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Enhancing the timing of the asset allocation process.

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ENHANCING THE TIMING OF THE ASSET ALLOCATION PROCESS

A Dissertation Presented

by

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To My Parents and Family

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ABSTRACT

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OF THE ASSET ALLOCATION PROCESS

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Much of previous research in finance has concentrated on explaining movements of individual securities rather than on explaining movements in the stock market as a whole. Although the available data are more limited than those for individual stocks, the movements in the stock market as a whole are extremely important for movements in individual stocks. Indeed, market events of the past ten years have sparked an interest in tactical asset allocation. The turbulence of October 1987 has only accelerated this interest.

This study seeks to develop a methodology that systematically incorporates currently available information into the tactical asset allocation process. The goal of this study is not to predict individual stock prices, or every small movement in the market. Rather we would like to use the currently available data to provide the investor with an estimate of the probabilities associated with the broad measure of either a "bullish" or "bearish" market period. Logit analysis is used to determine which of the various timely and readily available data significantly affect the probabilities of "bullish" and "bearish" market months. We use the estimated probabilities generated by the logit analysis to suggest the optimal allocation of funds between the risk-free asset and the market portfolio and compare several timing strategies with a buy-and-hold strategy. An Asset allocation strategy based on the probabilities assigned by the logit model outperformed a buy-and-hold strategy by achieving a greater terminal wealth with less variability of returns. We also find that one who used our model would have reduced downside risk and improved average performance over past cycles.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

The investment performance of a managed portfolio depends primarily on the manager's ability in three areas: (1) selectivity - forecasts of price movements of selected individual stocks (i.e."microforecasting"), (2) market timing - forecasts of price movements of the general stock market as a whole (i.e."macroforecasting"),[1] and (3) cost and efficiency -comprehensive cost/benefit analysis of these management activities.[2] Usually associated with security analysis, microforecasting involves the identification of individual stocks which are under- or overvalued relative to equities generally. Macroforecasting refers to forecasts of future realizations of the market portfolio. If an investment manager believes that he (or she)[3] can forecast market portfolio returns better than the average participant, he will adjust his portfolio risk level in anticipation of market movements. If successful, he will earn abnormal returns relative to an appropriate benchmark.

Much of the previous research in finance has concentrated on explaining movements of individual securities rather than on explaining movements in the stock market as a whole.[4] One reason for this concentration of effort is that we have vast

[1] Fama[51]

[2] Most literature on investing deals with what (1) and when (2) to trade. How to trade at the lowest costs (3) is often ignored or only briefly treated [See Loeb[109]].

[3] Here in after the investor will, for the sake of convenience, be assumed to be male

[4] See Treynor and Black[154], Treynor [152], Sharpe [140], and Jensen [90,91]. Jensen [92] provides

amounts of data on individual firms, but we have only one stock market as a whole. Although the available data are more limited than those for individual stocks, the movements in the stock market as a whole are extremely important for movements in individual stocks.[5] Indeed, market events of the past ten years have sparked an interest in tactical asset allocation.[6] The turbulence of October 1987 (the disappointing results of portfolio insurance during the Oct. 19, 1987 market crash and the awareness that asset allocation may add value) has only accelerated this interest.[7]

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a summary of the empirical studies about microforecasting. Umstead [157] undertakes investigation of aggregate quarterly stock market prices. Variance bounds literature asks whether prices vary too much to be explained only by changes in expected cash flows [Leroy and Porter [106], Shiller [145], Grossman and Shiller [142]]. Some studies show that prices are predictable based on mean reverting [Poterba and Summers [127], Fama and French [54,56], Campbell and Shiller [27]].

[5]The statisticians need large numbers of price changes or returns as raw material for their tests. The number of usable separate 10-year or even 5-year return intervals in the data base are insufficient to constitute the statistical equivalence of a quorum. Technical innovation did occur in the early 1980's, however, in the form of procedures that would work with "overlapping" intervals and thus greatly enlarge the usable sample of long-period returns.

[6]Definitions of the differences among tactical asset allocators, or between allocators and market timers, are as numerous as the firms claiming those designations. Tactical asset allocation (TAA) assumes that an investor can recognize and take advantage of the cyclical nature of financial markets, but it shares with strategic asset allocation the assumption that fundamental valuation relationships between asset classes hold over time. That is, the returns available in the market may be above or below "normal" levels at any point in time, but they will tend to revert to their norms over time. Market timers attempt to predict equity market peaks and troughs, using quantitative models with indicators such as market momentum, sentiment, price and monetary and economic conditions. Phillips [124] suggests that the differences between TAA and market timing can be characterized by five key dimensions. (1) Time frame: Market timing focus on the future. TAA focuses on current asset values. (2) Objective: The objective of a market timer is to maximize return. TAA is concerned with both risk and return. (3) Approach: The purpose of market timing is to capture market trends and move in or out of the market in anticipation of the trend. Although TAA recognizes cyclical trends in financial markets, the only prediction involved is that prices will adjust to bring returns to an equilibrium level established by the risk levels of the asset classes over the long term. (4) Decision: The market timer's decision ultimately comes down to whether to be in or out of equities. The TAA decision is one of balancing asset classes, based on valuations and the constraints of the strategic plan. (5) Performance measurement: The market timer tries to outperform the equity market on a quarterly and annual basis. The TAA manager tries to outperform a global multi-asset-class portfolio.

[7]*Pension & Investment Age* report that tactical asset allocation managers had \$38,374 billion under management in the product, an increase in late 1988 of 41% from 1987 summer [Table 1.1]. The managers also gained 138 pension fund clients during the 12 months ended Aug. 30, bringing the total number of TAA clients to 838[*Pension & Investment Age* (Sep. 5, 1988)]. But many allocators underperformed in 1987 - until the crash made them look good. TAA appears to have

Table 1.1 Largest Tactical Asset Allocation Managers

FIRM	AMOUNT ($ mils.)
Wells Fargo	9,127
Prudential	7,100
Mellon Capital	6,000
First Chicago	4,500
TSA	3,000
Boston Co.	2,300
Renaissance	1,510
Avatar	1,300
Citibank	1,250
Bankers Trust	1,050
J.P. Morgan	500
Chase Investors	300
Bailard Beihl & Kaiser	200
Matrix	187
Webster	50
TOTAL	38,374
SOURCE	*Pension & Investment Age*

This study seeks to develop a methodology that systematically incorporates currently available information into the tactical asset allocation process. The results of this procedure are then tested and evaluated.

First, logit analysis is used to help determine which of the various current sets of information affect the probabilities of risk environments. Second, those probabilities are employed to indicate the amounts of funds to be allocated to the risk-free asset and to the market portfolio of risky assets. Finally, we compare several timing strategies with a buy-and-hold strategy. The comparison is based on end-of-period wealth computation, risk and return measurements.

Chapter 2 evaluates the literature of market timing. In chapter 3, likely candidate variables are selected on the basis of sound theory. Such variables are expected to influence the risk environment of the stock market. In chapter 4, we introduce the data and explain the techniques. Chapter 5 discusses how to construct and validate our model. In chapter 6, several strategies are specified and empirical results are reported. Finally, a summary and directions for future research are explored in chapter 7.

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worked in 1987 and failed in 1988 [WSJ (May 16, 1989)].

CHAPTER 2

LITERATURE REVIEW

The theoretical justification for asset allocation as a portfolio management strategy stems from the Modern Portfolio Theory (MPT). Selected literature related to the development of MPT is presented to provide the necessary background for the asset allocation strategy. Theoretical and empirical studies of performance evaluation of market timings are reviewed. Asset allocation techniques currently being used by practitioners are also examined.

2.1 Modern Portfolio Theory

The asset allocation decision is an integral part of the portfolio management process. The evaluation of portfolio management performance requires a structural specification within which superior performance, if it exists, can be identified. Modern Portfolio Theory provides a measure of performance in the framework of the Capital Asset Pricing Model (CAPM). A key contribution to MPT is the assumption that portfolios can be selected on the basis of expected return and risk. A major work in the area of the measurement of risk is the article of Markowitz [111]. He provided investors with the concept of the interrelationship (covariance) among individual asset holdings and thus emphasized the importance of all the investor's holdings in the portfolio format. The efficient set of portfolios is comprised of those portfolios that offer the maximum expected return for a given level of risk. Risk is measured by the variance of the portfolio returns. However, the determination of the efficient set of portfolios requires the computation of all of the possible variance and covariance terms. The number of covariance calculations can be extensive. If N securities are analyzed, the variance-covariance matrix will have (1/2)(N-1)N different covariance elements. In his 1959 article, Markowitz demonstrated that the investor's portfolio decision problem could be stated in the form of a quadratic programming problem. The decision variable of the quadratic programming problem was shown to be the percentage to invest in a risky asset which minimizes variance subject to an expected return constraint.

Papers following the Markowitz article further refined the development of measures of risk, return, and efficient sets of portfolios. Sharpe [139] extended the concepts of Markowitz [111], Tobin [151], Hicks [85] into a market equilibrium theory of asset prices under conditions of risk. Sharpe describes the optimal investment policy for the individual by detailing an investment opportunity curve of risky assets and the linear efficient set of investments resulting from the introduction of a riskless asset in combination with a portfolio of risky assets. He demonstrates that all investors will choose to hold some combination of the risk-free asset and the market portfolio of risky assets (two-fund separation).

Sharpe extends the analysis to what is known as the CAPM by showing that the relevant risk measure of the individual asset is the covariance between returns of the risky asset and the market portfolio divided by the variance of the market portfolio. This risk measure, termed β, is the risk of the economy as a whole and is therefore undiversifiable. In equilibrium, every individual asset must be priced so that its risk-adjusted rate of return falls exactly on a straight line known as the Security Market Line.

MPT provides the basis for the asset allocation decision through the concepts of the capital market line, the market portfolio, the two-fund separation theory, and the theory of utility maximization. Relevant measures of performance for the portfolio and the individual asset are described within the framework of MPT and provide investors with an objective criterion for selecting assets.

2.2 Measuring Timing Performance

Using the tools of MPT, the investment manager seeks to create a portfolio that offers the highest expected return in relation to risk. The process can be dichotomized into the activities of stock selection and asset allocation. Stock selection involves forecasting price movements of individual stocks (microforecasting). The investment manager attempts to identify those individual stocks whose expected returns lie either significantly above or below the Security Market Line. The microforecaster is concerned with forecasting the nonsystematic (company-specific) component of the return on an individual stock. Given a specific portfolio, microforecasting can be a valuable tool in improving its performance. However, this technique is portfolio specific, i.e., its results cannot be generalized so as to apply to any portfolio since different portfolios incorporate different stocks having different returns.

The asset allocation decision is an attempt by the portfolio manager to forecast when the portfolio of risky assets will outperform the risk-free asset or when the risk-free asset will outperform the portfolio of risky assets (macroforecasting), assuming that the investment alternatives are limited to those two asset classes. The concept of macroforecasting implies a relationship between future states of the market and currently available information.

Fama [51] showed that security selection and market timing performances are additive if the intended beta is assumed to be equal to the actual beta. When the market timing performance measure is added to Jensen's selectivity index, we arrive at the risk premium of the portfolio. Fama refers to this overall risk premium as total performance.

$$\begin{aligned} R_p - R_f \quad &= \quad [R_p - R_f - (R_m - R_f)\beta_p] \quad + \quad (R_m - R_f)\beta_p \\ Total\ performance \quad &= \quad Security\ selection \quad + \quad Market\ timing \end{aligned}$$

This relationship provides a basis for measuring the security selection and market timing abilities of the portfolio manager simultaneously. To be meaningful, this decomposition of total performance requires that the manager be responsible for both security selection and market timing decisions.

The role of the CAPM in investment performance evaluation has been widely debated in the finance literature. Roll [134] has argued that the CAPM cannot be used to produce unambiguous rankings of investment performance. His objection is based on several considerations. First, the market portfolio is not uniquely defined in the theory. Whether this portfolio should consist of only equities, all marketable securities or all assets, marketable or not is not clear. Second, he showed that if a proxy for the market portfolio is used, an alternative proxy can always be constructed that would give exactly the reverse ranking of performances. Third, he showed that if the "true" market portfolio is found and the CAPM is correct then no portfolio can show superior or inferior performance.

Myers and Rice [114] have demonstrated that as long as information relevant to security valuation is not distributed evenly across all groups of investors, then the CAPM can identify superior or inferior performance. Dybvig and Ross [43,44] further clarified the circumstances under which the CAPM framework can be used for performance evaluation. They agree with Roll that, in the absence of consistent information asymmetries, CAPM based performance evaluation measures are ambiguous. They also agree with Mayer and Rice that, in the presence of superior information not generally available, CAPM based performance measures can give reliable evaluations. In generalizing some of the findings in the Dydvig and Ross [44] paper, Green [79] showed that the robustness of the SML paradigm is weakened considerably if the market return proxy is not mean-variance efficient. Errors in measuring the benchmark market portfolio are shown to be directly related to the deviations of individual asset and inefficiently diversified portfolios from the SML.[1] Green shows that the ranking of two investments using the SML based methodology can be reversed by changing the proxy used to measure the market portfolio. Therefore, even on a theoretical basis, a number of important research papers have questioned the usefulness of the CAPM framework for evaluating investment performance.

Connor and Korajczyk [36] have provided a new theory and methodology for evaluating portfolio performance using a competitive equilibrium version of the Arbitrage Pricing Theory (APT). Performance criteria analogous to Jensen's abnormal returns measure and the Treynor-Black risk adjusted return measure are developed and consistent estimators derived. The APT framework developed by Connor and Korajczyk produces meaningful performance measures as long as the market is assumed to consist of both informed and uninformed investors. The APT measures which are derived assume that the investors or fund managers do not engage in market timing activities. Therefore, while the APT model has been shown to be a useful framework for assessing the security selection skills of managers, further developments are needed so that timing activities can also be evaluated.

[1]The source of this measurement error is unobserved shifts in portfolio composition that results in a nonnormal unconditional distribution of returns. Kane and Marks [96] consider whether such a measurement error is likely to occur in practice by developing the exact condition under which the Sharpe measure will fail to order timers according to ability. They show that the Sharpe measure is in fact likely to be deficient under actual market conditions, given the current industry practice of using quarterly data to evaluate portfolio managers.

A number of empirical methods have been developed to explore whether managers have regularly engaged in timing activities and if so, the extent to which their efforts have been successful. Treynor and Mazuy [155] first looked for evidence of macroforecasting skills by analyzing return data on mutual funds. A number of papers have examined the intertemporal stability of mutual fund betas, thereby indirectly considering the topic of market timing. Jensen [91], Campanella [24] and Pogue and Conway [126] investigated the stability of fund betas by correlating estimates in different time periods.

Kon and Jen [103] applied a considerably more rigorous framework to the analysis of the timing activities of mutual fund managers. They find significant shortcomings when the standard ordinary least-squares technique is applied to the market timing problem. The technique which Kon and Jen employ is switching regression analysis. This approach does not require that the specific times at which the manager changes the volatility of the portfolio be prespecified. The other model assumes that such switches, if they are made at all, are made at the beginning of the prespecified bull and bear markets. Kon and Jen's approach, however, does arbitrarily assume the number of different risk regimes used by the manager.

In a later study, Kon [104] again used switching regression methods. The discriminant procedure enabled him to decide more accurately on the appropriate number of risk regimes to assume for a given sample of historic returns data. Aside from the general issue of whether managers engaged in timing activities, Kon also evaluated the effectiveness of the timing activities of fund managers. All of the studies considered thus far rely on the Capital Asset Pricing Model framework.[2]

Merton [115] considered the question of market timing from an entirely new perspective. His approach involves modeling the equilibrium value of market timing skills

[2]Specifically, they assume that stock returns are normally distributed and that relative to the "public" information set, securities are priced so as to satisfy the SML.

using options. The approach requires that the market timer forecasts whether stocks will beat bonds/T-bills as an investment medium for the coming period. He then described the value of perfect accuracy using a contingent claims framework.

Hendriksson and Merton [83] provided a sequel paper in which they added statistical procedures to test for superior market timing skills within the framework developed by Merton. Both parametric and non-parametric tests were presented. The former requires knowledge of the probability distribution of stock returns. Because of the difficulty in obtaining actual market forecasts of mutual fund managers, researchers have for the most part used the parametric test forms. Security returns are commonly assumed to be described adequately by the CAPM. Therefore, as applied, the Merton and Hendriksson tests remain CAPM based.

The ordinary least squares methods recommended by Hendriksson and Merton [83] and later applied by Hendriksson [82] and Chang and Lewellen [31] are not, however, free of conceptual problems. If fund managers actively manage their portfolios, they are likely to adjust their risk levels continually in the midst of periods characterized by bull and bear markets. The ordinary least squares method suggested by Hendriksson and Merton assumes, however, that a fund's portfolio beta is constant during any particular bull or bear market and common across all bull or bear periods.

We reviewed the literature on the theory and techniques of evaluating the security selection index and market timing simultaneously. We observed that significant advances have been made although problems persist. As Fama [51] pointed out, the performance measures that are appropriate for a particular portfolio manager must take into account the constraints under which he operates.

2.3 Macroforecasting

Empirical work in finance has traditionally concentrated on cross-sectional analysis of asset returns. Several studies have, however, successfully used economic data to predict stock market movements, thereby suggesting the feasibility of integrating macroeconomic variables into the asset allocation decision.[3] Umstead [157] undertook an extensive statistical investigation of aggregate quarterly stock prices (the S&P 500 Composite Index) and their relationship to the National Bureau of Economic Research Leading Composite Index. Box-Jenkins methodology was utilized to build a transfer function model relating changes in the leading economic index to subsequent stock price changes. The model was verified by computing a "hit rate" of forecasts of "up" and "down" markets. In addition, the accumulated wealth of a portfolio that switched between equities and Treasury bills was compared to a buy-and-hold strategy. Defining "up" and "down" markets as returns above or below the median return, Umstead's model made thirty-two out of fifty correct forecasts. The Umstead study suggested that readily available information contains enough predictive information to be useful to the portfolio manager in making the asset allocation decision. Note, however, that this effect is at least partially due to the fact that stock prices are one of the series that make up the Leading Composite Index.

Many practitioners also asserted that combinations of publicly available information may be used to construct technical market indicators that help them assess the market's mood and thus forecast its direction.[4] Some academicians found value in the indicators,[5] other studies failed to find technical stock market indicators helpful.[6]

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[3] Umstead [157], and Piccini [125]
[4] Zweig [160,161]
[5] Branch [15]
[6] Daigler and Fielitz [38]

Moreover, some studies suggested that the stock market leads certain market indicators (e.g., money supply).[7]

The efficient market hypothesis implies that predicting market returns is as difficult as identifying undervalued or overvalued stocks using information that is readily available to all investors. Moreover, a growing body of literature suggests that prices deviate from value, and that such departures can be substantial and long-lasting.[8] Modigliani and Cohn maintained, in 1979, that the stock market had been 50 per cent undervalued for as long as a decade because of inflation illusion. The emergence of a bull market after inflation subsided was consistent with their hypothesis.

Such significant and long-lasting departures from value run counter to conventional theory. They are more in line with the perspectives of such market observers as Shiller, who argues that "social movements, fashions or fads are likely to be important or even the dominant cause of speculative asset price movements."[9] Moreover, Summers [149] has pointed out that the whole litany of empirical tests supporting market efficiency is also consistent with an alternative "fads" hypothesis; he takes issue with the notion that market prices must represent rational assessments of fundamental value.

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[7] If investors have altered their outlook in anticipation of a change in an indicator, the stock market's moves may lead (rather than be led by) those of the indicator. See Branch and Schneeweis [18,19]

[8] The market has often appeared to depart widely from its underlying value. During the first three quarters of 1987, stocks outperformed bonds by 46.7 per cent. Equilibrium was practically restored in just one day - October 19. In the words of Summers, "If anyone did seriously believe that price movements are determined by changes in information about economic fundamentals, they've got to be disabused of that notion by Monday's 500-point improvement." [WSJ(Oct. 23, 1987)] While this particular market overvaluation was corrected quickly, mispricing can be longer lasting.

[9] Shiller does not totally dismiss rational expectations and the usefulness of fundamentals. In his "Comments" in Hogarth and Reder [86], Shiller states, "I think the truth may well be that financial prices can be successfully modeled as reflecting proper anticipations of those future movements in dividends that can be predicted plus a term reflecting the anticipation of fashions or fads among investors."

In the context of arguing that the stock market is inefficient because it is too volatile, Shiller [145] documented wide departures of historical prices from theoretical value. He cited these departures as evidence for the existence of fads.[10] Fama and French [56] found that dividend yields can explain over 25 per cent of the variance in future two to four-year returns and suggested, as one possible explanation, that prices behave whimsically in an irrational market.

Several studies, including those by DeBondt and Thaler [39] and Fama and French [56], have documented long-run reversals in security prices, which seem to be due to investor overreaction.[11] DeBondt and Thaler [39] showed reversals lasting up to five years, which occurred primarily in January. Fama and French [56] demonstrated that up to 40 per cent of the variance of three to five year returns is a predictable reversal of previous returns. Others, extending these findings, have generally concluded that such reversals represent evidence of serious market inefficiency.[12]

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[10]But Miller and McCormick [116] argue that the case for the existence of bubbles based on the supposed excessive volatility of stock prices must be regarded as still unproved. The excess volatility argument is presented and remains controversial. For a summary of the debate, see Camerer and Weigelt [33]. Shiller [146] discusses departures from value, rather than excess volatility, as evidence of fads in "Comments".

[11]Chan [29] claims that DeBondt and Thaler's reversal effect is explained by changing risk: Stocks suffering price declines become riskier, and this heightened risk explains their subsequent outperformance. However, Debondt and Thaler [40] demonstrate that losers subsequently have higher betas in up markets and lower betas in down markets, and thus reject the changing-risk explanation.

[12]Poterba and Summers [127], O'Brien [119] and Richardson [132] argues that the seeming departures from nonstationarity detected by the new procedures, properly calibrated may not really be larger than what might plausibly be expected from pure chance alone. A recent paper by Kim, Nelson and Startz [100] suggests that the transitory components may be reflecting nothing more than the huge up-and-down swings imposed both on stock prices and the U.S. economy by the Great Depression of the 1930's. They find no substantial transitory components in the 40 year postwar period 1946-1986.

How can such "mispricing" persist in the face of "smart money"? Summers [149] concluded that irrationality may be difficult to identify and risky to exploit, hence irrational prices need not be eliminated in time. Black [13] has argued that trading by those who do not possess useful information creates "noise"-that is, deviations of price from value.[13] These deviations induce information-based traders to enter the market, but the time required for them to correct pricing errors caused by noise traders is often measured in months or years. As evidence from economic theory, experimental markets and the real world has indicated, learning, competition and arbitrage may be insufficient to eliminate irrationality and market inefficiencies.[14]

Furthermore, institutional investors may be particularly susceptible to fads. Bernstein [12] has suggested that value models move in and out of favor with portfolio managers, based on their current effectiveness. Such "style" fads might affect prices. Camerer and Weigelt [33] have maintained that the relative performance goal of professional money managers is conducive to price bubbles. Friedman [67] noted that the professional investment community shares the same research sources and suggested that the asymmetry of rewards in money management leads to "herd" opinions and decisions. In a similar vein, Treynor [153] has demonstrated that "shared errors" can decrease price accuracy.

The studies reviewed thus far have implied that readily available information may be used (with some degree of success) to forecast stock market movements. A relevant question to be considered is, "How superior must one's predictions be to implement a market timing style effectively?"

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[13]French and Roll [64] found that a significant portion of market volatility is due to mispricing. DeLong, Shleifer, Summers [41] maintained that noise traders cause prices to deviate so far from fair value as to create serious consequences for society as a whole.

[14]Akelof and Yellen [1] demonstrated that small amounts of irrationality can have large economic effects.

2.4 Gains from Market Timing

Sharpe [141] showed that a timing strategy generates higher average returns and less variability of those returns than a buy-and-hold portfolio. Describing the less than perfect timing case, Sharpe indicates that at least a seventy percent accuracy rate in timing the market is required to make the practice worthwhile. Because achieving a seventy percent accuracy rate is unlikely, Sharpe's study suggests that portfolio managers minimize trading and emphasize a buy-and-hold strategy. Sharp's study, while providing some insights into the effects of imperfect market timing ability on investment performance, is limited in two respects. First, Sharpe assumed an investor was equally successful at forecasting bull markets as bear markets. Second, Sharpe's conclusions were based on the arithmetic mean of the gains over and above the returns from a passive buy-and-hold strategy.

Jeffrey [89] came to the same conclusion by observing that historically more years had been average or poor than spectacular. Therefore, if a manager's market timing activities lead him to miss a few of these rare spectacular years, he would usually have been better-off with a buy-and-hold strategy.

Chua and Woodward [33] used essentially the same framework employed by Sharpe, but corrected for these two limitations. They tested the relative importance of hitting the bull markets compared with avoiding the bear markets. They show that accuracy in forecasting bull markets is the primary variable deciding whether timing will pay. They also show that the interim returns that give the stock market its high average return tend to occur infrequently and over a proportionately small number of periods. This relationship helps explain why an investor engaged in market timing activities has such difficulty beating a buy-and-hold strategy.[15]

[15]The buy-and-hold strategy can be viewed as a strategy that has a 100% accuracy in forecasting bull markets and 0% accuracy in forecasting bear markets.

Using more recent data and more realistic assumptions about both the frequency of portfolio revisions and the level of transaction costs, Atchley and Ehrhardt [4] find that only a moderate degree of forecasting skill (sixty percent accuracy) is required to outperform the market.

Most recently, Clarke et al. [34] show that a market timer who follows optimal rules can expect higher returns and lower risk than a buy-and-hold stock investor.[16]

They also show that the returns on the market timer's portfolio increases as the level of information increases and that even modest amount of information can bring substantial advantage. For example, a model that predicts monthly stock returns with an R^2 of 0.09 can be expected to give a market timer a 5.9 percent annual return advantage over an investor who buys and hold stocks as presented in Table 2.1 without incurring transaction costs.[17]

2.5 Asset Allocation

Most of these studies imply that outperforming the market on a risk-adjusted basis is not possible. They do, however, address the problem of developing a procedure that is capable of achieving an acceptably accuracy rate in predicting market conditions. Such a procedure should help investors determine the amount of funds to allocate to either the risk-free asset or the market portfolio of risky assets.

Several techniques for making the asset allocation decision are currently available to the portfolio manager. Previous asset allocation studies tend to utilize allocation models with inputs of historical risk and return information and investor preference

[16]The expected return on the portfolio of a market timer is 21.4 percent, 5.9 percent higher than the 15.5 return on stocks. Moreover, the standard deviation of the returns of the market timers portfolio is 17.2 percent, 3.3 percent lower than the standard deviation of the return of stocks. [Figure 2.1]

[17]However, the 1.0 percent to transaction costs reduce the value added considerably, from 5.9 percent to 1.2 percent.

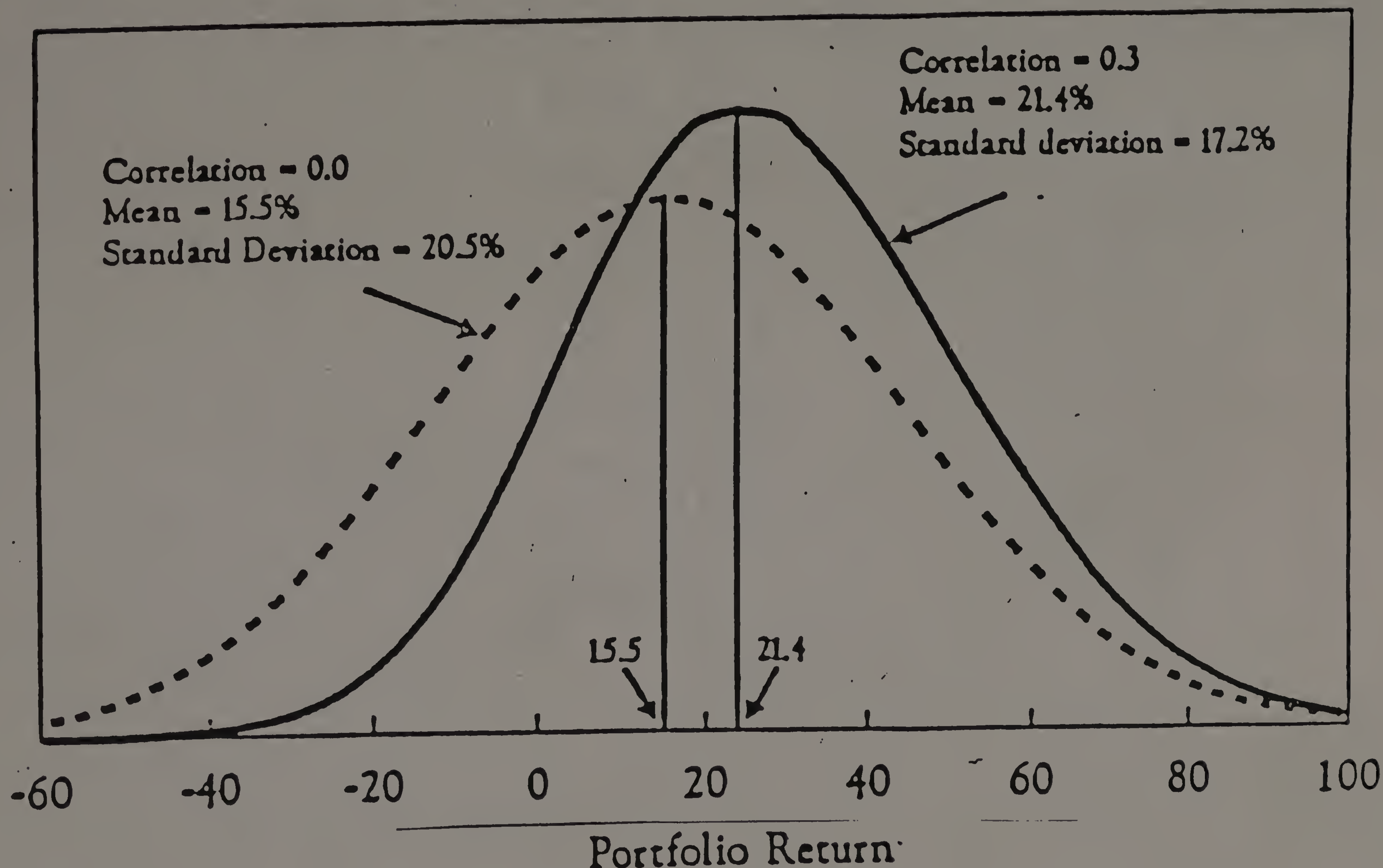

Figure 2.1 The distribution of returns on a market timer's portfolio

Table 2.1 The Risk and Return of a Market Timer's Portfolio

Correlation[a]	Value[b]	SD[c]	SD[d]	Value[e] 0 %	.1 %	1.0 %[f]
0.0	0.0	20.5	20.5	0.0	0.0	0.0
0.1	0.0	20.5	19.4	0.5	0.2	0.0
0.2	0.0	20.3	17.9	3.0	2.4	0.1
0.3	0.2	19.6	17.2	5.9	5.5	1.2
0.4	0.5	18.8	16.6	9.3	8.8	3.4
0.5	1.1	18.1	16.3	13.0	11.9	6.4
0.6	1.7	17.3	15.8	16.2	15.6	9.5
0.7	2.4	16.6	15.6	19.4	19.2	12.9
0.8	3.2	15.9	15.2	23.2	22.6	16.8
0.9	4.0	15.3	14.8	27.3	26.4	20.0
1.0	4.6	14.7	14.3	31.3	30.7	23.4

[a] Correlation between a signal and stock returns

[b] Value added by the market timer, relative to a buy and hold stock portfolio where switching is allowed only once a year

[c] Standard deviation where switching is allowed once a year

[d] Standard deviation where switching is allowed once a month

[e] Value added by the market timer, relative to a buy and hold stock portfolio where switching is allowed once a month

[f] one way transactions costs

constraints. Such procedures begin by examining a series of historic returns, such as the Ibbotson-Sinquerfield studies [87]. From these data, the portfolio manager calculates returns and standard deviations over various time periods relying on the premise that the historical relationships between risk and return will persist into the future. This approach is sensitive to the time period selected as a base. Moreover it depends upon the manager's ability to use the historic returns by projecting the future state of the economy.

Arnott and Germeten [2] presented a systematic approach to asset allocation. They deduced which asset classes are particularly attractive in any market condition by comparing the relative return estimates with "normal" relative returns. They found that normal relative returns amount to approximately two percent for long bonds and five percent for equities. They concluded that when long bond yields are more than two percent above cash yields, bonds subsequently do well and when the yield differential falls below two percent, bonds tend to perform poorly. They also found that trends in the relative calculated returns are just as important as the return calculations themselves.

Defining peak interest rates as the difference between cash returns and the latest 12-month percentage change in the Consumer Price Index, they found that the level of real interest rates is related to subsequent change in interest rates. The 12-month trailing rate of change in the Department of Commerce's leading indicators was found to be a valuable indicator for the relative returns of equities and bonds. A rising indicator was shown to favor equities over bonds; a falling indicator suggests the opposite. They found that implementing their strategy pays off handsomely during turbulent markets. The amount of asset deployment has a major impact on balanced performance. During the less turbulent years, asset allocation is less critical. Thus only modest value is added during those times.

Fielitz and Muller [59] provided another approach to asset allocation. For ease of discussion, they assumed that the feasible investment environment is limited to fixed income securities and equities. The asset allocation system is designed to assist the manager in assessing the trade-off between the expected return and risk of the two alternative asset classes. They employed a simulation program called SIMR which allows the investor to isolate the effects of the four input factors: risk, return, time horizon, and utility preference. This study demonstrated the importance of the multiscenario projection approach. The approach allows portfolio managers the opportunity to investigate a range of outcomes and the sensitivity of the asset allocation decision to the alternative input assumptions. They concluded with the importance of using probability values by stating that the values can be used to establish a boundary within which strategic asset allocation decisions can be made. They indicate the importance of assigning probabilities to the various expected returns within the portfolio.

Tilley and Latainer [156] showed that the asset allocation can dynamically be adjusted in such a way as to replicate the returns on an option. Investing a portion of the portfolio in a riskless asset (to guarantee a minimum return) and dynamically adjusting stock and bond positions (by borrowing from the cash position), can eliminate all downside risk while maintaining upside potential. They linked option pricing theory with traditional asset allocation by utilizing a special type of option - a call option that gives its holder the right to purchase a full position in the better performance of either stocks or bonds. Their solution to the asset allocation problem suggests that the investor set aside enough wealth in a riskless asset to assure a minimum return target over the holding period and use the remaining wealth to purchase these specialized calls. Although such options are not available in the market place currently, their return pattern can be "synchronized" by a trading strategy utilizing stocks, bonds and cash. They didn't explicitly consider the question concerning measurement of risk for such strategy. Since the payoff distribution of option based strategy are nonnormal, variance is no longer an adequate measure of risk. Future research is required to determine the proper measure of risk for a strategy involving options and a nonnormal payoff distribution.

Following the rapid development of the futures contracts on US stock indices and Treasuries, Wall Street houses have written a substantial amount on the use of the contracts in the asset allocation process. The availability of the contracts does not solve or alter the allocation problem, but provides more efficient means of restructuring a portfolio. Once the decision is made to change the portfolio exposure to the risk of a given asset class, futures contracts provide, in most circumstances, the least expensive way to effect the change. Aside from tracking error between the cash portfolio and the futures contracts, several problems remain.[18]

The studies reviewed thus far have reported some success in asset allocation. These studies do not necessarily imply that an appropriate asset-mix is possible to forecast over time. None the less, the activities of a significant portion of the asset allocators coupled with the evidence suggesting that value is added by these activities merits further academic research.

[18]First, the possibility that mispricing in the interest rate and stock index contracts do not cancel. Excess returns to arbitrage on the S&P 500 index contract have been well-publicized recently. Excess returns on the T-bond contract are imperfectly correlated with the S&P raising the possibility of unanticipated loss or gain on the above strategy.

Second, rolling over the hedge as contracts expire incurs pricing risks.

Third, the possibility of cash outflow and lost interest income as contracts are marked to market each day. And opportunities to use futures contracts outside the USA are currently limited.

This study addresses this issue. It attempts to incorporate more information than previously employed and to assign probabilities to future states of the stock market in a more rigorous manner.[19]

[19]Technical market models tried to forecast the changes in stock price using decision rules with little or no theoretical justification. Data mining may produce indicators that seem to have some period specific value but out of sample results are poor. Clarke et al. [34] show that a model predicting monthly stock returns with an correlation of 0.3 can be expected to give a market timer a 5.9 percent (1.2 percent with 1.0 percent transactions costs) annual return advantage over an investor who buys and holds stocks. An overestimation of the true correlation might occur if correlations, estimated based on past periods, do not persist into the future. A market timer who makes no allowance for such misestimation will make suboptimal decisions. For example, the value added by the market timer who has no information, but who overestimates his information as a correlation of 0.5, can expect to lose 8 percent per year when the one-way transaction cost is 1.0 percent.

CHAPTER 3
THEORETICAL CONSIDERATIONS

The objective of this study is to develop a procedure to test the merit of using probable states of the market as a guideline to asset allocation. The procedure is based on the concept that *ex ante* variables are related to the excess return. The objective is to identify the relationship and assign probabilities to expected future states of capital markets. The investor must be able to decide at the beginning of an investment period as to how he will allocate his funds across the various asset classes.

The existing literature (cited in Chapter Two) suggests that asset allocation has experienced some success. An investment manager who has some information which permits a forecast of market movements may anticipate a market return different from the consensus expectation and will adjust his portfolio accordingly. When an investor has information that other market participants do not have regarding the probable future state of the stock market, the greater the confidence the investor has in that information the greater his tendency to allocate funds based on that knowledge (towards either the risk free asset or the portfolio of risky assets depending upon the relative performance of the risk-free asset and the market portfolio). According to the efficient market hypothesis, a managed portfolio would not be expected to outperform the buy-and-hold strategy on a risk adjusted basis over the long run. However, in the short run, any excess returns to a portfolio managed by a forecasting technique may indicate that, although the forecaster is using readily available public information, the information is being processed into a form that is not being considered by all market participants. The implication of this process is, that as the data in that particular form becomes available to all investors, excess returns resulting from the use of that data will disappear. Recent studies demonstrating the likely existence of price bubbles in stock prices (cited in Chapter 2), in conjunction with the article by Clarke et al. [34] forms the basis for this timing of the asset allocation study.

3.1 Procedure

A three step procedure is used to integrate readily available variables into the asset allocation process. The first step is to find *ex ante* observable variables which can predict excess return. The second step involves the generation of state probabilities from a logit analysis of the sample data. The goal is not to predict individual stock prices, or every small movement in the market, but rather to use the currently available data to provide the investor with an estimate of the probabilities associated with the broad measure of either a "bullish" or "bearish" market period. Logit analysis is used to determine which of the various timely and readily available data significantly affect the probabilities of "bullish" and "bearish" market months. The final step of the procedure is to use the estimated probabilities generated by the logit analysis to suggest the optimal allocation of funds between the risk-free asset and the market portfolio.

3.2 Determinants of the Excess Return

The expected rate of return of the stock market can be decomposed into two components, namely, the return on a T-bill and equity risk premium (RPE). The RPE reflects on an ex ante basis how much additional return investors are demanding as a reward for taking on the additional risk of common stock ownership. An estimate of RPE offers us a clue to the relative merits of investing in stocks versus the less risky medium of T-bills. Note, however, that we never really know ex ante what RPE is or how it is changing. At best we can estimate its size and direction of movement.

Here, we shall ask whether any *ex ante* observable variables reliably predict excess return. Excess return can be written as follows:

$$\begin{aligned} ExcessReturn &= TotalReturn - RiskFreeReturn \\ ER_t &= \frac{P_t - P_{t-1} + D_t}{P_{t-1}} - TB_t \qquad (3.1) \end{aligned}$$

This market excess return provides a measure of the attractiveness of stocks relative to the risk-free rate. Hence it offers a guideline for allocating assets between stocks and cash.

Consider a discrete-time perfect-certainty model in which D_t, the dividend per share for the time period from t-1 to t, grows at the constant rate g, and the market interest rate that relates the stream of future dividends to the stock price P_{t-1} at time t-1 is the constant k. In this model, the price P_{t-1} is

$$P_{t-1} = \frac{D_t}{1+k}\left(1 + \frac{1+g}{1+k} + \frac{(1+g)^2}{(1+k)^2} + \ldots\right) = \frac{D_t}{k-g}. \qquad (3.2)$$

We can restate equation (3.1) into equation (3.3) using equation (3.2).

$$ER_t = \frac{\Delta D_t/(k-g) + D_t}{D_t/(k-g)} - TB_t \qquad (3.3)$$

While the form of equation (3.3) does not lend itself to empirical estimation, it does provide the theoretical foundation for the hypothesis represented by equation (3.4).[1]

[1] Much has been written on the performance of stocks stratified by PEs and another body of

$$ER = f[k, g, D, TB] \tag{3.4}$$

3.2.1 Determinants of Appropriate Discount Rate

An investor's required rate of return is determined by: (1) the economy's risk-free rate (RFR), sometimes referred to as the pure time value of money, (2) the expected rate of price increase during the period of the investment, and (3) a risk premium for common stocks that reflects investor uncertainty regarding future returns.

The "real" risk-free rate is generally considered to be a function of the "real" growth rate of the economy, which in turn is determined by the growth of productivity. The nominal RFR is the "real" RFR plus the expected rate of inflation during the period. While the real RFR is difficult to derive, a reasonable proxy for the real RFR is the yield on U.S. government securities. We use the U.S. government yield series as a proxy for the nominal RFR and adjust it for the rate of inflation to derive an estimate for the "real" RFR. Given the adjustment to derive an estimate of the "real" RFR, we wish to consider whether the expected rate of inflation has any independent impact.

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literature seeks to explain the level of a firm's PE ratio. The market PE has, in contrast, received relatively little academic attention. Note, however, that the market is simply an aggregation of individual stocks. Accordingly, equation (3.2) should be applicable to the total market. In fact, equation (3.2) may be more suitably applied to the market as a whole than to individual stocks. Errors in measuring inputs may well tend to cancel out in the aggregate. That is, overestimates of individual dividend forecasts are likely to be offset by underestimates. Thus the DDM can be used to examine how the stock market is viewing the future. Branch [17] suggests that Dividend Discount Model could have been helpful in the economic analysis of the overall stock market around the time of the stock market crash of 1987. Showing that the market's growth expectations were very different just before the crash than they had been a year earlier, he suggests that the growth rate, in conjunction with consideration of a PE ratio might be a useful indicator of market signal. Francis [63] argued that the simplified nature of the dividend discount model could lead to conclusions which are true for the model but not true in general. [See Francis [63] pp. 239-256]. Chen, Roll and Ross [32] and Keim and Stambaugh [98] utilize equation (3.2) to suggest that the factors contributing to stock-price variability can be reviewed either as factors that change expected cash flows or as factors that change discount rates.

We shall consider the default spread as *ex ante* yield variables to forecast the excess stock returns. We use the difference between the yield on a long term below Baa rated corporate bond portfolio and the yield on a long term Aaa rated bond portfolio to represent the default spread.

Previous evidence of *ex ante* variables that predict risk premiums is confined primarily to specific types of assets and specific time periods. For example, a number of researchers have found that excess returns on common stocks are negatively correlated with measures of expected inflation during the post-1953 period, but this result does not generalize to other types of assets or to other subperiods.[2] What we lack is evidence that one or several variables consistently predict risk premiums over a long period.

The finance profession appears to believe that expected returns fluctuate through time as well as across stocks. These results are interpreted as describing the time variation in the "risk premium."

A bit of casual empiricism suggests that fashions and fads in investor attitudes cause stocks (groups or the entire market) to be at times overpriced, and at other times underpriced. Moreover, each of these fads eventually comes to an end. Such behavior would lead us to expect a high return when stock prices are low relative to dividends (or earnings or some other variable whose importance varies with the fashion of the day) and expect a low return when stock prices are high relative to dividends (or earnings). This type of relationship would imply that the following naive investment strategy should pay off: buy when price is low relative to dividends or earnings and sell when it is high.

[2]See, for example, Jaffe and Mandelker [88] and Fama and Schwert [58]. The negative correlation is particularly strong when the measure of expected inflation is simply the Treasury bill yield, but the phenomenon is evidently confined to the post-1953 period. Indeed, Fama [52] argues that the observed correlation is spurious.

That stock returns exhibit a peculiar seasonal pattern is now well known.[3] Those who have studied the issue generally have found that, on average, January returns are significantly higher than the returns for other months. Several studies have examined seasonality in risk premiums.[4] Tinic and West [150] examined the risk premiums of the two-parameter CAPM. They observed the previously reported seasonality and high January premium. They also found that January is the only month having a consistently positive, statistically significant relationship between expected return and risk. Recently, using the two-stage procedure with the maximum-likelihood factor analysis, Gultekin and Gultekin [81] show that the risk premia of the APT tend to be significant only in January.

In view of the above studies, we shall check for any seasonal patterns in excess returns of aggregate market. These considerations suggest the discount rate (k) model shown at equation (3.5).

$$k = f[DS, EI(or UI), D/P(or E/P), JS] \tag{3.5}$$

where;

DS: the default spread

EI (or UI): the expected inflation rate (or the unexpected inflation rate)

D/P (or E/P): the dividend-price ratio (or the earnings-price ratio)

JS: the seasonality dummy

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[3]Branch [16], Reinganum [130], DeBondt and Thaler [39] and Gultekin and Gultekin [81]. Following Branch [16], many authors have suggested tax-loss selling as an explanation of the January seasonal.

[4]Rozeff and Kinney [137] found that seasonality appeared in the risk premiums obtained from a two-parameter CAPM and that January displayed a relatively large risk premium compared with the other months. Keim [97] also found seasonality in the risk premiums.

Default Spread

We plan to use the default spread as *ex ante* yield variables to forecast the excess stock returns. The difference between the yields on long-term below Baa rated corporate bonds and the yield on the highest grade (Aaa) bond portfolio is used to reflect the market implied default spread.

The default spread represents a direct measure of the degree of risk aversion implicit in pricing. We hope that default spread would reflect much of the unanticipated movement in the degree of risk aversion and in the level of risk implicit in the market's pricing of stocks. This *ex ante* yield variable, which reflects the level of low-grade bond prices (relative to promised payments), shares its motivation with another bond market variable proposed by Chen, Roll and Ross [32] and Keim and Stambaugh [98].

Chen, Roll and Ross [32] examined the correlation between stock returns and the contemporaneous (*ex post*) difference between returns on low-grade bonds and U.S. Government bonds. They argued that changes in the relative prices of low-grade bonds proxy for changes in expected risk premiums. They found that stock returns are positively correlated with the contemporaneous bond return spread. This result is consistent with an increase in expected risk premiums (low bond return spread) accompanying a decrease in the stock price (low stock return). Sharing the motivation with Chen, Roll and Ross [32], Keim and Stambaugh [98] used the difference between yields on long-term below BAA rated (low-grade) corporate bonds and short-term (approximately one-month) U.S. Treasury bills as an ex ante yield variable to forecast stock returns.

Most recently, Fama and French [55] show that predictable variations in bond and stock returns is, in addition to the dividend yields, tracked by measures of default and term premia in expected returns.[5] Their results show that the default spread is clear a business-cycle variables.[6]

The low-grade bond return series is for nonconvertible corporate bonds, and it is obtained from Ibbotson Associates [87] for the period prior to 1986. A detailed description of the sample is contained in Ibbotson Associates [87]. The low-grade series is extended through 1987 by choosing 10 bonds whose ratings were below Baa.

Inflation Rate

According to most financial theories, expected inflation should be the basic underlying influence in asset pricing. It tends to affect both the expected cash flows and the discount rate.

Expected cash flows change because of both real and nominal forces. Changes in the expected rate of inflation would influence nominal expected cash flows as well as the nominal rate of interest. To the extent that assets are priced in real terms, unanticipated price-level changes will have a systematic effect on both pricing and expected returns. Moreover, to the extent that relative prices change along with

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[5] The default-premium variable (called the default spread) is the difference between the yield on a proxy for the market portfolio of corporate bonds and the yield on the highest grade (Aaa) bond portfolio. At the end of September 1987, the default spread (measured as the spread of Baa yields over Aaa yields) was .27 % (27 basis points), about half its mean value (.55 %) for the 1957-86 period. The default spread rose sharply around October 19th, and at the end of 1987, the spread, at .50 %, was still below but close to its 1957-86 mean [See Fama [53]].

[6] As such those variables are high when business is poor and low when the economy is strong. They interpret these results as follows: business conditions are poor, wealth is low and expected returns on stocks must be high to induce substitution from consumption to investment. Conversely, when times are good and wealth is high, the market clears at lower levels of equilibrium expected returns. Variation in expected returns over the business cycle may also be due to variation in the risk of stocks. The fact that the default spread signals variations in expected stock returns suggests that the spread is better interpreted as a general proxy for business conditions rather than as a simple measure of default risk.

general inflation, asset valuation changes are associated with changes in the average inflation rate.

Early empirical work indicates a significant negative relation between inflation and stock prices[7] Fama and Schwert [58] used expected and unanticipated inflation as well as changes in expectations as explanatory variables. They found a consistent negative relation between stock returns and each of these three variables. Fama [52] claimed that the negative stock-inflation relations are induced by negative relations between inflation and real activity which in turn are explained by a combination of money demand and the quantity theory of money.[8] Similarly Geske and Roll [69] have developed and tested a model that explains the negative relation between stock returns and inflation as due to rational investors realizing the adverse impact of inflation on future economic policy.

Unanticipated inflation is defined as

$$UI_t = I_t - EI_t, \tag{3.6}$$

where I(t) is the realized monthly first difference in the logarithm of the Consumer Price Index for period t. The series of expected inflation, EI_t is obtained from Fama and Gibbons' interest rate model [66].

If ER_{t-1} denotes an expected real return for month and EI_{t-1} denotes an expected inflation rate, then Fisher's equation asserts that

$$TB_{t-1} = ER_{t-1} + EI_{t-1}. \tag{3.7}$$

Hence, $TB_{t-1} - I_t$ measures the *ex post* real return on Treasury bills in the period. From a time-series analysis of this variable, Fama and Gibbons [66] constructed a

[7]Lintner [108], Jaffe and Mandelker [88] and Fama and Schwert [58] found a negative relation between stock returns and both expected and unanticipated inflation.

[8]Both Fama's theoretical model and empirical tests seem to support his contention that the observed simple stock market/inflation results from the proxy effects of an underspecified model.

time series for EI_{t-1}. Our expected inflation variable is defined by subtracting their time series for the expected real rate from the TB_{t-1} series.[9]

Dividend-Price Ratio

Most previous studies of the dividend-price ratio have been concerned with the cross-sectional relationship between dividend-price ratios and average returns. The ability of the dividend-price ratio to predict returns has, however, been noted by several authors.[10]

From equation (3.2), the dividend yield is the interest rate less the dividend growth rate in dividends,

$$\frac{D_t}{P_{t-1}} = k - g. \tag{3.8}$$

In the certainty model, the interest rate k is the discount rate for dividends and the period-by-period return for the stock.[11] The direct relation between the dividend yield and the interest rate in the certainty model (3.8) suffices, however, to illustrate that yields are likely to capture variation in expected returns. The intuition of the hypothesis that dividend yields forecast returns is as follows: stock prices are low relative to dividends when discount rates and expected returns are high, and vice versa. Thus yields capture variation in expected returns. A similar intuition applies for the earnings-price ratio (E/P).

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[9] If positive (negative) stock returns are associated with negative (positive) changes in the real interest rate, stock returns may be negatively correlated with changes in the Treasury bill rate, the proxy for expected inflation, even when stock returns and inflation are not directly related. A change in the real rate of interest should be a true cause of *ex post* stock returns, because an increase (decrease) in the real interest rate induces a reduction (increase) in all asset values. Thus, the beginning-of-period T-bill rate's real interest component and the subsequent expected stock returns may be positively related.

[10] Shiller [146] and Flood, Hodrick, and Kaplan [61]

[11] The transition from certainty to a model that (a) accommodates uncertain future dividends and discount rates and (b) shows that the correspondence between discount rates and time-varying expected returns is difficult [See Campbell and Shiller [26] and Poterba and Summers [127]].

The efficient market hypothesis has been traditionally associated with the assertion that future price changes are unpredictable. Many early observers of financial markets, however, believed that security prices could diverge from their fundamental values.[12] More recently, the idea that fashions and fads in investor attitudes (or other types of systematic "irrationality") may affect stock prices has gained new respectability.[13]

However, so long as prices have any tendency to gravitate back to fundamentals, they will be mean-reverting over long horizons. That is, they are somewhat predictable and not a random walk. In particular, if one takes a long-term perspective, then stock returns display significant negative serial correlation. In other words, prices are mean reverting.[14] The proposition that prices are mean reverting implies that prices are predictable.

Rozeff [136] showed that the equity risk premium can be proxied by the prospective dividend yield based on the Golden Rule of Accumulation in the context of the Gordon growth Model.[15] He defines the equity risk premium as the required return on equity minus the riskless rate of interest. He then converts real growth and the real riskless interest rate into nominal values by adding the expected inflation rate to

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[12]For example Keynes [99]

[13]See Chapter Two, Shiller [146], De Long, Shleifer, Summers, and Waldmann [41], and Shefrin and Statman [142] investigated economies with both rational "information" traders and irrational "noise" traders. In a world populated by noise traders, rational traders do not necessarily dominate the market nor do noise traders become extinct, even in the long run. Also, prices do not necessarily equal intrinsic value.

[14]One type of mean reversion in cross-sectional stock prices has been discussed in the literature at least since the time of Graham [72]. Modern empirical work suggests that simple contrarian strategies do yield excess returns [Basu [7]]. Substantial evidence in the psychology literature imply that individuals tend to overweight recent data in making forecasts and judgements [Kahneman and Tversky [95]]. Shiller [146] argues that mass psychology may well be the dominant cause of movements in the price of the aggregate stock market. If this behavior is manifest in financial markets, then we should observe mean-reverting returns to stocks that have experienced extremely good or poor returns over the past few years.

[15]If the economy maximizes consumption per capita, then the rate of growth of output equals the physical marginal productivity of capital, which in turn equals the rate of interest.

each. Essentially a Fisher effect adjustment is applied to both variables. When he subtracts the riskless rate from both sides of the Gordon growth model, he derives his equation.[16]

$$\text{risk premium} = \frac{D(1+g)}{P} + (G+I) - (R+I) \tag{3.10}$$

where D is the current dividend level, I is the expected rate of inflation, g is the nominal rate of growth in dividends, G is the real rate of growth in dividends, P is the price of the stock, R is the real riskless rate of interest.

Invoking the Golden Rule of Accumulation[17], the above expression can be simplified to his equation (3.11):[18] E

$$\text{risk premium} = \frac{D(1+r)}{P} \tag{3.11}$$

where r(the nominal riskless rate) has replaced g in the dividend yield formulation, due to their assumed equality. Since (D x r) tends to be small compared to D, the equity risk premium approximately equals the current dividend yield on stocks.

Using annual data, he shows that the stock return earned in the following years rises as the dividend yield in the prior year increases. His results imply that high

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[16]The expected rate of return on the stock market is equal to the dividend yield variable on the market plus the anticipated growth rate of dividend, $(\frac{D(1+g)}{P} + g)$, therefore,

$$\text{risk premium} = \frac{D(1+g)}{P} + g - (R+I) = \frac{D(1+g)}{p} + (G+I) - (R+I) \tag{3.9}$$

[17]the growth rate of physical output equals the real rate of interest in an equilibrium in which consumption per capita is maximized

[18]Johnson [93] showed that Rozeff's results holds only for (1) long time periods, as opposed to individual years, (2) the aggregate stock market, as opposed to an individual firm's equity.

returns tend to occur when the environment is perceived to be so risky that investors demand a high premium for holding stocks and low returns tend to occur when the environment is perceived to hold such modest risk that investors demand a low risk premium for holding stocks.[19]

Most recently, Fama and French [54,56] use regressions of returns on dividend yields to track expected returns. As in earlier works, these regressions explain small fractions of monthly and quarterly return variances. But excess of 30% of variances are commonly explained for return horizons (holding periods) beyond a year.[20]

Campbell and Shiller [27] use the dividend-price ratio model to compute the implications of this predictability for the behavior of the dividend-price ratio. They utilize the vector autoregressive methods(VAR) finding that the lagged log dividend-price ratio has a positive relation to stock returns. Thus the dividend-price ratio appears to be an appropriate candidate for explaining the risk environment of the stock market over time. We plan to use yields based on annual dividends to avoid seasonals in dividends.

Earnings-Price Ratio

Earnings data are appropriate candidate variables for forecasting stock returns. A similar intuition can be applied for the earnings-price ratio as for the dividend-price

[19] At the end of September 1987, the dividend/price ratio for the S&P 500 was 2.78 %, compared to its average value for the 1957-86 period of about 3.8 %. At the end of December, the dividend/price ratio for the S&P 500 was 3.71 %, still below but not far from its mean, 3.8 %, for the last 30 years [See Fama [53]].

[20] Suppose shocks to expected returns and shocks to rational forecasts of dividends are independent. Then the cumulative effect of a shock on expected returns must be exactly offset by an opposite adjustment in the current price. It follows that mean-reverting equilibrium expected returns can give rise to mean-reverting (temporary) components of stock prices [See Poterba and Summers [127]]. On the other hand, temporary components of prices and the forecast power of yields are also consistent with common models of an inefficient market, in which stock prices take long temporary swings away from fundamental values [cited in chapter Two]. In this view, high dividend-price ratios signal that future returns will be high because stock prices are temporarily irrationally low. Conversely, low dividend-ratios signal irrationally high prices and low future returns.

ratio. The notion underlying such propositions is that if stocks are underpriced relative to fundamental value (high E/P), subsequent returns tend to be high; the converse holds if stocks are overpriced.

The ratio of earnings to market price reflects the investment community's degree of optimism or pessimism regarding the outlook for future earnings. The earnings-price ratio theoretically expresses a market discount rate that serves as a positive and straight-forward contribution to the stock return. Many empirical studies support the hypothesis that *ex post* stock returns correlate positively with *ex ante* earnings-price ratios.[21]

Recently, Campbell and Shiller [27] show that the earnings-price ratio is a powerful predictor of the returns and excess returns on stocks, particularly when the return is measured over several years. Sorensen and Arnott [147] show that the equity market risk premium based on earnings yield has a 26% correlation with the one-month equity market excess return.

The economic cycle may impair the effectiveness of the simple earnings- price ratio based model. Specifically, reported earnings may be overstated during an economic boom and understated during recession, leading to an overestimation of the stock market's attractiveness during a boom and an understated appeal during a recession.

[21] Most studies conclude that stocks with high earnings-price ratios tend to have superior returns; see Basu [7], Cook and Rozeff [36]. Whether stocks with a high earnings-price ratio will have a relatively high return has been the subject of much discussion in the literature. Simple correlation across firms has been found between such ratios and returns. Basu [7] concluded that risk-adjusted returns are positively correlated with the earnings-price ratio even after controlling for firm size. As Basu notes, however, his tests depend on the risk measurement assumed. Elgers, Callahan and Strock [48] claimed that Basu's findings were due to (1) a classification bias inherent in the market index earnings expectation model used, and (2) failure of the returns conditioning model to incorporate a share price effect on security returns. They showed empirically that when a suitable model for expected earnings is used and the influence of share price upon security returns is controlled for, earnings yields are unrelated to the unexpected earnings-security association.

By using a long-term average of earnings, we smooth out the impact of valuation errors that occur because of peak earnings or depressed earnings. Accordingly, a 3-year double exponential moving average of earnings is used to give the greatest weight to the more recent observation.[22]

Thus we believe that the earnings-price ratios is a possible candidate for explaining the risk environment of the stock market over time.

Excess Return Seasonality

Many researchers document stock market anomalies that challenge the efficient markets hypothesis. While the existence of seasonal patterns is difficult to contest, the cause of such patterns is much in dispute.

One explanation offered by Branch [16] and Dyl [45] for the January seasonal suggests that tax-loss selling pressures in December temporarily drive security prices below their equilibrium levels and cause abnormal gains in January when incentives to sell for tax purposes are gone.[23]. A second explanation for the January seasonal is that macroeconomic forces that help determine security returns follow a seasonal pattern themselves. This argument is implicit in Chan, Chen, and Hsieh's [30] attempt to eliminate the January stock seasonal by examining return residuals from a multifactor model in which each factor was a macroeconomic variable.

[22]The use of an average of earnings in computing the earnings-price ratio has a long history. Graham and Dodd [73] recommended an approach that "shifts the original point of departure, or basis of computation, from the current earnings to the average earnings, which should cover a period of not less than five years, and preferably seven to ten years." Exponential moving average of earnings will slowly forget the relevance of past data.

[23]Branch [16], Dyl [45], Reinganum [130]

To date, no single explanation accounts totally for the observed stock market seasonals. Nor do we attempt to provide such an explanation here. We plan to check for any seasonal patterns in excess returns of the aggregate stock market.

3.2.2 Determinants of the Appropriate Growth Rate

The expected mean growth rate of earnings, g, is a function of both short and long-term factors. We assume that over the long-run profits represent a relatively constant percentage of GNP. Thus the economy's long-term growth rate in output should approximate the long-term growth rate in corporate earnings. And thus, with an approximately constant payout rate, also be equivalent to the long-term growth rate for dividends. Such forces as the rates of technological change, capital accumulation and population growth largely determine the long-term trend in the economy. Such factors should be sufficiently stable to produce a relatively constant long term trend. Most fluctuations in stock prices are, however, a reaction to shorter term changes. The actual growth rate, g, will vary from its long term trend as a result of two basic factors: (1) where the economy is relative to its trend line value and (2) how stimulative or restrictive an economic policy is pursued.

An economy that is producing goods and services at well below its potential rate can, in the short run, expand much more rapidly than can an economy that is operating close to capacity. A rapidly expanding economy will tend to produce even more rapidly growing earnings because initially at least, revenues tend to increase much faster than capacity. Thus so called "fixed costs" are spread over an ever larger revenue base thereby allowing price-cost margins to expand. The process works in reverse for a contracting economy: profits fall proportionately more than sales. Realizing these relationships, the market expects the economy to generate rapidly growing (declining) profits once it begins to emerge from (go into) a recession. The position of the economy relative to the long term trend in capacity can be measured by the level of industrial production activity.

Some evidence suggests that an ability to foresee business cycle turning points for several months ahead improves the ability to foresee major turning points in the general level of stock prices.[24] The evidence does not imply that every bear market must be accompanied by an economic recession or vice versa. However, stock prices have evidenced a pronounced tendency to decline prior to an economic downturn. Accordingly, if a recession or a slowdown of economic growth appears to lie ahead, the odds are high that it will be preceded by a significant stock market downturn some months in advance.[25]

If we can forecast business cycles earlier and/or more accurately than the market and allocate funds accordingly, we can avoid the recession induced drop in the market portfolio and outperform the market during a recession.

We quantify the degree to which investors are out of step using the implied market growth rate from equation (3.2). Such a mispricing creates attractive relative valuation opportunities involving stocks and cash. We also plan to use a direct measure of actual growth in earnings per share during alternative past periods.

Putting the above factors together we have;

$$g = f[G, \Delta IP, CI, UI(or EI)] \tag{3.12}$$

where;

G: the implied market growth rate

ΔIP: the changes in the industrial production,

CI: the cycle indicator,

UI (or EI): the unexpected inflation rate (or the expected inflation rate), and

[24] Umstead [157]

[25] For example, Piccini [125] concluded that the best time to sell stocks is probably one to three months before a recession begins.

Industrial Production

Changes in the expected level of real production would affect the current real value of cash flows. Insofar as the risk-premium measure does not capture industrial production uncertainty, the changes in the rate of productive activity should have an influence on stock returns through their impact on cash flows.

The basic series is the growth rate in U.S. industrial production which was obtained from the *Survey of Current Business*. If IP_t denotes the rate of industrial production in month t, then the monthly growth rate is

$$\Delta IP_t = \log IP_t - \log IP_{t-1} \tag{3.13}$$

Implied Growth Rate

Equation (3.2) provides a means for developing explicit return estimates for both individual stocks as well as the aggregate market. Transforming equation (3.2) to solve for the implied growth rate, g yields the following:

$$g = k - \frac{D}{P} \tag{3.14}$$

We can convert equation (3.14) into a real implied growth rate, g', by subtracting an inflation rate, I, from the nominal implied growth rate, g:

$$g' = k - \frac{D}{P} - I \tag{3.15}$$

Note that the real implied growth rate (g') is equal to the appropriate required rate of return (k) minus the dividend-price ratio and the inflation rate. Thus with estimates for k, D/P and I (appropriate required rate of return, dividend yield, the expected inflation rate) we can solve for the implied market expected real growth rate in dividends, g', and the degree to which the implied market expected real growth rate in dividends are out of step from the average market growth rate in the past, $\bar{g} - g'$.

While these proxies are imperfect, they are probably reasonably close to the market's actual expectations. Hopefully imperfections in the proxies do not lead to systematic errors over the time of this analysis. Since the expected growth of the economy has ramifications for stock investing, a reliable model of the expected growth might provide a useful benchmark that could help one forecast the market risk environment.

Rather than examining indirect measures of growth rates in earnings, we also use a direct measure of actual growth rate in earnings per share during alternative past periods. These growth rates are similar to the variables used in past studies.[26] For each month, a yearly average of the prior twelve months is derived and then computed the percentage change during the last year. Average growth rates are derived for one- and three-year periods by computing the average percent change for each interval on a moving basis.

Cycle Indicators

Piccini [125] explores the relationship between stock market movements and business cycles. He shows that the investor should sell stocks one to three months before a recession begins rather than wait until a clear indication of a recession is present.[27] Previous studies have found that composite indicators are able to predict (with errors) business cycles.[28]

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[26] Malkiel and Cragg [117]

[27] Because the averages have moved over a fairly narrow range prior to cyclical peaks, investors would probably do nearly as well by selling eight months before the peak in economic activity. Cautious investors should probably wait at least six months into a recession before they start reacquiring stocks.

[28] Umstead [157]

The search for leading, coincident and lagging indicators of general economic activity has been one of the major continuing projects of the National Bureau of Economic Research (NBER). Business Conditions Digest classifies indicators by their participation in the stage of economic process and their relationship to business cycle movements.

Moore and Zarnowitz [159] show that early and confirming signals of business cycle peaks and troughs are produced sequentially on a current basis by a system of monitoring smoothed rates of change in the composite indexes of leading and coincident indicators.[29]

We believe that a ratio of coincident to lagging indicators may offer better timing signals, at least for those cycles in which stocks led the way and business followed and the lagging indicators contain series such as interest rates, unit costs of output, etc., and a rise in these factors operates to brake a rise in business and profits alike.[30]

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[29]The expected sequence of signals at business cycle peaks, then, is when each of the following conditions is first observed: First signal (P1): The leading index falls below 3.3%, while the coincident index rate is positive ($L < 3.3$; $C > 0$). Second signal (P2): The leading index rate becomes negative, and the coincident index rate falls below 3.3% ($L < 0$; $C < 3.3$). Third signal (P3): Both the leading index rate and the coincident rate become negative ($L < 0$; $C < 0$). At business cycle troughs, the signals they have selected are slightly different, occurring when each of the following conditions is first observed: First signal (T1): the leading index rate rises above zero, while the coincident index rate is negative ($L > 0$; $C < 0$). Second signal (T2): The leading index rate rises above 3.3%, and the coincident index rate rises above zero ($L > 3.3$; $C > 0$). Third signal (T3): Both the leading index rate and the coincident index rate exceed 3.3% ($L > 3.3$; $C > 3.3$).

[30]*Wall Street Journal* editor Malabre also seem convinced that this ratio gives earlier warning of turns in business than do the leading indicators.[WSJ, Feb. 14, 1978] The ratio of the coincident index to the lagging index contains information that is related to stock market activity. Coincident indicators historically reach their turning points at about the same time as the general economy. Lagging indicators reach their peaks and troughs at a time later than the corresponding business cycle turns. The index of four roughly coincident indicators is composed of (1) number of employees on non-agricultural payrolls, (2) index of industrial production, (3) personal income, less transfer payments, (4) manufacturing and trade sales. The index of 6 roughly lagging indicators is composed of (1) index of labor costs, (2) manufacturing and trade inventories, (3) commercial and industrial loans outstanding, (4) average duration of unemployment in weeks, (5) ratio, consumer installment credit to personal income, (6) average prime rate charged by banks. A composite of the coincident and lagging indicators may provide information that is useful in predicting stock market condition.

In contrast to using some business cycle indicators, we shall also consider some direct measure of the stock market cycle. Technical analysts frequently follow the trends of moving averages, comparing them to the trend of the current data. This approach provides them with a trading signal. When current prices are rising and the current price rises above the moving average, technical analysts see a buy signal; when current prices are falling and the current price falls below the moving average, it is a sell signal. For example, at market tops, when prices have been rising, the current price will be above the moving average since the moving average is being pulled along behind. When a downtrend in prices begins, current prices will fall more rapidly than the moving average, and eventually they will cut through the trailing moving average. This is a signal that the market has started to turn down. Technical analysts view this as the time to sell. The opposite scenario occurs at market bottoms.

Moving average trading systems are trend-following systems. That is, they signal a move in the market after the trend has changed. Thus, such systems are not expected to get an investor into the market at the exact bottom or out at the exact top. Rather, the systems are designed to keep an investor on the right side of the market for the longer trends. The longer the moving average, the slower the indicator is to signal a change in trend. But a longer moving average also provides fewer false signals. We plan to include 7-month S&P 500 moving average. (or exponential moving average)[31]

The following variables are initial candidates to predict business cycles.

1. Ratio, Coincident Composite Index to Lagging Composite Index

2. 7-month S&P 500 moving average

3. Criteria from Moore and Zarnowitz

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[31] "200-day moving average" has been recommended by many authors. See Remaley [129], and WSJ [May 12, 1989]

3.2.3 Determinants of the Dividends

Earnings represent a useful summary of the available information about the future cash flows from an equity investment. Stock valuation models commonly employ some measure of earnings as their major parameter. Earnings per share emerge from various studies as the single most important accounting variable in the eye of investors. A substantial body of research has dealt with the information content of earnings numbers. The main findings is that earnings are correlated with factors that determine prices.[32]

Virtually everyone agrees that the prices of investments are largely determined by their expected cash flows. Thus knowledge of the average value of these expectations should already be incorporated in the price, and buying on the basis of average expectations should not lead to excess returns. Few people need to be convinced that expectations play an important role in determining prices. Accordingly, one should be able to earn larger excess returns by knowing (at least directional) the error in the earnings forecasts. Investment in a period with high actual earnings should not necessarily lead to excess returns unless the market was forecasting low earnings. Therefore, knowledge concerning differences between actual earnings and forecasted earnings (unexpected earnings) should lead to higher excess returns than knowledge concerning actual earnings itself. Thus, an unanticipated change in earnings causes a predictable change in the next period's dividends.

We have;

$$D = f[EF(orUE)] \tag{3.16}$$

[32] Ball and Brown [5] and Beaver, Lambert, and Morse [8]

where;

EF (or UE): the earnings forecasts (or the unexpected earnings)

Recently, earnings expectational data have become more available. Accordingly, more attention has been directed toward the examination of the properties of analysts forecasts of earnings, the information content of these forecasts, and the manner by which earnings forecast revisions impact security prices. These studies find that revisions in analysts' forecasts of earnings stir market reaction. Furthermore, information on these revisions may be used to construct profitable investment strategies.[33] That is, financial analysts' forecasts are, to a degree, a leading indicator of individual securities' price change. Numerous studies, starting with Ball and Brown [5], also documented a relation between *ex post* unexpected earnings and *ex post* unexpected stock returns.[34]

Examination of the association between unexpected earnings and security returns requires a suitable measure of the market's expectation of earnings. Prior studies have relied upon either time-series models[35] or upon published financial analysts' forecasts.[36] Several studies demonstrate that analysts' forecasts are more accurate than those from univariate models, presumably because of the broader information set they can incorporate.[37] But only scant evidence bears on the extent to which aggregate measures of analysts' forecasts of earnings can be used as an appropriate proxy of the stock market as a whole. Data gathering difficulties are probably the

[33]Givoly and Lakonishok [71], Elton, Gruber, and Gultekin [49], and Brown, Griffin, Hagerman, and Zmijewski [20]

[34]Brown, Griffin, Hagerman and Zmijewski [20]

[35]Foster [62] and Brown and Rozeff [22]

[36]Fried and Givoly [66], Brown, Griffin, Hagerman and Zmijewski [20,21]

[37]Brown, Griffin, Hagerman and Zmijewski [20,21] conducted a comprehensive comparison of quarterly unexpected earnings measures based upon analysts' forecasts and three univariate time-series models. They report that analysts' forecasts are a superior single proxy for market earnings expectations. They further suggest that researchers use financial analysts' forecasts rather than time-series models as a proxy for market earnings expectations.

most serious obstacle to use financial analysts' forecasts.[38] We use a Box-Jenkins model to forecast earnings.

3.2.4 Determinants of T-bill Return

Following Fisher [60], the one-month interest rate, TB_{t-1}, observed at the end of month t-1 can be broken into an expected real return for month t, ER_{t-1}, and expected inflation rate, EI_{t-1},

$$TB_{t-1} = ER_{t-1} + EI_{t-1}. \tag{3.17}$$

From equation (3.18),

$$TB_t = TB_{t-1} + \Delta EI_{t-1}.^{39} \tag{3.19}$$

These considerations suggests the T-bill rate model (TB) shown at equation (3.21).

$$TB_t = f[TB_{t-1}(or \Delta TB_{t-1}), \Delta EI(or UI)] \tag{3.20}$$

where;

ΔTB_{t-1}: the changes in the T-bill rate,

$\Delta EI(or UI)$: the expected inflation (or the unexpected inflation rate).

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[38] Indeed, several financial services are being engaged in the collection and publication of forecasts for a multiple of companies. Institutional Brokers Estimates System (IBES), Standard and Poor's Earnings Forecaster lists and Icarus Services by Zacks Investment Research, Inc. The IBES data are available to us only in the years 1976-1987.

[39] From equation (3.18),

$$TB_t - TB_{t-1} = \Delta ER_{t-1} + \Delta EI_{t-1}. \tag{3.19}$$

The evidence of Hess and Bicksler [84], Garbade and Wachtel [68] and Fama and Gibbons [66] suggests a model in which the expected real return is a random walk. I=Af the expected real return is a random walk, we can use equation (3.20) instead of (3.18)

CHAPTER 4

DATA AND METHODOLOGY

A two step procedure is used to integrate appropriate variables into the asset allocation process. The first step involves the generation of state probabilities from a logit analysis of the sample data.[1] Each month within the time periods included in the study is categorized as either a "bullish" market months (total return on stocks, including dividends, exceeds the return on cash equivalent) or as a "bearish" market month (the reverse of a "bullish" market). The goal is to use the data to provide the investor with an estimate of the probabilities associated with the broad measure of either a "bullish" or "bearish" market period. Logit analysis is used to determine which of the various data significantly affect the probabilities of "bullish" and "bearish" market months. Determination of how well the model performs in predicting "bullish" ("bearish") market months is based on;

- the sample used to estimate the logit coefficients; and
- extra sample data.

The extra sample data is used in the model verification process.

[1]We believe that investment timing depends more on a proper forecast of the direction than of the magnitude of risk environment. Furthermore, logit analysis is superior in generating probabilities of risk environment as compared to OLS. Since the forecast of the risk environment of the coming month is the main emphasis of this study, we compare the model using logit analysis with the model using OLS in terms of rate of return in Chapter 6.

The second step of the procedure is to use the estimated probabilities generated by the logit analysis to suggest the optimal allocation of funds between the risk-free asset and the market portfolio. An asset allocation strategy is developed for the purpose of evaluating the feasibility of the procedure.

4.1 Data

The asset allocation procedure requires a comparison of the relative performance of the market portfolio and the risk-free asset. The market portfolio is represented by the total return on the S&P 500 Composite Index. The S&P 500 is selected as the market series because "it is readily available, carefully constructed, market value-weighted benchmark of common stock performance".[2] The risk-free asset is represented by the total return on 1-month U.S. Treasury bills. We use U.S. Treasury index which Ibbotson and Sinquerfield [87] has constructed. They use the data in the CRSP U.S. Government Bond file through 1976, and *The Wall Street Journal* thereafter. They construct each month a one-bill portfolio containing the short-term bill having not less than one month to maturity. To measure holding period returns for the one-bill portfolio, they price the bill as of the last trading day of the previous month-end and as of the last trading day of the current month. The price of the bill at each time is given as (1 - rt/360), where r is the yield on the bill at that time (the average of bid and ask quotes in *The Wall Street Journal*, converted to decimal form) and t is the number of days to maturity. The month-end price divided by the previous month-end price, minus one, is the return on the bill over the month in question. A 1-month excess return is the difference between the continuously compounded 1-month

[2] By market value weighted, we mean that the weight of each stock in the index is proportionate to its price times the number of shares outstanding. [Ibbotson and Sinquerfield [87]] *WSJ* reports that The S &P 500's performance in 1988 differed by as much as half a percentage point, depending on which of investment firms did the computing. The tabulation and factors such as when the dividends are considered to be received may be handled in a variety of legitimate ways. [*WSJ*, Jan.26, 1989]

on stock portfolio and the continuously compounded 1-month Treasury bill return from Ibbotson associates [87].

Monthly data on all of these variables is gathered for the time period from January 1962 to December 1988. Twenty-seven years is long enough to contain several major market cycles and therefore sufficiently long to justify the use of asymptotic statistical theory. Each month, beginning with the first month of 1962 and continuing through the last month of 1976, is evaluated by comparing the monthly return on the market portfolio represented by the S&P 500 Index to the monthly return on the risk-free asset (U.S. Treasury bills) to determine whether the month was a "bullish" or "bearish" month as previously defined. The classification of the state of each month becomes the dichotomous dependent variable for the logit model ("bullish" = 1 and "bearish" = 0). A holdout sample, comprised of all months beginning in 1977 and continuing through the last month of 1987, is evaluated for the purpose of model verification.

The sources of data include various issues of the *Business Conditions Digest*, *Survey of Current Business*, *The Wall Street Journal*, *The SEC Statistical Bulletin* and Ibbotson and Sinquerfield [87].

To be useful, the data must be available to the investor at the time the asset allocation decision is made. Therefore, the publication lags of all variables used in this study are taken into consideration.[3]

Table 4.1 reports the variables, definitions and data sources.

[3]Figure 4.1 illustrates the typical sequence of events which result in the publication of the CPI. First, the price data are sampled in the middle of the month, so that the January inflation rate measures price changes which occur between December 15 and January 15. This is referred to as the measurement month. Second, previous researchers have used stock returns from the end of one month to the end of the next month, thus measuring the stock market reaction to January's inflation over the calendar month from January 1 to January 31. Third, the Bureau of Labor Statistics doesn't announce the CPI until approximately three weeks after the end of the calendar month. Thus, the January inflation rate is announced on about February 21 [See Schwert [138]]. Umstead [157] suggests a one-month publication lag for the leading composite index published by the National Bureau of Economic Research.

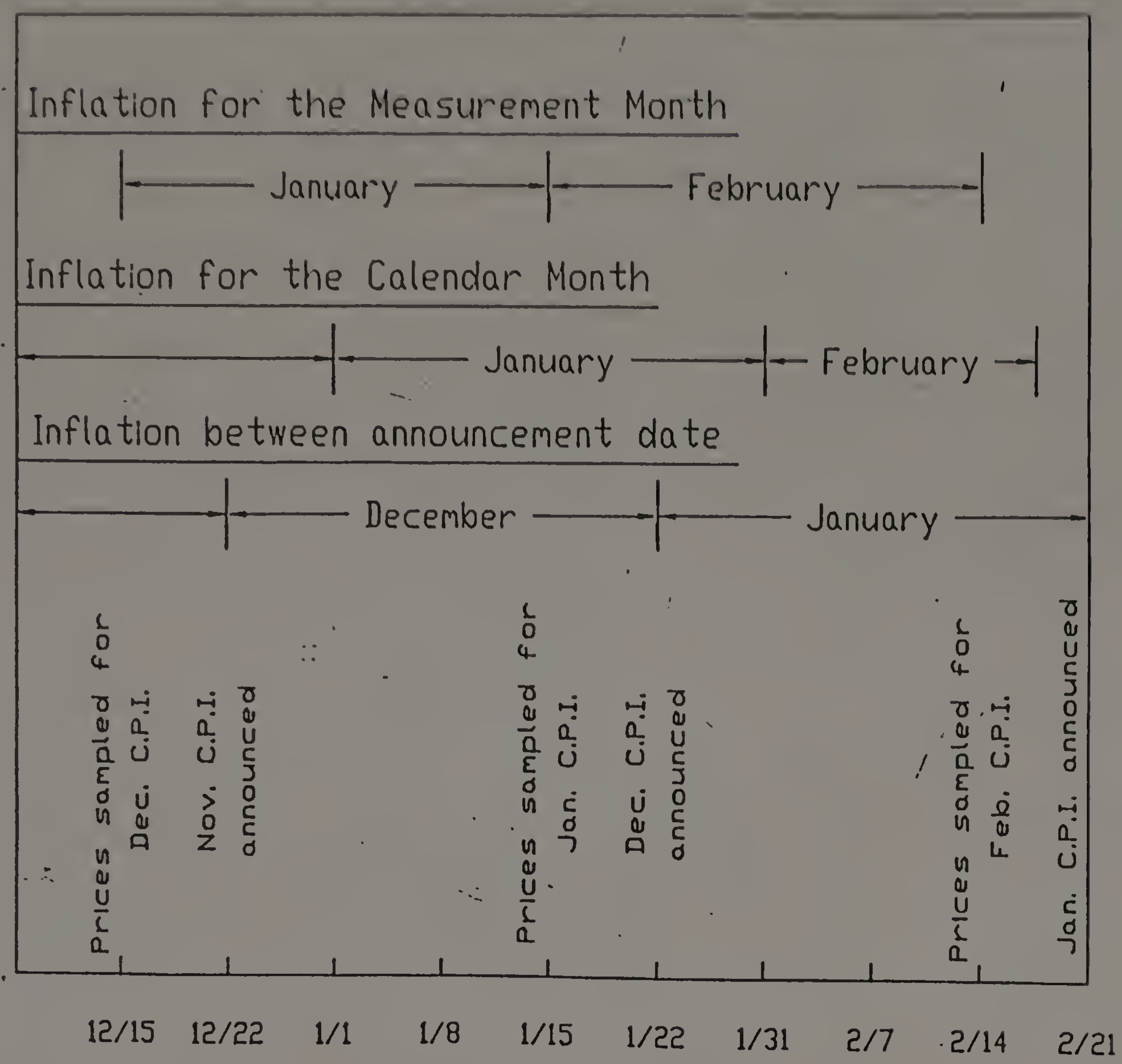

Figure 4.1 Typical Chronology of the Consumer Price Index

Table 4.1 Variables, Definitions and Data sources

Variable	Definition or Source
Stock return	Return on $S\&P$ 500 from Ibbotson and Sinquerfield [87], updated for 1987-1988 (CRSP)
Treasury bill return	Return on 1-month T-bill from Ibbotson and Sinquerfield [87], updated for 1987-1988 (CRSP)
Yield on below Baa-rated long-term bonds	Yields from *Business Statistics* and *Survey of Current Business*
Yield on Aaa-rated bonds	Yields from *Business Statistics* and *Survey of Current business*
Monthly growth, industrial production	$\log IP_t - \log IP_{t-1}$ from *Business Statistics* and *Survey of Current Business*
The dividend-price ratio	Yields based on annual dividends from *Business Statistics* and *Survey of Current Business*
The Composite Index	published by the U.S. Department of Commerce in the *Business Conditions Digest*

4.2 Logit Analysis

The problem to be addressed herein is the prediction of "bullish" and "bearish" market months from appropriate data. The questions to be answered are:

- What are the appropriate variables that significantly affect the probability of the market's excess return; and
- How accurately does the model predict a given state of the market?

Superficially, the problem appears appropriate for the use of ordinary least squares regression analysis (OLS). However, several problems are encountered with that technique due to the categorical nature of the dependent variable. Regression analysis assumes that the data satisfies the following assumptions:

$$Y = B_0 + B_1 X_{i1} + \ldots + B_{p-1} X_{i,p-1} + e_i \qquad (4.1)$$

where

$B_0, B_1, \ldots, B_{p-1}$ are unknown parameters

$X_{i1}, \ldots, X_{i,p-1}$ are known, non-stochastic variables

e_i are error terms that are independent, and N(0,σ^2)

$i = 1, \ldots, n$

The purpose of the regression model is to specify the relationship between X and Y by estimating the actual parameters, B_{p-1}, which generated by sample data. OLS passes a line through the data which minimizes the sum of the squared deviations of the observed points from corresponding points on the fitted line with the same X coordinates. Under classical regression assumptions, the estimates generated by the OLS procedure are the Best Linear Unbiased Estimates (BLUE) of the population parameters. If the error term "e" is normally distributed, then the least squares estimates are identical with the maximum likelihood estimates.

However, due to the categorical nature of the dependent variable used in this study, the assumptions of the regression model are not met. The difficulties of the standard regression model when the dependent variable is dichotomous are adequately explained by Judge, Griffiths, Hill, and Lee [94]. The regression model implicitly assumes a cardinal dependent variable. Therefore, regression is an inappropriate tool for the analysis of "bullish" and "bearish" stock market periods as defined in this study. The logit model is developed specifically to overcome the problems encountered with OLS when the dependent variable is categorical.[4] Multicollinearity can affect the signs of logit coefficients; however, unlike regression analysis, multicollinearity is expected to have no effect on testing the significance of individual variables in a logit equation. In regression analysis, multicollinearity biases the standard errors of the regression coefficients which in turn are used in individual t tests. Since such standard errors are not considered in maximum likelihood ratio tests, multicollinearity is expected to have no effect on these tests. The computation cost of logit analysis is likely to be greater than that of discriminant analysis. Discriminant analysis, however, requires very restrictive assumptions, including multivariate normality of the independent variables and equal covariances across all groups. Further, discriminant analysis does not generate accurate probabilities and unique discriminant coefficients. In view of these problems and limitations, discriminant analysis is not an appropriate statistical technique for constructing market timing models.

[4]Probit and logit deal with the identical problem of predicting the level of a dependent variable that is measured on a nominal or ordinal scale. The difference lies solely in the assumption made about the frequency distribution of this response. In probit it is taken to be normally distributed; in logit, a logistic distribution is assumed. The choice of model is largely a matter of personal preference rather than practical significance. Empirically it makes little difference, first because all the formulas and results central to probit can be simply rewritten in terms of the logistic transformation. Second, the results of both transformations are very similar. Very large data sets would be needed to show that one gives a better fit than the other for any particular study. Most economists have favored logit because of the direct interpretability of the logistic function.

Logit analysis will generate the $Y(X_i)$ from the linear combination of the explanatory variables as shown by the equation:

$$\underline{Y} = X\underline{\beta} + \underline{\epsilon} \tag{4.2}$$

where; $\underline{Y}$ is (Nx1) vector of response variable, X is an (NxP) matrix of n observations of k explanatory variables, $\underline{\beta}$ is a (Px1) vector of unknown coefficients and $\underline{\epsilon}$ is an (Nx1) vector of error terms.

For the i^{th} observation, the first category (R_1) will be observed if: $Y(X_i) \leq U_1$, the second category (R_2) will be observed if $U_1 \leq Y(X_i) \leq U_2$.

Thus the probability of observing a particular response R_j is:

$$P(R_j) = P(U_{j-1} \leq Y(X_i)) \tag{4.3}$$

$$P(R_j) = F(\hat{Y}(X_i) - \frac{U_{j-1}}{\sigma}) - F(\hat{Y}(X_i) - \frac{U_j}{\sigma}) \tag{4.4}$$

where: $F(.)$ is the cumulative logistic probability distribution function and $\hat{Y}(X_i)$ is the mean of $Y(X_i)$ for the i^{th} observation $(E(Y_i) = \sum_{m=1}^{p} B_m X_{m,i})$.

As can be observed from equation (4.3) and (4.4), the problem of estimating the $P(R_j)$ is the same as estimating the $\hat{Y}$ and the U_j's. The estimation of $\hat{Y}$ only requires the joint estimation of B and U in order to determine the probability of observing particular responses for the dependent variable given the values of the independent variable.

Maximum likelihood estimation is an appropriate procedure for the joint estimation of B and U. One of the principal advantages of using maximum likelihood estimation rather than discriminant analysis is that the statistical properties of the maximum likelihood estimators are both known and desirable. The general expression for the jth response for the ith observation is determined following:

$$P(R_{j,i}) = F(\sum B_m X_{m,i} - U_{j-1}) - F(\sum B_m X_{m,1} - U_j) \tag{4.5}$$

The corresponding log likelihood function is

$$L^*(B,U) = \sum_{i=1}^{n}\sum_{j=1}^{N} l_n[F(\sum_{m=1}^{p} B_m X_{m,i} - U_{j-1}) - F(\sum_{m=1}^{p} B_m X_{m,i} - U_j)] \tag{4.6}$$

The first order condition for maximum likelihood estimates is given by partially differentiating (4.6) with respect to B_m and U_j and setting each partial derivative to zero as follows:

$$\frac{\partial L^*(B,U)}{\partial B_m} = 0, m = 1, \ldots, p \tag{4.7}$$

$$\frac{\partial L^*(B,U)}{\partial U_j} = 0, j = 2, \ldots, N \tag{4.8}$$

Simultaneously solving the resulting system of P+N-2 non-linear (in the B's and U's) equations can be accomplished through the use of gradient methods, e.g. the Gauss-Newton optimization technique. The estimates of B and U are then used to find the probability of a particular response (j) for a given observation (i) $P(R_{j,i})$ by substituting the estimated values into (4.4).

CHAPTER 5

CONSTRUCTION AND VALIDATION OF THE MODEL

5.1 Explanatory Variable Structure

This section describes the basic characteristics for all the sample months, bullish market months only, and bearish market months.[1]

Table 5.1 reviews the explanatory variables used in the analysis and represents the abbreviations used in subsequent statistical tables. Table 5.2 presents the descriptive statistics of explanatory variables and reveals some interesting characteristics about the sample data.

The eight proxies selected as independent variables are not normally distributed. In particular, since normal distributions are symmetrical and unimodal, they have skewness indices of zero and kurtosis indices of three. As can be seen from Table 5.2, however, the descriptive statistics associated with the eight independent variables selected show that these variables have non-zero skewness indices. Therefore, the selected variables are not univariate normal and hence, not multivariate normal.[2]

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[1]While we consider all the variables we have discussed in Chapter 3, we have listed only the variables with a significant relation to the dependent variable.

[2]Univariate normality is a necessary but not sufficient condition of multivariate normality. Thus, these variables that are not univariate normal cannot be multivariate normal.

Table 5.1 Explanatory Abbreviations

Variable Abbreviation	Variable Definition
DS	Default Spread
DP	Dividend-Price Ratio
EP	Earnings-Price Ratio
G	Growth Rate from DDM
ERNG	Average Earinings Growth Rate for one-year on a Moving Basis
CI	Cycle Indicators
DTB	The Change in 1-month T-bill Rate
PTB	T-bill Rate in Previous Month

Table 5.2 Descriptive Sample Statistics

Explanatory Variables	Descriptive Statistics	All	Bullish	Bearish
DS	Mean	0.008573	0.008691	0.008485
	Standard Deviation	0.003867	0.004160	0.003523
	Skewness	1.111	1.048	1.188
	Kurtosis	0.789	0.454	1.319
DP	Mean	3.3897	3.4065	3.3698
	Standard Deviation	0.5363	0.554	0.518
	Skewness	1.659	1.678	1.648
	Kurtosis	3.091	2.972	3.469
EP	Mean	0.0597	0.05955	0.06024
	Standard Deviation	0.0145	0.015	0.014
	Skewness	1.357	1.463	1.219
	Kurtosis	1.109	1.425	1.109
G	Mean	0.00018	-0.00103	0.00161
	Standard Deviation	0.00783	0.00790	0.00755
	Skewness	-0.270	-0.206	-0.335
	Kurtosis	-1.076	-1.067	-1.171
ERNG	Mean	0.00590	0.00505	0.00709
	Standard Deviation	0.00765	0.00738	0.00799
	Skewness	-0.523	-0.720	-0.412
	Kurtosis	-0.327	0.367	-0.493
CI	Mean	103.723	102.344	105.354
	Standard Deviation	7.5607	7.053	7.855
	Skewness	0.904	1.132	0.696
	Kurtosis	-0.334	0.367	-0.836
DTB	Mean	0.000011	-0.000845	0.000112
	Standard Deviation	0.000596	0.005621	0.000619
	Skewness	-0.427	-1.726	0.609
	Kurtosis	4.412	7.332	1.229
PTB	Mean	0.004030	0.003833	0.004260
	Standard Deviation	0.001300	0.001192	0.001377
	Skewness	0.674	0.750	0.536
	Kurtosis	0.022	0.295	-0.248

Thus, the multivariate normality assumption required by discriminant analysis is violated.

Table 5.3 were developed for each group of months to explore whether differences between months could be used to categorize a period as either bullish or as bearish.

As indicated above, the proposed theory predicts that as compared to bullish market months, bearish market months have higher levels of G, ERNG, CI, DTB, PTB and lower levels of DS, and DP. The rest of the variables are insignificant. As shown in Table 5.3, the means of eight independent variables generally exhibit such relationships. As can be seen from Table 5.3, the univariate tests provide evidence that the expected relationships do exist. For example, bullish market periods have mean DTB of -.0010, which is lower than that of bearish market periods (.0010), and mean DP of 3.4065, which is higher than that of bearish market periods (3.3698).

To examine the characteristics of the sample data further, the variance-covariance matrices for both bullish periods and bearish periods are computed. These matrices are presented in Table 5.4.

Tables 5.4, clearly shows that bullish and bearish market periods did not have equal covariances during the test period. Thus, both the multivariate normality and equal covariances assumptions are violated by the sample data. Consequently, discriminant analysis is not an appropriate statistical technical technique to use in the construction of our timing model. It would be appropriate if its less restrictive assumptions are met. However, logit analysis is still appropriate because it requires less restrictive assumptions.

5.2 Construction of the Model

The initial base model is constructed on the basis of the 179 months from 2/62 to 12/76. This data base's summary characteristics are described in the section above.

Table 5.3 Univariate Statistics Showing the Relationship

Variables	Expected Sign	Bullish Mean	Bearish Mean	t-test p-value[a]
DS	+	0.0087	0.0084	0.660
DP	+	3.4065	3.3698	0.649
EP	+	.0599	0.0595	0.853
G	-	-0.0010	0.0016	0.024
ERNG	-	0.0050	0.0069	0.105
CI	-	102.3443	105.3537	0.008
DTB	-	-0.0001	0.0001	0.022
PTB	-	0.0038	0.0043	0.024

[a]two-sided tests

Table 5.4 Variance-Covariance Matrix for All Periods

		DS	DP	EP	G	ERNG	CI	DTB	PTB
DS		1.000							
DP	All	0.667	1.000						
	Bullish	0.475							
	Bearish	0.590							
EP	All	0.811	0.927	1.000					
	Bullish	0.698	0.909						
	Bearish	0.765	0.918						
G	All	0.508	-0.044	0.266	1.000				
	Bullish	0.492	-0.012	0.284					
	Bearish	0.488	-0.356	0.272					
ERNG	All	-0.536	-0.222	-0.333	-0.455	1.000			
	Bullish	-0.450	0.064	-0.019	-0.130				
	Bearish	-0.496	-0.094	-0.188	-0.277				
CI	All	0.272	-0.026	0.273	0.610	0.082	1.000		
	Bullish	0.417	0.103	0.407	0.662	0.342			
	Bearish	0.319	0.268	0.063	0.645	0.230			
DTB	All	-0.155	-0.413	-0.338	0.181	0.033	0.113	1.000	
	Bullish	-0.023	0.140	0.128	-0.074	0.071	-0.007		
	Bearish	-0.100	-0.159	-0.120	0.088	0.027	0.084		
PTB	All	0.498	0.562	0.649	0.456	-0.220	0.284	-0.271	1.000
	Bullish	0.240	0.568	0.551	0.466	0.224	0.312	0.042	
	Bearish	0.365	0.547	0.592	0.474	0.027	0.322	-0.077	

Based on these sample data, logit analysis results are contained in Table 5.5 and Table 5.6.

Because model 2 was best in predicting the direction of the markets, this is the model that is used in the subsequent simulation of actual investment policy.

Model 2 yields the following market timing prediction model:

$$Y_i = F(Z_i) \tag{5.1}$$

Z_i=0.11 - 646.32 x DTB - 433.83 x PTB + 0.58 x DP - 25.74 x ERNG

where: Y_i = conditional probability of bullish market periods

F(.) = the cumulative logistic probability distribution function

Z_i = theoretical index

The overall significance level of the model 2 is 0.0026 indicating a good fit. Two variables, changes in T-bill (DTB) and T-bill in previous month (PTB), are significant at 5%, and 1% level, respectively. Two variables, dividend-price ratio (DP) and growth rate in earnings (ERNG), are not significant at 10% level. However, the overall accuracy rate drops from 64 % to approximately 62 % when these two variables are not included in the model. Apparently these variables are contributing information to the overall model even though these variables are found to be insignificant at the .10 level.

The signs of the coefficients are consistent with the proposed theory. As suggested by the proposed theory, DP has positive coefficient, DTB, PTB, and ERNG have negative coefficients. Thus, our model and the proposed theory are mutually supportive. The positive coefficient for the DP variable reveal that high dividend-price ratios signal that future returns will be high because stocks are temporarily low. The negative coefficient for the ERNG variable indicates that if earnings growth rate is too high, the price may not be reflecting fundamental growth prospects and should be expected

Table 5.5. Results from Logit Analysis

Model	1 Coefficient	2 Coefficient	3 Coefficient	4 Coefficient	5 Coefficient
Constant (T-ratio)	-.1914 (-.181)	.1087 (.099)	4.1551 (1.383)	.0182 (.016)	3.0242 (1.194)
DTB (T-ratio)	-650.134 (-2.193)**[a]	-646.324 (-2.155)**	-620.420 (-2.101)**	-643.114 (-2.146)**	-610.619 (-2.048)**
PTB (T-ratio)	-401.073 (-2.189)	-433.828 (-2.828)***[b]	-417.478 (-2.230)	-427.871 (-2.767)***	-366.243 (-2.252)**
BMA (T-ratio)				-21.588 (-.355)	
DP (T-ratio)	.5886 (1.497)	.5808 (1.546)	.6288 (1.574)	.6634 (1.498)	.5184 (1.365)
G (T-ratio)	-11.029 (-.443)		17.5226 (.561)		
ERNG (T-ratio)		-25.744 (-1.210)		-30.515 (-1.211)	-19.752 (-.910)
CI (T-ratio)					-.0290 (-1.275)
Chi-square (Significance)	15.018 (.0047)	16.311 (.0026)	17.424 (.0038)	16.437 (.0057)	17.944 (.0030)

[a]** Significant at the 5 percent level.
[b]***Significant at the 1 percent level

Table 5.6 In-Sample Classification Results

Model	Actual Status	No. of Cases	Predicted Status Bullish	Predicted Status Bearish	Accuracy Rate
1	Bullish	97	72	25	74.2 %
	Bearish	82	41	41	50.0 %
	Overall				63.1 %
2	Bullish	97	85	12	87.6 %
	Bearish	82	51	31	37.8 %
	Overall				64.8 %
3	Bullish	97	76	21	78.4 %
	Bearish	82	43	39	47.6 %
	Overall				64.2 %
4	Bullish	97	77	20	79.4 %
	Bearish	82	48	34	41.5 %
	Overall				62.0 %
5	Bullish	97	75	22	77.3 %
	Bearish	82	41	41	50.0 %
	Overall				64.7 %
6	Bullish	97	76	21	78.4 %
	Bearish	82	44	38	46.3 %
	Overall				63.6 %

to decline. The negative coefficients for the PTB (proxy for expected inflation) and DTB (proxy for the changes in expected inflation) confirm that since the empirical proxy for expected inflation is the Treasury-bill rate at the beginning of the period, changes in stock prices could be associated with opposite changes in the proxy if real interest rate changes are negatively correlated with stock returns.

The in-sample accuracy rates of the model 2 are 87.6% for bullish periods, 37.8% for bearish periods. This corresponds to the misclassification of 12 bullish periods, 51 bearish periods, respectively.[3] Table 5.6 presents the details.

The overall accuracy rate of our model is computed as a weighted average of the individual accuracy rates for bullish and bearish market periods. The weights used are derived from the relative occurrence of bullish and bearish market periods, which is 0.542 to 0.458.[4] With this computation procedure, a classification that predicts all periods as bullish has an overall accuracy rate of 54.2%. Given that 54.2% of all periods are bullish, our model's 87.6% accuracy rate for predicting bullish is not surprising. Predicting a relatively common occurrence (i.e. bullish periods) correctly is more important than predicting a relatively rare occurrence (i.e. bearish periods) correctly. Thus, this model of only four variables can be used to predict objectively

[3]Chua and Woodward [33] defined accuracy in a *ex ante* or *ex post* sense. In the *ex ante* sense, accuracy would be the probability of forecasting a bull/bear market with the market in the subsequent period turning out to be bull/bear market. In the *ex post* sense, accuracy is the probability that the market in a period has been observed to be bullish/bearish when the forecast for the period, made at the beginning of the time interval, was bullish/bearish. In an *ex post* performance evaluation study, the question to be answered is how well a market-timing strategy would have done. We first consider whether the market was bullish or bearish in a given period, then we check whether we had forecast a bull or bear market for that period to determine what return would have earned. Chua and Woodward [33], as well as Sharpe [141] and Jeffrey [89], analyzed the accuracy of a market timer in what Chua and Woodward [33] call the *ex post* framework. We focus on the accuracy here in the *ex post* sense. Chua and Woodward [33] concluded that a market timer must be correct in at least 80 percent of all bull periods and 50 percent of all bear periods for market timing to pay with annual timing. Droms [42] showed that a market timer must be correct in at least 60 percent of all bull periods and 40 percent of all bear periods for market timing to pay with monthly timing.

[4]Sharpe [141] and Clarke et al [34] used .67 to .33 because Sharpe found that returns on stocks exceeded returns on cash in 67% of his sample years 1934-1972.

the probabilities of either a "bullish" or "bearish" market month. The weighted average accuracy rate of 64% also indicates the degree of fit of our model. The higher the number of correct classifications the better the fit of our model. A accuracy rate of greater than 50% indicates that the model performs better than naive approach relying on chance.[5]

Note that the predictive accuracy of the models depend on the value of the cutoff probability used.[6] Presumably investors have attitudes toward risk which lead them to to prefer different cutoff points.[7] Thus results derived for a given cutoff probability do not necessarily help them decide which model fits their needs. Clearly the rewards or costs associated with the different types of correct or incorrect classifications determine the investor's optimal cutoff probability. This issue is further explored in the next section.

Table 5.7 explaining the classificatory power of a model is quite different from the table regularly used.

Column (1) lists the cutoff percentages used to classify a period as bullish or bearish. The number of misclassified bullish is shown in column (2) (Type II error), column (3) contains the number of misclassified bearish periods (Type I error), and column (4) shows how many periods had calculated probabilities less than the cutoff level. The number of correctly classified periods is given in column (5). The percentage of periods correctly classified (column 6) is determined by dividing the number in column (5) by the total number of periods in the test. Note that the maximum

[5]These results of our model predictions exceeded those achieved by the best naive model at the 0.01 significance level.

[6]Logit analysis generates conditional probabilities but does not dictate what the cut-off probability between the groups(i.e., bullish and bearish market periods) should be. In contrast, discriminant analysis computes an optimal Z-score to classify the observations into groups given the prior probabilities and sample data.

[7]The cutoff points represent a probability; for example, if the cutoff point was 0.20, a period with a probability below that level would be classified as bearish (a 0); a probability above 0.20 would be classified as bullish (a 1).

Table 5.7 Classification Accuracy

Proposed Cutoff	Predict-0 Actual-1	Predict-1 Actual-0	No. Below Cutoff	No. Correct	Percent Correct
.00	0	82	0	97	54.2
.05	0	82	0	97	54.2
.10	0	82	0	97	54.2
.15	3	79	4	99	55.3
.20	2	77	7	100	55.9
.25	3	75	10	101	56.4
.30	3	74	11	102	57.0
.35	5	64	23	110	61.5
.40	6	59	29	114	63.7
.45	11	53	40	115	64.2
.46	12	51	43	116	64.8 M[a] P[b]
.50	19	45	56	115	64.2 E[c]
.55	35	33	84	111	62.0
.60	49	22	109	108	60.3
.65	67	15	134	97	54.2
.70	87	6	163	96	53.6
.75	91	2	171	86	48.0
.80	94	0	176	85	47.5
.85	96	0	178	83	46.4
.90	96	0	178	83	46.4
.95	97	0	179	82	45.8
1.00	97	0	179	82	45.8

[a]M - Maximum Accuracy Level
[b]P - Proportional probability cutoff
[c]E - Equal probability cutoff

accuracy level is a "data driven" cutoff point and it can vary based on changes in the database. The 50 % cutoff assumed equal probabilities of groups; proportional probabilities should also be considered.

Figure 5.1 depicts the frontier trading of one error against another, when the errors are expressed as percentages. Figure 5.2 shows the mapping from cutoff points to the two different types of errors. The cutoff point which minimizes the sum of errors is .46. At that point, 12.4% of the bullish periods and 62.2% bearish periods are misclassified. Note also that if we select a cutoff point equal to .10, then no Type II error occurs and if we select a cutoff point equal to .80, then no Type I error occurs.

As discussed above, our model is very conservative in the sense that it attempts to predict bullish periods correctly at the expense of bearish periods. Recall that their relative occurrence is 54.2 to 45.8. However, this conservative model may not be optimal when the misclassification cost of predicting a bearish periods incorrectly as a bullish periods (i.e., Type I error) is very much higher than the misclassification cost of predicting bullish periods incorrectly as bearish periods (i.e., Type II error). Under such circumstances, predicting a rare occurrence incorrectly is very costly and thus, attempting to predict bullish periods correctly at the expense of bearish periods may not be appropriate.

All the accuracy rates presented above are in-sample accuracy rates. In other words, the accuracy rates are computed on the basis of the estimation sample. Since the same 179 periods are also used to construct our model, the in-sample accuracy rates are upward biased. Thus, the in-sample accuracy rates provide only a biased indication of the predictive ability of our model. Consequently, hold-out accuracy rates need to be computed before the predictive ability of our model can be assessed. The hold-out accuracy rates for our model, as computed using subsequent periods and the Lachenbruch jackknife method, are presented in the next section.

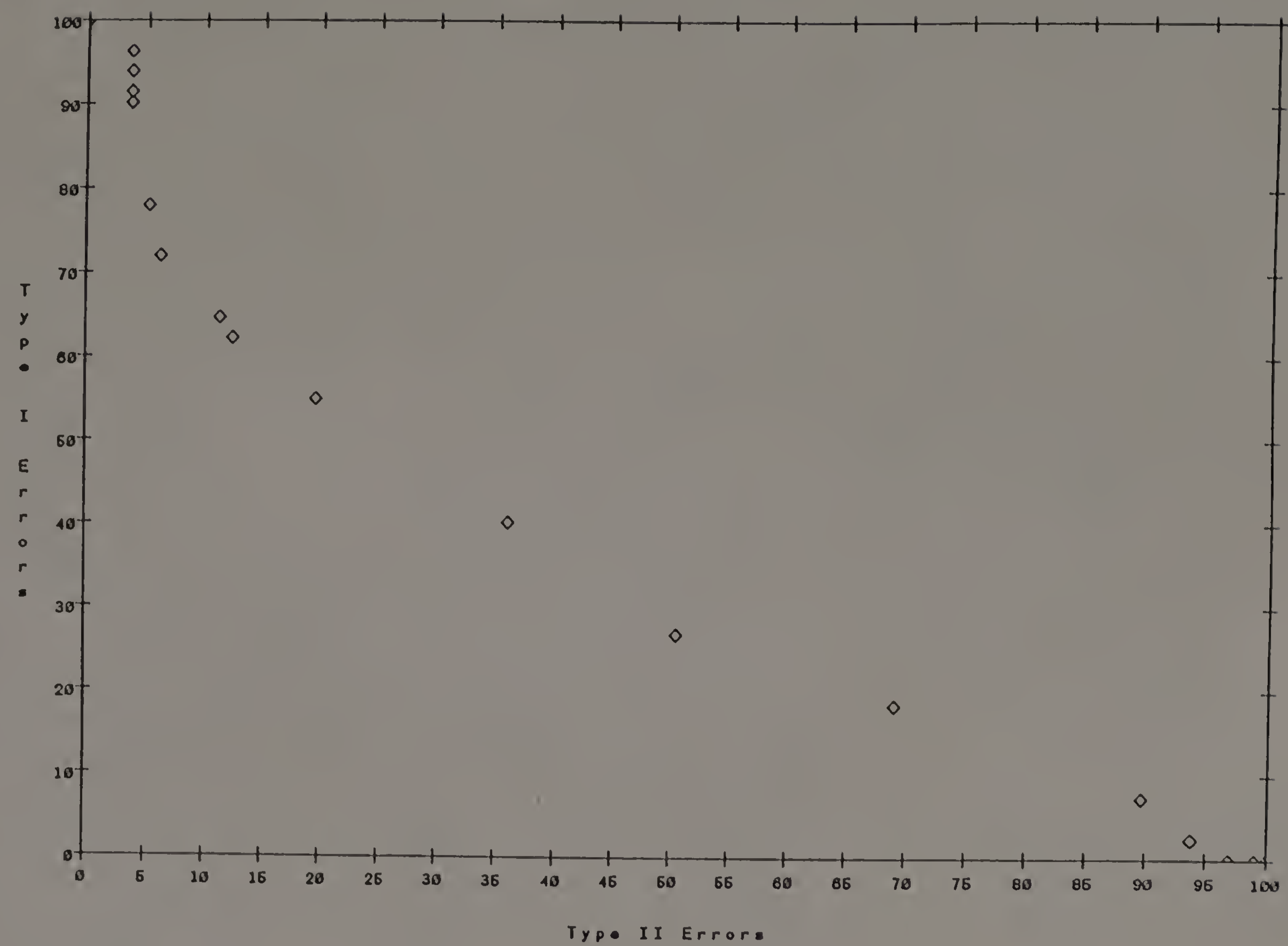

Figure 5.1 Tradeoff between Errors

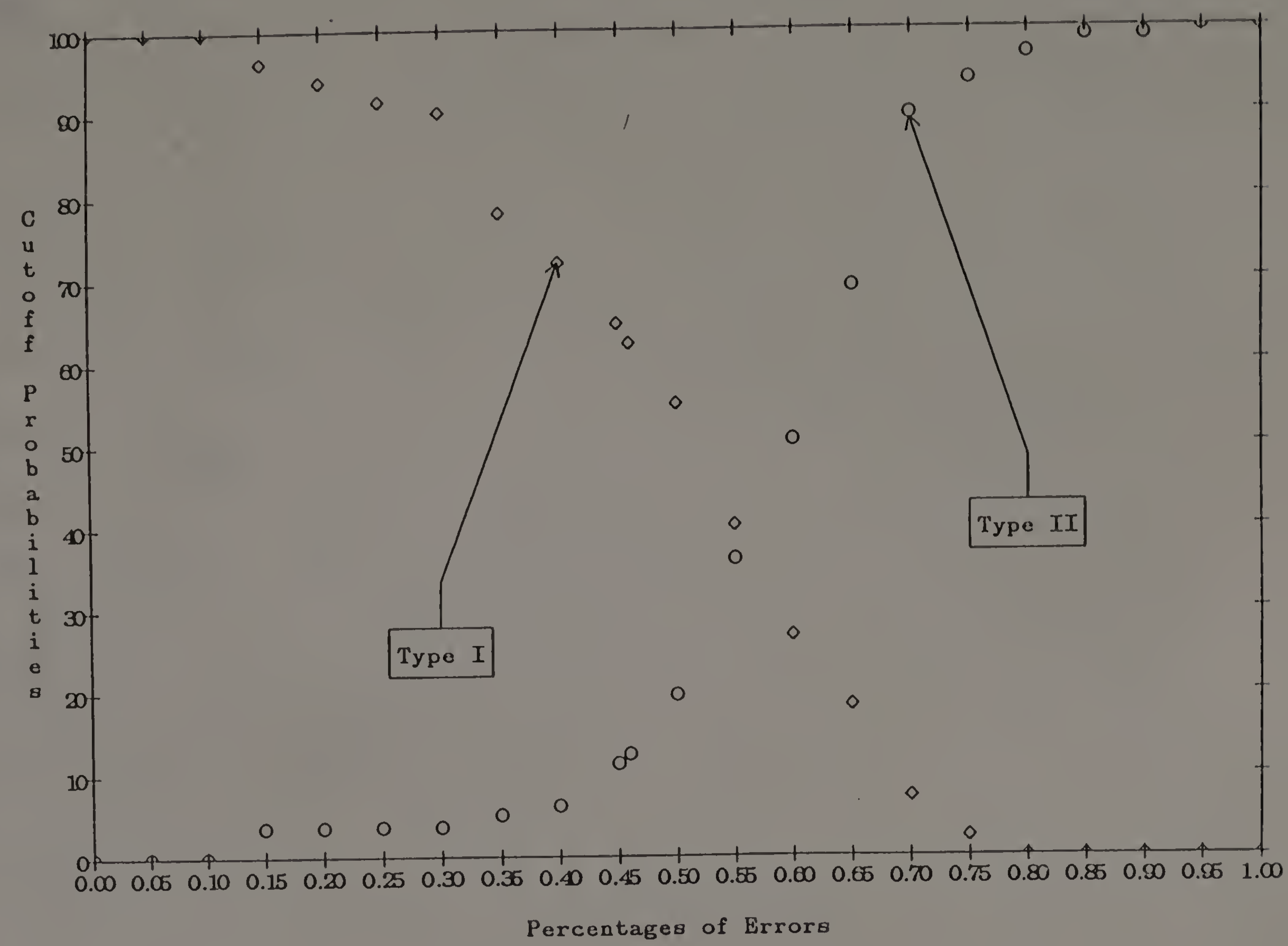

Figure 5.2 Frequency of Errors

5.3 Lachenbruch Jackknife Method

To test the predictive power of our model in discriminating between bullish and bearish market periods, the Lachenbruch jackknife method is used.[8] The jackknife technique avoids the problem of testing the model on the same data used to fit the model. It is also distribution-free and does not require multivariate normality, equal dispersion matrices.

The Lachenbruch method consists of the following steps. First, one sample period among the 179 sample periods is held out and a logit model is constructed on the remaining 178 sample periods. Second, the resulting logit model is used to compute the conditional probability of bullish and bearish market periods for the held-out period. Third, the above procedure is repeated for every sample periods. For our model, the Lachenbruch method generates 179 logit models and 179 conditional probabilities since there are 179 sample observations. The means and standard deviation of the 179 sets of coefficients resulting from the Lachenbruch method are given in Table 5.8.

As expected, the means of the 179 sets of coefficient are close to the coefficients in our model. Further, Table 5.8 shows that the logit coefficient resulting from the Lachenbruch method are rather stable. This implies that our model is also a stable timing prediction model. In particular, the coefficients of our model are not influenced by any specific sample period. Instead, they reflect the general characteristics of bullish and bearish market periods.

5.4 Predictive Ability of Our Model

As discussed in the previous section, the in-sample accuracy rates of our model are upward biased because the validation sample that is used to compute the in-sample accuracy rates is also the estimation sample that is used to construct our model. Thus,

[8] P.A. Lachenbruch [105]

Table 5.8 Means and Standard Deviation of our Model

Coefficients	Mean	Standard Deviation
Constant	0.10862	0.08384
DTB	-647.962	23.0025
PTB	-434.195	13.2027
DP	0.58169	0.03139
ERNG	-25.690	1.6120

to assess the predictive ability of our model in a more appropriate manner, an eleven-year (132-month) hold-out sample is evaluated. Observations of each of the four independent variables are taken from readily available published sources as previously described and evaluated with prediction using logit equation. The predictions are generated as follows. We begin by building an initial base model using data from the 180 months from 1/62 to 12/76. Given these base model coefficients, we input actual lagged data for 12/76 and generate probabilities of market risk environment for 1/77. Subsequently, we input actual values for 1/77 and derive an probability of market risk environment for 2/77. We do this for all twelve months in 1977. Then the base model is updated twelve months (we drop the twelve months in 1962 and add the 1977 data). We then use this new base model to predict probabilities of market risk environment for 1978.

Table 5.9 shows the results of our model during the hold-out sample period (1977-1987). These results indicate that our model is still statistically significant and maintains a significance level of 1%. The coefficients remain reasonably stable, particularly DTB and ERNG variable. The DTB and the PTB variable continue to be significant at the 5% level or less during almost all periods. Interestingly, the DP variable and the ERNG variable appears stronger and are now significant at the 5% level.

The resulting probabilities of each month are compared to the actual state of the month to determine our model's overall accuracy rate. The hold-out sample accuracy rates of our model are 73.8% for bullish periods, 43.3% for bearish periods corresponding to the overall accuracy rate of 60.1%. Our model performed better than a naive approach relying on chance. These results are similar to the in-sample results. However, as expected, the hold-out accuracy rates are lower than the in-sample accuracy rates since the latter are upward biased because the estimation sample is used to validate the model. The relatively high number of correct classification in the holdout

Table 5.9 Results from Logit Analysis during Hold-out Sample Period

Period	Constant (T-ratio)	DTB (T-ratio)	PTB (T-ratio)	DP (T-ratio)	ERNG (T-ratio)	Chi-square (Significance)
'63-'77	1.8349 (1.870)*[a]	-758.301 (-2.465)**[b]	-327.405 (-2.042)**	-.0377 (-.123)	-47.7622 (-2.256)**	17.368 (.0016)
'64-'78	1.0592 (1.295)	-667.489 (-2.270)**	-331.454 (-1.981)**	.2013 (.814)	-46.3444 (-2.187)	15.580 (.0036)
'65-'79	-.3902 (-.556)	-569.843 (-2.034)**	-91.1316 (-.597)	.2987 (1.243)	-46.0593 (-2.229)**	12.167 (.0162)
'66-'80	-1.2499 (-1.782)*	-545.418 (-2.388)**	14.2720 (.105)	.413664 (1.733)*	-61.8932 (-2.913)***	19.282 (.0007)
'67-'81	-.8288 (-1.212)	-363.624 (-1.924)*	-150.556 (-1.689)*	.4766 (2.109)**	-41.4571 (-2.136)**	12.200 (.0159)
'68-'82	-.6797 (-1.024)	-313.774 (-1.801)*	-176.958 (-1.994)**	.4570 (2.149)**	-40.9971 (-2.200)**	12.904 (.0118)
'69-'83	-1.0736 (-1.498)	-306.543 (-1.751)*	-185.897 (-2.094)**	.5532 (2.504)**	-43.9431 (-2.592)***	16.150 (.0028)
'70-'84	-.9879 (-1.290)	-308.905 (-1.800)*	-171.742 (-1.966)**	.5180 (2.254)**	-44.4255 (-2.765)***	16.480 (.0024)
'71-'85	-.9973 (-1.267)	-363.925 (-2.091)**	-167.415 (-1.905)*	.5143 (2.208)**	-41.482 (-2.556)**	16.330 (.0026)
'72-'86	-.8330 (-1.032)	-340.902 (-1.984)**	-167.844 (-1.912)*	.4848 (2.095)**	-43.716 (-2.752)***	16.287 (.0027)
'73-'87	-1.4462 (-1.728)*	-273.298 (-1.664)*	-134.430 (-1.544)	.5733 (2.465)**	-53.047 (-3.259)***	19.065 (.0008)

[a]*Significant at the 10 percent level
[b]**Significant at the 5 percent level

sample period indicates that the probabilities generated by the logit model during the within sample period could be considered as accurate probabilities for that time period.

5.5 Consideration of Misclassification Costs

Logit analysis generates conditional probabilities but does not dictate what the cut-off probability between the groups (i.e., bullish and bearish) should be. Therefore, to use our model to predict the status of a period, a cut-off probability between bullish and bearish must be determined. Bullish periods occur more frequently than bearish periods. Therefore, Predicting the status of bullish periods correctly may be more important than to predict the status of bearish periods correctly if we ignore misclassification costs.[9] Another justification for recommending a conservative timing model is derived from previous research.[10]

Although our model is appropriate in general, less conservative prediction models might also be used. In fact, less conservative models may be more appropriate when the costs of misclassifying bearish periods as bullish periods (i.e., Type I errors) are very much higher than the costs of misclassifying bullish periods as bearish periods (i.e., Type II errors). Under such circumstances, while bearish periods occur more rarely, the misclassifications of these relatively rare occurrences are very costly.

Up to this point, misclassification costs have been ignored. When they are considered explicitly, the procedure to be used to determine the optimal cut-off probability differs significantly from that used so far. Specifically, when misclassification costs

[9] To predict bearish periods correctly may be more important than to predict bullish periods if the amount lost in the bearish periods is far greater than that made in a typical bullish period.

[10] Chua and Woodward [33], and Clarke et al [34] showed that accuracy in forecasting bull markets is more important than accuracy in forecasting bear markets. For example, eighty percent bull market forecasting accuracy outperforms buying and holding regardless of bear market forecasting ability without transaction costs. By comparison, seventy percent bear market forecasting accuracy outperforms buying and holding only if bull market forecasting exceeds fifty percent.

are considered explicitly, the optimal cut-off probability for our model is no longer that probability that minimizes the misclassifications of bearish periods, given that bullish periods are classified correctly. Instead, the optimal cut-off probability is that probability that minimizes the expected misclassification costs of using our model.

The expected misclassification costs of using our model can be expressed as follows:

$$EC = (P_{BR})(P_I)(C_I) + (P_{BL})(P_{II})(C_{II}) \tag{5.2}$$

where EC = expected misclassification costs of using our model

P_{BR} = prior probability of bearish periods (0.458)

P_{BL} = prior probability of bullish periods (0.542)

P_I = conditional probability of Type I errors (no. of Type I errors/179)

P_{II} = conditional probability of Type II errors (no. of Type II errors/179)

C_I = misclassification costs of a Type I error

C_{II} = misclassification costs of a Type II error

In the above formula, C_I and C_{II} are unknown parameters. Therefore, C_I and C_{II} can only be speculated to determine the optimal cut-off probability for our model. Instead, the expected misclassification costs of using our model are computed under alternative assumptions about the relative misclassification costs of Type I and Type II errors (i.e., $C_I : C_{II}$). This procedure is illustrated below.

Given the values of P_{BR}, P_{BL}, P_I, and P_{II}, EC can be expressed as follows:

$$EC = (0.458)(N_I/179)(C_I) + (0.542)(N_{II}/179)(C_{II}) \tag{5.3}$$

where N_I = number of Type I errors ; N_{II} = number of Type II errors

That is,

$$EC = 0.0025586 \times (N_I \times C_I) + 0.0030279 \times (N_{II} \times C_{II})$$

The above formula shows that because bullish periods occur more frequently than bearish periods, misclassifying bullish periods (i.e., N_{II}) contributes more to EC than misclassifying bearish periods (i.e., N_I) when misclassification costs (i.e., C_I and C_{II}) are ignored. The different EC's for our model under different cut-off probabilities and optimal cut-off rate when $C_I : C_{II}$ is 1:1 are presented in Table 5.10. This table illustrates the determination of the optimal cut-off probability when $C_I : C_{II}$ is 1:1.

As can be seen from Table 5.10, when the misclassification cost of a Type I error is equal to the misclassification cost of a Type II error, the optimal cut-off probability and the corresponding optimal cut-off standard deviate are .46 and -.1603, respectively. (These optimal cut-off values are identical to those specified by the model in previous section.) With this optimal cut-off probability, the expected misclassification costs of using our model is .16731.[11] All other cut-off probabilities lead to higher EC's when $C_I : C_{II}$ is 1:1. Thus, when $C_I : C_{II}$ is 1:1, our model as specified in Table 5.10 is appropriate. This specification of our model uses an optimal cut-off probability of .46 in its prediction rule. However, this specification of our model may not be optimal for other values of C_I and C_{II}. In particular, different relative misclassification costs may lead to different optimal cut-off values. Accordingly, the optimal cut-off probabilities and expected misclassification costs for using our model are computed for $C_I : C_{II}$ ranging from 1:4 to 4:1. The results are summarized in Table 5.10.

[11] In this study, the expected misclassification costs of using our model are computed only for the purpose of determining the optimal cut-off probability. They do not have units and are not interpretable unless actual values of C_I and C_{II} are used. In other words, only when the actual values of C_I and C_{II} including transaction costs are available, the actual expected misclassification costs of using our model can be computed in terms of dollar amounts.

Table 5.10 Summary of Optimal Cut-off Probabilities

$C_I : C_{II}$	Y	Z	N_I	N_{II}	EC
1 : 4	.10	-2.1972	82	0	.21074
1 : 3.5	.10	-2.1972	82	0	.21074
1 : 3	.40	-.4055	59	6	.20599
1 : 2.5	.40	-.4055	59	6	.19693
1 : 2	.40	-.4055	59	6	.18787
1 : 1.5	.40	-.4055	59	6	.17881
1 : 1	.46	-.1603	51	12	.16731
1.5: 1	.50	-.0009	45	19	.23085
2 : 1	.60	.4055	22	49	.26106
2.5: 1	.80	1.3863	0	94	.28388
3 : 1	.80	1.3863	0	94	.28388
3.5: 1	.80	1.3863	0	94	.28388
4 : 1	.80	1.3863	0	94	.28388

As can be seen from Table 5.10, our model is sensitive to varying relative misclassification costs for $C_I : C_{II}$ ranging from 1:3 to 2:1, which is, optimal cut-off probability (Y) for our model vary between .4 and .6. But, for $C_I : C_{II}$ ranging above 1:3.5, optimal cut-off probability remains at .1 and for $C_I : C_{II}$ ranging below 2.5:1, optimal probability remains at .8.

CHAPTER 6

CREATING A STRATEGY AND EMPIRICAL RESULTS

The probabilities generated by the logit model are used to construct a portfolio at the beginning of each month during the test period. The logit model used in our study provides categorical information. The probabilities produced are in relation to "bullish" and "bearish" market periods. They are state probabilities and do not specifically predict a return on the market or on the risk-free asset.

6.1 Asset Allocation Strategy

Five strategies, as presented in Table 6.1, is evaluated on the basis of their end of period wealth.

Strategy 1 buys U.S. Treasury bills and represents the return on the risk-free asset during the test period. Strategy 2 buys and hold the S & P 500 Index through the entire period. S & P 500 Index is widely used despite its limitations as a proxy for "THE" market. Buy-and-hold strategies are "do nothing" strategies: No matter what happens to relative values, no rebalancing is required. Buy-and-hold strategies are easy to analyze. They also serve as anchor points for more complex approaches.

Table 6.1 Strategies

Strategy 1; Buys U.S. Treasury bills and represents the return on the risk-free asset during the test period.

Strategy 2; Buys and holds the S&P 500 Index through the entire period

Strategy 3; Switches between one hundred percent U.S. Treasury bills and one hundred percent equities (one hundred percent T-bills if bearish, one hundred percent equities if bullish).

Strategy 4; Manages portfolio according to the state probabilities generated by the logit analysis. Comparison of Strategy 3 and Strategies 4 is to explore whether allocating funds on the basis of probabilities is superior or if simple switching policy is just as effective.

Strategy 5; Considers option-like payoff portfolio. For most investors, the achievement of some guaranteed minimum return is the most important consideration; for them, the mean-variance tradeoffs of MPT are insufficient for determining appropriate asset allocations. To secure a minimum return while retaining upside potential, option strategy is considered.

s

Table 6.2 Asset Allocation of Strategy 4

Probabilities of A Bullish Month	Percentage of Funds Allocated to Equity
.65 - 1.00	100 (bullish)
.20 - .65	90 or 10 (neutral)
.00 - .20	0 (bearish)

Strategy 3 was to switch to one hundred percent equities whenever the logit model signaled a "bullish" market month (probabilities greater than .46) and to move to one hundred percent U.S. Treasury bills whenever the logit model signaled a "bearish" upcoming market month (probabilities less than .46). Transaction costs for the timing portfolio were the full two percent when moving into or out of equities.

Strategy 4 was based on the rationale that we should not attempt to make frequent shifts in the portfolio asset mix based on modest change in probabilities. Those shifts will add value only when we have a high degree of confidence because of the impact of transaction costs. The asset allocation schedule (Table 6.2) is proposed for investors based on simulation results during in sample period.[1]

As we can see from the Figure 6.1, The probability range of .20 - .65 is termed the "neutral market periods." Probabilities in that range are too close to neutral to make any reliable judgements about the outlook for the next month. If we were already committed at the 100% level and the probability for the upcoming month was in the neutral periods, it is assumed that we would move to 90% level for the upcoming month rather than incur a transaction cost to move from the 100% level back to the

[1]This strategy is derived after a lot of trial and error.

close to 0% level. If we were already committed at the 0% level and the probability for the upcoming month was in the problem range, we would move to 10% level for the upcoming month. If we were already committed at the 90% or 10% level and the probability for the upcoming month was in the problem range, we would stay at the present level for the upcoming month.[2] During within sample period (1962-76), this strategy signalled 61 switches between S & P 500 Index and T-bills (Figure 6.2).

Strategy 5 considers an option-like payoff portfolio. For most investors, the achievement of some guaranteed minimum return is also an important consideration. To secure a minimum return while retaining upside potential, we consider a stable mix strategy (40% equity and 60% T-bills).[3] Strategy 2 does not always depict the strategic choice a portfolio manager must make. We employ both buy and hold S & P 500 Index and a stable asset mix index for comparison against the record of a timing approach.

6.2 Results of the Allocation Strategies

Table 6.3 contains a summary of the performance results from investment using predictions from our model. Results are reported both with and without adjustments for commissions. Transaction costs are assumed to be two percent when moving into or out of securities, which is obviously conservative in an era of negotiated commissions.[4] No commissions are assumed to be incurred on the purchase of T-bills (i.e., acquisition at the original auction).[5] Transaction costs are calculated on the

[2]Strategy 4-1 is based on the probability range of .15 - .65 instead of .20 - .65

[3]Perold [122] has recently offered a portfolio insurance decision rule as Constant Proportion Portfolio Insurance (CPPI). This strategy is basically, a special case of a more general set of policies that also embrace the constant-mix. As pointed out by Perold and Sharpe [123], many investment managers have been using it without knowing it.

[4]actual commissions would probably lower

[5]Sharpe [141] assumed a transaction cost of two percent. This may have been a realistic level for individual investors in 1975, but is not representative of the transaction costs now incurred by institutional investors. Wells Fargo's market timing model charged .25 percent one way for changes

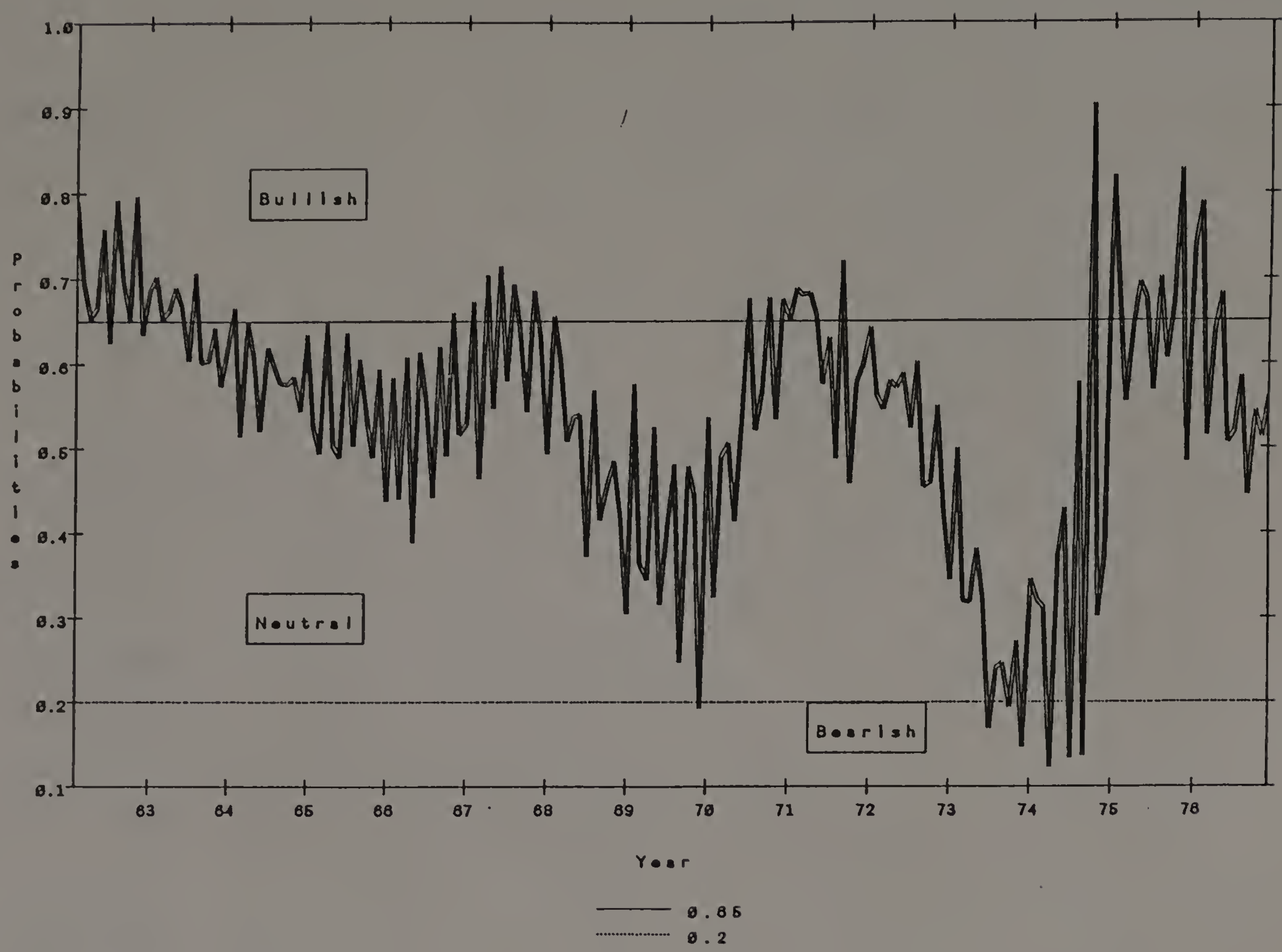

Figure 6.1 Probabilities of Market Risk (In-Sample)

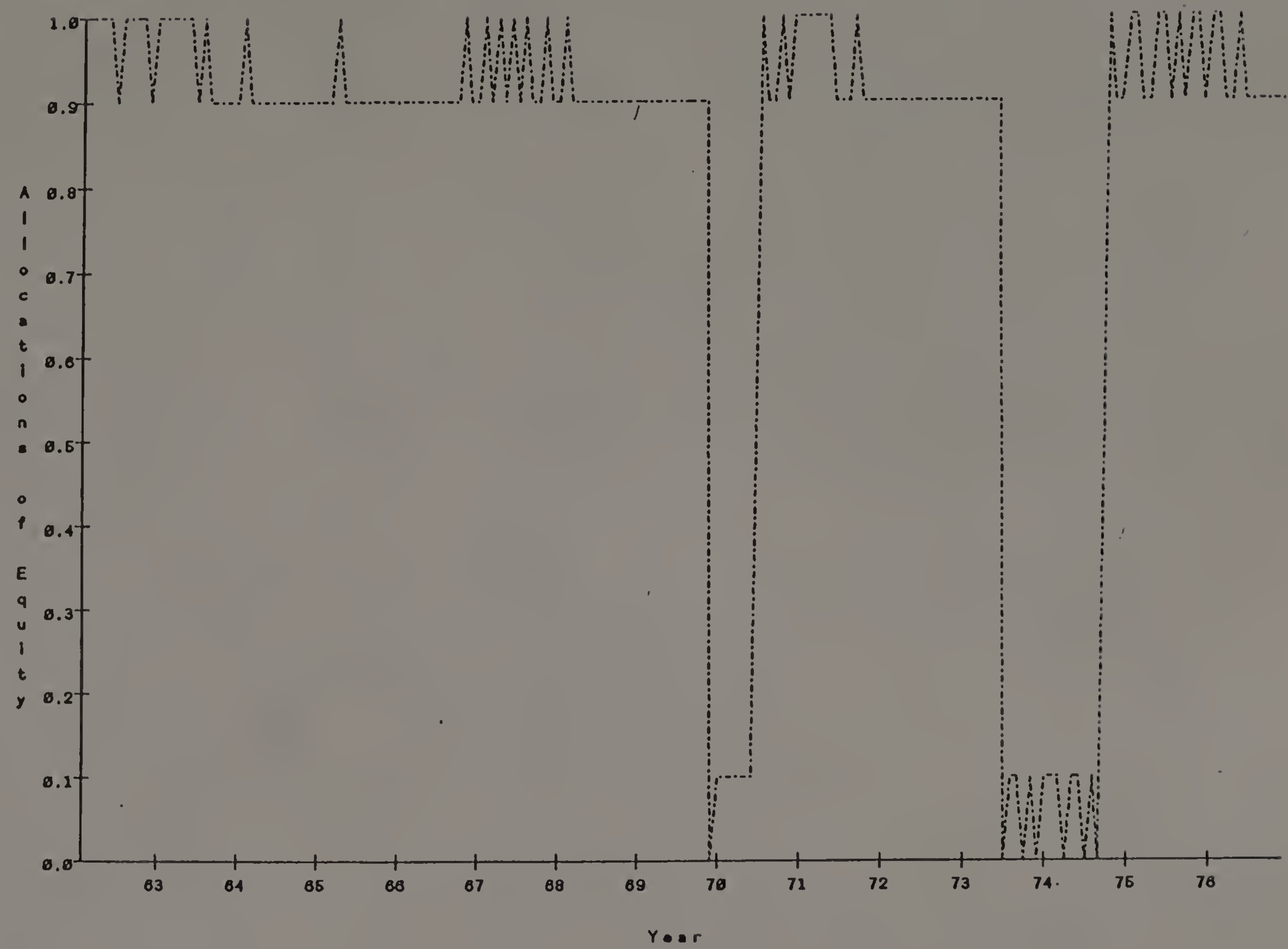

Figure 6.2 Allocation of Funds (In-Sample)

percentage of funds allocated to stocks each month. When only a percentage of the funds are allocated to stocks, the two percent transaction cost applied only to the corresponding percentage of funds that are moved either into or out of stocks.

Strategy 3 (Switches between one hundred percent T-bills and one hundred percent equities) has the highest growth rate during the test period without transaction costs. With 2% transaction costs, strategy 4 has the highest growth rate. The terminal wealth attained by strategy 4 is 114% greater than that attained by strategy 2 (Buy and Hold S & P Index) over the test period.[6] Thus, we can see some advantages to allocating funds in relation to the state probabilities generated by the logit model when we assess the transaction costs. During the test period, strategy 3, 4, and 4-1 provide performance superior to strategy 1, and 2 with and without transaction costs.

To be valid a test of this (and any other predictive) model needs to evaluate the model using data that were not included in the development of the model. In other words, the model should be confirmed with a holdout sample. To test the consistency, the rules derived from these periods are tested for the subsequent 132 months from 1/77 to 12/87. Table 6.4 shows the results of our model during hold out sample period (1977-1987). These results are similar to the in-sample results. The terminal wealth attained by strategy 4 is 25% greater than that attained by the B & H strategy.[7] Strategy 3 outperformed the B & H strategy on a gross profit basis but the terminal wealth attained by strategy 3 is 50% lower than that attained by the B & H strategy on a net profit basis. These results confirm the idea that we should not

in the equity and bond portfolio based on its trading experience [Vandell and Stevens [158]]. Atchley and Ehrhardt [4] also employed transactions costs of .25 percent. We also plan to compare results with one and .25 percent transaction cost.

[6]The terminal wealth attained by strategy 4-1 is 57 % greater than that attained by strategy 2.

[7]As we can see from the Figure 6.4, the terminal wealth by strategy 4 is 3.8% greater than that attained by B & H strategy until 1986 before the stock market crash. But the terminal wealth by strategy 4-1 is consistently 20% greater than that attained by the B & H strategy even before the stock market crash and its aftermath.

Table 6.3 Summary of Results for Investment Analysis (In-sample)

Commission	Strategy	Beginning Wealth	Ending Wealth	Rate of Return
0 %	1	$ 10,000	$ 20,626	4.9448 %
	B & H		$ 27,847	7.0661 %
	3		$ 77,688	21.1848 %
	4		$ 58,872	12.5453 %
	4-1		$ 43,678	10.3276 %
	5		$ 25,775	6.5156 %
1 %	1	$ 10,000	$ 20,626	4.9448 %
	B & H		$ 27,574	6.9958 %
	3		$ 51,560	11.5546 %
	4		$ 53,684	11.8802 %
	4-1		$ 40,583	9.7884 %
	5		$ 25,623	6.4736 %
2 %	1	$ 10,000	$ 20,626	4.9448 %
	B & H		$ 27,301	6.9248 %
	3		$ 34,077	8.5169 %[a]
	4		$ 48,931	11.1661 %[b]
	4-1		$ 37,696	9.2496 %[c]
	5		$ 25,470	6.4311 %

[a]number of transactions : 41
[b]number of transactions : 61
[c]number of transactions : 55

attempt to make frequent shifts in portfolio mix based on modest change in market risk environment especially when we consider transaction costs. Those shift will add value only when we have a high degree of confidence in our assessment of the risk environment of the following periods. Figure 6.6 and 6.7 show probabilities of market risk and allocations of funds during hold-out sample period (1977-1987), respectively.

Figure 6.3 illustrates investment results for six strategies in terms of the growth of a dollar during 1/62-12/76. As the figure indicates, strategy 3, 4, and 4-1 outperformed strategy 1, 2, and 5. Figure 6.4 and Figure 6.5 show the hold-out results and whole sample results.

As we mentioned in Chapter 4, we also test the model using OLS. The multiple regression results are contained in Table 6.5. The overall results are generally acceptable, since all the R^2 are significant at the .01 level and the Durbin-Watson (D-W) statistics that measure serial correlation in the residual are in the acceptable range.

We pick the following timing prediction model (Model 1):

ER_i = - 0.03 - 21.93 x DTB - 10.37 x PTB + .02 x DP - .57 x ERNG

Table 6.6 and 6.7 contains comparative results for a model based on probabilities and a model based on OLS. The model using OLS has better performance than the models using logit analysis and strategy 2 during the within sample period with 1% transaction cost and without transaction costs while the model using logit analysis has better performance than the model using OLS with 2% transaction costs. On the other hand, that model using OLS has far worse performance than strategy 4 and 4-1 using logit analysis during hold out sample period with and without transaction costs. These results imply that investment timing may depend more on a proper forecast of the direction than of the magnitude of risk environment and logit analysis may be superior in generating probabilities of risk environment as compared to OLS.

Table 6.4 Summary of Results for Investment Analysis(Hold-Out Sample)

Commission	Strategy	Beginning Wealth	Ending Wealth	Rate of Return
0 %	1	\$ 10,000	\$ 25,278	8.7960 %
	B & H		\$ 38,369	13.0028 %
	3		\$ 44,688	10.4959 %
	4		\$ 58,437	17.4083 %
	4-1		\$ 53,620	16.4937 %
	5		\$ 33,696	11.6765 %
1 %	1	\$ 10,000	\$ 25,278	8.7960 %
	B & H		\$ 37,966	12.8944 %
	3		\$ 30,047	10.5189 %
	4		\$ 52,359	16.2419 %
	4-1		\$ 49,211	15.5885 %
	5		\$ 33,488	11.6136 %
2 %	1	\$ 10,000	\$ 25,278	8.7960 %
	B & H		\$ 37,562	12.7846 %
	3		\$ 20,123	6.5635 %[a]
	4		\$ 46,787	15.0590 %[b]
	4-1		\$ 45,139	14.6845 %[c]
	5		\$ 33,280	11.5504 %

[a]number of transactions : 39
[b]number of transactions : 48
[c]number of transactions : 39

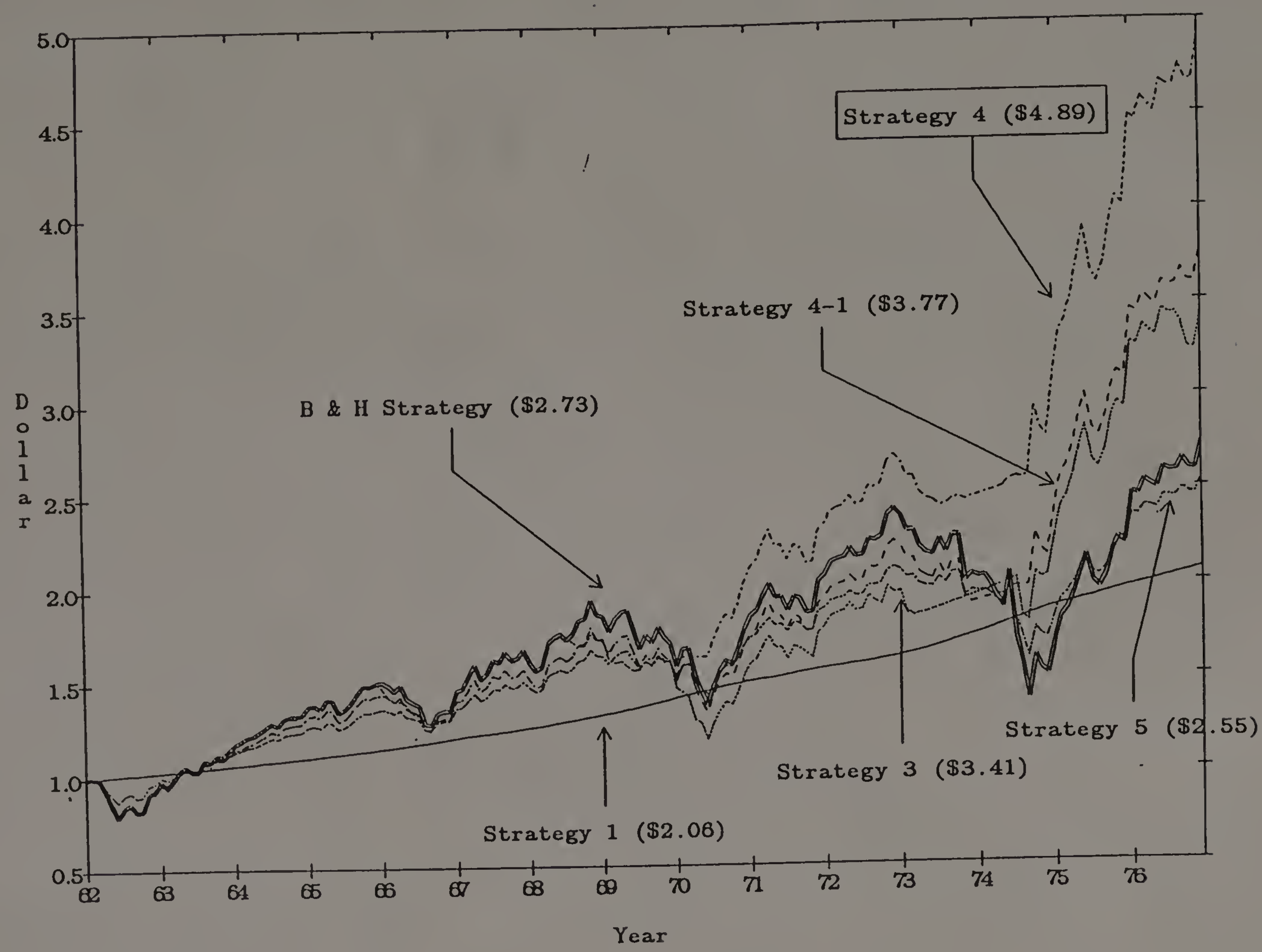

Figure 6.3 Comparison of Strategies (In-sample Results)

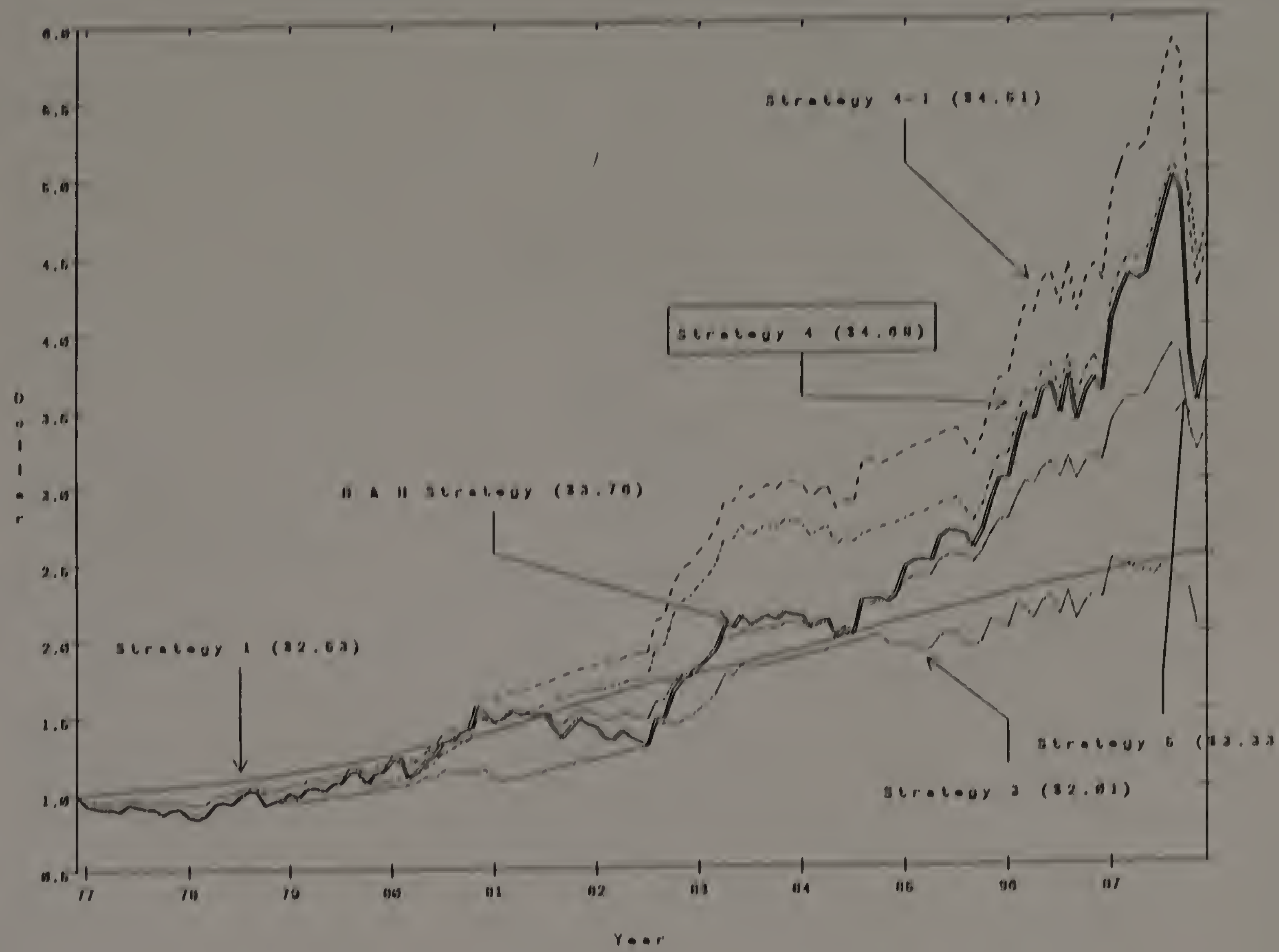

Figure 6.4 Comparison of Strategies (Hold-out Sample Results)

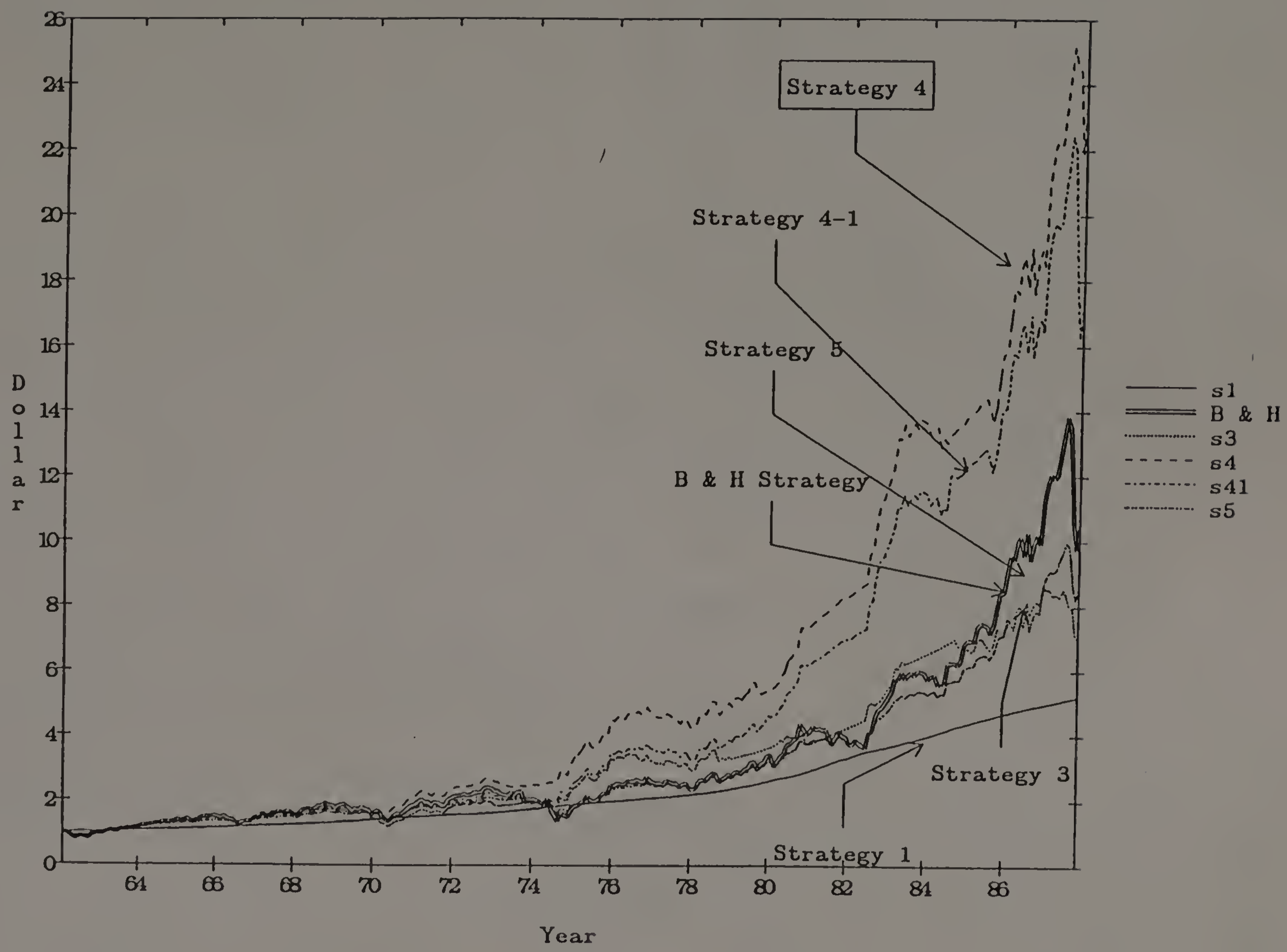

Figure 6.5 Comparison of Strategies (Whole Sample Results)

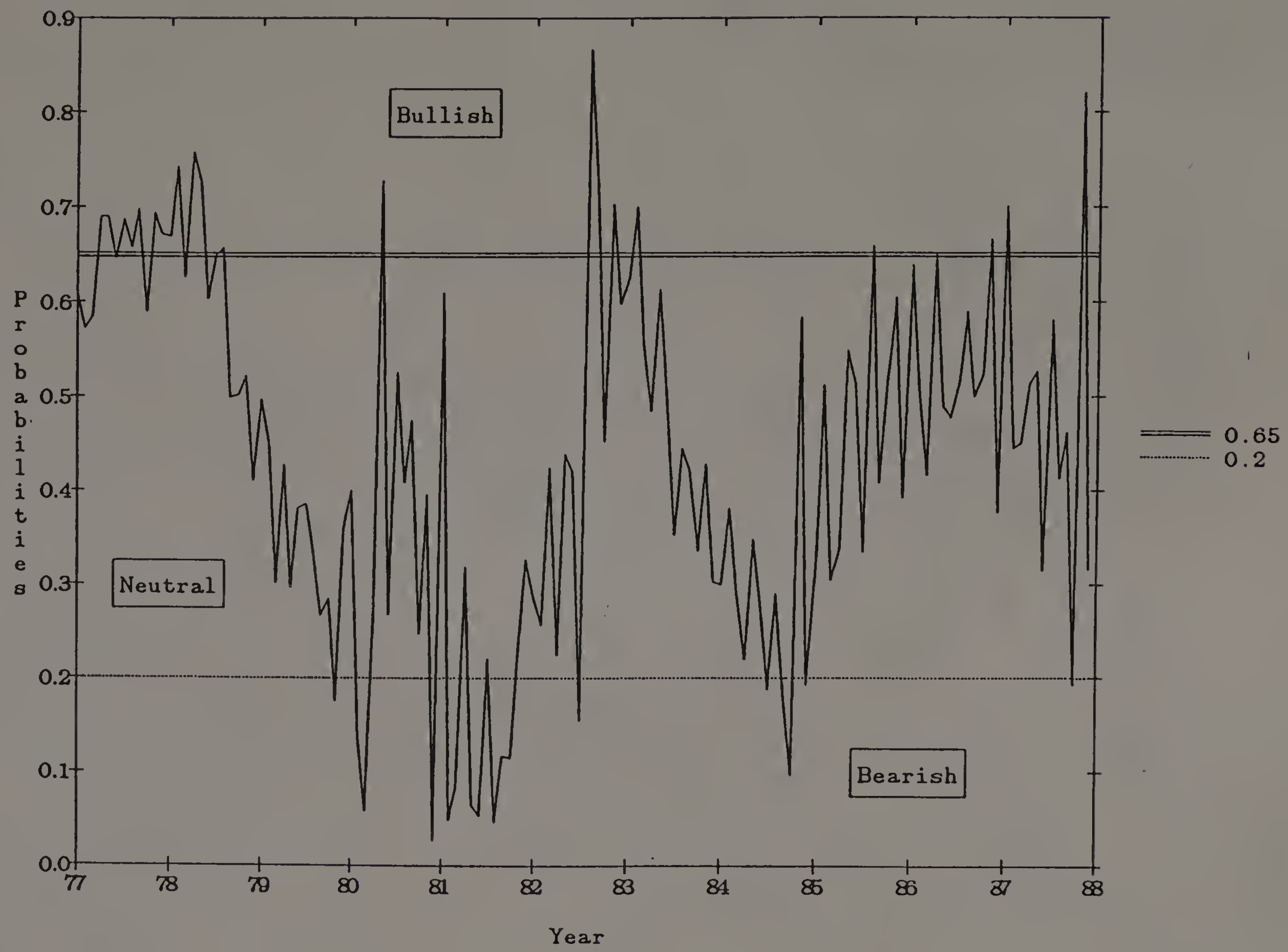

Figure 6.6 Probabilities of Market Risk (Hold-out Sample)

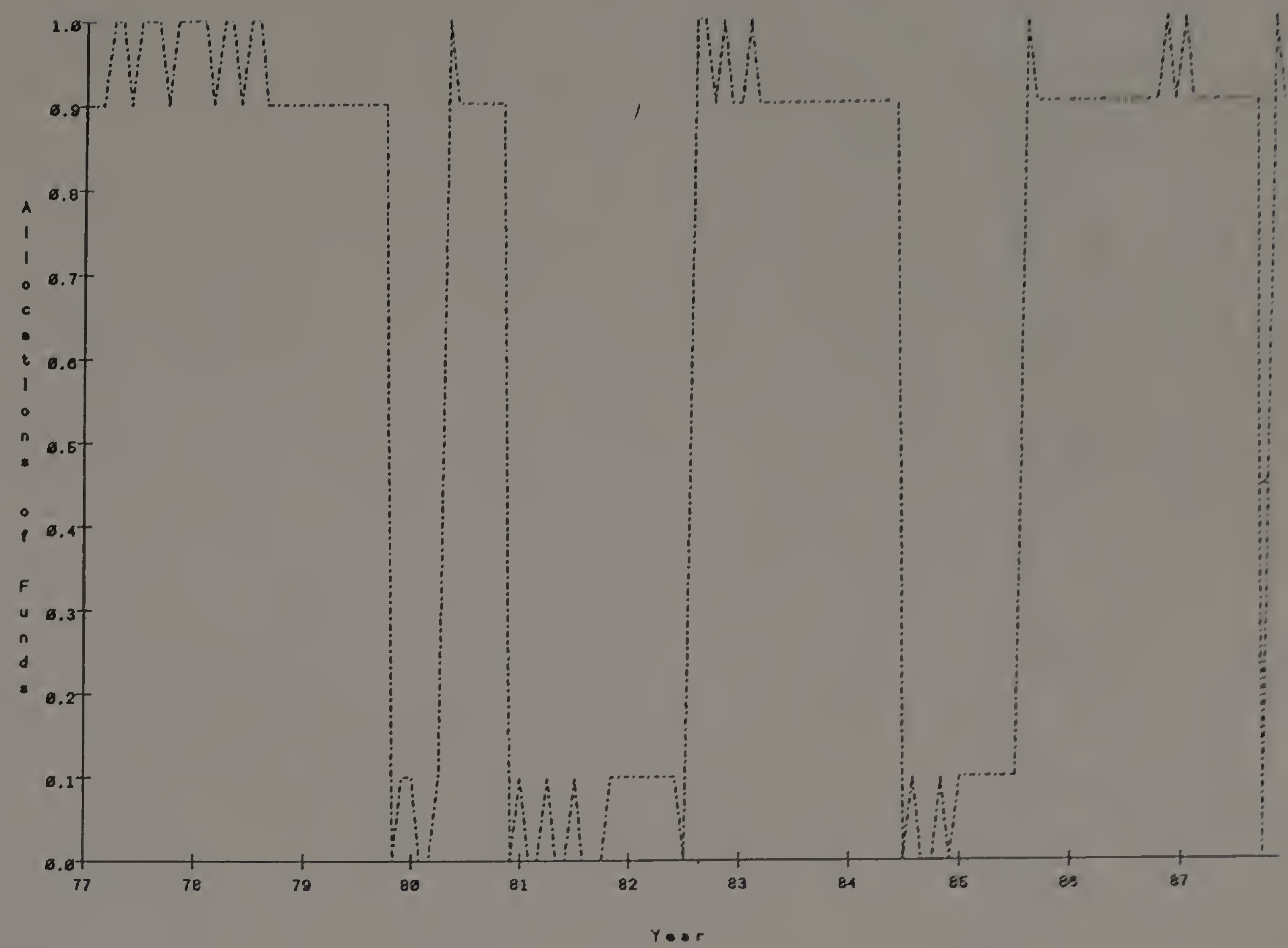

Figure 6.7 Allocations of Funds (Hold-out Sample)

Table 6.5 OLS results

Model	1 Coefficient	2 Coefficient	3 Coefficient	4 Coefficient	5 Coefficient
Constant (T-ratio)	-.0291 (-1.444)	-.0027 (-.048)	-.0155 (-1.101)	-.0363 (-1.830)	-.0385 (-.784)
DTB (T-ratio)	-21.9347 (-4.236)***[a]	-20.4895 (-3.866)***	-20.6762 (-3.903)***	-22.7763 (-4.370)***	-22.3903 (-4.288)***
PTB (T-ratio)	-10.3681 (-3.687)***			-12.5184 (-3.594)***	-10.8308 (-3.577)***
BMA (T-ratio)		2.8950 (3.115)***	3.4681 (2.484)**[b]		
DP (T-ratio)	.0228 (3.307)***			.0264 (3.554)***	.0240 (3.446)***
G (T-ratio)		-1.2263 (-2.173)**	-1.3835 (-2.975)**	.4175 (.862)	
ERNG (T-ratio)	-.5718 (-1.427)				
CI (T-ratio)		-.0002 (-.342)			.00003 (.078)
EP (T-ratio)			-.1866 (-.554)		
Adjusted R^2	.1749	.1423	.1433	.1688	.1653
D-W	2.0548	2.0457	2.0747	2.0586	2.0353

[a]***Significant at 1 percent level
[b]**Significant at 5 percent level

Table 6.6 Comparison between Logit analysis and OLS (In-Sample)

Commission	Strategy	Beginning Wealth	Ending Wealth	Rate of Return
0 %	B & H	$ 10,000	$ 27,847	7.0661 %
	Logit 4		$ 58,872	12.5453 %
	Logit 4-1		$ 43,678	10.3276 %
	OLS		$ 66,753	13.4919 %
1 %	B & H	$ 10,000	$ 27,574	6.9958 %
	Logit 4		$ 53,684	11.8802 %
	Logit 4-1		$ 40,583	9.7884 %
	OLS		$ 59,793	12.6618 %
2 %	B & H	$ 10,000	$ 27,301	6.9248 %
	Logit 4		$ 48,931	11.1661 %
	Logit 4-1		$ 37,696	9.2496 %
	OLS		$ 46,915	10.8547 %

Table 6.7 Comparison between Logit analysis and OLS (Hold-Out Sample)

Commission	Strategy	Beginning Wealth	Ending Wealth	Rate of Return
0 %	B & H	$ 10,000	$ 38,369	13.0028 %
	Logit 4		$ 58,437	17.4083 %
	Logit 4-1		$ 53,620	16.4957 %
	OLS		$ 49,810	15.7157 %
1 %	B & H	$ 10,000	$ 37,966	12.8944 %
	Logit 4		$ 52,359	16.2419 %
	Logit 4-1		$ 49,211	15.5885 %
	OLS		$ 39,860	13.3951 %
2 %	B & H	$ 10,000	$ 37,562	12.7841 %
	Logit 4		$ 46,787	15.0590 %
	Logit 4-1		$ 45,139	14.6845 %
	OLS		$ 30,304	10.6045 %

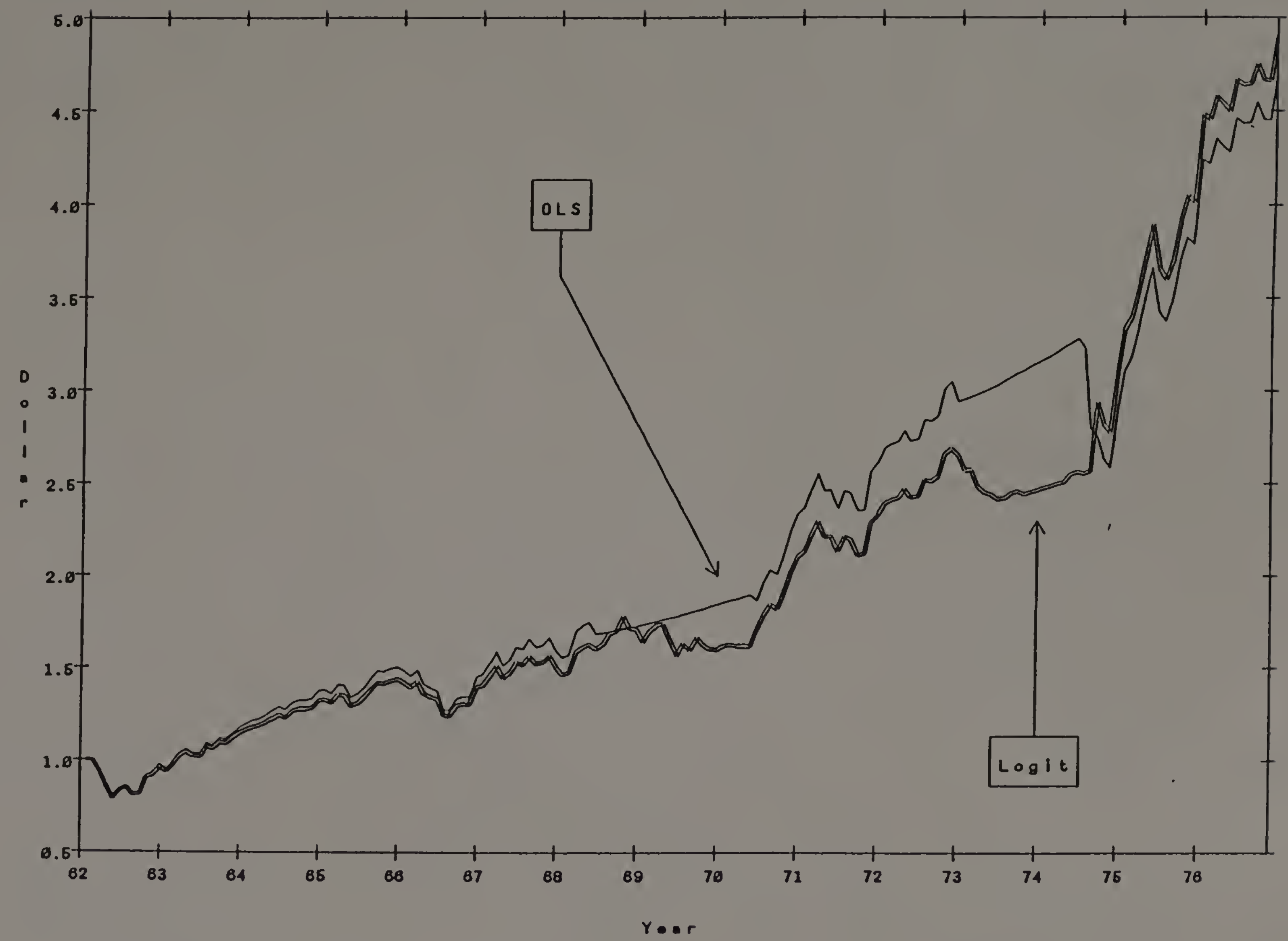

Figure 6.8. Performance of Model using Logit and OLS (In Sample)

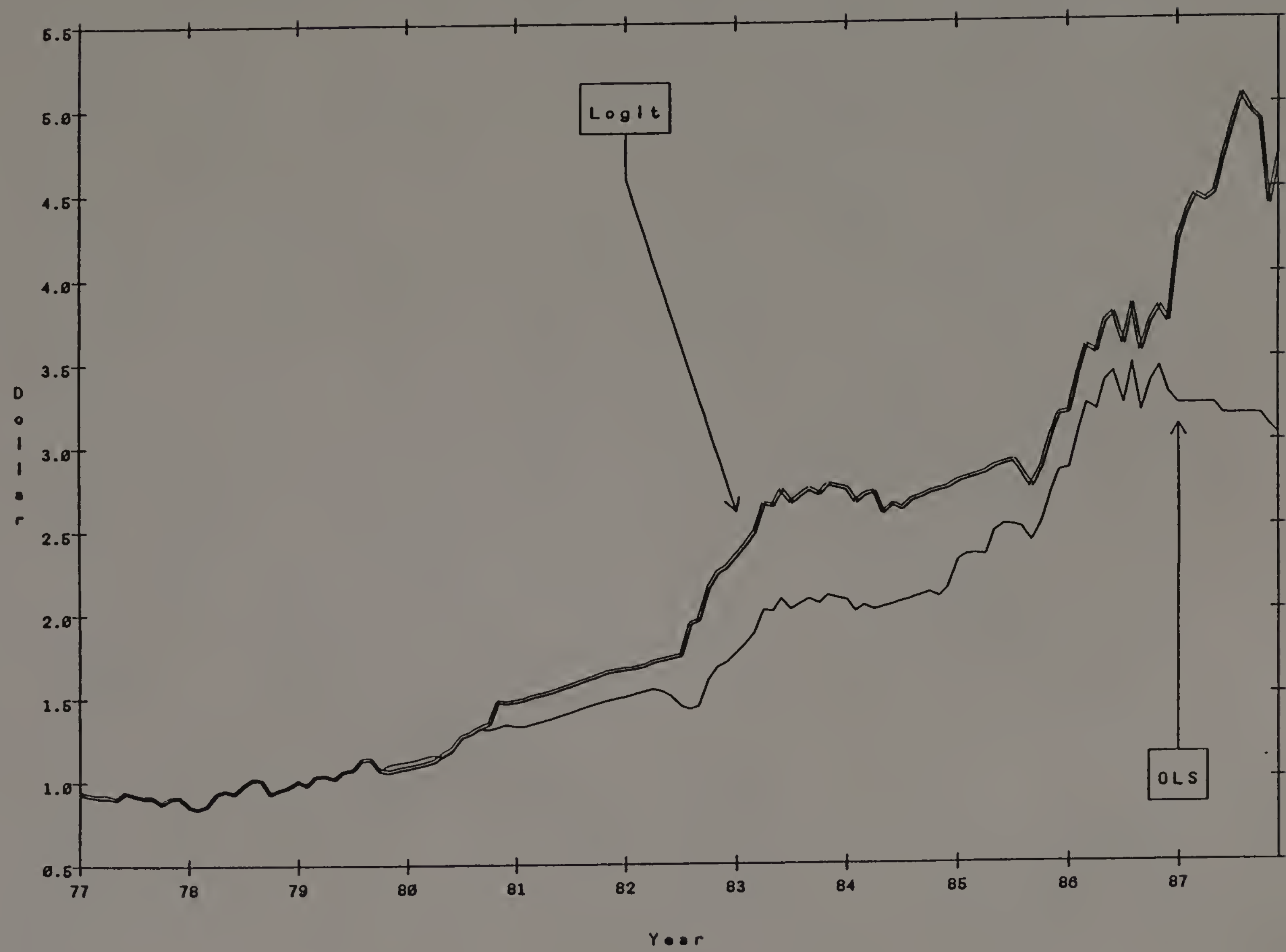

Figure 6.9 Performance of Model using Logit and OLS (Hold-Out Sample)

Figure 6.9 and Figure 6.9 show the performance of the model using logit analysis and the model using OLS.

Table 6.8 contains a summary of the results for several strategies in terms of monthly rates of return (arithmetic and geometric) and standard deviation of the monthly returns when we assess 2% transactions costs.

These results strongly support our timing model (especially strategy 4) compared to B & H strategy. Not only is the monthly rate of return substantially higher (i.e. .76% to 1.02% versus less than 0.26%), but the risk measured by the standard deviation is higher for the B & H strategy than for timing models (strategy 4 and 4-1). This result occurred because timing models evidently avoided a number of the adverse impact of major market declines by switching into T-bills. The comparison between strategy 5 and strategy 4 is less clear. These results indicate higher rate of return for the strategy 4 (0.69% to 1.02% versus less than 0.33%), but the standard deviation for strategy is much lower.

A more relevant way of comparing risk is to look at total performance over a cycle. Figure 6.10 and 6.11 show the one-year moving (annualized) performance of our model relative to the B & H strategy and strategy 5. Strategy 4 didn't have a worse performance than the B & H strategy except 1985-1986. Especially in the poor market years, strategy 4 was distinctly better than the B & H strategy. Figure 6.12 and 6.13 produce the yearly performance characteristic line for strategy 4 against the B & H strategy and strategy 5. The portfolio beta of 0.659 indicates a moderately less risky portfolio than the market. The alpha of 0.076 per year is statistically significant at the .01 level. Figure 6.12 shows a tendency for strategy 4 to do well in bad markets and to match the B & H strategy in good markets. Figure 6.13 shows that strategy 4 outperforms strategy 5 in both strong and weak markets.

Table 6.8 Average Monthly Return and Standard Deviation

Period	Strategy	Arithmetic Mean	Standard Deviation	Geometric Mean
'62-'87	1	0.53 %	0.24 %	0.53 %
	2	0.86 %	4.57 %	0.76 %
	3	0.69 %	3.51 %	0.63 %
	4	1.08 %	3.42 %	1.02 %
	4-1	0.99 %	3.81 %	0.92 %
	5	0.73 %	2.74 %	0.69 %
'62-'76	1	0.41 %	0.13 %	0.41 %
	2	0.66 %	4.42 %	0.56 %
	3	0.76 %	3.72 %	0.69 %
	4	0.95 %	3.39 %	0.95 %
	4-1	0.81 %	3.68 %	0.74 %
	5	0.56 %	2.64 %	0.52 %
'77-'87	1	0.71 %	0.24 %	0.71 %
	2	1.14 %	4.75 %	1.01 %
	3	0.60 %	3.20 %	0.53 %
	4	1.25 %	3.45 %	1.18 %
	4-1	1.24 %	3.96 %	1.15 %
	5	0.97 %	2.84 %	0.92 %

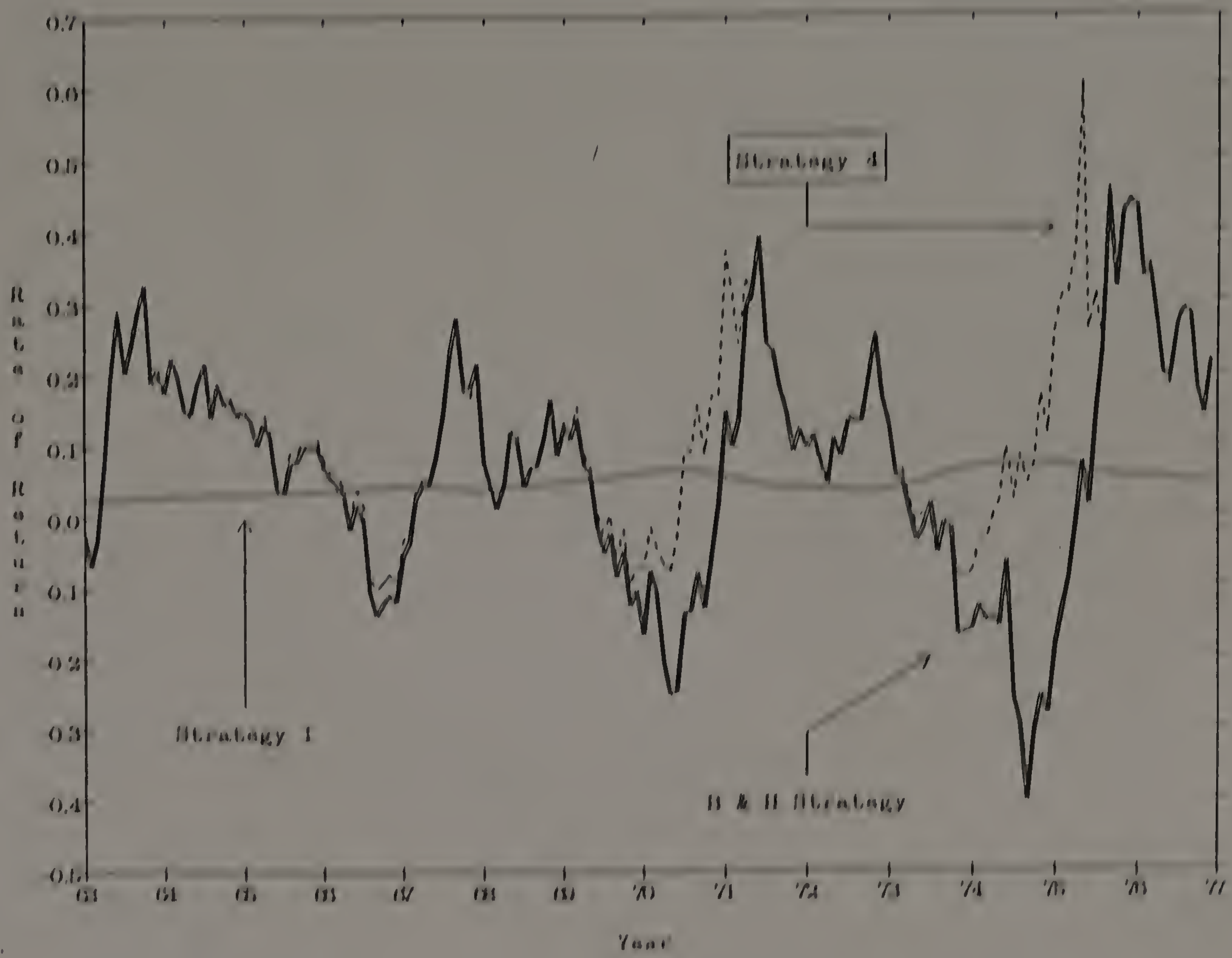

Figure 6.10 Moving Annual Return (In Sample Period)

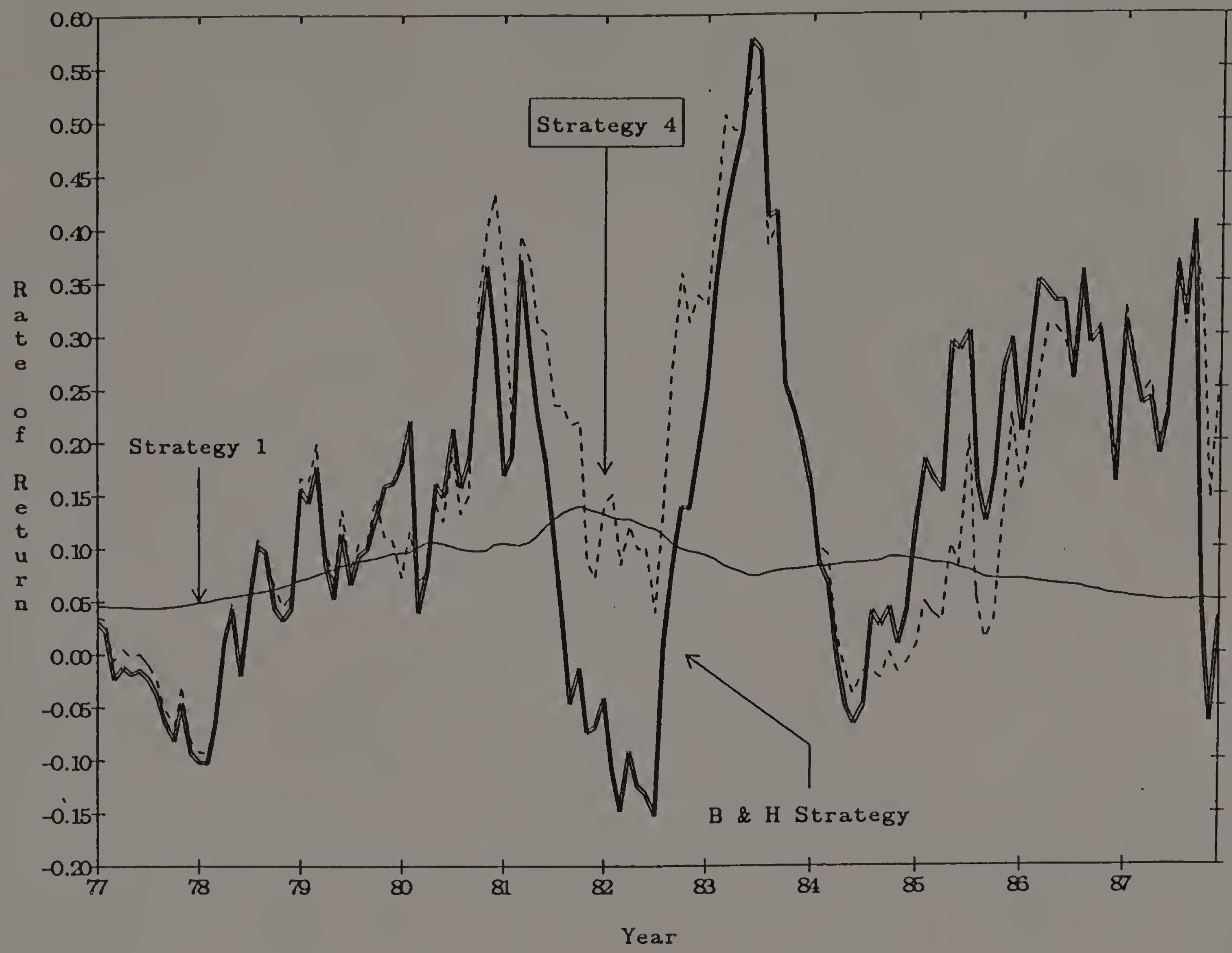

Figure 6.11 Moving Annual Return (Hold-out Sample Period)

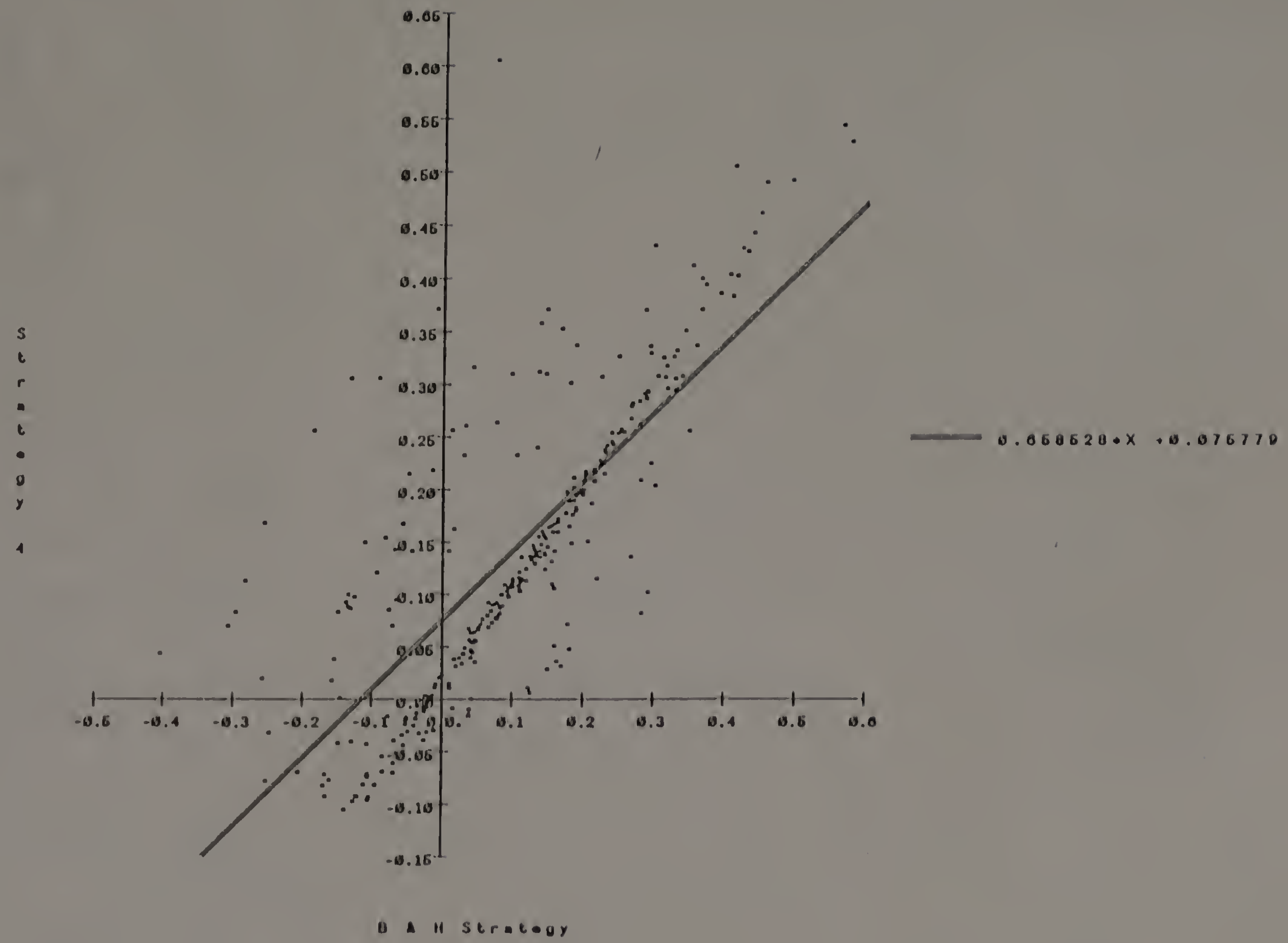

Figure 6.12 Performance Characteristic Line (Strategy 4 vs. Strategy 2)

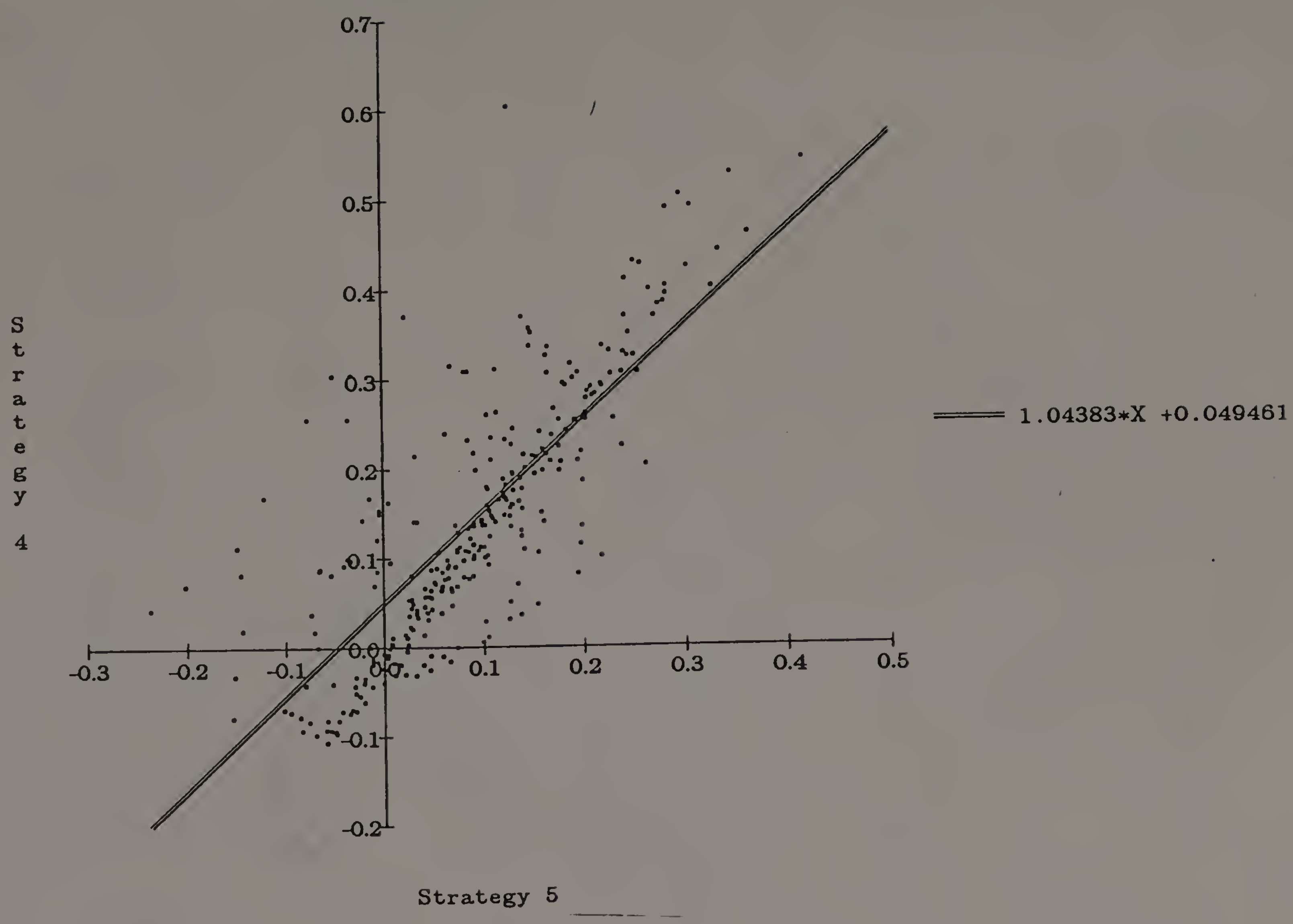

Figure 6.13 Performance Characteristic Line (Strategy 4 vs. Strategy 5)

Table 6.9 Results without 1979-1981

Period	Strategy	Beginning Wealth	Ending Wealth	Rate of Return
'62 - '78	B & H	$ 10,000	$ 26,977	6.0114 %
	4		48,355	9.7111 %
'77 - '78	B & H		9,673	-.0165 %
	4		9,711	-.0145 %
'77 - '87	B & H		25,096	10.7645 %
	4		27,414	11.8571 %
'82 - '87	B & H		26,474	17.6170 %
	4		28,230	18.8827 %
'62 - '87	B & H		69,990	14.9105 %
	4		136,449	20.5228 %

Strategy 4 has better performance than B & H strategy even when we ignore the the typical down markets (1979-1981) with 2% transactions costs. Table 6.9 shows these results.

We compared portfolio performance in up and down markets to check whether our model works through the cycle. Table 6.10, and Figure 6.14, 6.15, 6.16 show these comparison. Strategy 4 did comparatively well relative to the B & H strategy in down markets. Strategy 4 did better than the strategy 1 in up markets. It nearly matched the B & H strategy under those circumstances. This results show that our model can reduce downside risk and improve average performance over a cycle.

Table 6.10 Performance Results in Up and Down Markets

Period	Strategy 1	B & H Strategy	Strategy 3	Strategy 4	Strategy 5
Up Markets					
8/63-2/65	3.28 %	19.62 %	19.62 %	17.80 %	12.86 %
10/66-11/68	4.73 %	21.34 %	16.06 %	18.33 %	14.59 %
7/70-4/71	3.57 %	37.83 %	37.83 %	35.43 %	23.14 %
10/74-12/76	5.64 %	35.62 %	33.23 %	33.18 %	23.22 %
3/78-11/80	9.62 %	25.43 %	11.84 %	26.61 %	19.21 %
8/82-11/83	8.48 %	46.17 %	30.69 %	41.14 %	30.13 %
6/84-3/86	8.37 %	34.41 %	6.59 %	22.92 %	23.59 %
Compound Average	6.69 %	31.02 %	20.89 %	27.72 %	20.99 %
Down Markets					
2/62-7/63	2.80 %	2.36 %	2.36 %	1.28 %	2.89 %
3/65-9/66	4.29 %	-5.13 %	-5.46 %	-4.22 %	-1.34 %
12/68-6/70	6.64 %	-19.62 %	-21.99 %	-17.20 %	-9.68 %
5/71-9/74	5.23 %	-13.90 %	-13.90 %	-13.58 %	-6.54 %
1/77-2/78	5.23 %	-13.90 %	-13.90	-13.58 %	-6.54 %
12/80-7/82	14.00 %	-10.52 %	7.60 %	10.55 %	-1.21 %
12/83-5/84	9.42 %	-14.28 %	9.42 %	-12.11 %	5.35 %
4/86-12/87	5.65 %	5.21 %	-4.20 %	5.18 %	6.26 %
Compound Average	6.86 %	-8.64 %	-3.92 %	-2.29 %	-3.35 %

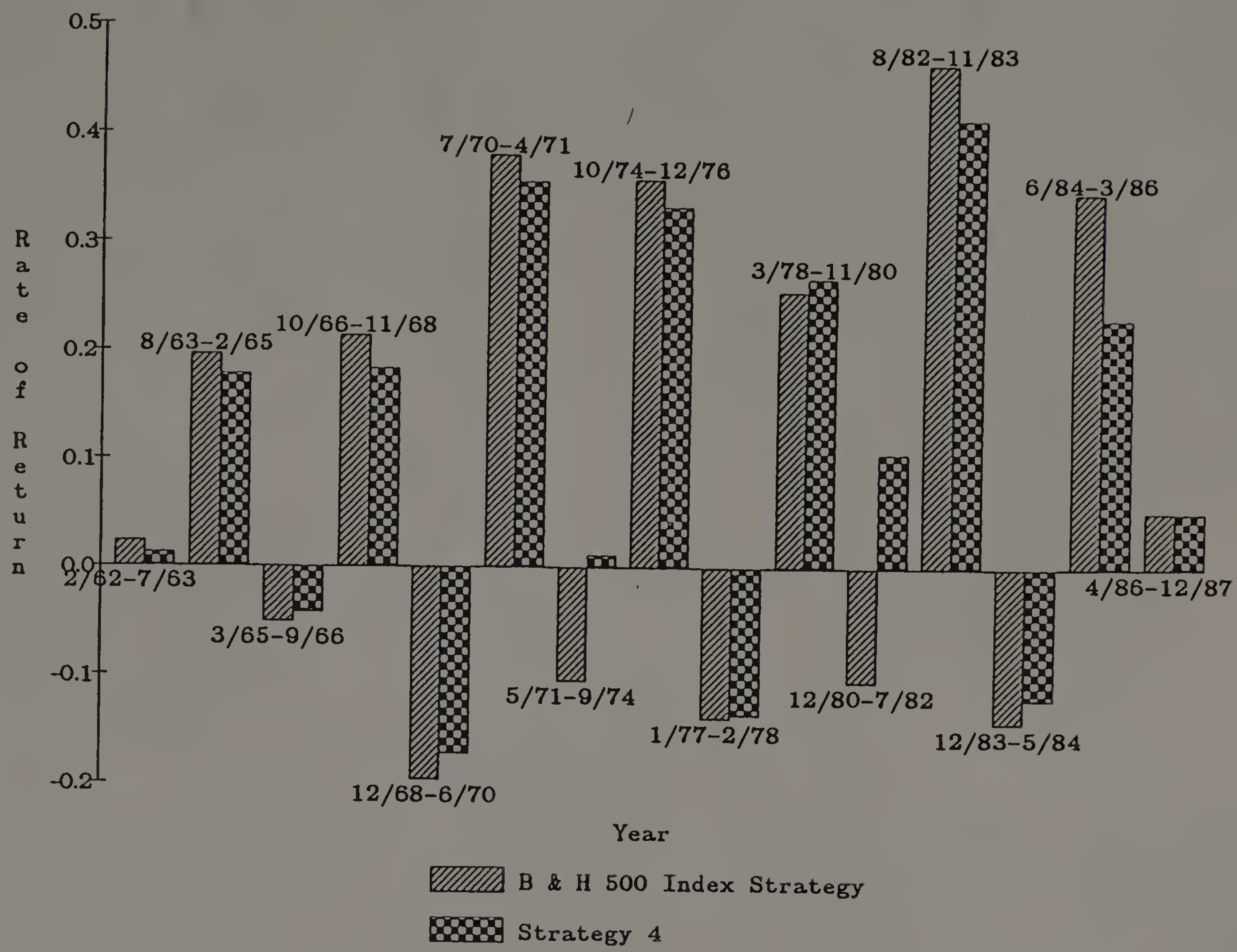

Figure 6.14 Comparison of Performances in Up and Down Markets

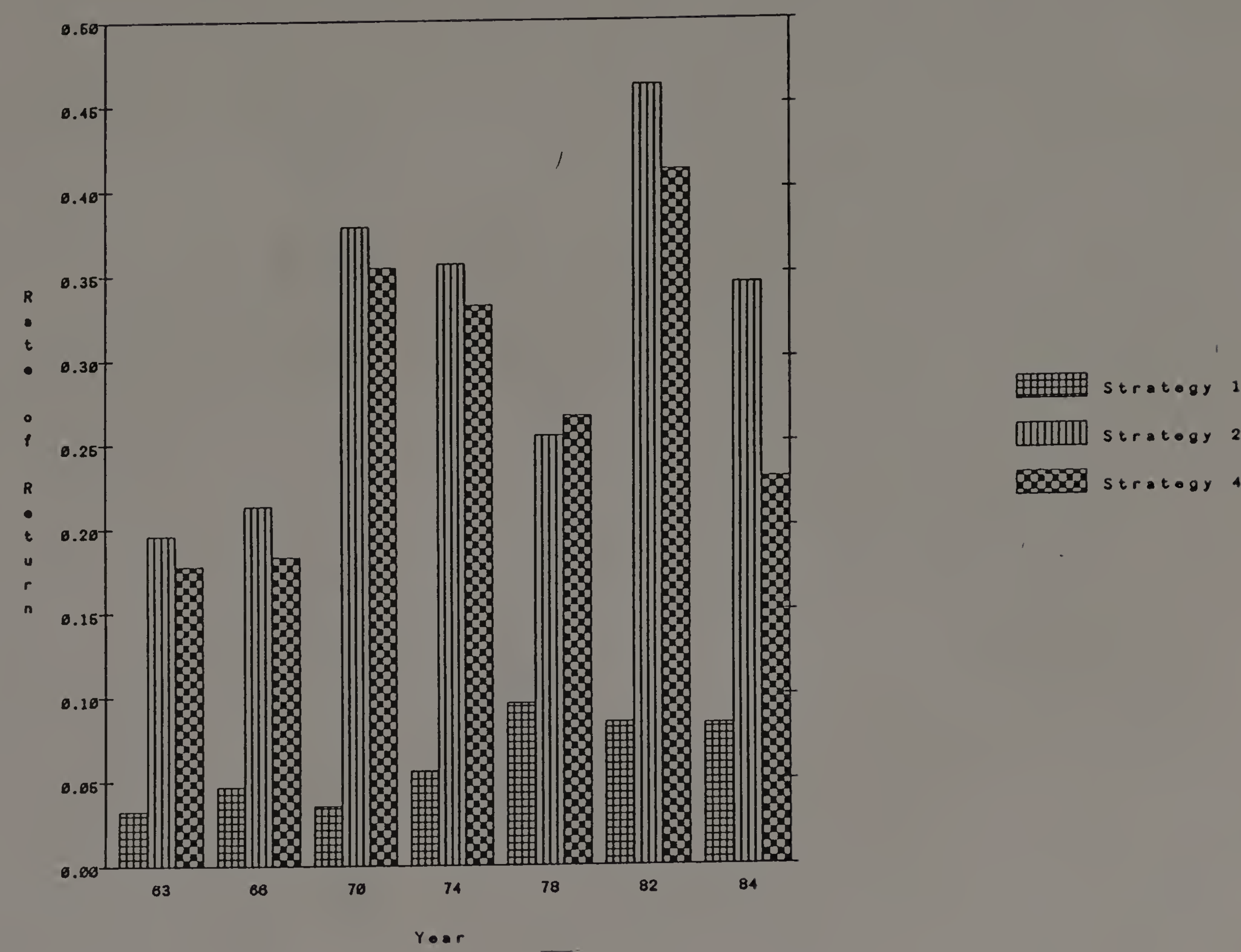

Figure 6.15 Comparison of Performances in Up Markets

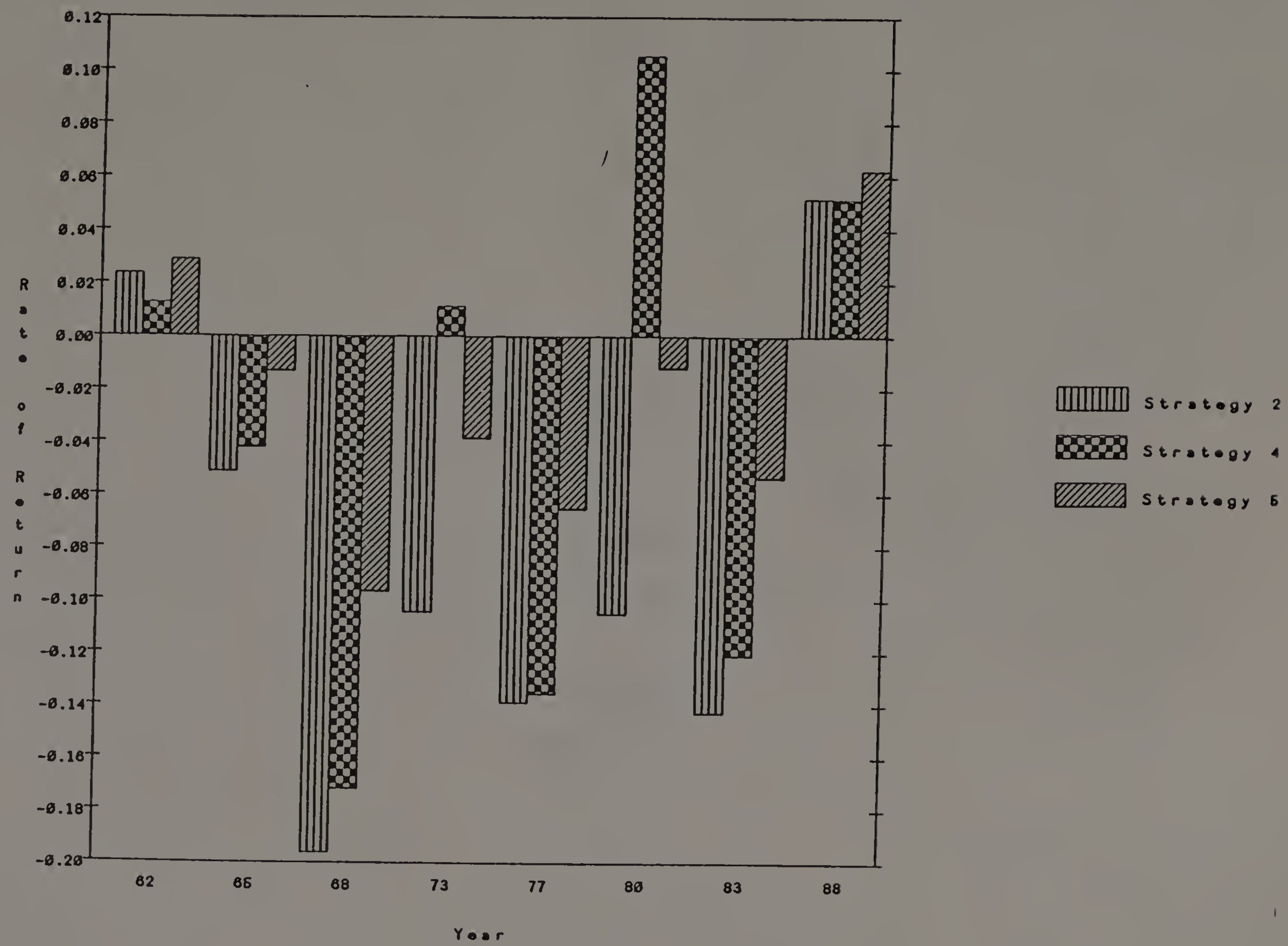

Figure 6.16 Comparison of Performance in Down Markets

CHAPTER 7

SUMMARY AND CONCLUSION

Much of previous research in finance has concentrated on explaining movements of individual securities rather than on explaining movements in the stock market as a whole. Although the available data are limited, the movements in the stock market as a whole are extremely important for movements in individual stocks. Indeed, market events of the past ten years have sparked an interest in tactical asset allocation. The turbulence of October 1987 (the disappointing results of portfolio insurance during the Oct. 19, 1987 market crash and the awareness that asset allocation adds value) has only accelerated this interest.

A review of the related literature showed that the returns on the market timer's portfolio increases as the level of information increases and that even a modest amount of information can bring substantial advantage.

This study seeks to develop a methodology that systematically incorporates currently available information into the tactical asset allocation process. The goal is not to predict individual stock prices, or every small movement in the market. Rather we would like to use the currently available data to provide the investor with an estimate of the probabilities associated with the broad measure of either a "bullish" or "bearish" market period. Our study focused on how state probabilities could be generated from the appropriate variables based on theory and utilized in the asset allocation process. This procedure was evaluated to determine if portfolio performance was improved over a buy-and-hold strategy.

7.1 Methodology

The methodology employed in our study was a three step procedure. The first step is to find *ex ante* observable variables which can predict the excess return. The second step involved the generation of state probabilities from a logit analysis of the sample data. Appropriate variables based on theory were collected over a 15-year time period and used in the development of a logit model for predicting "bullish" and "bearish" stock market months. The data were collected with regard to publication lag time to ensure that the data would have been available to the investor at the beginning of each month. The 180 months were classified as either "bullish" (total return on stock, including dividends, exceeded the return on Treasury Bills) or as a "bearish" (inverse of a "bullish" market month) months. A dichotomous logit analysis using a "0,1" (0 = "bearish", 1 = "bullish") coded dependent variable was used to analyze the 15-year period. A significant logit model was developed from the data relating to the 15-year within sample period. The model was verified with a 11-year holdout sample.

The third step of the procedure used the probabilities generated by the logit model to suggest the optimum allocation of funds between two asset classes; a market portfolio and a risk free asset. The surrogate for the market portfolio was the S & P 500 Index. The risk-free asset was represented by U.S. Treasury bills. An asset allocation schedule was developed based on the probabilities assigned by the logit model. For comparison purposes, several strategies were evaluated.

7.2 Findings

The logit analysis of the sample data produced a statistically significant model for predicting "bullish" and "bearish" stock market months. The model correctly classified 116 out of the 179 months of the within sample period. The implication of a statistically significant model is that the appropriate variables based on theory for the within sample period could have been used to objectively predict the probabilities of "bullish" and "bearish" market months. The model was verified with a 11-year holdout sample period.

During the within sample period, An asset allocation procedure based on the probabilities generated by the verified logit model has shown better performance than buy-and-hold S & P 500 Index strategy even when we assess 2% transactions costs. These results were confirmed with a holdout sample. Not only is the monthly rate of return substantially higher, but the risk measured by the standard deviation is higher for B & H strategy than for timing models. This result occurred because timing models avoided a number of the adverse impact of major market declines by switching into T-bills. We also find that timing models did comparatively well relative to the B & H strategy in down markets and nearly matched the B & H strategy in up markets. These results showed that our model can reduce downside risk and improve average performance over a cycle.

7.3 Conclusion

Our results have a number of implications for investing and portfolio management.

First, this study suggest some possibilities that portfolio performance can be improved by successful market timing model. When viewed over time, risks were controlled and returns were enhanced. By timing the extreme markets, lost opportunities for gains in bullish markets were more than made up when dramatic downturns occurred. This result also confirm other studies that a market timer who follows optimal rules can expect higher return and lower risk than a buy-and-hold investor. The results obtained during hold-out sample period (1977-1987) did not differ significantly from the results based on a 15-year in sample period (1962-1976). Thus the benefits derived from our timing model appear to be robust-at least in the kind of economic environment that characterized the last 30-year in the United States.

Second, this study shows that readily available information can be used to aid the investment manager in assigning probabilities to the future states of the stock market. Those probabilities can be effectively used in the asset allocation decision process.

Third, our analysis highlights the importance of transaction costs. Our results confirm the idea that we should not attempt to make frequent shifts in portfolio mix based on modest change in market risk environment. Those shift will add value only when we have a high degree of confidence in our assessment of the risk environment.

Our analysis using monthly data also point out some possibility that shortening the time horizon for timing decision is advantageous. Performance improves as the relative volatility of the market return increases - that is, as the length of the timing horizon is decreased. But, this effect is limited by several practical considerations. The accuracy of predictions is likely to decrease as the time horizon is shortened.[1] Transactions costs definitely will increase as the length of the time horizon decreases and thus the number of transactions increases. Both of these influences will limit the extent to which shortening the time horizon for timing decision is advantageous.

Since our model is basically a market timing prediction model, the primary use is to aid investment managers in asset allocation decision. Our model is both inexpen-

[1]This contention is based on the view that the accuracy of any prediction is reduced by the occurrence of unpredictable random events. If these random events are unrelated, then they will tend to offset each other over time. Therefore, we might expect their reduction of the accuracy of prediction to be smaller, the longer the time horizon over which the prediction is made.

sive and easy to use. Input to our model can be obtained readily from public sources and classification can be made simply by calculating the probability of bullish (or bearish) market months with the model coefficients and comparing it to the optimal cutoff probability. Our model is also objective and unambiguous. It does not depend on subjective judgement, the probability of bullish market months is determined statistically, and the prediction rule is clear. Although we can really identify optimal cutoff probabilities to minimize the expected costs only when the actual misclassification costs are available, the relatively high number of correct classification in the holdout sample indicates that the probabilities generated by the logit model during the within sample could be considered as accurate probabilities.

This study is simplified in several ways. First, it includes only two types of assets; stocks and Treasury bills ignoring all other assets such as bond and real estate. This concept can also be extended to another asset classes.

Second, one question that arises naturally in a study such as this is whether additional *ex ante* variables have predictive ability. We have chosen to define this study by restricting the number of *ex ante* variables, but the investigation could be extended across a range of *ex ante* variables as well. The lag time of the various independent variable observations could also be varied extensively in hopes of obtaining a stronger predictive model.

Third, the linear relationship may not be optimal. A fundamental and widespread economic change should affect the structural relationships in the market. The structural relationships between securities are almost certainly not constant.

Further studies should include a variation on the time intervals applied in this study. For example, weekly variables could be compared to a weekly return on the market portfolio. An asset allocation strategy could then be tested to learn if value is likely to be created from a weekly adjustment of a portfolio. Another alternative would be to sample quarterly or yearly data based on the premise of adjusting the portfolio quarterly or annually. Also, many different variations of the asset allocation strategy could be evaluated to achieve the ultimate value from the logit probabilities.

BIBLIOGRAPHY

[1] Akerlof, G. and Yellen, J. "Can Small Deviations from Rationality Make Significant Differences to Economic Equilibria?" *American Economic Review*, No. 4, 1985, pp. 708-720.

[2] Arnott, R.D. and von Germeten, J. N."Systematic Asset Allocation," *Financial Analysts Journal*, November-December 1983, pp. 31-38

[3] Arrow, K. "Risk Perception in Psychology and Economics," *Economic Inquiry* January 1982, p.7.

[4] Atchley, J.H and Ehrhardt, M. C."Likely Gains from Market Timing," *Working Paper, University of Tennesse*, February 1988

[5] Ball, R. and Brown, P."An Empirical Evaluation of Accounting Income Numbers," *Journal of Accounting Research*, Autumn 1968, pp. 159-178.

[6] Barnes, L. "Business Forecasting with Higher Order Indicators- A Neglected Art," *Business Economics*, September 1980.

[7] Basu, S. "Investment Performance of Common Stocks in Relation to J-Their Price Earnings Ratios: A Test of the Efficient Market Hypothesis," *Journal of Finance*, June 1977, pp. 663–682

[8] Beaver, W., Lambert, R. and Morse, D."The Information Content of Security Prices," *Journal of Accounting and Economics*, 1980, pp. 3-28.

[9] Beaver, W. and Morse, D."What Determines Price-Earnings Ratios?" *Financial Analysts Journal*, July/August 1978, pp.65–76

[10] Beaver, W. and Wright, W.F.,"The Association between Unsystematic Security Returns and The Magnitude of Earnings Forecast Errors," *Journal of Accounting Research*, Autumn 1979, pp. 316-340.

[11] Benari, Y."An Asset Allocation Paradigm," *Journal of Portfolio Management*, Winter 1988, pp. 47–51

[12] Bernstein, P. "The Ill-Behaved E's," *Journal of Portfolio Management*, Summer 1987, p.1.

[13] Black, F."Noise" *Journal of Finance*, July 1986, pp. 529-543.

[14] Bookstaber, R."The Use of Options in Performance Structuring," *Journal of Portfolio Management*, Summer 1985, pp. 36-50

[15] Branch, B. "The Predictive Power of Market Indicators," *Journal of Financial and Quantitative Analysis*, June 1976, pp. 269-286.

[16] Branch, B.,"A Tax Loss Trading Rule," *Journal of Business*, 1977, pp. 198-207.

[17] Branch, B."The 1987 Crash: Which Timing Methods Predicted It?," *Working Paper*, University of Massachusetts, 1988,pp. 1–14

[18] Branch, B. and Schneeweis, T."Capital Market Efficiency in the Fixed Income Market," *Review of Economics and Business*, Winter 1980, pp. 115-121

[19] Branch, B. and Schneeweis, T. "Market Movements and Technical Market Indicators," *The Mid-Atlantic Journal of Business*, Summer 1986, pp 31-41

[20] Brown, L.D., Griffin, G., Hagerman, R. and Zmijewski, M."Security Analysts Superiority Relative to Univariate Time Series Models in Forecasting Quarterly Earnings,"*Journal of Accounting and Economics*, March 1987,

[21] Brown, L.D., Griffin, P., Hagerman, R. and Zmijewski, M."An Evaluation of Alternative Proxies for the Market's Assessment of Unexpected Earnings," *Journal of Accounting and Economics*, July 1987,

[22] Brown, L.D. and Rozeff, M.S." Adaptive Expectations, Time Series Models and Analyst Forecast Revision," *Journal of Accounting Research*, Autumn 1979, pp. 341-351.

[23] Camerer, C. and Weigelt, K."Rational Price Bubbles in Asset Markets: A Review of Theory and Evidence," *Working Paper*, Salomon Brothers Center, New York University, March 1986.

[24] Campanella, F.B."The Measurement of Portfolio Risk Exposure; Use of the Beta Coefficient." Lexington, Massachusetts: Lexington Books, 1972.

[25] Campbell, J."Stock Returns and the Term Structure," *Journal of Financial Economics*, 1987, pp. 372-399

[26] Campbell, J. and Shiller, R."Cointegration and Tests of Present Value Models," *Journal of Political Economy*, 1987, pp. 1062-1088

[27] Campbell, J. and Shiller, R."Stock Prices, Earnings and Expected Dividends," *Journal of Finance*, September 1988, pp. 661-676

[28] Campbell, J. and Shiller, R."The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors." *The Review of Financial Studies*, 1989, pp. 195-228

[29] Chan, K.C."On the Return of the Contrarian Investment Strategy," *Journal of Business*, April 1988, pp. 147-163

[30] Chan, K.C., Chen, N.F. and Hsieh, D.A."An Explanatory Investigation of the Firm Size Effect," *Journal of Financial Economics*, 1985, pp. 451-471.

[31] Chang, E.C. and Lewellen, W.G."Market Timing and Mutual Fund Performance," *Journal of Business*, January 1984, pp. 57-72

[32] Chen, N., Roll, R. and Ross, S."Economic Forces and the Stock Market," *Journal of Business*, 1986, pp. 383–403

[33] Chua, J.H. and Woodward, R.S."Gains from Stock Market Timing," Salomon Brothers Center for the Study of Financial Institutions, 1986, pp.1-75.

[34] Clarke, R., FitzGerald, M., Berent, P. and Statman, M. "Market Timing with Imperfect Information," *Working Paper*, 1989

[35] Connor, G. and Korajczyk, R.A."Performance Measurement with the Arbitrage Pricing Theory: A New Framework for Analysis," *Journal of Financial Economics*, March 1986, pp. 373-394

[36] Cook, T. and Rozeff, M."Size and Earnings/Price Ratio Anomalies: One Effect or Two?" *Journal of Financial and Quantitative Analysis*, December 1984, pp. 449–466

[37] Copeland, B."Inflation, Interest rates and Equity Risk Premia," *Financial Analysts Journal*, May/June 1982, pp. 32–43

[38] Daigler, R.T. and Fielitz, B.D."A Multiple Discriminant Analysis of Technical Indicators at the New York Stock Exchange," *Journal of Financial Research*, Fall 1981, pp. 169-182.

[39] DeBondt W. and Thaler, R."Does the Stock Market Overreact?" *Journal of Finance*,1985, pp. 793-805

[40] DeBondt, W. and Thaler, R."Further Evidence on Investor Overreaction and the Stock Market Seasonality," *Journal of Finance*, July 1987, pp. 557-581.

[41] DeLong, B., Shleifer, A., Summers, L. and Waldman, R."The Economic Consequences of Noise Trading," *Working Paper*, Center for Research in Security Prices, September 1987.

[42] Droms, W.G.,"Market Timing as an Investment Policy," *Financial Analysts Journal*, January-February 1989, pp. 73-76.

[43] Dybvig, P.H. and Ross, S.A. "Differential Information and Performance Measurement Using a Security Market Line," *Journal of Finance* June 1985A, pp. 383-400

[44] Dybvig, P.H. and Ross, S.A. "The Analytics of Performance Measurement Using a Security Market Line," *Journal of Finance*, June 1985B, pp. 401-416

[45] Dyl, E.,"Capital Gains Taxation and Year-end Stock Market Behavior," *Journal of Finance*, 1977, pp. 165-176.

[46] Efron, B.,"The Bootstrap, the Jackknife and Other Resampling Plans," Philadelphia: *SIAM*, 1982.

[47] Efron, B. and G. Gong,"A Leisurely Look at the Bootstrap, the Jackknife, and Cross-Validation," *The American Statistician*, February 1983, pp. 36-48.

[48] Elgers, P., C. Callahan and E. Strock,"The Effect of Earnings Yields Upon the Association between Unexpected Earnings and Security Returns: A Reexamination," *The Accounting Review*, October 1987, pp. 763-773.

[49] Elton, E.J., M.J. Gruber and M. Gultekin,"Earnings Expectations and Share Prices," *Management Science*, September 1981, pp. 975-987.

[50] Evnine, J. and R. Henriksson, "Asset Allocation and Options," *Journal of Portfolio Management*, Fall 1987, pp. 56-61

[51] Fama, E. "Components of Investment Performance," *Journal of Finance*, June 1972, pp.551-567

[52] Fama, E."Stock Returns, Real Activity, Inflation and Money," *American Economic Review*, September, 1981, pp. 545–565

[53] Fama, E. "Perspectives on October 1987: What do we Learn from the Crash?" In *Black Monday and the Future of Financial Markets*, Kamphuis, R.W., R.C. Kormendi and J.W. Watson, (eds.), Dow-Jones Irwin, 1988

[54] Fama, E. and K. French, "Permanent and Temporary Components of Stock Prices." *Journal of Political Economy*, 1987A, pp. 246-273

[55] Fama, E. and K. French, "Forecasting Returns on Corporate bonds and Common Stocks," *Working Paper, Graduate School of Business, University of Chicago*,1987B

[56] Fama, E. and K. French, "Dividend Yields and Expected Stock Returns." *Journal of Financial Economics*, 1988, pp. 3-25

[57] Fama, E. and M. Gibbons, "A Comparison of Inflation Forecasts," *Journal of Monetary Economics*, 1984, pp. 327-348

[58] Fama, E. and G.W. Schwert, "Asset Returns and Inflation," *Journal of Financial Economics*, November 1977, pp. 115-46

[59] Fielitz, B.D. and F.L. Muller, "The Asset Allocation Decision," *Financial Analysts Journal*, July-August 1983, pp. 44-50

[60] Fisher, I.,"The Theory of Interest," New York, 1930.

[61] Flood, R., R. Hodrick, and P. Kaplan, "An Evaluation of Recent Evidence on Stock Market Bubbles," *Unpublished Manuscript, National Bureau of Economic Research*, 1986

[62] Foster, G.,"Quarterly Accounting Data: Time-series Properties and Predictive-ability Results," *The Accounting Review*, 1977, pp. 1-21.

[63] Francis, J., Investments, 1976.

[64] French, K. and R. Roll,"Stock Return Variances: The Arrival of Information and the Reaction of Traders," *Journal of financial of Economics*, 1986, pp. 5-26.

[65] French, K., W. Schwert, and R. Stambaugh, "Expected Stock Returns and Volatility," *Journal of Financial Economics*, 1987, pp. 3-29

[66] Fried, D. and D. Givoly,"Financial Analysts' Forecasts of Earnings: A Better Surrogate for Market Expectations," *Journal of Accounting and Economics*, October 1982, pp. 85-107.

[67] Friedman, B. "Discussion: Stock Prices and Social Dynamics," *Brookings Papers on Economic Activity*, Vol. 2, 1984, pp. 507-508.

[68] Garbade, K. and P. Wachtel,"Time Variation in the Relationship between Inflation and Interest Rates," *Journal of Monetary Economics*, 1978, pp. 755-765.

[69] Geske, R. and R. Roll,"The Fiscal and Monetary Linkage Between Stock Returns and Inflation," *Journal Finance*, March 1983, pp. 1-34.

[70] Givoly, D. "The Formation of Earnings Expectations," *Accounting Review*, July 1985, pp. 372-386

[71] Givoly, D. and J. Lakonishok,"Aggregate Earnings Expectations and Stock Market Behavior," *Journal of Accounting, Auditing and Finance*, 1984, pp. 117-137.

[72] Graham, B. "The Intelligent Investor: A Book of Practical Counsel," New York: Harper and Brothers, 1949.

[73] Graham, B. and D.L. Dodd,"Security Analysis," New York, McGraw-Hill, 4th edition, 1962, pp. 744-49.

[74] Granger, C. and P. Newbold, "Forecasting Economic Time Series," *Academic Press, New York*, 1977

[75] Grant, D."Market Timing and the Cost of Timing Decisions," *Journal of Finance*, 1977, pp. 295-312

[76] Gray, W. "The Application of Discount Rates in Forecasting Returns for Stocks and Bonds,"*Financial Analysts Journal*, May/June 1974, pp. 53–61

[77] Gray, W. "Developing a Long-term Outlook for the U.S. Economy and Stock Market,"*Financial Analysts Journal*, July/August 1979, pp. 29–39

[78] Gray, W. "The Stock Market and the Economy in 1988," *Journal of Portfolio Management*, Summer 1984, pp.73–80

[79] Green, R. "Benchmark Portfolio Inefficiency and Deviations from the Security Market Line."*Journal of Finance*, June 1986, pp. 295-312

[80] Grosssman, S.J. and R.J. Shiller, "The Determinants of the Variability of Stock Market Prices," *American Economic Review*, June 1981, pp. 222-227.

[81] Gultekin, M.N. and N.B. Gultekin,"Stock Return Anomaly and the Tests of the APT," *Journal of Finance*, December 1987, pp. 1213-1224.

[82] Hendriksson, R.D."Market Timing and Mutual Fund Performance: An Empirical Investigation,"*Journal of Business*, January 1984, pp. 73-96

[83] Hendriksson, R.D. and R.D. Merton, "On Market Timing and Investment Performance: Statistical Procedures for Evaluating Forecasting Skills," *Journal of Business*, October 1981, pp. 513-533

[84] Hess, P.J. and J.L. Bicksler,"Capital Asset Prices Versus Time Series Models as a Predictors of Inflation." *Journal of Financial Economics*, December 1975, pp. 341-60.

[85] Hicks, J.R."Liquidity." *Economic Journal*, December 1962, pp. 787-802

[86] Hogarth, R. and M. Reder, eds.,*Rational Choice: The Contrast Between Economic and Psychology* (Chicago: University of Chicago Press, 1987)

[87] Ibbotson, R.G. and R.A. Sinquerfield, "Stocks, Bonds, Bills, and Inflation: the Past and the Future," Yearbook, 1988.

[88] Jaffe, F.J. and G. Mendelker, "The Fisher Effect for Risky Assets: An Empirical Investigation," *Journal of Finance*, May 1976, pp. 447-58

[89] Jeffrey, R.H. "The Folly of Stock Market Timing," *Harvard Business Review*, July-August 1984, pp. 102-110

[90] Jensen, M.C. "The Performance of Mutual Funds in the Period 1945-1964," *Journal of Finance*, May 1968, pp. 398-416.

[91] Jensen, M.C. "Risk, the Pricing of Capital Assets, and the Evaluation of Investment Portfolios," *Journal of Business*, April 1969, pp. 167-247.

[92] Jensen, M.C. "Optimal Utilization of Market Forecast and the Evaluation of Investment Performance" in Szego, G. and K. Shell (eds.) *Mathematical Models in Investment and Finance*, Amsterdam: North-Holland Publishing.

[93] Johnson, L. "Dividend Yields are Equity Risk Premiums: Comment," *Journal of Portfolio Management*, Winter 1986, pp.81-83

[94] Judge, G.G., W.E. Griffiths, C.R. Carter, and L.T. Chao, "The Theory and Practice of Econometrics," New York: John Wiley and Sons, 1980.

[95] Kahneman, D. and A. Tversky, "Prospect Theory: An Analysis of Decision Under Risk," *Econometrica*, March 1979, pp.263-291.

[96] Kane, A. and S.G. Marks, "Performance Evaluation of Market Timers: Theory and Evidence," *Journal of Financial and Quantitative Analysis*, 1989, pp. 425-435.

[97] Keim, D.B., "Size Related Anomalies and Stock Return Seasonality: Further Empirical Evidence," *Journal of Financial Economics*, 1983, pp.13-32.

[98] Keim, D.B. and R. Stambaugh, "Predicting Returns in the Stock and Bond Markets." *Journal of Financial Economics*, 1986, pp. 357-390

[99] Keynes, J., "The General Theory of Employment, Interest and Money," New York, Brace and World, 1964

[100] Kim, M.J., C.R. Nelson and R. Startz, "Mean Reversion in Stock Prices? A Reappraisal of the Empirical Evidence." *Working Paper*, University of Washington, November 21, 1988

[101] Kirtzman, M. and J.C. Ryan, "A Short-Term Approach to Asset Allocation," *Journal of Portfolio Management*, Summer 1981, pp. 45-49

[102] Kleidon, A. "Variance Bounds Tests and Stock Price Valuation Models," *Journal of Political Economy*, October 1986, pp. 953-1001

[103] Kon, S. and F. Jen, "The Investment Performance of Mutual Funds: An Empirical Investigation of Timing, Selectivity, and Market Efficiency," *Journal of Business* April, 1979, pp. 263-289

[104] Kon, S. "The Market Timing Performance of Mutual Fund Manager," *Journal of Business*, July 1983, pp. 323-347

[105] Lachenbruch, P.A. "An Almost Unbiased Method of Obtaining Confidence Intervals for the Probability of Misclassification in Discriminant Analysis," *Biometrics*, December 1967, pp. 639-645.

[106] LeRoy, S. and R. Porter, "The Present Value Relation: Tests Based on Implied Variance Bounds." *Econometrica*, March 1981

[107] Leonard, D. and M. Solt, "Recent Evidence on the Accuracy and Rationality of Popular Inflation Forecasts," *Journal of Financial Research*, Winter 1986, pp. 281-290

[108] Lintner, J.,"Inflation and Security Returns," *Journal of Finance*, May 1975, pp. 259-80.

[109] Loeb, T."Trading cost: The Critical Link between Investment Information and Results," *Financial Analysts Journal* May-June 1983, pp. 39-45

[110] Malkiel, B. and J. Cragg, "Expectation and the Structure of Share Prices," *American Economic Review*, September 1970, pp. 601–617

[111] Markowitz, H.M."Portfolio Selection." *Journal of Finance*, March 1952, pp. 77-91

[112] Marsh, T. and R. Merton, "Dividend Variability and Variance Bounds Tests for the Rationality of Stock Market Prices", *American Economic Review*, June 1986, pp. 483-498

[113] Marsh, T. and R. Merton, "Dividend Behavior for the Aggregate Stock Market," *Journal of Business*, January 1987, pp. 1–40

[114] Mayers, D. and E.M. Rice, "Measuring Portfolio Performance and the Empirical Content of Asset Pricing Models." *Journal of Financial Economics*, March 1979, pp. 3-28

[115] Merton, R.C."On Market Timing and Investment Performance: An Equilibrium Theory of Value for Market forecasts," *Journal of Business*, July 1981, pp.363-406

[116] Miller, M. and R.R. McCormick, "The Crash of 1987: Bubble or Fundamental?" *Working Paper*, University of Chicago, February 1989

[117] Modigliani, F. and R. Cohen, "Inflation, Rational Valuation and the Market," *Financial Analysts Journal*, March/April 1979, pp. 24–44

[118] Nelson, C. and G. Schwert, "Short-term interest rates as predictors of inflation: On Testing the Hypothesis that the Real Rate of Interest rate is Constant," *American Economic Review*, 67, 1977, pp. 478-486

[119] O'Brien, J. "Testing for Transient Elements in Stock Prices," Working Paper, Board of Governors of the Federal Reserve System, September 1987.

[120] Ohlson, J. "Price-Earnings Ratios and Earnings Capitalization under Uncertainty," *Journal of Accounting Research*, Spring 1983, pp. 141–154

[121] Pearce, D. "Comparing Survey and Rational Measures of Inflation: Forecast Performance and Interest Rate Effects," *Journal of Money, Credit and Banking* 11, 1979, pp. 447-456

[122] Perold, A.F., "Constant Proportion Portfolio Insurance," Working Paper, Harvard Business School, 1986

[123] Perold, A.F., and W. Sharpe, "Dynamic Strategies for Asset Allocation," *Financial Analysts Journal*, January-February 1988, pp. 16-27.

[124] Phillips, D. "Differentiating Tactical Asset Allocation from Market Timing." *Financial Analysts Journal*, March-April 1989, pp. 14-16

[125] Piccini, R. "Stock Market Behavior around Business Cycle Peaks," *Financial Analysts Journal*, July-August 1980, pp. 55-57

[126] Pogue, G. and W. Conway, "On the Stability of Mutual Fund Beta Values," Unpublished Working Paper, *MIT*, June 1972.

[127] Poterba, J. and L. Summers, "Mean Reversion in Stock Returns: Evidence and Implication." *Journal of Financial Economics*, 1988,

[128] Reilly, F., F. Griggs, and W. Wong, "Determinants of the Aggregate Stock Market Earnings Multiple," *Journal of Portfolio Management*, Fall 1983, pp. 36-45

[129] Remaley, W.A., "Moving Averages as Market Timing Indicators," *AAII Journal*, October 1987.

[130] Reinganum, M.R., "The Anomalous Stock Market Behavior of Small firms in January: Empirical Tests for Tax-loss Selling Effects," *Journal of Financial Economics*, 1983, pp. 89-104.

[131] Renshaw, E. "A Risk Premium Model for Market Timing," *Journal of Portfolio Management*, Summer 1985, pp.33-35

[132] Richardson, M. "Temporary Components of Stock Prices: A Skeptic's View." *Working Paper*, Stanford University, November 1988.

[133] Rozeff, M.,"Money and Stock Prices: Market Efficiency and The Lag in Effect of Monetary Policy," *Journal of Financial Economics*, September 1974, pp. 245-302.

[134] R. Roll, "Ambiguity when Performance is Measured by the Securities Market Line," *Journal of Finance*, September 1978, pp. 1051-1069.

[135] Roll, R.,"Vas ist Das? The Turn of the Year Effect and the Return Premium of Small Firms," *Journal of Portfolio Management*, 1983, pp. 18-28.

[136] Rozeff, M."Dividend yields are equity risk premiums," *Journal of Portfolio Management*, Fall 1984, pp.68–75

[137] Rozeff, M.S. and W.R. Kinney,"Capital Market Seasonality: The Case of Stock Returns," *Journal of Financial Economics*, 1976, pp. 379-402.

[138] Schwert, G.W.,"The Adjustment of Stock Prices to Information About Inflation." *Journal of Finance*, March 1981, pp.15-30.

[139] Sharpe, W."Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk." *Journal of Finance*, September 1964, pp. 425-442

[140] Sharpe, W."Mutual Fund Performance," *Journal of Business*, January 1966, pp. 119-138.

[141] Sharpe, W. "Likely Gains from Market Timing,"*Financial Analysts Journal*, March/April 1975, pp. 60-69

[142] Shefrin and Statman,"The Disposition to Sell Winners Too Early and Ride Losers too Long: Theory and Evidence," *Journal of Finance*, July 1985, pp. 777-792.

[143] Shiller, R."Theories of Aggregate Stock Price Movements," *Journal of Portfolio Management*, Winter 1984, pp. 28–37

[144] Shiller, R."The Use of Volatility Measures in Assessing Market Efficiency," *Journal of Finance*, May 1981, pp. 291–311

[145] Shiller, R."Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?", *American Economic Review*, June 1981, pp. 421-436

[146] Shiller, R."Stock Prices and Social Dynamics." *Brookings Paper on Economic Activity*, 1984,. pp. 457-498

[147] Sorensen, E. and R. Arnott,"The Risk Premium and Stock Market Performance," *Journal of Portfolio Management*, Summer 1988, pp. 50-55

[148] Stultz, R."Asset Pricing and Expected Inflation," *Journal of Finance*, March 1986, pp. 209–223

[149] Summers, L."Does the Stock Market Rationally Reflect Fundamental Values?" *Journal of Finance*, July 1986, pp. 591–602

[150] Tinic, S.M. and R.R. West,"Risk and Return: January vs. the Rest of the Year," *Journal of Financial Economics*, December 1984, pp. 561-74.

[151] Tobin, J."Liquidity Preferences as Behavior Towards Risk." *The Review of Economic Studies*, February 1958, pp. 65-86

[152] Treynor, J."How to Rate Management of Investment Funds," *Harvard Business Review*, January-February 1965, pp. 63-75.

[153] Treynor, J."Market Efficiency and the Bean Jar Experiment," *Financial Analysts Journal*, May-June 1987, pp. 50-53.

[154] Treynor, J. and F. Black, " How to use Security Analysis to improve Portfolio Selection," *Journal of Business*, January 1973, pp. 66-86.

[155] Treynor, J. and K. Mazuy, "Can Mutual Funds Outguess The Market?" *Harvard Business Review*, July-August 1966, pp. 131-136

[156] Tilley, J.A. and G.D. Latainer, "A Synthetic Option Framework for Asset Allocation," *Financial Analysts Journal*, May-June 1985, pp. 32-43

[157] Umstead, D.A."Forecasting Stock Market Prices," *Journal of Finance*, May 1977, pp. 427-441

[158] Vandell, R.F. and J.L. Stevens,"Evidence of Superior Performance from Timing," *Journal of Portfolio Management*, Spring 1989, pp.38-42.

[159] Zarnowitz, V/ and G.A. Moore, "Sequential Signals of Recession and Recovery," *Journal of Business*, 1982, pp. 57-85

[160] Zweig, M., "Uncanny Floor Traders," *Barron's*, April 22 1974, p.11.

[161] Zweig, M., "Winning on Wall Street," Warner Books, 1986.