicles & Related Industry	3710	8
Aircraft and Related Industry	3720	6
Measuring and Controlling Devices	3820	8
Air Transportation	4510	13
Natural Gas Distribution	4920	1
Electrical Appliances	5060	5
Department Stores	5310	4
Grocery Stores	5410	14

APPENDIX C

Distribution of Sample Companies and Outliers

Based on Industry Classification Scheme

Table (i): Two-Digit SIC Code

Industry Description	Two-Digit SIC Code	Sample (347)	Outlier (37)
Metal Mining	1000	9	0
Oil and Gas Extration	1300	13	2
Food and Kindred Products	2000	16	1
Textile Mill Products	2200	9	3
Apparel and Fabric Products	2300	12	0
Lumber and Wood Products	2400	7	0
Paper and Allied Products	2600	10	0
Printing and Publishing	2700	7	1
Chemical and Allied Products	2800	32	3
Petroleum Refining	2900	3	1
Rubber and Plastic Products	3000	13	0
Stone, and Concrete Product	3200	9	2
Primary Metal Industries	3300	16	7
Fabricated Metal Products	3400	25	0
Machinery, except Electrica	3500	32	2
Electical and Electronic	3600	33	1
Transportation Equipment	3700	16	2
Measuring Instruments and Misc.	3800	17	0
Misc. Manufacturing Industries	3900	7	1
Transportation By Air	4500	6	7
Communication	4800	8	0
Wholesale Trade - Durable	5000	10	1
Wholesale Trade - Nondurable	5100	5	0
General Merchandise Stores	5300	6	0
Food Stores	5400	11	2
Misc. Retail	5900	6	0
Credit Agencies Other Than Banks	6100	2	0
Business Services	7300	7	0

Table (ii): Three-Digit SIC Code

Industry Description	Three-Digit SIC Code	Sample (175)	Outlier (24)
Crude Petroleum and Natural Gas	1310	11	2
Flour and Grain Mill Products	2040	3	0
Beverages	2080	2	0
Fabric Mills, Cotton	2210	4	2
Men's Clothings	2320	8	0
Industrial Chemicals	2810	4	1
Biochemical Products	2830	6	0
Detergents and Cosmetics	2840	7	1
Petroleum Refining	2910	2	1
Tires and Inner Tubes	3010	5	0
Misc. Plastic Products	3070	5	0
Furnaces and Steel Works	3310	11	4
Nonferrous Products	3350	4	1
Fabricated Metal Products	3490	6	0
Machinery and Equipment	3530	8	0
Metalworking Machinery	3540	5	0
General Industrial Equipment	3560	3	0
Electronic Office Equipment	3570	10	1
Household Appliances	3630	5	0
Telephone and Telegraph Apparatus	3660	9	0
Electronic Components	3670	8	0
Motor Vehicles & Related Industry	3710	7	2
Aircraft and Related Industry	3720	6	0
Measuring and Controlling Devices	3820	10	0
Air Transportation	4510	6	7
Telephone Communication	4810	3	0
Department Stores	5310	6	0
Grocery Stores	5410	11	2

Table (iii): Two-Digit LOB Code

Industry Classification	Two-Digit LOB Code	Sample (352)	Outlier (38)
Metal Mining	1000	8	0
Oil and Gas Extraction	1300	8	0
Food and Kindred Products	2000	16	1
Textile Mill Products	2200	11	4
Apparel and Fabric Products	2300	13	0
Lumber and Wood Products	2400	8	0
Paper and Allied Products	2600	10	0
Printing and Publishing	2700	11	1
Chemical and Allied Products	2800	33	2
Petroleum Refining	2900	14	4
Rubber and Plastic Products	3000	12	0
Stone, and Concrete Products	3200	11	2
Primary Metal Industries	3300	25	6
Fabricated Metal Products	3400	21	1
Machinery, except Electrical	3500	43	2
Electical and Electronic	3600	37	1
Transportation Equipment	3700	17	2
Measuring Instruments and Misc.	3800	12	0
Misc. Manufacturing Industries	3900	5	0
Transportation By Air	4500	13	7
Communication	4800	7	0
Electric, Gas and Sanitary Ser.	4900	1	0
Wholesale Trade - Durable	5000	14	2
Wholesale Trade - Nondurable	5100	6	0
General Merchandise Stores	5300	7	1
Food Stores	5400	14	2
Misc. Retail	5900	7	0
Business Services	7300	6	0

Table (iv): Three-Digit LOB Code

Industry Description	Three-Digit LOB Code	Sample (199)	Outlier (28)
Crude Petroleum and Natural Gas	1310	6	0
Food and Kindred Products	2000	6	0
Beverages	2080	2	0
Textile Mill Products	2200	8	2
Apparel and Other Fabric Products	2300	13	0
Paper and Allied Products	2600	6	0
Books: Publishing and Printing	2730	4	1
Chemical and Allied Products	2800	5	1
Biochemical Products	2830	5	0
Detergents and Cosmetics	2840	9	1
Petroleum Refining	2910	14	4
Rubber and Misc Plastic Products	3000	7	0
Misc. Plastic Products	3070	5	0
Furnaces and Steel Works	3310	16	4
Fabricated Metal Products	3490	6	1
Machinery and Equipment	3530	11	0
Metalworking Machinery	3540	5	0
General Industrial Equipment	3560	4	0
Electronic Office Equipment	3570	13	1
Telephone and Telegraph Apparatus	3660	14	0
Electronic Components	3670	8	1
Motor Vehicles & Related Industry	3710	8	1
Aircraft and Related Industry	3720	6	1
Measuring and Controlling Devices	3820	8	0
Air Transportation	4510	13	7
Natural Gas Distribution	4920	1	0
Electrical Appliances	5060	5	0
Department Stores	5310	4	0
Grocery Stores	5410	14	2

APPENDIX D

Listing of Sample Companies

Abbott Laboratories	Cabot Corp
Adams-Millis Corp	California Portland Cement
Aegis Corp	Callahan Mining Corp
Aileen Inc	Campbell Red Lake Mines
Alaska Airlines Inc	Campbell Soup Co
Albertson's Inc	Carlisle Corp
Alcan Aluminium Ltd	Carnation Co
Allied Products	Carpenter Technology
Allied Stores	Castle (A.M.) & Co
Amax Inc	Caterpillar Tractor Co
American Bldg Maintenance	Cbs Inc
American Broadcasting	Ceco Corp
American Cyanamid Co	Certain-teed Corp
American Maize-Products-Cl A	Champion Home Builders Co
American Petrofina-Cl A	Champion Spark Plug
Amp Inc	Chesapeake Corp of Va
Anderson, Clayton & Co	Chicago Pneumatic Tool Co
Andrea Radio Corp	Chicago Rivet & Machine Co
Angelica Corp	Cincinnati Bell Inc
Apl Corp	Clark Consolidated Inds
Armada Corp	Clark Equipment Co
Armstrong Rubber	Clarostat Manuf Co Inc
Aro Corp	Cleveland-Cliffs Iron Co
Arrow Electronics Inc	Clopay Corp
Asamera Inc	Cole national Corp
Athlone Inds	Coleco Inds
Avery International	Coleman Co Inc
Bard (C.R.) Inc	Colgate-Palmolive Co
Barnes Group Inc	Collins & Aikman Corp
Baruch-Foster Corp	Commercial Metals Co
Bausch & Lomb Inc	Compudyne Corp
Bdi Investments Corp	Computer Sciences Corp
Bell Industries Inc	Connelly Containers Inc
Berkey Photo Inc	Consolidated Foods Corp
Big Three Industries	Continental Materials Corp
Blair (john) & Co	Cooper Tire & Rubber
Boeing Co	CPC International Inc
Borg-warner Corp	Crown Central Petroleum Cp-a
Braun Engineering	Crown Cork & Seal Co Inc
Brown & Sharpe Mfg Co	Crown Industries

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Del Laboratories Inc	Great Lakes Chemical Corp
Delta Air Lines Inc	GTI Corp
Diebold Inc	Guardsman Chemicals Inc
Digital Equipment	Gulton Industries Inc
Dome Mines Ltd	Handleman Co
Donnelley (R.R.) & Sons Co	Handy & Harman
Dover Corp	Hanna Mining Co
DWG Corp	Harnischfeger Corp
E-Systems Inc	Hartmarx Corp
Eagle-Picher Inds	Hastings Mfg Co
Easco Corp	Hayes-albion Corp
Eastern Co	Hazeltine Corp
Edo Corp	Heinicke Instruments
Electronic Associates Inc	Helene Curtis Industries
Electronics Corp of America	Helmerich & Payne
Emhart Corp	Hercules Inc
Ennis Business Forms	Hewlett-Packard Co
Essex Chemical Corp	Homestake Mining
Ex-Cell-O Corp	Honeywell Inc
Fairmount Chemical Co Inc	Hormel (Geo. A.) & Co
Farah Mfg Co	Houghton Mifflin Co
Federal Signal Corp	House of Fabrics Inc
Federal-Mogul Corp	Howell Industries Inc
Ferro Corp	Imperial Oil Ltd-Cl A
Fieldcrest Mills	Inland Steel Co
Fischer & Porter Co	Interlake Inc
Fleetwood Enterprises	Intl Flavors & Fragrances
Flexi-Van Corp	Intl Paper Co
Fluke (John) Mfg Co	Intl Rectifier Corp
Ford Motor Co of Canada Ltd	ISS Intl Service System
Forest Laboratories Inc-Cl A	Johnson & Johnson
Foxboro Co	Jonathan Logan Inc
Frontier Holdings Inc	Jorgensen (Earle M.) Co
Fruehauf Corp	Joy Mfg Co
Gannett Co	K Mart Corp
Garan Inc	Kaiser Cement Corp
General Host Corp	Kay Corp
General Instrument Corp	Kellogg Co
Gerber Products Co	Ketchum & Co
Giant Yellowknife Mines Ltd	Kinark Corp
Gillette Co	Kleer-Vu Industries Inc
Goodrich (B.F.) Co	Kollmorgen Corp
Gordon Jewelry Corp	Kroger Co
Grainger (w.w.) Inc	Kysor Industrial Corp

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Lehigh Press Inc	Ormand Industries
Lehigh Valley Inds	Outboard Marine Corp
Libbey-Owens-Ford Co	Owens-Corning Fiberglas Corp
Lockheed Corp	Owens-Illinois Inc
Lodge & Shipley Co	Oxford Industries Inc
Lubrizol Corp	Ozark Air Lines Inc
Lucky Stores Inc	Pantasote Inc
Lukens Inc	Papercraft Corp
Lynch Communication System	Park Chemical Co
Lynch Corp	Parker Pen Co
Macy (R.H.) & Co	Penney (J.C.) Co
Malone & Hyde Inc	Pepsico Inc
Mangood Corp	Petrolane Inc
Manhattan Industries Inc	Philips Industries Inc
Masco Corp	Phillips-Van Heusen
Maytag Co	Pitney-Bowes Inc
Mcdonnell Douglas Corp	Pittsburgh-Des Moines Corp
Mcgraw-Edison Co	Pittway Corp
Mei Corp	Ply-Gem Industries
Mem Co	Plymouth Rubber Co-Cl A
Mercantile Stores Co Inc	Polaroid Corp
Mesa Petroleum	Portec Inc
Metromedia Inc	Potlatch Corp
Milton Bradley Co	Prairie Oil Royalties Co Ltd
Monsanto Co	Premier Industrial Corp
Motorola Inc	Prentice-Hall Inc
Mott's Super Markets Inc	Products Research & Chemical
Movie Star Inc-Cl A	Proler International Corp
Murphy Oil Corp	PSA Inc
Murray Ohio Mfg Co	Pueblo International Inc
Nashua Corp	Quaker State Oil Refining
National Gypsum Co	Quanex Corp
National Presto Inds Inc	Ranco Inc
National Semiconductor Corp	Raymond Industries Inc
Ncr Corp	Raytheon Co
New Process Co	Redman Industries Inc
Newcor Inc	Reichhold Chemicals Inc
NL Industries	Republic Corp
Northwest Airlines Inc	Republic Steel Corp
Northwestern Steel & Wire Co	Revco D. S. Inc
Norton Co	Revlon Inc
Nucor Corp	Richardson-vicks Inc
NVF Corp	Riegel Textile Corp
Oakite Products	Robertshaw Controls

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Robins (A.H.) Co	Texaco Inc
Rohm & Haas Co	Texas Instruments Inc
Rubbermaid Inc	Texas Oil & Gas Corp
Russ Togs Inc	Thomas Industries Inc
Rymer Co	Thriftimart Inc-Cl A
Safeguard Scientifics Inc	Todd Shipyards Corp
Safeway Stores Inc	Tokheim Corp
Salem Corp	Tonka Corp
Savin Corp	Tootsie Roll Industries Inc
SCM Corp	Trans-Lux Corp
Scott & Fetzer Co	Tranzonic Cos
Scovill Inc	Tyco Laboratories Inc
Scurry-Rainbow oil Ltd	Tyler Corp
Seaboard Corp	U S Gypsum Co
Sedco Inc	UNC Resources Inc
Selas Corp of America	Vnion Camp Corp
Servo Corp of America	Union Corp
Shopwell Inc	Union Pacific Corp
Sierracin Corp	Uniroyal Inc
Skyline Corp	United Aircraft Products Inc
Smith (A.O.) Corp-cl A	United Telecommunications
Smith International Inc	Universal Cigar Corp
Smucker (J.M.) Co	Upjohn Co
Southland Royalty Co	Van Dorn Co
Sparton Corp	Vermont American-Cl A
Sperry Corp	Vernitron Corp
Springs Industries Inc	VF Corp
Sps Technologies Inc	Voplex Corp
Standard Motor Products Inc	Walgreen Co
Standard Oil Co (Calif)	Wallace Computer Svcs Inc
Standard Products Co	Watkins-Johnson
Steego Corp	Watsco Inc
Stepan Chemical Co	Weis Markets Inc
Sterling Extruder Corp	West Point-Pepperell
Sun Chemical Corp	Western Union Corp
Super Valu Stores Inc .	Westvaco Corp
Superscope Inc	Whirlpool Corp
Taft Broadcasting Co	Winn-dixie Stores Inc
Tandy Corp	Witco Chemical Corp
Tec Inc	Wrigley (WM.) Jr Co
Tektronix Inc	Wurlitzer Co
Teledyne Inc	Zayre Corp
Teleflex Inc	Zero Corp
Tensor Corp	Zimmer Corp

APPENDIX E

Summary Statistics of Independent and Dependent Variables

Table (i) (a): Two-Digit SIC Code

	Period I (1976-79)		Period II (1977-80)	
	Mean	Std. Dev.	Mean	Std. Dev.
Independent Variable:				
Security Return	0.0157	0.0136	0.0125	0.0141
Dependent Variables:				
Market-Related Syetematic Risk				
Market Model	1.3027	0.5067	1.0624	0.4168
Mean Reversion Model	1.2031	0.3394	1.2747	0.3863
Order Bias Adjustment Model	1.2374	0.4828	1.2491	0.4964
Bayesian Adjustment Model	1.2495	0.2784	1.3181	0.3202
Industry-Related Systematic Risk	1.1531	0.5576	1.0723	0.4881
Company Variables				
Accounting Beta	0.4650	1.5123	2.0654	3.9192
Operating Leverage	4.1219	3.1954	4.1359	3.2383
Financial Leverage	1.4200	1.4083	1.4532	1.4227
Dividend Covariability	0.6601	0.9417	0.4137	0.6132
Cash Flow Beta	0.5537	1.2497	0.6084	1.3237
Profitability	0.6283	0.2919	0.6203	0.3025
Growth	0.0307	0.0203	0.0307	0.0213

Table (i) (b): Two-Digit SIC Code

	Period III (1978-81)		Period IV (1979-82)	
	Mean	Std. Dev.	Mean	Std. Dev.
Independent Variable:				
Security Return	0.0118	0.0112	0.0146	0.0128
Dependent Variables:				
Market-Related Syetematic Risk				
Market Model	1.0572	0.4369	0.9569	0.4021
Mean Reversion Model	1.1379	0.2776	1.2812	0.4457
Order Bias Adjustment Model	1.2338	0.5961	1.2981	0.7000
Bayesian Adjustment Model	1.1911	0.2633	1.3216	0.3583
Industry-Related Systematic Risk	1.0685	0.4580	0.9829	0.4825
Company Variables				
Accounting Beta	1.3576	1.7605	0.1599	0.5951
Operating Leverage	4.2703	3.1518	4.1219	3.1954
Financial Leverage	1.4522	1.3989	1.4911	1.3994
Dividend Covariability	0.2209	0.3793	0.1160	0.3747
Cash Flow Beta	0.5936	1.5436	0.6302	1.8889
Profitability	0.6014	0.2890	0.5473	0.2964
Growth	0.0299	0.0206	0.0226	0.0226

Table (ii) (a): Three-Digit SIC Code

	Period I (1976-79)		Period II (1977-80)	
	Mean	Std. Dev.	Mean	Std. Dev.
Independent Variable:				
Security Return	0.0166	0.0135	0.0138	0.0137
Dependent Variables:				
Market-Related Syetematic Risk				
Market Model	1.3089	0.5241	1.0810	0.4350
Mean Reversion Model	1.2076	0.3275	1.2796	0.3809
Order Bias Adjustment Model	1.2284	0.4624	1.2450	0.5288
Bayesian Adjustment Model	1.2558	0.2703	1.3238	0.3131
Industry-Related Systematic Risk	1.1393	0.5869	1.0727	0.5092
Company Variables				
Accounting Beta	0.6129	1.4944	1.9389	3.7903
Operating Leverage	3.9817	3.2437	3.9705	2.9862
Financial Leverage	1.4526	1.3280	1.4753	1.2831
Dividend Covariability	0.7426	1.0685	0.4629	0.6853
Cash Flow Beta	0.6801	1.5455	0.7335	1.5745
Profitability	0.6135	0.2671	0.6011	0.2599
Growth	0.0331	0.0216	0.0331	0.0217

Table (ii) (b): Three-Digit SIC Code

	Period III (1978-81)		Period IV (1979-82)	
	Mean	Std. Dev.	Mean	Std. Dev.
Independent Variable:				
Security Return	0.0120	0.0113	0.0141	0.0131
Dependent Variables:				
Market-Related Syetematic Risk				
Market Model	1.0798	0.4627	0.9684	0.3969
Mean Reversion Model	1.1406	0.2761	1.2813	0.4477
Order Bias Adjustment Model	1.2370	0.6536	1.3160	0.7855
Bayesian Adjustment Model	1.1944	0.2557	1.3149	0.3525
Industry-Related Systematic Risk	1.0621	0.4909	0.9559	0.5156
Company Variables				
Accounting Beta	1.1751	2.6730	0.1231	0.5542
Operating Leverage	4.1328	3.0671	3.9817	3.2457
Financial Leverage	1.4715	1.2336	1.5125	1.2214
Dividend Covariability	0.2535	0.3863	0.1449	0.3600
Cash Flow Beta	0.6517	1.8212	0.6912	2.1599
Profitability	0.5853	0.2620	0.5341	0.2807
Growth	0.0327	0.0191	0.0247	0.0208

Table (iii) (a): Two-Digit LOB Code

	Period I (1976-79)		Period II (1977-80)	
	Mean	Std. Dev.	Mean	Std. Dev.
Independent Variable:				
Security Return	0.0158	0.0135	0.0127	0.0141
Dependent Variables:				
Market-Related Syetematic Risk				
Market Model	1.3101	0.5225	1.0688	0.4241
Mean Reversion Model	1.2030	0.3424	1.2778	0.3895
Order Bias Adjustment Model	1.2361	0.4925	1.2537	0.4991
Bayesian Adjustment Model	1.2501	0.2804	1.3205	0.3220
Industry-Related Systematic Risk	1.1640	0.5708	1.0775	0.4888
Company Variables				
Accounting Beta	0.4719	1.5050	2.0884	3.9290
Operating Leverage	4.1250	3.1765	4.1627	3.2349
Financial Leverage	1.4222	1.4003	1.4508	1.4136
Dividend Covariability	0.6529	0.9376	0.4097	0.6106
Cash Flow Beta	0.5468	1.2421	0.6015	1.3156
Profitability	0.6193	0.2928	0.6219	0.3030
Growth	0.0306	0.0202	0.0306	0.0212

Table (iii) (b): Two-Digit LOB Code

	Period III (1978-81)		Period IV (1979-82)	
	Mean	Std. Dev.	Mean	Std. Dev.
Independent Variable:				
Security Return	0.0119	0.0113	0.0147	0.0128
Dependent Variables:				
Market-Related Syetematic Risk				
Market Model	1.0649	0.4460	0.9619	0.4059
Mean Reversion Model	1.1403	0.2801	1.2879	0.4534
Order Bias Adjustment Model	1.2402	0.6041	1.3077	0.7133
Bayesian Adjustment Model	1.1932	0.2643	1.3264	0.3625
Industry-Related Systematic Risk	1.0725	0.4581	0.9878	0.4831
Company Variables				
Accounting Beta	1.3749	2.7759	0.1535	0.6029
Operating Leverage	4.2945	3.1445	4.1250	3.1765
Financial Leverage	1.4462	1.3906	1.4834	1.3925
Dividend Covariability	0.2189	0.3780	0.1142	0.3736
Cash Flow Beta	0.5892	1.5340	0.6293	1.8794
Profitability	0.6040	0.2912	0.5500	0.2987
Growth	0.0300	0.0205	0.0227	0.0225

Table (iv) (a): Three-Digit LOB Code

	Period I (1978-81)		Period II (1979-82)	
	Mean	Std. Dev.	Mean	Std. Dev.
Independent Variable:				
Security Return	0.0160	0.0140	0.0131	0.0140
Dependent Variables:				
Market-Related Syetematic Risk				
Market Model	1.3119	0.5035	1.0712	0.4223
Mean Reversion Model	1.2020	0.3101	1.2709	0.3579
Order Bias Adjustment Model	1.1978	0.3938	1.2176	0.4809
Bayesian Adjustment Model	1.2572	0.2596	1.3230	0.2964
Industry-Related Systematic Risk	1.1116	0.5382	1.0293	0.4753
Company Variables				
Accounting Beta	0.5255	1.5180	1.8884	3.8263
Operating Leverage	4.1238	3.1498	4.0421	2.8854
Financial Leverage	1.3347	1.2313	1.3796	1.2896
Dividend Covariability	0.7199	0.9964	0.4645	0.6755
Cash Flow Beta	0.6398	1.4059	0.7321	1.4875
Profitability	0.6123	0.2689	0.6054	0.2693
Growth	0.0310	0.0201	0.0351	0.0206

Table (iv) (b): Three-Digit LOB Code

	Period III (1978-81)		Period IV (1979-82)	
	Mean	Std. Dev.	Mean	Std. Dev.
Independent Variable:				
Security Return	0.0123	0.0114	0.0146	0.0130
Dependent Variables:				
Market-Related Syetematic Risk				
Market Model	1.0616	0.4529	0.9602	0.3907
Mean Reversion Model	1.1303	0.2587	1.2674	0.4202
Order Bias Adjustment Model	1.2002	0.5988	1.2645	0.7201
Bayesian Adjustment Model	1.1909	0.2394	1.3157	0.3350
Industry-Related Systematic Risk	1.0229	0.4524	0.9463	0.4901
Company Variables				
Accounting Beta	1.1675	2.7062	0.1302	0.5765
Operating Leverage	4.2133	3.0685	4.1238	3.1498
Financial Leverage	1.3863	1.2715	1.4322	1.2741
Dividend Covariability	0.2533	0.3897	0.1280	0.3749
Cash Flow Beta	0.7351	1.8301	0.7732	2.1908
Profitability	0.5964	0.2717	0.5487	0.2851
Growth	0.0317	0.0193	0.0242	0.0208

APPENDIX F

Correlation Statistics Among Independent Variables

Table (i) (a): Two-Digit SIC Code

Period I (1976 - 1979)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)	β_i^I	ABETA	GMDOL	LEV	DIVCO	CFBETA	PROFIT	GR	COFAC
β_i^m(OLS)		0.450[a] 0.001[b]	0.445 0.001	0.416 0.001	0.523 0.001	0.085 0.114	0.056 0.292	0.183 0.001	-0.159 0.002	-0.160 0.002	-0.107 0.044	-0.054 0.310	-0.185 0.001
β_i^m(MR)	0.273 0.001		0.843 0.001	0.956 0.001	0.369 0.001	-0.092 0.086	-0.065 0.226	0.048 0.363	-0.120 0.025	-0.130 0.015	-0.057 0.287	-0.041 0.446	-0.063 0.243
β_i^m(OB)	0.238 0.001	0.815 0.001		0.671 0.001	0.421 0.001	-0.047 0.382	0.057 0.286	0.096 0.074	-0.169 0.001	-0.145 0.006	-0.113 0.034	-0.060 0.264	-0.158 0.003
β_i^m(BA)	0.281 0.001	0.962 0.001	0.644 0.001		0.341 0.001	-0.095 0.075	-0.114 0.032	0.040 0.457	-0.090 0.093	-0.129 0.015	-0.019 0.714	-0.012 0.815	-0.020 0.708
β_i^I	0.294 0.001	0.398 0.001	0.396 0.001	0.379 0.001		0.109 0.041	0.243 0.001	0.304 0.001	-0.211 0.001	-0.225 0.001	-0.252 0.001	-0.133 0.012	-0.370 0.001
ABETA	0.130 0.015	0.014 0.784	0.061 0.253	0.003 0.945	0.076 0.152		0.076 0.156	-0.064 0.233	-0.017 0.749	-0.003 0.951	0.042 0.426	0.095 0.076	0.015 0.775
GMDOL	-0.042 0.425	-0.034 0.526	0.070 0.190	-0.077 0.151	0.122 0.022	0.118 0.027		0.334 0.001	-0.269 0.001	-0.082 0.124	-0.490 0.001	-0.426 0.001	-0.738 0.001
LEV	0.043 0.415	0.094 0.080	0.111 0.037	0.089 0.095	0.246 0.001	0.072 0.175	0.373 0.001		-0.179 0.001	-0.102 0.055	-0.547 0.001	-0.258 0.001	-0.743 0.001
DIVCO	0.005 0.922	-0.077 0.149	-0.131 0.013	-0.051 0.334	-0.145 0.006	-0.034 0.525	-0.262 0.001	-0.142 0.007		0.200 0.001	0.216 0.001	0.173 0.001	0.512 0.001
CFBETA	-0.142 0.007	-0.164 0.002	-0.156 0.003	-0.169 0.001	-0.174 0.001	-0.046 0.391	-0.085 0.113	-0.089 0.095	0.158 0.003		0.052 0.330	0.037 0.491	0.258 0.001
PROFIT	0.055 0.305	-0.124 0.020	-0.151 0.004	-0.089 0.095	-0.173 0.001	-0.052 0.330	-0.480 0.001	-0.545 0.001	0.209 0.001	0.055 0.299		0.510 0.001	0.817 0.001
GR	0.146 0.006	-0.042 0.434	-0.062 0.248	-0.016 0.756	0.009 0.858	0.148 0.005	-0.384 0.001	0.260 0.001	0.175 0.001	0.073 0.174	0.558 0.001		0.488 0.001
COFAC	0.005 0.916	0.106 0.047	0.176 0.001	0.069 0.196	0.257 0.001	0.193 0.001	0.756 0.001	0.749 0.001	-0.470 0.001	-0.235 0.001	-0.809 0.001	-0.479 0.001	

Period II (1977 - 1980)

[a] product moment correlation coefficient

[b] level of significance

Table (i) (b): Two-Digit SIC Code

Period III (1978 - 1981)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)	β_i^I	ABETA	GMDOL	LEV	DIVCO	CFBETA	PROFIT	GR	COFAC
β_i^m(OLS)		0.225 [a] 0.001 [b]	0.186 0.001	0.239 0.001	0.352 0.001	0.024 0.655	-0.103 0.055	-0.002 0.957	-0.011 0.834	-0.098 0.067	0.080 0.132	0.234 0.001	-0.045 0.395
β_i^m(MR)	0.084 0.114		0.809 0.001	0.939 0.001	0.368 0.001	-0.010 0.848	-0.030 0.574	0.034 0.524	-0.075 0.162	-0.092 0.085	-0.084 0.114	-0.057 0.285	0.057 0.287
β_i^m(OB)	0.036 0.500	0.819 0.001		0.582 0.001	0.358 0.001	0.070 0.190	0.066 0.214	0.074 0.167	-0.122 0.023	-0.111 0.038	-0.135 0.011	-0.098 0.067	0.148 0.005
β_i^m(BA)	0.121 0.024	0.944 0.001	0.603 0.001		0.341 0.001	-0.044 0.410	-0.077 0.152	0.021 0.686	-0.050 0.345	-0.082 0.127	-0.039 0.460	-0.005 0.923	0.008 0.877
β_i^I	0.099 0.064	0.309 0.001	0.364 0.001	0.251 0.001		-0.003 0.948	0.096 0.073	0.195 0.001	-0.136 0.011	-0.172 0.001	-0.129 0.015	0.048 0.366	0.192 0.001
ABETA	-0.049 0.358	0.035 0.511	0.033 0.529	0.029 0.589	-0.030 0.573		0.236 0.001	0.189 0.001	-0.072 0.180	-0.079 0.141	-0.189 0.001	-0.068 0.203	0.424 0.001
GMDOL	-0.118 0.027	0.030 0.571	0.136 0.011	-0.014 0.786	0.216 0.001	0.096 0.071		0.376 0.001	-0.236 0.001	-0.105 0.048	-0.482 0.001	-0.354 0.001	0.738 0.001
LEV	-0.082 0.123	0.093 0.082	0.120 0.024	0.081 0.130	0.190 0.001	0.152 0.004	0.276 0.001		-0.198 0.001	-0.099 0.063	-0.547 0.001	-0.298 0.001	0.745 0.001
DIVCO	-0.037 0.487	-0.034 0.522	-0.045 0.399	-0.024 0.650	-0.090 0.092	0.055 0.303	-0.153 0.004	-0.113 0.034		0.106 0.048	0.266 0.001	0.166 0.001	-0.482 0.001
CFBETA	-0.003 0.948	-0.058 0.279	-0.095 0.075	-0.040 0.452	-0.080 0.136	-0.010 0.843	-0.126 0.018	-0.084 0.116	0.067 0.208		0.105 0.048	0.060 0.264	-0.261 0.001
PROFIT	0.207 0.001	-0.129 0.016	-0.137 0.010	-0.107 0.045	-0.069 0.198	-0.229 0.001	-0.335 0.001	-0.543 0.001	0.211 0.001	0.129 0.016		0.552 0.001	-0.809 0.001
GR	0.352 0.001	0.092 0.086	0.093 0.081	0.059 0.272	0.039 0.465	-0.102 0.056	-0.190 0.001	-0.342 0.001	0.139 0.009	0.080 0.134	0.586 0.001		-0.472 0.001
COFAC	-0.157 0.003	0.120 0.025	0.174 0.001	0.086 0.106	0.192 0.001	0.354 0.001	0.623 0.001	0.754 0.001	-0.362 0.001	-0.282 0.001	-0.828 0.001	-0.490 0.001	

Period IV (1979 - 1982)

[a] product moment correlation coefficient

[b] level of significance

Table (ii) (a): Three-Digit SIC Code

Period I (1976 - 1979)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)	β_i^I	ABETA	GMDOL	LEV	DIVCO	CFBETA	PROFIT	GR	COFAC
β_i^m(OLS)		0.461[a] 0.001[b]	0.476 0.001	0.418 0.001	0.620 0.001	0.232 0.002	0.153 0.043	0.229 0.002	-0.171 0.023	-0.138 0.066	-0.102 0.178	-0.099 0.190	0.259 0.001
β_i^m(MR)	0.323 0.001		0.844 0.001	0.955 0.001	0.422 0.001	-0.101 0.179	-0.037 0.622	0.036 0.635	-0.102 0.179	-0.136 0.070	0.052 0.491	0.052 0.493	-0.003 0.964
β_i^m(OB)	0.271 0.001	0.801 0.001		0.667 0.001	0.496 0.001	0.021 0.775	0.097 0.200	0.100 0.186	-0.141 0.061	-0.141 0.062	-0.013 0.862	0.042 0.575	0.121 0.110
β_i^m(BA)	0.329 0.001	0.957 0.001	0.608 0.001		0.373 0.001	-0.140 0.062	-0.087 0.247	0.010 0.888	-0.073 0.334	-0.138 0.068	0.068 0.364	0.057 0.449	-0.049 0.518
β_i^I	0.343 0.001	0.450 0.001	0.428 0.001	0.417 0.001		0.198 0.008	0.320 0.001	0.324 0.001	-0.193 0.010	-0.185 0.014	-0.287 0.001	-0.159 0.035	0.425 0.001
ABETA	0.155 0.039	0.046 0.544	0.129 0.088	-0.006 0.931	0.062 0.408		0.257 0.001	0.120 0.113	-0.074 0.325	-0.026 0.731	-0.062 0.411	-0.033 0.664	0.335 0.001
GMDOL	0.019 0.793	-0.037 0.619	0.072 0.340	-0.074 0.326	0.194 0.009	0.189 0.012		0.380 0.001	-0.286 0.001	-0.041 0.582	-0.486 0.001	-0.347 0.001	0.785 0.001
LEV	0.045 0.545	0.075 0.321	0.073 0.332	0.071 0.349	0.283 0.001	0.134 0.076	0.434 0.001		-0.132 0.081	-0.078 0.304	-0.546 0.001	-0.319 0.001	0.744 0.001
DIVCO	0.013 0.856	0.008 0.908	-0.058 0.439	0.031 0.675	-0.154 0.040	0.034 0.653	-0.271 0.001	-0.124 0.100		0.210 0.005	0.152 0.043	0.164 0.029	-0.448 0.001
CFBETA	-0.142 0.059	-0.156 0.038	-0.135 0.073	-0.161 0.033	-0.176 0.019	0.004 0.953	-0.057 0.453	-0.084 0.266	0.167 0.026		0.010 0.889	-0.001 0.982	-0.179 0.017
PROFIT	0.034 0.655	-0.037 0.619	-0.091 0.228	-0.010 0.889	-0.205 0.006	-0.022 0.770	-0.494 0.001	-0.585 0.001	0.192 0.010	0.024 0.751		0.525 0.001	-0.781 0.001
GR	0.145 0.054	0.081 0.283	0.052 0.490	0.085 0.259	-0.010 0.893	0.145 0.054	-0.304 0.001	0.268 0.001	0.128 0.088	0.045 0.550	0.551 0.001		-0.472 0.001
COFAC	0.036 0.635	0.043 0.566	0.123 0.103	0.008 0.907	0.303 0.001	0.222 0.003	0.786 0.001	0.788 0.001	-0.422 0.001	-0.173 0.021	-0.812 0.001	-0.430 0.001	

Period II (1977 - 1980)

[a] product moment correlation coefficient

[b] level of significance

Table (ii) (b): Three-Digit SIC Code

Period III (1978 - 1981)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)	β_i^I	ABETA	GMDOL	LEV	DIVCO	CFBETA	PROFIT	GR	COFAC
β_i^m(OLS)		0.274[a] 0.001[b]	0.219 0.003	0.291 0.001	0.392 0.001	0.044 0.556	-0.048 0.523	-0.050 0.510	-0.070 0.351	-0.111 0.141	0.057 0.453	0.301 0.001	-0.023 0.760
β_i^m(MR)	0.286 0.001		0.797 0.001	0.934 0.001	0.433 0.001	-0.068 0.364	-0.048 0.525	0.024 0.749	0.019 0.802	-0.044 0.554	-0.045 0.546	0.120 0.112	-0.001 0.993
β_i^m(OB)	0.252 0.001	0.816 0.001		0.552 0.001	0.384 0.001	0.036 0.634	0.066 0.383	0.048 0.520	-0.066 0.381	-0.085 0.261	-0.133 0.078	0.029 0.697	0.116 0.124
β_i^m(BA)	0.292 0.001	0.962 0.001	0.647 0.001		0.399 0.001	-0.132 0.081	-0.102 0.179	0.002 0.972	0.045 0.550	-0.017 0.816	0.019 0.797	0.167 0.027	-0.068 0.365
β_i^I	0.305 0.001	0.397 0.001	0.401 0.001	0.377 0.001		-0.022 0.767	0.152 0.044	0.240 0.001	-0.155 0.039	-0.152 0.043	-0.178 0.018	0.094 0.212	0.245 0.001
ABETA	0.136 0.010	0.025 0.638	0.073 0.166	0.011 0.829	0.078 0.143		0.245 0.001	0.160 0.033	0.018 0.804	-0.053 0.478	-0.118 0.117	0.012 0.868	0.343 0.001
GMDOL	-0.033 0.526	-0.036 0.499	0.071 0.182	-0.078 0.140	0.124 0.019	0.125 0.018		0.438 0.001	-0.220 0.003	-0.104 0.168	-0.502 0.001	-0.329 0.001	0.778 0.001
LEV	0.042 0.422	0.089 0.093	0.109 0.040	0.085 0.111	0.245 0.001	0.070 0.189	0.370 0.001		-0.155 0.040	-0.104 0.168	-0.569 0.001	-0.270 0.001	0.777 0.001
DIVCO	-0.005 0.914	-0.083 0.117	-0.137 0.009	-0.057 0.280	-0.152 0.004	-0.033 0.531	-0.259 0.001	-0.142 0.007		0.085 0.263	0.230 0.002	0.100 0.185	-0.405 0.001
CFBETA	-0.144 0.006	-0.163 0.002	-0.158 0.002	-0.168 0.001	-0.176 0.001	-0.048 0.367	-0.088 0.098	-0.089 0.095	0.160 0.002		0.106 0.161	0.028 0.712	-0.247 0.001
PROFIT	0.065 0.217	-0.100 0.060	-0.133 0.012	-0.067 0.207	-0.169 0.001	-0.042 0.422	-0.474 0.001	-0.544 0.001	0.204 0.001	0.054 0.307		0.524 0.001	-0.815 0.001
GR	0.142 0.007	-0.042 0.428	-0.066 0.211	-0.016 0.764	0.004 0.936	0.140 0.008	-0.385 0.001	-0.259 0.001	0.176 0.001	0.075 0.157	0.551 0.001		-0.422 0.001
COFAC	0.007 0.882	0.097 0.068	0.171 0.001	0.061 0.252	0.259 0.001	0.191 0.001	0.755 0.001	0.749 0.001	-0.467 0.001	-0.238 0.001	-0.806 0.001	-0.479 0.001	

Period IV (1979 - 1982)

[a] product moment correlation coefficient

[b] level of significance

Table (iii) (a): Two-Digit LOB Code

Period I (1976 - 1979)

	β^m_i(OLS)	β^m_i(MR)	β^m_i(OB)	β^m_i(BA)	β^I_i	ABETA	GMDOL	LEV	DIVCO	CFBETA	PROFIT	GR	COFAC
β^m_i(OLS)		0.434[a] 0.001[b]	0.428 0.001	0.405 0.001	0.537 0.001	0.094 0.076	0.057 0.279	0.179 0.001	-0.165 0.001	-0.160 0.002	-0.081 0.126	-0.049 0.359	-0.175 0.001
β^m_i(MR)	0.148 0.050		0.844 0.001	0.957 0.001	0.343 0.001	-0.090 0.089	-0.066 0.213	0.041 0.441	-0.118 0.025	-0.127 0.016	-0.035 0.510	-0.038 0.472	-0.050 0.345
β^m_i(OB)	0.097 0.198	0.820 0.001		0.675 0.001	0.397 0.001	-0.047 0.375	0.055 0.300	0.090 0.089	-0.167 0.001	-0.143 0.007	-0.099 0.062	-0.057 0.279	-0.149 0.004
β^m_i(BA)	0.185 0.014	0.934 0.001	0.579 0.001		0.321 0.001	-0.093 0.080	-0.115 0.030	0.033 0.534	-0.091 0.088	-0.127 0.016	0.001 0.990	-0.011 0.831	-0.009 0.856
β^I_i	0.173 0.021	0.389 0.001	0.409 0.001	0.306 0.001		0.116 0.029	0.236 0.001	0.304 0.001	-0.218 0.001	-0.225 0.001	-0.242 0.001	-0.133 0.011	-0.367 0.001
ABETA	-0.018 0.805	-0.017 0.816	0.006 0.929	-0.032 0.665	-0.056 0.458		0.078 0.141	-0.063 0.236	-0.018 0.726	-0.005 0.923	0.044 0.403	0.096 0.070	0.013 0.798
GMDOL	-0.064 0.396	0.105 0.163	0.208 0.005	0.035 0.640	0.223 0.003	0.100 0.184		0.333 0.001	-0.267 0.001	-0.082 0.120	-0.485 0.001	-0.422 0.001	-0.736 0.001
LEV	-0.082 0.275	0.075 0.321	0.076 0.315	0.060 0.423	0.141 0.061	0.093 0.220	0.348 0.001		-0.179 0.001	-0.103 0.052	-0.546 0.001	-0.259 0.001	-0.744 0.001
DIVCO	-0.078 0.303	0.057 0.453	-0.020 0.791	0.087 0.248	-0.148 0.049	0.034 0.647	-0.199 0.008	-0.063 0.401		0.202 0.001	0.210 0.001	0.175 0.001	0.510 0.001
CFBETA	0.014 0.850	-0.031 0.681	-0.085 0.259	0.003 0.965	-0.045 0.554	0.041 0.581	-0.092 0.222	-0.073 0.336	0.068 0.364		0.050 0.343	0.038 0.476	0.259 0.001
PROFIT	0.163 0.030	-0.092 0.221	-0.110 0.144	-0.061 0.422	-0.052 0.489	-0.117 0.120	-0.293 0.001	-0.569 0.001	0.197 0.008	0.086 0.254		0.506 0.001	0.814 0.001
GR	0.416 0.001	0.015 0.843	-0.026 0.731	0.054 0.473	0.096 0.202	0.103 0.174	-0.134 0.076	0.331 0.001	0.088 0.243	0.073 0.332	0.575 0.001		0.487 0.001
COFAC	-0.112 0.139	0.095 0.208	0.161 0.032	0.041 0.587	0.181 0.016	0.225 0.002	0.663 0.001	0.791 0.001	-0.368 0.001	-0.216 0.004	-0.805 0.001	-0.431 0.001	

Period II (1977 - 1980)

[a] prodcut moment correlation coefficient

[b] level of significance

Table (iii) (b): Two-Digit LOB Code

Period III (1978 - 1981)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)	β_i^I	ABETA	GMDOL	LEV	DIVCO	CFBETA	PROFIT	GR	COFAC
β_i^m(OLS)		0.238[a] 0.001[b]	0.202 0.001	0.249 0.001	0.365 0.001	0.046 0.385	-0.092 0.083	-0.007 0.892	-0.022 0.677	-0.098 0.065	0.097 0.069	0.239 0.001	-0.043 0.420
β_i^m(MR)	0.096 0.070		0.811 0.001	0.939 0.001	0.374 0.001	0.008 0.870	-0.034 0.513	0.029 0.585	-0.083 0.118	-0.089 0.093	-0.053 0.313	-0.051 0.333	0.048 0.367
β_i^m(OB)	0.049 0.357	0.822 0.001		0.584 0.001	0.365 0.001	0.094 0.075	0.061 0.251	0.069 0.195	-0.130 0.014	-0.111 0.037	-0.107 0.044	-0.093 0.080	0.141 0.007
β_i^m(BA)	0.131 0.013	0.944 0.001	0.607 0.001		0.346 0.001	-0.032 0.547	-0.079 0.136	0.017 0.748	-0.057 0.282	-0.079 0.139	-0.014 0.788	-0.001 0.998	0.000 0.993
β_i^I	0.103 0.052	0.324 0.001	0.373 0.001	0.266 0.001		0.007 0.885	0.095 0.073	0.193 0.001	-0.144 0.006	-0.172 0.001	-0.116 0.028	0.052 0.327	0.192 0.001
ABETA	-0.050 0.345	0.047 0.372	0.044 0.410	0.037 0.478	-0.031 0.550		0.233 0.001	0.184 0.001	-0.074 0.162	-0.080 0.132	-0.169 0.001	-0.062 0.240	0.413 0.001
GMDOL	-0.119 0.025	0.033 0.525	0.137 0.009	-0.011 0.828	0.215 0.001	0.099 0.061		0.371 0.001	-0.232 0.001	-0.108 0.042	-0.476 0.001	-0.349 0.001	0.736 0.001
LEV	-0.083 0.116	0.078 0.139	0.108 0.041	0.068 0.201	0.181 0.001	0.148 0.005	0.273 0.001		-0.197 0.001	-0.099 0.063	-0.544 0.001	-0.299 0.001	0.746 0.001
DIVCO	-0.044 0.403	-0.046 0.382	-0.061 0.249	-0.032 0.545	-0.097 0.068	0.055 0.298	-0.152 0.004	-0.111 0.037		0.106 0.046	0.255 0.001	0.165 0.001	-0.479 0.001
CFBETA	-0.001 0.976	-0.052 0.330	-0.094 0.076	-0.032 0.538	-0.075 0.154	-0.008 0.876	-0.127 0.016	-0.085 0.110	0.067 0.205		0.106 0.046	0.060 0.259	-0.265 0.001
PROFIT	0.213 0.001	-0.093 0.079	-0.115 0.030	-0.072 0.173	-0.049 0.355	-0.215 0.001	-0.329 0.001	-0.542 0.001	0.202 0.001	0.135 0.010		0.548 0.001	-0.803 0.001
GR	0.354 0.001	-0.080 0.129	-0.088 0.096	-0.047 0.377	0.043 0.419	-0.097 0.069	-0.190 0.001	-0.343 0.001	0.138 0.009	0.083 0.116	0.587 0.001		-0.470 0.001
COFAC	-0.159 0.002	0.104 0.049	0.166 0.001	0.070 0.187	0.181 0.001	0.344 0.001	0.622 0.001	0.755 0.001	-0.356 0.001	-0.291 0.001	-0.825 0.001	-0.491 0.001	

Period IV (1979 - 1982)

a product moment correlation coefficient

b level of significance

Table (iv) (a): Three-Digit LOB Code

Period I (1976 - 1979)

	β^m_i(OLS)	β^m_i(MR)	β^m_i(OB)	β^m_i(BA)	β^I_i	ABETA	GMDOL	LEV	DIVCO	CFBETA	PROFIT	GR	COFAC
β^m_i(OLS)		0.423[a] 0.001[b]	0.491 0.001	0.360 0.001	0.594 0.001	0.197 0.005	0.115 0.105	0.154 0.029	-0.153 0.030	-0.194 0.005	-0.121 0.087	-0.077 0.276	0.214 0.002
β^m_i(MR)	0.365 0.001		0.851 0.001	0.966 0.001	0.348 0.001	-0.113 0.110	-0.048 0.499	-0.030 0.668	-0.103 0.144	-0.185 0.008	0.019 0.785	-0.029 0.683	0.004 0.954
β^m_i(OB)	0.318 0.001	0.792 0.001		0.705 0.001	0.438 0.001	-0.033 0.635	0.133 0.059	0.006 0.929	-0.165 0.019	-0.170 0.015	-0.085 0.229	-0.063 0.373	0.139 0.049
β^m_i(BA)	0.352 0.001	0.961 0.001	0.609 0.001		0.308 0.001	-0.136 0.054	-0.119 0.091	-0.030 0.665	-0.076 0.281	-0.198 0.005	0.052 0.461	-0.013 0.847	-0.040 0.568
β^I_i	0.341 0.001	0.405 0.001	0.403 0.001	0.371 0.001		0.189 0.007	0.284 0.001	0.299 0.001	-0.198 0.005	-0.240 0.001	-0.299 0.001	-0.159 0.024	0.405 0.001
ABETA	0.141 0.046	0.052 0.464	0.084 0.235	0.023 0.746	0.029 0.681		0.168 0.017	-0.001 0.992	-0.083 0.238	-0.034 0.633	-0.008 0.908	0.016 0.813	0.163 0.021
GMDOL	-0.032 0.653	-0.028 0.686	0.096 0.174	-0.084 0.233	0.112 0.114	0.165 0.019		0.417 0.001	-0.324 0.001	-0.086 0.223	-0.491 0.001	-0.382 0.001	0.784 0.001
LEV	-0.054 0.442	0.023 0.740	0.016 0.821	0.037 0.597	0.221 0.001	0.027 0.697	0.438 0.001		-0.171 0.015	-0.084 0.234	-0.560 0.001	-0.291 0.001	0.749 0.001
DIVCO	0.019 0.782	-0.045 0.526	-0.089 0.210	-0.027 0.697	-0.150 0.034	-0.017 0.807	-0.289 0.001	-0.140 0.048		0.273 0.001	0.213 0.002	0.110 0.118	-0.538 0.001
CFBETA	-0.134 0.058	-0.220 0.001	-0.157 0.025	-0.242 0.001	-0.186 0.008	-0.037 0.595	-0.072 0.308	-0.053 0.454	0.197 0.005		0.022 0.755	-0.003 0.955	-0.256 0.001
PROFIT	0.051 0.471	-0.051 0.466	-0.110 0.121	-0.021 0.764	-0.173 0.014	-0.049 0.485	-0.474 0.001	-0.574 0.001	0.213 0.002	0.023 0.744		0.546 0.001	-0.787 0.001
GR	0.177 0.012	0.014 0.838	-0.018 0.792	0.029 0.678	0.037 0.595	0.131 0.063	-0.325 0.001	-0.273 0.001	0.101 0.152	0.045 0.524	0.554 0.001		-0.461 0.001
COFAC	-0.031 0.660	0.051 0.473	0.122 0.084	0.019 0.780	0.237 0.001	0.179 0.011	0.782 0.001	0.771 0.001	-0.475 0.001	-0.188 0.007	-0.806 0.001	-0.439 0.001	

Period II (1977 - 1980)

[a] product moment correlation coefficient

[b] level of significance

Table (iv) (b): Three-Digit LOB Code

Period III (1978 - 1981)

	β_i^m(OLS)	β_i^m(MR)	β_i^m(OB)	β_i^m(BA)	β_i^I	ABETA	GMDOL	LEV	DIVCO	CFBETA	PROFIT	GR	COFAC
β_i^m(OLS)		0.307[a] 0.001[b]	0.248 0.001	0.308 0.001	0.404 0.001	0.032 0.652	-0.076 0.260	-0.121 0.088	-0.053 0.452	-0.111 0.115	0.092 0.194	0.303 0.001	-0.070 0.320
β_i^m(MR)	0.192 0.006		0.793 0.001	0.938 0.001	0.383 0.001	-0.068 0.337	-0.023 0.737	-0.022 0.753	-0.062 0.379	-0.103 0.146	-0.078 0.267	0.022 0.757	0.029 0.681
β_i^m(OB)	0.109 0.123	0.803 0.001		0.557 0.001	0.356 0.001	-0.008 0.910	0.072 0.306	-0.002 0.969	-0.100 0.158	-0.094 0.184	-0.137 0.052	-0.023 0.742	0.106 0.135
β_i^m(BA)	0.234 0.001	0.937 0.001	0.563 0.001		0.346 0.001	-0.099 0.162	-0.080 0.257	-0.023 0.746	-0.057 0.417	-0.106 0.136	-0.025 0.724	0.057 0.420	-0.014 0.835
β_i^I	0.174 0.013	0.370 0.001	0.381 0.001	0.302 0.001		-0.059 0.401	0.082 0.244	0.208 0.003	-0.166 0.019	-0.179 0.011	-0.127 0.072	0.107 0.131	0.196 0.005
ABETA	-0.022 0.748	-0.006 0.925	0.001 0.989	-0.011 0.875	-0.020 0.774		0.222 0.001	0.119 0.093	-0.043 0.539	-0.069 0.331	-0.114 0.105	0.044 0.533	0.319 0.001
GMDOL	-0.072 0.307	0.110 0.118	0.214 0.002	0.037 0.596	0.190 0.007	0.061 0.387		0.429 0.001	-0.262 0.001	-0.108 0.127	-0.453 0.001	-0.332 0.001	0.754 0.001
LEV	-0.129 0.068	0.012 0.865	0.009 0.896	0.025 0.725	0.157 0.026	0.150 0.033	0.358 0.001		-0.206 0.003	-0.091 0.200	-0.553 0.001	-0.312 0.001	0.762 0.001
DIVCO	-0.090 0.205	0.001 0.997	-0.025 0.717	0.007 0.914	-0.090 0.205	0.018 0.797	-0.199 0.004	-0.114 0.108		0.113 0.110	0.294 0.001	0.116 0.102	-0.517 0.001
CFBETA	-0.052 0.457	-0.066 0.353	-0.082 0.249	-0.062 0.382	-0.066 0.350	0.010 0.881	-0.167 0.017	-0.077 0.275	0.094 0.186		0.102 0.148	0.044 0.530	-0.256 0.001
PROFIT	0.170 0.016	-0.070 0.324	-0.083 0.240	-0.053 0.452	-0.003 0.959	-0.132 0.061	-0.317 0.001	-0.573 0.001	0.269 0.001	0.105 0.139		0.559 0.001	-0.799 0.001
GR	0.412 0.001	-0.018 0.792	-0.028 0.687	0.007 0.916	0.089 0.209	0.121 0.087	-0.177 0.012	-0.344 0.001	0.115 0.103	0.076 0.283	0.568 0.001		-0.446 0.001
COFAC	-0.116 0.102	0.076 0.280	0.123 0.082	0.048 0.494	0.150 0.034	0.245 0.001	0.661 0.001	0.780 0.001	-0.444 0.001	-0.284 0.001	-0.808 0.001	-0.435 0.001	

Period IV (1979 - 1982)

[a] product moment correlation coefficient

[b] level of significance

APPENDIX G

Summary Statistics of Four-Factor Model

Table (i)
Market-Related Systematic Risk: Market Model
Industry Classification: Two-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.314	-0.877	-0.081	0.516
(t-value)	(-1.454)	(-4.368)**	(-0.505)	(2.818)**
Regression Coefficients:				
β_i^m (10^{-2})	0.147	0.762	0.289	-0.103
(t-value)	(0.994)	(4.974)**	(2.295)*	(-0.668)
β_i^I (10^{-1})	0.089	0.560	0.403	0.673
(t-value)	(6.252)**	(4.150)**	(3.358)**	(5.405)**
Company Index (10^{-1})	1.283	-0.225	-0.206	-0.273
(t-value)	(2.379)*	(-4.523)**	(-5.261)**	(-5.606)**
Growth	0.218	0.238	0.174	0.167
(t-value)	(6.063)**	(7.116)**	(6.106)**	(5.317)**
F-statistic	28.644	50.880	40.260	35.809
S_e^2(10^{-1})	0.119	0.112	0.093	0.108
R^2	0.251	0.373	0.320	0.295
R_a^2	0.242	0.366	0.312	0.287
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.496	0.446	0.307	0.412
MFE (10^{-2})	-0.071	0.235	0.471	-
MAFE (10^{-2})	0.966	0.884	0.928	-
MSFE (10^{-3})	0.147	0.127	0.141	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (ii)
Market-Related Systematic Risk: Mean Reversion Model
Industry Classification: Two-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.160	-0.328	0.097	0.102
(t-value)	(-0.602)	(-1.245)	(0.415)	(2.818)**
Regression Coefficients:				
β_i^m (10^{-2})	-0.388	-0.010	-0.014	-0.103
(t-value)	(-1.922)	(-0.056)	(-0.073)	(-0.668)
β_i^I (10^{-2})	0.105	0.754	0.501	0.673
(t-value)	(7.954)**	(5.181)**	(4.080)**	(5.405)**
Company Index (10^{-2})	1.380	-0.225	-0.207	-0.273
(t-value)	(2.558)**	(-4.374)**	(-5.242)**	(-5.606)**
Growth	0.216	0.256	0.187	0.157
(t-value)	(6.028)**	(7.543)**	(6.602)**	(5.317)**
F-statistic	29.544	41.680	38.356	35.809
S_e^2(10^{-1})	0.118	0.116	0.094	0.108
R^2	0.257	0.328	0.310	0.295
R_a^2	0.248	0.320	0.302	0.287
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.492	0.478	0.311	0.412
MFE (10^{-2})	-0.083	0.211	0.462	-
MAFE (10^{-2})	0.992	0.848	0.916	-
MSFE (10^{-3})	0.156	0.116	0.137	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (iii)
Market-Related Systematic Risk: Order Bias Adjustment Model
Industry Classification: Two-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.030	-0.382	0.078	0.240
(t-value)	(-0.137)	(-1.809)	(0.478)	(1.505)
Regression Coefficients:				
β_i^m (10^{-2})	-0.213	0.052	0.007	0.235
(t-value)	(-1.468)	(0.375)	(0.072)	(2.646)**
β_i^I (10^{-1})	0.104	0.731	0.495	0.545
(t-value)	(7.731)**	(5.067)**	(4.080)**	(4.159)**
Company Index (10^{-1})	1.283	-0.226	-0.207	-0.282
(t-value)	(2.384)*	(-4.389)**	(-5.247)**	(-5.817)**
Growth	0.219	0.256	0.187	0.166
(t-value)	(6.084)**	(7.568)**	(6.621)**	(5.588)**
F-statistic	29.033	41.731	38.356	38.131
S_e^2(10^{-1})	0.118	0.116	0.094	0.107
R^2	0.254	0.328	0.310	0.308
R_a^2	0.245	0.320	0.302	0.300
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.494	0.479	0.312	0.404
MFE (10^{-2})	-0.090	0.210	0.459	-
MAFE (10^{-2})	0.981	0.846	0.915	-
MSFE (10^{-3})	0.152	0.116	0.137	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (iv)
Market-Related Systematic Risk: Bayesian Adjustment Model
Industry Classification: Two-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	0.288	-0.344	0.056	0.072
(t-value)	(0.916)	(-1.208)	(0.224)	(0.298)
Regression Coefficients:				
β_i^m (10^{-2})	-0.475	0.006	0.028	0.317
(t-value)	(-1.944)	(0.026)	(0.136)	(1.896)
β_i^I (10^{-2})	0.105	0.750	0.492	0.606
(t-value)	(7.979)**	(5.179)**	(4.055)**	(4.758)**
Company Index (10^{-2})	1.410	-0.225	-0.207	-0.274
(t-value)	(2.606)**	(-4.368)**	(-5.217)**	(-5.639)**
Growth	0.217	0.256	0.187	0.164
(t-value)	(6.050)**	(7.552)**	(6.639)**	(5.497)**
F-statistic	29.573	41.679	38.361	36.925
S_{e^2} (10^{-1})	0.118	0.116	0.094	0.107
R^2	0.257	0.328	0.310	0.302
R_a^2	0.248	0.320	0.302	0.293
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.491	0.477	0.311	0.408
MFE (10^{-2})	-0.081	0.212	0.456	-
MAFE (10^{-2})	0.996	0.848	0.914	-
MSFE (10^{-3})	0.157	0.116	0.137	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (v)
Market-Related Systematic Risk: Market Model
Industry Classification: Three-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.262	-0.934	-0.168	0.366
(t-value)	(-0.867)	(-3.516)**	(-0.758)	(1.372)
Regression Coefficients:				
β_i^m (10^{-2})	0.433	0.118	0.562	0.126
(t-value)	(1.950)	(5.809)**	(3.184)**	(0.505)
β_i^I (10^{-2})	0.716	0.370	0.289	0.336
(t-value)	(3.379)**	(2.048)**	(1.731)	(2.978)**
Company Index (10^{-2})	-0.077	-0.202	-0.228	-0.217
(t-value)	(-0.994)	(-3.089)**	(-4.063)**	(-2.977)**
Growth	0.163	0.194	0.138	0.165
(t-value)	(3.392)**	(4.537)**	(3.124)**	(3.149)**
F-statistic	12.114	28.086	19 627	12.305
S_e^2(10^{-1})	0.121	0.108	0.095	0.117
R^2	0.222	0.398	0.316	0.225
R_a^2	0.204	0.384	0.300	0.206
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.264	0.211	0.163	0.248
MFE (10^{-2})	-0.092	0.101	0.414	-
MAFE (10^{-2})	0.894	0.911	0.959	-
MSFE (10^{-3})	0.127	0.134	0.154	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (vi)
Market-Related Systematic Risk: Mean Reversion Model
Industry Classification: Three-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	0.186	-0.226	-0.184	0.153
(t-value)	(0.486)	(-0.695)	(-0.557)	(0.524)
Regression Coefficients:				
β_i^m (10^{-2})	-0.179	0.010	-0.083	0.309
(t-value)	(-0.561)	(0.374)	(-0.276)	(1.411)
β_i^I (10^{-2})	1.009	0.683	0.504	0.444
(t-value)	(5.128)**	(3.275)**	(2.850)**	(2.313)*
Company Index (10^{-2})	-0.087	-0.202	-0.230	-0.217
(t-value)	(-1.086)	(-2.816)**	(-3.958)**	(-2.997)**
Growth	0.164	0.228	0.175	0.176
(t-value)	(3.368)**	(4.910)**	(3.978)**	(3.665)**
F-statistic	11.018	16.444	16.158	12.892
S_e^2(10^{-1})	0.122	0.118	0.098	0.116
R^2	0.206	0.279	0.276	0.233
R_a^2	0.187	0.262	0.258	0.215
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.268	0.254	0.174	0.245
MFE (10^{-2})	-0.171	0.076	0.415	-
MAFE (10^{-2})	0.940	0.857	0.947	-
MSFE (10^{-3})	0.139	0.120	0.152	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (vii)
Market-Related Systematic Risk: Order Bias Adjustment Model
Industry Classification: Three-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	0.080	-0.170	-0.158	0.303
(t-value)	(0.258)	(-0.597)	(-0.699)	(1.337)
Regression Coefficients:				
β_i^m (10^{-2})	-0.071	0.028	-0.064	0.194
(t-value)	(-0.306)	(0.147)	(-0.523)	(1.569)
β_i^I (10^{-2})	0.987	0.706	0.515	0.430
(t-value)	(4.935)**	(3.469)**	(3.015)**	(2.233)*
Company Index (10^{-2})	-0.080	-0.204	-0.227	-0.223
(t-value)	(-1.015)	(-2.853)**	(-3.938)**	(-3.081)**
Growth	0.164	0.228	0.175	0.177
(t-value)	(3.361)**	(4.915)**	(3.975)**	(3.097)**
F-statistic	10.948	16.402	16.226	13.015
S_e^2(10^{-1})	0.122	0.118	0.098	0.116
R^2	0.205	0.279	0.276	0.234
R_a^2	0.186	0.262	0.259	0.216
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.269	0.257	0.181	0.244
MFE (10^{-2})	-0.175	0.070	0.410	-
MAFE (10^{-2})	0.939	0.859	0.947	-
MSFE (10^{-3})	0.138	0.121	0.152	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (viii)
Market-Related Systematic Risk: Bayesian Adjustment Model
Industry Classification: Three-Digit SIC Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	0.322	-0.346	-0.052	0.100
(t-value)	(0.697)	(-0.853)	(-0.141)	(0.281)
Regression Coefficients:				
β_i^m (10^{-2})	-0.291	0.020	0.066	0.318
(t-value)	(-0.768)	(0.614)	(0.206)	(1.206)
β_i^I (10^{-2})	1.021	0.664	0.468	0.482
(t-value)	(5.293)**	(3.227)**	(2.675)**	(2.588)*
Company Index (10^{-2})	-0.092	-0.199	-0.226	-0.215
(t-value)	(-1.142)	(-2.775)**	(-3.882)**	(-2.962)**
Growth	0.163	0.227	0.174	0.173
(t-value)	(3.366)**	(4.910)**	(3.949)**	(3.612)**
F-statistic	11.104	16.326	16.146	12.691
S_e (10^{-1})	0.122	0.118	0.098	0.117
R^2	0.207	0.280	0.275	0.230
R_a^2	0.189	0.263	0.258	0.212
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.267	0.253	0.173	0.246
MFE (10^{-2})	-0.168	0.081	0.391	-
MAFE (10^{-2})	0.942	0.855	0.939	-
MSFE (10^{-3})	0.140	0.120	0.148	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (ix)
Market-Related Systematic Risk: Market Model
Industry Classification: Two-Digit LOB Code

	Period I 1976-79)	eriod II 1977-80)	eriod III 1978-81)	eriod IV 1979-82)
Constant (10^{-2})	-0.255	-0.857	-0.083	-0.487
(t-value)	(-1.215)	(-4.321)**	(-0.515)	(-2.668)**
Regression Coefficients:				
β_i^m (10^{-2})	0.132	0.762	0.301	-0.079
(t-value)	(0.919)	(5.085)**	(2.419)*	(-0.521)
β_i^I (10^{-2})	0.845	0.559	0.406	0.686
(t-value)	(6.077)**	(4.159)**	(3.355)**	(5.574)**
Company Index (10^{-2})	0.120	-0.226	-0.212	-0.274
(t-value)	(2.254)*	(-4.574)**	(-5.382)**	(-5.654)**
Growth	0.220	0.231	0.173	0.168
(t-value)	(6.153)**	(7.064)**	(6.007)**	(5.372)**
F-statistic	28.288	51.062	40.876	37.282
S_e^2(10^{-1})	0.118	0.112	0.094	0.108
R^2	0.246	0.371	0.320	0.301
R_a^2	0.237	0.363	0.312	0.293
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.502	0.452	0.317	0.416
MFE (10^{-2})	-0.067	0.231	0.469	-
MAFE (10^{-2})	0.961	0.884	0.929	-
MSFE (10^{-3})	0.145	0.127	0.140	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (x)
Market-Related Systematic Risk: Mean Reversion Model
Industry Classification: Two-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.162	-0.345	0.025	-0.071
(t-value)	(-0.616)	(-1.427)	(0.108)	(-0.361)
Regression Coefficients:				
β_i^m (10^{-2})	-0.336	0.021	0.063	0.035
(t-value)	(-1.709)	(0.120)	(0.322)	(2.606)**
β_i^I (10^{-2})	0.987	0.755	0.495	0.573
(t-value)	(7.782)**	(5.221)**	(4.008)**	(4.464)**
Company Index (10^{-2})	0.130	-0.227	-0.212	-0.273
(t-value)	(2.427)**	(-4.427)**	(-5.321)**	(-5.699)**
Growth	0.219	0.253	0.188	0.170
(t-value)	(6.118)**	(7.475)**	(6.585)**	(5.735)**
F-statistic	28.974	41.511	38.798	39.611
S_{e^2}(10^{-1})	0.118	0.116	0.095	0.107
R^2	0.250	0.324	0.309	0.314
R_a^2	0.242	0.316	0.301	0.306
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.498	0.485	0.322	0.409
MFE (10^{-2})	-0.077	0.209	0.448	-
MAFE (10^{-2})	0.985	0.849	0.911	-
MSFE (10^{-3})	0.153	0.116	0.135	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (xi)
Market-Related Systematic Risk: Order Bias Adjustment Model
Industry Classification: Two-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.008	-0.387	0.055	-0.228
(t-value)	(-0.036)	(-1.841)	(0.338)	(-1.451)
Regression Coefficients:				
β_i^m (10^{-2})	-0.180	0.072	0.035	0.024
(t-value)	(-1.262)	(0.529)	(0.383)	(2.785)
β_i^I (10^{-2})	0.971	0.733	0.494	0.550
(t-value)	(7.576)**	(5.105)**	(4.040)**	(4.232)**
Company Index (10^{-2})	0.121	-0.229	-0.213	-0.281
(t-value)	(2.269)*	(-4.455)**	(-5.367)**	(-5.867)**
Growth	0.221	0.253	0.188	0.169
(t-value)	(6.171)**	(7.500)**	(6.594)**	(5.712)**
F-statistic	28.536	41.609	38.814	39.956
S_{e^2}(10^{-1})	0.118	0.116	0.095	0.107
R^2	0.248	0.324	0.309	0.315
R_a^2	0.239	0.316	0.301	0.307
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.501	0.486	0.323	0.407
MFE (10^{-2})	-0.083	0.205	0.455	-
MAFE (10^{-2})	0.976	0.847	0.913	-
MSFE (10^{-3})	0.150	0.115	0.136	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (xii)
Market-Related Systematic Risk: Bayesian Adjustment Model
Industry Classification: Two-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.282	-0.368	-0.014	0.025
(t-value)	(-0.907)	(-1.303)	(-0.057)	(2.143)*
Regression Coefficients:				
β_i^m (10^{-2})	-0.421	0.040	0.099	0.035
(t-value)	(-1.761)	(0.192)	(0.481)	(2.143)*
β_i^I (10^{-2})	0.987	0.751	0.490	0.609
(t-value)	(7.810)**	(5.228)**	(4.007)**	(4.818)**
Company Index (10^{-2})	0.133	-0.226	-0.211	-0.273
(t-value)	(2.474)*	(-4.455)**	(-5.292)**	(-5.668)**
Growth	0.219	0.253	0.188	0.167
(t-value)	(6.136)**	(7.482)**	(6.606)**	(5.624)**
F-statistic	29.034	41.519	38.844	38.825
S_e^2(10^{-1})	0.118	0.116	0.095	0.107
R^2	0.251	0.324	0.309	0.309
R_a^2	0.242	0.316	0.301	0.301
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.498	0.485	0.322	0.411
MFE (10^{-2})	-0.075	0.210	0.443	-
MAFE (10^{-2})	0.989	0.849	0.910	-
MSFE (10^{-3})	0.154	0.116	0.135	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (xiii)
Market-Related Systematic Risk: Market Model
Industry Classification: Three-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.662	-1.007	-0.228	-0.300
(t-value)	(-2.273)*	(-4.061)**	(-1.120)	(-1.247)
Regression Coefficients:				
β_i^m (10^{-2})	0.434	1.071	0.505	0.089
(t-value)	(2.060)*	(5.505)**	(3.065)**	(0.397)
β_i^I (10^{-2})	0.851	0.407	0.409	0.785
(t-value)	(4.039)**	(2.299)*	(2.495)*	(4.724)**
Company Index (10^{-2})	-0.102	-0.214	-0.237	-0.283
(t-value)	(-1.455)	(-3.551)**	(-4.637)**	(-4.519)**
Growth	0.242	0.238	0.159	0.139
(t-value)	(5.050)**	(5.679)**	(3.978)**	(3.011)**
F-statistic	18.760	36.553	27.885	19.738
S_e^2(10^{-1})	0.120	0.107	0.092	0.111
R^2	0.279	0.430	0.365	0.289
R_a^2	0.264	0.418	0.352	0.275
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.296	0.234	0.174	0.252
MFE (10^{-2})	-0.005	0.206	0.435	-
MAFE (10^{-2})	0.880	0.906	0.936	-
MSFE (10^{-3})	0.120	0.130	0.143	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (xiv)
Market-Related Systematic Risk: Mean Reversion Model
Industry Classification: Three-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.346	-0.743	-0.078	0.070
(t-value)	(-0.898)	(-2.266)*	(-0.242)	(0.258)
Regression Coefficients:				
β_i^m (10^{-2})	-0.023	0.463	0.103	0.293
(t-value)	(-0.075)	(1.867)	(0.367)	(1.458)
β_i^I (10^{-2})	1.103	0.592	0.581	0.700
(t-value)	(5.821)**	(3.051)**	(3.459)**	(3.976)**
Company Index (10^{-2})	-0.108	-0.223	-0.241	-0.282
(t-value)	(-1.494)**	(-3.471)**	(-4.604)**	(-4.524)**
Growth	0.242	0.272	0.189	0.149
(t-value)	(4.999)**	(6.129)**	(4.748)**	(3.516)**
F-statistic	17.323	26.384	24.408	20.429
S_{e}^2(10^{-1})	0.121	0.114	0.094	0.110
R^2	0.263	0.352	0.335	0.296
R_a^2	0.248	0.339	0.321	0.282
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.301	0.266	0.183	0.249
MFE (10^{-2})	-0.098	0.195	0.405	-
MAFE (10^{-2})	0.903	0.848	0.914	-
MSFE (10^{-3})	0.127	0.115	0.136	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (xv)
Market-Related Systematic Risk: Order Bias Adjustment Model
Industry Classification: Three-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.368	-0.517	-0.002	0.220
(t-value)	(-1.124)	(-1.896)	(-0.007)	(1.058)
Regression Coefficients:				
β_i^m (10^{-2})	-0.000	0.265	0.024	0.180
(t-value)	(-0.000)	(1.437)	(0.200)	(1.529)
β_i^I (10^{-2})	1.098	0.632	0.593	0.694
(t-value)	(5.678)**	(3.266)**	(3.591)**	(3.938)**
Company Index (10^{-2})	-0.107	-0.231	-0.242	-0.286
(t-value)	(-1.500)	(-3.593)**	(-4.641)**	(-4.597)**
Growth	0.242	0.271	0.189	0.149
(t-value)	(5.008)**	(6.094)**	(4.738)**	(3.503)**
F-statistic	17.321	25.844	24.373	20.504
S_{e^2} (10^{-1})	0.121	0.114	0.094	0.110
R^2	0.263	0.348	0.335	0.297
R_a^2	0.248	0.334	0.321	0.283
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.303	0.269	0.185	0.248
MFE (10^{-2})	-0.099	0.159	0.418	-
MAFE (10^{-2})	0.902	0.847	0.918	-
MSFE (10^{-3})	0.127	0.115	0.138	-

* significant at the 0.05 level

** significant at the 0.01 level

Table (xvi)
Market-Related Systematic Risk: Bayesian Adjustment Model
Industry Classification: Three-Digit LOB Code

	Period I (1976-79)	Period II (1977-80)	Period III (1978-81)	Period IV (1979-82)
Constant (10^{-2})	-0.331	-0.959	-0.203	0.005
(t-value)	(-0.721)	(-2.458)*	(-0.572)	(0.015)
Regression Coefficients:				
β_i^m (10^{-2})	-0.035	0.610	0.220	0.315
(t-value)	(-0.097)	(2.072)*	(0.735)	(1.283)
β_i^I (10^{-2})	1.104	0.590	0.561	0.728
(t-value)	(5.885)**	(3.087)**	(3.396)**	(4.243)**
Company Index (10^{-2})	-0.108	-0.219	-0.239	-0.281
(t-value)	(-1.492)	(-3.423)**	(-4.559)**	(-4.514)**
Growth	0.242	0.271	0.189	0.147
(t-value)	(4.997)**	(6.134)**	(4.757)**	(3.466)**
F-statistic	17.324	26.690	24.560	20.261
S_e(10^{-1})	0.121	0.114	0.094	0.110
R^2	0.263	0.355	0.336	0.295
R_a^2	0.248	0.342	0.323	0.280
C_p Statistic	5.000	5.000	5.000	5.000
PRESS (10^{-1})	0.301	0.264	0.182	0.249
MFE (10^{-2})	-0.098	0.204	0.390	-
MAFE (10^{-2})	0.903	0.851	0.910	-
MSFE (10^{-3})	0.127	0.115	0.135	-

* significant at the 0.05 level

** significant at the 0.01 level

APPENDIX H

Model Selection Process

Average statistics of the estimated models are examined to determine which model provides the "best" explanation and prediction of security returns. A description of the decision process involved in determining the "best" return model is given as follows:

1. the selection process begins with examining the explanatory power of the full model;
2. R^2 of the full model is always the highest in value, because it has included all regressor variables in the model;
3. R_a^2 is then examined, because this statistic takes into account the difference in number of regressor variables included in different models;
4. surprisingly, R_a^2 of the full model is either the highest or second highest among all models examined;
5. thus, there is no ambiguity with respect to which model provides the "best" explanation of security returns, and it is the full model; (note: decision based on R_a^2 is the same as that based on S_{e^2})
6. it is desirable that the selected "best" return model performs well both in explaining and predicting security returns, thus when the predictive criteria (PRESS, Mallow's C_p, MFE, MAFE and MSFE) of the model are evaluated, its explantory power is also taken into consid-

eration in making the decision;

7. therefore, models whose R^2 and R_a^2 are substantially less than those of the full model are eliminated regardless of how low its predictive statistics are;
8. this eventually reduces the number of submodels that are comparable with the full model;
9. the PRESS statistic of the full model is the lowest among all models examined, and its Mallow's C_p statistic always equal to 10, this serves as the benchmark for deciding which models should be examined further;
10. submodel 2 -- RETURN = f(β_i^m, β_i^I, ABETA, GMDOL, LEV, DIVCO, CFBETA, PROFIT, GR) -- is the only model that exhibits low PRESS and C_p statistics, and is competitive to the full model in providing good explanation and prediction of security returns;
11. the set of possible return models is reduced to two: the full model and submodel 2, in this case, the forecast errors of these two models are compared to determine which is the best;
12. in some cases, submodel 2 outperforms the full model in terms of the forecast errors, and in others, the opposite is true;
13. the magnitude of the forecast errors is so small (e.g., 10^{-2} for MAFE) that Mallow's C_p statistic and PRESS are relied upon more heavily in making the final decision;
14. the final decision is that the full model is the "best" both in terms of explaining and predicing security returns among the sixteen mod-

els examined;

15. finally, the full model is compared to the four-factor model, it is found that the full model outperforms the four-factor model substantially in R^2, R_a^2, and PRESS; (note: Mallow's C_p statistic is irrelevant in this case because the C_p value for the four-factor model always equals 5)
16. the four-factor model is preferred in terms of the forecast errors in most cases, but the magnitude is too small to be of any significance;
17. therefore, the conclusion of the selection process is that the full model provides the "best" explanation and prediction of security returns.

In this selection process, subjective judgement of the author plays an important role in making the final decision. Since there is no substantial difference in the criteria, it is plausible that different persons will prefer other models to the full model. Some may argue that for the reason of parsimony, other simpler models should be chosen. The author, however, believes that by including all regressors, the applicability of the model can be extended to a larger population of interest. Besides, multicollinearity among regressor variables does not affect the overall explanatory power and predictive ability of the model. Furthermore, underspecification of a regression model will introduce bias in prediction, which is not desirable for the present study.

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