A Model to Explain Shareholder Returns: Marketing Implications

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This study attempts to lend empirical evidence to the relevance of the arbitrage pricing theory in providing economic interpretation to stock market factors. A multistage model to explain the stock returns of a representative set of U.S. companies is developed. Monthly returns data for individual securities are obtained and the cross-sectional interdependencies between securities are identified. The returns of the securities are found to be related to at least three, and possibly four, factors. The hypotheses related these factors to broad economic aggregates such as cost and supply of money, in addition to the market return index. The presence of idiosyncratic industry effect in the market is also demonstrated. The replication of the analysis with another sample from a different time period yields similar results. Marketing implications are drawn based on the findings of this study.

Every organization has multiple stakeholders—employees, shareholders, and management, to name a few whose performance expectations may be different. Shareholders may believe that organizational performance is excellent if the earnings per share is high; management may be satisfied with a performance that meets internal rate of return, profitability, and market share requirements; and employees may be satisfied if organizations have the ability to meet their salary and promotion expectations. The multiple constituency perspective is best illustrated by Lloyds Bank which reported a big loss in 1989, yet the CEO claimed it was a good year for the shareholders.

Most previous research on organizational performance has adopted the perspective of management and examined the effects of several strategy and process factors on performance measures such as profitability and market share. For example, the strategy literature has primarily been concerned with how organizations perceive the markets they operate in and make decisions regarding the posture to adopt in those markets (Porter, 1980). The organization behavior literature, on the other hand, has focused on the contingent relationships between design and performance.

Based on the studies examining organizational performance from the shareholder’s perspective, the general argument made is that stock returns are idiosyncratic and cannot be predicted. The focus of the present study is to address this assumption. Specifically, the present study develops a multistage model to explain the stock returns of a representative sample of companies listed in the New York Stock Exchange. In the first stage, the study uses capital asset pricing model (CAPM) principles to evaluate the common variation in stock returns with the market return index. In the second stage, the study uses a model based on the arbitrage pricing theory (APT) suggested by Roll and Ross (1995) to identify and evaluate the effects of two additional factors, namely the cost of money and the availability of supply of money. In the third stage, the study evaluates if there is a systematic variation in stock returns with the industry to which a particular company belongs.

Empirical support for the conceptual model of the study would indicate that stock movements are not idiosyncratic and can, in fact, be predicted (Ferson and Harvey, 1991). The significance of hypothesized factors in the present study may provide clear evidence of whether and to what extent movements in stock prices can be explained. Previous studies have shown the relationship between stock returns and measures of brand equity (e.g., market-to-book equity, corporate and brand reputation). If so, subsequent studies can enable researchers to...
evaluate the degree to which the factors governing stock returns are related to measures of marketing variables such as corporate and brand reputation and therefore, brand equity.

**Motivation and Hypotheses**

Early attempts at predicting stock returns were based on the CAPM. CAPM explains the common variation in stock returns in terms of a market return index. The systematic risk of the $i^{\text{th}}$ security associated with market index, often denoted by $\beta$, is given by

$$\beta_i = \frac{\text{Cov} (R_i, R_m)}{\text{Var} (R_m)}$$

(1)

The CAPM assumes

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

(2)

where $R_i$ is the expected rate of return, and $E(R_m)$ is the expected return on a market portfolio of securities, consisting of every asset outstanding in proportion to its total value. One can infer from CAPM that higher the value of $\beta$, the greater the impact of market variability on variability of returns on the security. Researchers have observed, however, that the CAPM is testable only because it is difficult to observe the exact composition of the true market portfolio.

**Arbitrage Pricing Theory**

The arbitrage pricing theory (APT) paradigm focuses on the covariance between asset returns and multiple factors in the return generating process. Compared to CAPM, APT which requires less restrictive and presumably more plausible assumptions, is more readily testable since it does not require the measurement of the market portfolio, and may be better able to explain the anomalies found in the application of the CAPM to asset returns (Dhrymes, Friend, and Gultekin, 1984). APT hypothesizes that variations in stock values could be attributed to the presence of a few systematic components of risk (Breyal and Myers, 1996). The model postulates that

$$E(R_i) = R_f + a_1b_{i1} + a_2b_{i2} + \ldots + a_nb_{ijn}$$

(3)

where $E(R_i)$ is expected return on asset $i$, $b_{ij}$ is the reaction coefficient describing the change in asset $i$'s return for a unit change in factor $j$, $R_f$ is the return on an asset that is risk free because all its $b_{ij}$'s are zero, and $a_i$ is the premium for risk associated with factor $j$.

The reaction coefficients that characterize an asset are estimated from a market model,

$$r_i = b_o + b_{i1}d_{it} + b_{i2}d_{it} + \ldots + b_{in}d_{in} + e_i$$

(4)

where $r_i$ is the return on asset $i$ in period $t$, $d_{ij}$ is the value at time $t$ of the mean zero factor $j$ common to the returns of all assets, $b_{ij}$ is the estimated reaction coefficient of asset $i$ to factor $j$, $b_{o}$ is the estimated return on asset $i$ when all $d_{ij}$ values are zero, and $e_i$ is an error term with $E(e_i) = 0$ denoting residual risk. An important feature of APT is that it will be useful if we are unable to identify these additional risk factors that are relevant and their definition.

Additionally, Dhrymes et al. (1984) raise an important concern regarding the number of relevant risk factors. Dhrymes et al. (1984) noted that: “If, after prolonged empirical investigations, the number of factors found is stabilized, and an economic/financial interpretation is attached to them, we may, at that stage, think of such risk factors as reflecting fundamental economic forces at work in the securities market.” This is the challenge that the present study has undertaken. If our attempt is successful, then marketers can monitor those economic forces to develop contingency plans to improve their firms’ or brands’ performance. In other words, APT attempts to measure the various dimensions of market related risk in terms of several underlying economic factors which systematically affect the price of all shares. Roll and Ross (1984) in their reply to Dhrymes et al. (1984) observe that an increase in the number of the stocks from the same industry could also increase the number of factors (industry effect). But they argued that such a factor would not be priced because it was not pervasive. Chan, Hamao, and Lakonishok (1993) conclude that it very well may be the case that returns are driven not only by market risk but also by a host of other factors.

Previous research has attempted to examine additional factors that may be relevant for asset pricing. Most of these studies derive the multi-factor specification by identifying systematic factors in the residuals obtained from single factor. Chen, Roll, and Ross (1986) explored a set of economic state variables as systematic influences on stock market returns and examined their influence on asset pricing. Several of the economic variables they chose were found to be significant in explaining stock returns. The primary concern with most previous research has been the ad hoc nature of the conceptualization of risk factors. Brennan (1981), in his discussion of Oldfield and Rogalski’s (1981) article, referred to ad hoc manipulation of data and attempts to correlate factors with other economic time series without any underlying theoretical structure. Chen (1983) suggests that providing an economic interpretation of the common stock market factors should be the most important direction for future research. Chen et al. (1986) acknowledge the fact that they have not used all the influential economic variables.

Recently, Elton, Gruber, and Mei (1994) identified five principal factors that could affect either the cash flows themselves or the discount rate of the cash flows. These five factors include yield spread, interest rate, exchange rate, real GNP, and inflation. Thus, there is increasing evidence that there are systematic factors that affect the expected returns. The challenge is to provide a consistent meaning to the systematic factors found in the stock returns. In fact, Shanken (1992) calls for a new direction of empirical work on APT. A major advantage of identifying the economic factors is that marketing managers of mutual fund companies can anticipate and buy.
funds. If the performance of the funds are good, then they can increase the market share of the customers’ dollars.

Srivastava, McInish, and Wood (1996) argue that managers can create corporate and brand equity by enhancing the reputation of their firms. They show the reputation of a firm is related to stock returns. Rosenberg, Reid, and Lanstein (1985) have shown that stock returns are related to a firm’s market-to-book equity (a measure of brand equity). Therefore, if the factors affecting the stock returns can be identified, then brand managers can anticipate the consequence of variations in those factors on brand and corporate equity. In fact, Fama and French (1992) suggest that examining the relations between the returns on these portfolios and economic variables might help expose the nature of the economic risks captured by book-to-market equity. Thus, it is useful to identify the factors affecting stock returns since those factors can also govern corporate and brand equity.

**Rationale for the Choice of Multiple Factors**

In our study, we propose to overcome the previous criticisms with a discussion of the relevant economic factors (supply of money and cost of money factors) that are likely to impact the return generating process. A rationale for the choice of these factors is given in the following discussion.

The choice of supply of money factor is based on many issues. The return from a stock is determined by the accrual of income from dividends and capital gains from changes in its market price. The capital gain expectation is dependent on a company's ability to pay dividends in the future and the capitalization rate used by investors. It is true that, in general, dividends are above average during periods of economic upturn. Periods of economic growth are characterized by increased output and higher incomes, increased money supply, low inflation rates, and surging demand for goods and services.

Past studies have established that a relationship exists between changes in money supply and changes in the price of other assets held in an investor’s portfolio (e.g., Kim and Wu, 1987). This theory of monetary impact has usually been called the quantity theory of money with respect to asset pricing. An important component in the asset portfolio of investors is financial assets, including common stocks (Roll, 1977). Since it can be expected that the time response of investors may be delayed, it has been hypothesized that changes in money supply can cause changes in stock prices. There is support for this observation from the monetary portfolio model. This model explains how changes in money supply influence stock prices through rearrangement of investor portfolios. It implies a lag effect on prices resulting from money supply changes. Studies by past researchers (e.g., Kim and Wu, 1987), confirm a strong linkage between money supply and stock prices. Therefore, three surrogate indicators are chosen to reflect changes in the supply side of the economy, viz. percent changes in the (1) total personal income (PTPI), (2) consumer installment credit (PCIC), and (3) money supply (PM) between any two consecutive time periods, $t_n$ and $t_{n+1}$.

The cost of money factor is chosen because the capitalization rate used by investors reflects their attitude toward the risk associated with the particular asset in question, as well as returns on alternative investments like bonds and treasury bills. This risk free return or the investors’ cost of capital is directly related to interest rates. In recent years, there have been large changes in the levels of interest rates, which in turn have caused large changes in the market value of bonds, mortgages, stocks, and other securities (Spiro, 1990). In general, the valuation and hence prices of securities, are based on investors’ expectations regarding the ability of a security to outperform the risk free rate, adjusting for risk.

For the decade of 1970s stock prices were negatively related to nominal interest rates in a number of countries (Elton et al., 1994). Fogler, John, and Tipton (1981) also provide evidence for interest rate variables being important causes of differential movements of stock groups. If this relationship is the result of systematic biases in valuation on the part of investors, factors that reduce long-term earnings potential for firms have to be investigated. In general, the market value of stocks can be considered to be inversely related to the level of interest rates. Analysts from Wall Street indicate that the stock market will be increasingly sensitive to changes in interest rates. That is because as the growth rate of corporate earnings slows down, earnings play less of a role in determining the value of stocks. So, interest rates take on even more importance (Bernstein, 1997). Two surrogate indicators are chosen to represent the cost side of the economy, viz. the level of interest rates (INTCO), and the percent change in interest rates between any two consecutive time periods, $t_n$ and $t_{n+1}$ (PINTCO).

Previous research findings (e.g., Elton et al., 1994) have uniformly shown that the market return index accounts for, on the average, 20 to 25% of the variation in stock returns. Most recently, a popular press reported that stock prices and therefore returns are possibly governed by inflationary pressures and fluctuations in interest rates (Laderman, 1997; USA Today, 1996). We hypothesize that the additional factors used in this study will explain a significant amount of the residual variance in addition to the market return index.

**H1**: Stock returns are related not only to the market return index, but also to cost and supply of money factors.

**Industry Effect**

Ross’s (1976) work makes it possible to construct a more general multi-factor model. Only recently, there has been empirical evidence supporting the existence of factors other than the market factor that systematically affects a stock’s return. However, one factor which numerous studies have researched is the industry effect. Unfortunately, there is conflicting evidence regarding the presence of industry effect.
Table 1. Data Description

<table>
<thead>
<tr>
<th></th>
<th>Estimation Sample</th>
<th>Validation Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of industries represented</td>
<td>21</td>
<td>17</td>
</tr>
<tr>
<td>Number of securities selected</td>
<td>100</td>
<td>75</td>
</tr>
<tr>
<td>Maximum sample size per security or stock</td>
<td>102</td>
<td>84</td>
</tr>
</tbody>
</table>

Selection Criteria: Industries selected to be representative of the diverse nature of the population of industries. Securities within each industry were chosen at random to take care of any extraneous variations.

Basic Data Unit: Return adjusted for all capital changes and including dividends.

Source: Center for Research in Security Prices Graduate School of Business University of Chicago Monthly Returns File.

While some studies (e.g., Fertuck, 1975) have shown positive industry effects, other studies (e.g., Lessard, 1976) have shown that the industry effect is of little importance.

To understand the industry effect, the definition of industry must first be clarified. Industries can be identified based on the four-digit S.I.C. codes. Industry classifications became extremely difficult after the 1970s because of the market compulsion for firms to diversify into various fields to balance risk and increase profitability. The financial resource of heavy equipment, financial services, technology and other capital intensive industries are affected by interest rates and changes in the interest rates. Similarly, the financial performance of industries belonging to durable and non-durable goods (e.g., toys, apparel, and electronic equipment) can be affected by the changes in the amount of disposable personal income and consumer installment credit. The APT implies that an asset must pay a premium to compensate for its exposure to systematic economic factors but not for its exposure to industry specific factors (Thorbecke, 1994). Since we also believe that both cost and supply of money can act as surrogates for the industry effect, we postulate that the industry effect, in addition to the cost and supply of money factors, will not be significant in explaining the variation in stock returns. However, it is necessary to test for the presence or absence of idiosyncratic industry effect on stock returns to provide evidence to that effect.

H2: Industry groupings, in addition to cost and supply of money factors, will not be a significant systematic factor in explaining the variance of stock returns.

Research Method

Data

The data are described in Table 1. The sample used for estimating the models includes 21 industries and 100 firms and the 102 monthly observations span the period January 1976 to June 1984. The market index used is the CRSP value weighted returns index. The industries are selected to be representative of the diverse nature of the population of industries—core industries such as metal, equipment and machinery, utilities such as communication and electric works, and a variety of industries that include department stores, hotel, apparel, chemicals, financial services, electronics, toys, paints, etc. Twenty-one industries are chosen as shown in Table 2 along with the number of firms from each of those industries. Stratified random sampling is used on the S.I.C. codes to select stocks within each industry. However, this proportionality could not be strictly maintained due to missing data problems. The data on the supply and cost economic variables are extracted from the Survey of Current Business and Business Conditions Digest.

To validate the findings (i.e., to show the temporal stability of the results) a validation sample is created. This sample includes 17 industries and 75 firms. The data are generated for a seven-year period from July 1984 to June 1991 resulting in 84 observations. In others words, our study deals with two samples that cover a period of 15 years.

Most empirical work in single-factor and multiple-factor asset pricing models has been based on daily returns data, whereas the present study uses monthly data. The reasons for choosing a month as the frequency of the data series are:

Table 2. List of Industries (Estimation Sample)

<table>
<thead>
<tr>
<th>Industry Name</th>
<th>Number of firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paints and varnishes</td>
<td>4</td>
</tr>
<tr>
<td>Toys and amusement sports goods</td>
<td>5</td>
</tr>
<tr>
<td>Real estate</td>
<td>3</td>
</tr>
<tr>
<td>Paper and allied products</td>
<td>6</td>
</tr>
<tr>
<td>Personal credit institutions</td>
<td>6</td>
</tr>
<tr>
<td>Photo equipment and supplies</td>
<td>3</td>
</tr>
<tr>
<td>Commercial services</td>
<td>3</td>
</tr>
<tr>
<td>Apparel</td>
<td>9</td>
</tr>
<tr>
<td>Chemicals</td>
<td>6</td>
</tr>
<tr>
<td>Metal working machinery and equipment</td>
<td>6</td>
</tr>
<tr>
<td>Agricultural chemicals</td>
<td>4</td>
</tr>
<tr>
<td>Engines and turbines</td>
<td>3</td>
</tr>
<tr>
<td>Computers</td>
<td>5</td>
</tr>
<tr>
<td>Electronics equipment</td>
<td>5</td>
</tr>
<tr>
<td>Financial services</td>
<td>3</td>
</tr>
<tr>
<td>Household appliances</td>
<td>6</td>
</tr>
<tr>
<td>Department stores</td>
<td>5</td>
</tr>
<tr>
<td>Industrial equipment and services</td>
<td>4</td>
</tr>
<tr>
<td>Hotels</td>
<td>4</td>
</tr>
<tr>
<td>Steel industries</td>
<td>4</td>
</tr>
<tr>
<td>Electrical utilities</td>
<td>6</td>
</tr>
</tbody>
</table>
1. The daily returns are much more sensitive to random disturbances in the market which might affect the interpretation of the data. These random disturbances can be expected to be nullified over a longer time period such as a month.

2. The objective is to measure the relationship between security returns and economic variables, and data on economic variables are available only on a monthly basis, with the exception of interest rate.

Data interval does not seem to affect the number of factors extracted from stock returns. While Huang and Jo (1995) show the presence of two factors consistently across data intervals, they do not attempt to provide meaning to these factors.

**Framework**

The framework used to assign economic meaning to stock market factors is described in Figure 1. Specifically, several multivariate techniques are used to provide rigor and validity for the suggested approach. First, factors underlying the stock return generating process are extracted using factor analysis. The factor analytic model is

\[ R_i = a_{i1}F_1 + a_{i2}F_2 + \ldots + a_{ik}F_k + d_iU_i + e_i \]  

where

- \( R_i \) is the return for the \( i^{th} \) stock in standardized form
- \( F_j \) is the \( j^{th} \) common factor (\( j = 1, \ldots, k \), the number of common factors)
- \( a_{ij} \) is the correlation coefficient relating the return on stock \( i \) and common factor \( j \) (\( a_{ij} \) is known as factor loading)
- \( U_i \) is a unique factor for stock \( i \)
- \( d_i \) is the structural correlation coefficient relating stock \( i \) and unique factor \( U \)
- \( e_i \) is the error term.

Next, economic interpretation of these stock market factors (\( F_1, F_2, \ldots, F_k \)) is provided using a two-step procedure. In the first step, the systematic variation of each stock’s returns with the market return index and with the cost and supply variables is extracted using regression analysis. Both the dependent and the independent variables are in standardized form in the regression model shown below:

\[ R_i = \beta_{i1}MKT_i + \beta_{i2}PCIC_i + \beta_{i3}PM_i + \beta_{i4}PTPI_i + \beta_{i5}INTCO_i + \beta_{i6}PINTCO_i + v_i \]  

where

- \( R_i \) is the return for the \( i^{th} \) stock,
- \( PCIC_i, PM_i, PTPI_i \) are the three “supply of money” variables,
- \( INTCO_i, PINTCO_i \) are the two “cost of money” variables,
- \( MKT_i \) is the market return index, and
- \( \beta_{i1} \)‘s are the Beta (standardized regression) weights corresponding to each of the \( k \) independent variables for the \( i^{th} \) stock.
- \( v_i \) is the error term.

The incremental variance explained by variables representing cost and supply of money and the number of significant relationships for each variable are estimated to show the significance of additional factors in this step. In the second step, the beta weights (from Equation 6) and the factor loadings (from Equation 5) are related to each other using canonical analysis procedure. Since a stock return can load high on more than one factor, it is only appropriate to use canonical analysis (McGowan and Dobdon, 1993). Canonical analysis relates a linear combination of the criterion variables to the linear combination of the predictor variables. This allows for the economic interpretation of factors in terms of supply and cost of money variables. Of course, one would expect market returns to be aligned with the main (largest) common factor.

In general, for each canonical function, the canonical model derived is

\[ c_1\beta_{i1} + c_2\beta_{i2} + \ldots + c_m\beta_{im} \text{ correlated with} \]
\[ d_1\beta_{i1} + d_2\beta_{i2} + \ldots + d_n\beta_{in} \]  

where the coefficients \( a_{ij} \)’s and \( \beta_{ij} \)’s are interpreted as above (i.e., are factor loadings and standardized regression coefficients or beta weights, respectively), and \( c_1, c_2, \ldots, c_m \) represent the canonical loadings associated with the “\( m \)” stock return factors, and \( d_1, \ldots, d_n \) represent the canonical loadings associated with the six predictor variables. The \( c \) and \( d \) coefficients are used to interpret the identity of the particular canonical function. It is noted that the maximum number of canonical functions that can be derived is based on the minimum of the number of variables in the predictor and criterion variables set.

While, in theory, a single canonical analysis could have been conducted relating 100 stock returns with six predictors across 102 time periods, this analysis would have been subject to chance correlations and would have resulted in a larger number of canonical functions. By examining the relationship between factor loadings and beta weights across stocks, we are able to focus on the explained systematic (as opposed to total, including chance) variation in returns across stocks as captured by the factor structure and regressions. Thus, H1 can be tested with canonical analysis of Equation (7).

The industry effect is tested by comparing two nested canonical models:

\[ c_1\beta_{i1} + c_2\beta_{i2} + \ldots + c_m\beta_{im} \text{ correlated with} \]
\[ d_1\beta_{i1} + d_2\beta_{i2} + \ldots + d_n\beta_{in} \]  

where \( c_1, c_2, \ldots, c_m \) are the canonical loadings associated with the industries \( 1, \ldots, s \) coded as dummy variables. Further, a comparison of the canonical models provided in Equations 8 and 9 with Equation 10 will indicate the extent to which
the cost and supply of money factors subsume the industry effect. In other words, the proportion of industry effect accounted for by the cost and supply of money factors can be used to illustrate the magnitude of the industry effect. The model specified in Equation 10 relates the factor loadings to the market index ($\beta_1$) and the industry grouping in a canonical analysis. 

$$c_1a_1 + c_2a_2 + \ldots + c_ma_m$$

$$g_1\beta_1 + g_2l_1 + g_3l_2 + \ldots + g_{s+1}l_s$$

(10)

where $c_1$, $c_2$, and $c_m$ are as defined earlier, and $g_1$, $g_2$, $\ldots$, $g_{s+1}$ represent the canonical loadings associated with the market index and the industry groupings. Thus, H2 can be tested.
with the results of canonical analysis of Equations (8) and (9). More details about this test are provided in the discussion of results.

**Discussion of Results**

**Extraction of Factors**

The procedure adopted to extract multiple factors is through the use of maximum likelihood factor analysis on the given covariance matrix. Factor analysis of the 100 stock returns yielded 21 factors with eigenvalues greater than 1.0. Factor analysis of a similar sized matrix of random numbers yielded 38 factors with eigenvalues greater than 1.0. The “scree” plot for the stock returns initially sloped steeply down and then gradually became flat, as the number of factors increased from 1 to 100. The factor solution for the random numbers was relatively stable and was almost flat. Thus, using the scree test, the optimum number of factors given by the intersection of these two plots was found to be at least three and possibly four. The latter was based on the reasoning that the point at which the curve first begins to flatten out (which is four in our case) was considered to be the maximum number of factors to be extracted. Beyond four factors, too large a proportion of unique variance would be included in the factor solution and hence those factors would not be acceptable. The first three factors explained 47.8% of the total variance in the data which conformed with the results of previous research on common variance in stock returns. In addition to this, the number of significant factors was found to be three using likelihood ratio (LR) test, and therefore these three factors were retained for further analysis.

**Test of Significance of Additional Factors**

The presence of multiple factors was further demonstrated by a high loading of all stock returns on Factor 1, and a loading of 0.25 or more for 35 and 32 stock returns on Factors 2 and 3, respectively. Next, the factor loadings corresponding to stocks were related to the response coefficients generated by regressing individual stock returns with market index and cost and supply of money variables. Individual stock returns were expressed as a linear regression function of the six predictor variables. The residuals from the regressions were tested by means of the Durbin-Watson Statistic and showed no signs of auto-correlation. Coefficient of determination ($R^2$) is used to explain the significance or explanatory power of the simple and multiple regression equations. The amount of additional variance extracted by the addition of the economic variables to the market return variable was tested for significance. The market return index explained, on the average, about 25.5% of the variation in stock returns. The variance explained in stock returns increased to an average of 62.7% in the presence of all the six predictor variables, which included the market return index. The existence of multiple factors (economic factors, in addition to market return) in the stock returns data was proved with the aid of significant results. For each stock, the significance of cost and supply of money variables was tested by the F-ratio (typically used to compare the full and the nested models).

The F-ratio so obtained was found to be significant for 63 stocks of the 100 stocks at $\alpha = 0.05$. This provided strong evidence for the presence of cost and supply of money factors in addition to the market return factor.

In addition to the F-tests performed above, a t-test was performed to evaluate the significance of each of the six predictor variables shown in Equation 6. In general, at least one of the supply of money factor and one of the cost of money factor variables were significant ($\alpha = 0.05$). These results clearly suggest the usefulness of introducing the cost and supply of money factors in addition to the market return index. The next step is to provide interpretation for the three factors chosen from using the scree and LR tests.

**Identification and Interpretation of Factors**

Canonical analysis was used to provide meaning to the three factors. The (100 $\times$ 3) factor loadings matrix and the (100 $\times$ 6) beta coefficient matrix were used as the criterion and predictor variables sets (as shown in Equation 7) respectively in the canonical analysis. Beta coefficients of the six predictor variables were used instead of the variables themselves because (1) only the beta coefficients can capture the response effect on individual stock returns; (2) the beta coefficients are a measure of risk; and (3) beta weights are a measure of the common variation between the set of predictor variables and the stock returns.

Significant values, if obtained for more than one canonical variate, would not only indicate the importance of additional factors but would also help to identify those factors in terms of the predictor variables chosen. The results of the canonical analysis are given in Table 3.

The three criteria that were used to interpret the canonical functions included the level of statistical significance of the function, the magnitude of the canonical correlation, and the redundancy index for the percent of variance explained in the criterion set. Bartlett’s chi-square test indicated that three canonical functions were necessary to express the dependency between the two sets of variables. All three functions were significant at the 0.003 level. The canonical correlation coefficient between the first pair of linear composites was found to be 0.884. Hence 78% of the variance in one canonical variate (linear composite of criterion variable set) was explained by another canonical variate (linear composite of predictor variable set). Of the remaining unexplained variation, 61% of the variation was explained by the second set of linear composites. The third set of linear composites explained about 15% of the residual variance, after what the first and the second linear composites had accounted for.

Canonical loadings are simple correlations between the variables in a set and the set’s canonical variate. If the squared
Table 3. Canonical Analysis of the Factor Loadings (Criterion Set) and the Beta Coefficients of the Six Predictor Variables (Predictor Set)

<table>
<thead>
<tr>
<th>Functions Sets</th>
<th>Canonical Function 1</th>
<th>Canonical Function 2</th>
<th>Canonical Function 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Loading</td>
<td>Squared Loading</td>
<td>Loading</td>
</tr>
<tr>
<td>Criterion variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor 1</td>
<td>0.81*</td>
<td>0.65</td>
<td>0.61*</td>
</tr>
<tr>
<td>Factor 2</td>
<td>-0.74</td>
<td>0.55</td>
<td>0.57*</td>
</tr>
<tr>
<td>Factor 3</td>
<td>-0.24</td>
<td>0.06</td>
<td>-0.25</td>
</tr>
<tr>
<td>Average</td>
<td>0.42</td>
<td></td>
<td>0.25</td>
</tr>
<tr>
<td>Predictor variables</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>MKT</td>
<td>0.85*</td>
<td>0.72</td>
<td>0.08</td>
</tr>
<tr>
<td>PCIC</td>
<td>-0.17</td>
<td>0.03</td>
<td>0.22</td>
</tr>
<tr>
<td>PTPI</td>
<td>0.56*</td>
<td>0.31</td>
<td>-0.24</td>
</tr>
<tr>
<td>PM</td>
<td>0.11</td>
<td>0.01</td>
<td>0.24</td>
</tr>
<tr>
<td>INTCO</td>
<td>-0.22</td>
<td>0.05</td>
<td>0.36*</td>
</tr>
<tr>
<td>PINTCO</td>
<td>0.61*</td>
<td>0.37</td>
<td>-0.65*</td>
</tr>
<tr>
<td>Average</td>
<td>0.25</td>
<td></td>
<td>0.12</td>
</tr>
<tr>
<td>Canonical correlation</td>
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<tr>
<td>Significance level</td>
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<td>0.78</td>
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<tr>
<td></td>
<td>0.0001</td>
<td></td>
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<tr>
<td>Criterion Redundancy index</td>
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<tr>
<td>Beta weights for 6 predictors without industry grouping (equation 8)</td>
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<tr>
<td>Beta weights for 6 predictors with industry grouping (equation 9)</td>
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</table>

* Significant loadings.

Lastly, Factor 3 loaded high on the third canonical variate; correspondingly PCIC and INTCO loaded high on this variate for the predictor variable set. This implied that the third variate represented both cost and supply of money factors. Thus, stocks loading high on Factor 3 tend to have lower returns in periods characterized by high interest rates and increases in consumer installment credit.

Thus, the loading structure of the predictor variables on all three canonical variates clearly revealed the presence of cost and supply of money factors in addition to the market return index. Thus, we find support for hypothesis 1.

The pattern of canonical loadings for both the factor loadings and the predictor variables provided some interesting results. A post-test analysis of the firms belonging to Factors 1 and 2 revealed that in general, firms belonging to industries such as toys and amusement sports goods, apparel, photo equipment and supplies, paints and varnishes, computers, etc., loaded relatively high on Factor 1; whereas firms belonging to industries such as household appliances, financial services, personal credit institutions, loaded high on both Factors 1 and 2. The results make intuitive interpretation since firms belonging to Factor 1 depend on cash flow (supply of money) to a large extent since their revenues are governed by purchases. Firms associated with Factor 2 largely depend on the cost of money, as governed by borrowings. Finally, firms associated with Factor 3 represented stocks that were sensitive to high interest rates and had stock returns which moved counter to the market return. The industries associated with the last factor were real estate, agricultural chemicals, department stores, etc.
These industries experienced gains during periods of low interest rates and also when the market return was low. Thus, a manager interested in managing and building brand and corporate equity can anticipate the consequences due to changes in factors affecting the stock market factors and plan for minimizing the erosion of brand and corporate equity.

The results from the computation of redundancy measure indicated that 54% of the variance in the criterion variables has been explained by all three canonical variates for the predictor variable set. The remaining 46% of the variance in the factor structure is related to variables other than the market index and cost and supply of money variables. Therefore, the cost and supply of money factors provided enough evidence to justify their inclusion in a multifactor model. It remains to be seen if industry classification can be significant, in addition to cost and supply of money factors, in explaining the variation in stock returns.

Test for Industry Effect

The industry groupings were coded as dummy variables for testing the presence of industry effect. For example, if a company belonged to a particular industry, the dummy variable representing that industry got a value of 1 and the remaining dummy variables were coded as zeroes. Canonical analysis of the factor loadings and the market index and industry groupings (Equation 10) provided a redundancy index of 0.52. The result clearly indicates the presence of industry effect by itself. Further, the magnitude and direction of the canonical loadings for the industry dummy variates conform to intuitive expectations (for example, real estate industry exhibiting a positive association with Factor 3 in a canonical variate). However, it should be interesting to observe whether the industry effect observed here is over and above the variation already explained by the cost and supply of money factors.

The presence of idiosyncratic industry effect was tested by comparing two nested canonical models:

1. Factor loadings vs. beta coefficients (Equation 8).
2. Factor loadings vs. beta coefficients + Industry groupings (Equation 9).

Redundancy index was used to evaluate the two models (Equations 8 and 9) which would provide much stronger evidence that is needed to prove the idiosyncratic industry effect. Results shown in Table 3 indicated that 72% of the variance in the criterion variables was explained by the canonical variate for the (6 beta weights and 21 industries) 27 predictor variables set. Previous results indicated that 54% of the variance in the same criterion variables was explained by the canonical variate for the six predictor variables set. The increase in the redundancy index of 18% was tested for statistical significance using an F-test and was found to be significant at the 0.01 level. This showed that the idiosyncratic industry effect was significant even in the presence of the market, cost and supply of money factors. Therefore, we reject H2.

The above results showed that the variation explained by idiosyncratic industry effect was 18%. Therefore, the amount of variation explained by the common variation between the six beta weights and the industry effect was 34% (52% – 18%) and hence the proportion of industry effect explained by the cost and supply of money factors was 65% (34/52). This finding reconfirms our faith that cost and supply of money can act as surrogates for the industry effect.

The framework adopted in Figure 1 was tested again with the validation sample. Factor analysis of 75 stock returns yielded 3 significant factors which explained about 49% of the variance. When individual stock returns were regressed with the six predictor variables, 26.2% of the variance, on the average, was explained by market return index. The variance explained with all the six predictor variables, on the average, was 63.8%. Canonical analysis of 3 factor loadings matrix with the beta weights of the 6 predictor variables yielded 3 significant canonical functions. These functions explained 77%, 59% and 17% of the appropriate variance. The canonical loadings pattern was as before and similar results were observed for the test of industry effect. For example, about 70% of the variance in the criterion variables was explained by the canonical variate for the 27 predictor variable set. Here again about 54% of the variance in the same criterion variables was explained by the canonical variate for the six predictor variable set. This translates to an increase in the redundancy index of 16% which was significant at α = 0.01. Thus, the findings show consistency of results across two time periods.

Marketing Implications

The purpose of this study was to develop a model to explain stock returns. In doing so, the study accomplished two major tasks: first, it showed that stock returns are influenced by important economic forces (beyond the general market factor) and second, it assigned economic meaning to such forces.

The results of the study show that the multiple factor model does a good job of predicting stock returns. It is interesting to note that multiple factor models are increasingly being used in portfolio management and risk factors associated with inflation rates, the term structure of interest rates, economic output and money availability are being factored in to predict the variability in individual stock returns (Ferson and Harvey, 1991; Spiro, 1990). Our study adds to this stream of research and empirically shows that cost and supply of money factors add significantly to the variability accounted for by the market risk factor. One specific advantage in including additional factors is that the estimate of the cost of equity (and thus the cost of capital for the firm) will be more accurate.

The interdependence between various functional areas such as finance and marketing has not received much attention in the business literature (Zinkhan and Zinkhan, 1994). Also, it is not obvious that financial managers are aware of the interests of marketing groups in the development of appro-
propriate business strategy (Zinkhan and Pereira, 1994). Therefore, in this research we attempt to show the link between marketing and finance through the subsequent discussion of our results.

It is well known that systematic risk is the only risk that matters to stockholders because they cannot diversify it away while they can diversify away the unsystematic risk component (Lubatkin and Chatterjee, 1994). In general, the lower the systematic risk, the higher the price of a firm, everything else being constant. What this implies in the context of our study is that the addition of significant factors other than the market factor (i.e., cost and supply of money) increases the level of systematic risk and thus should decrease the price of the firm. When systematic risk is high, firms will face higher interest payments which reduce their cash flows thereby making them vulnerable to environmental uncertainties. From a marketing perspective, while all firms will be exposed to the same macro-economic factors such as cost and supply of money, firms can lessen the impact of such forces by their choice of appropriate marketing strategies. For example, a firm that can increase the level of loyalty toward and equity of its brands may be less sensitive to the effects of environmental forces. Previous research by Simon and Sullivan (1993) and Lane and Jacobsen (1995) indirectly supports this argument. Although some may argue that stockholder returns are at the corporate and not at the brand level, it should be noted that our recommendation is for organizations to simultaneously increase the equities of all of its brands and of the corporate entity. At the least, our recommendation would be more relevant for firms that use an umbrella branding strategy. Additionally, firms may reduce their sensitivity to interest rate factors by shifting their mix of offerings to be less dependent on products and focus more on services and consumables.

Another important point to note is that breaking down systematic risk into different categories can be very helpful in the marketing of investment companies and managers. One way is to use it as a forecasting tool to emphasize certain characteristics in the portfolio of an investment company or manager which signal better future performance. The strategic decisions determining the level of exposure to systematic economic factors influence the average return, but the tactical decisions can be made without any sacrifice of portfolio return, because they deal merely with idiosyncratic risk (Roll and Ross, 1995). As a fine-tuning tool it can be very helpful in forward-looking portfolio construction. The development of new products (e.g., combination of stocks) is possible if the manager of financial portfolios is aware of the systematic risks associated with the stocks.

The findings of the study also have implications for how investment companies rate and invest in emerging markets and timing and order of entry into these markets can be developed. For example, investment managers can use the findings of the present study not only to choose the particular market where they would like to invest, but also to make decisions on when to go in or pull out their investments. Conversely, emerging markets can market themselves to foreign investors better by signaling the favorable aspects of their macro-economic environment in comparison to other markets that compete for the same resources.

The study results show that industry membership has an impact on stock returns controlling for the effects of economic variables. The underlying theory is that a portfolio's total risk can be explained by commonalities which span individual stocks, the most intuitive of which may be the industry membership. Past research has shown that as more industries were represented in the analysis, the probability of finding more than three stock factors increases. The analysis of the present study showed that even with the inclusion of 21 diverse industries in the sample only three stock return factors were generated. Additionally, the number of factors was found to be consistent in a second time period thus providing evidence of the robustness of the findings.

Future research should be directed toward identifying other macro factors that are systematically related to stock returns. Further, the analyses could employ non-linear models to augment the explanatory power of the systematic factors identified in the present study. Finally, attempts should be made to link measures of aggregate corporate and brand equity explicitly with the factors affecting the stock returns process.

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References


