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The goal of this study is to test the accuracy of various mutual fund timing and selectivity models under a range of portfolio managerial skills and varying market conditions. Portfolio returns in a variety of skill environments are generated using a simulation procedure. The generated portfolio returns are based on the historical patterns and time series behavior of a market portfolio proxy and on a sample of mutual funds.

The proposed timing and selectivity portfolio returns mimic the activities of actual mutual fund managers who possess varying degrees of skill. Using the constructed portfolio returns, various performance models are compared in terms of their power to detect timing and selectivity abilities, by means of an iterative simulation procedure.

The frequency of errors in rejecting the null hypotheses

of no market timing and no selectivity abilities shape the analyses between the models for power comparison. The results indicate that time varying beta models of Lockwood-Kadiyala and Bhattacharya-Pfleiderer rank highest in tests of both market timing and selectivity. The Jensen performance model achieves the best results in selectivity environments in which managers do not possess timing skill. The Henriksson-Merton model performs most highly in tests of market timing in which managers lack timing skill.

The study also investigates the effects of heteroskedasticity on the performance models. The results of analysis before and after model correction for nonconstant error term variance (heteroskedasticity) for specific performance methodologies do not follow a consistent pattern.

A Power Comparison of Mutual Fund Timing and Selectivity Models Under Varying Portfolio and Market Conditions

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Chapter 1

INTRODUCTION

An area of interest in the field of finance that has brought forth considerable debate among academicians and the investment community is investment performance evaluation. From the academic and theoretical perspective, the topic of investment performance has been debated to offer answers and insights on research areas such as the capital asset pricing model (CAPM) and the efficient market hypothesis (EMH). Part of the research has attempted to provide explanations as to whether portfolio active management is a viable task as practiced by the professional investors (money managers) who might possess superior information. In academics, this is referred to as a test of market efficiency in the strong form. The traditional performance evaluation techniques rely on the portfolio's risk-adjusted returns, which is a comparison of managed and naively selected (not professionally managed) portfolios with similar risk characteristics. In the context of EMH, this translates to informed investors, who achieve higher returns on a risk-adjusted basis than do the uninformed, who do not act on quality information. An efficient market is defined as an investment environment where consistently "beating the market" is not possible. Superior returns would be due to mere chance, and any attempts to outperform the market would produce subaverage results due to incurred costs in resource usage.

Mutual funds, one area of professional portfolio management activities, have experienced considerable growth in recent years. The diversity and variety of the forms of portfolio management practices in the mutual fund industry have provided unlimited research opportunities for theoreticians in the field of finance, with EMH being a main focus of interest. This study is mainly concerned with the performance techniques that are used to evaluate mutual fund managers.

The financial literature points to various problems that investment performance evaluators face when examining professional portfolio managers. Aside from model misspecification, incomplete knowledge about the portfolio managers' activities in portfolio risk adjustments cause biases when the portfolio's risk-adjusted returns are measured based on risk. Another controversial issue among academicians is the appropriateness of market indices used as proxies for the market portfolio. It has been suggested that the market portfolio is not observable.

Part of the research in the area of performance evaluation has concentrated on formulating models that measure investment performance. A recent development is the distinction between managerial skills in market timing (macroforecasting) and selectivity (microforecasting) abilities. Market timing is defined as forecasting the broad movements of the market as a whole and predicting how various asset categories will perform. At the micro-level, selectivity skill is the ability to identify superior securities within a broad asset category which will outperform others.

The justification of an active management strategy would be trivial if the performance models were flawless. A perfect evaluation model would show the true skills of a portfolio manager and, therefore, it would be possible to assess the effectiveness of decisions made by following a designed active strategy. However, imperfect and approximate models, together with data contaminated with noise, would produce results that warrant complex analysis to understand the investment activities of the portfolio managers. It is possible that the formulated performance models are accurate in differentiating among the range of managerial skill levels. However, if the performance models are marginally accurate, the results of performance studies would be biased.

This study is organized as follows. The results of the literature review are presented in Chapter 2. This part of the thesis also includes a brief description of the theoretical concepts behind the state of the art mutual fund timing and selectivity models. Furthermore, the empirical studies based on these models are examined. The lack of attention to the power of performance models in previous mutual fund timing and selectivity studies demonstrates the need for this study. We question the empirical findings of the recent mutual fund studies, that fund managers, on average, do not possess timing and selectivity skills. Our primary concern is with the performance models that are used to evaluate fund managers. A simulation procedure is devised which provides the means for model comparison. The models chosen include Jensen, Henriksson-Merton, Lockwood-Kadiyala, and Bhattacharya-Pfleiderer. These models have been used extensively in mutual fund performance studies.

In Chapter 3, the time series behavior and distributional properties of the market return series are discussed. The procedures for designing timing and selectivity portfolios, as well as those for the noise model, are also addressed in Chapter 3. The characteristics of a sample of mutual funds and the data on a market portfolio proxy provide the means for constructing simulated mutual fund portfolio returns. Furthermore, a flowchart summarizes the designed simulation model, and the proposed model is validated in the latter part of Chapter 3. The basis for this part of the analysis is to investigate whether the generated timing and selectivity portfolios' returns are adequate and satisfy the simulation model's assumptions. The constructed mutual fund returns will then be used to test the timing and selectivity models in terms of their accuracy.

The experimental design is described in the final section of Chapter 3.

Chapter 4 presents the results on how the models perform and whether the models can be differentiated in terms of their accuracy. The models are examined in terms of their power to uncover true managerial timing and selectivity abilities, which are classified as no-skill, semi-skilled, and skilled. In other words, hypothetical mutual fund returns are constructed to simulate the abilities of managers with varying degrees of information. In testing the hypotheses of no market timing and no selectivity abilities, the frequency of errors committed are used to compare the power of various models.

A viable model should be able to detect a manger's abilities separately in terms of timing and selectivity skills. Using various methodologies, the simulated mutual fund returns, controlled portfolios, and their performance in terms of timing and selectivity will provide explanations regarding the models' usefulness in performance evaluation studies.

It has been shown that the results of timing studies are biased if the performance models are not modified to account for nonconstant error term variance, which in econometrics is referred to as heteroskedasticity. The effects of correction for nonconstant error term variance will also be addressed in this part of the analysis. In the final phase of the study, a summary of the findings and conclusions are presented.

Our goal is to compare different state of the art mutual fund timing and selectivity models in a designed experiment that simulates fund managers' investment behavior. This study's simulation environment relies on the empirical distributions of the market risk-premium returns and equity mutual funds' asset allocations to Treasury bills. The results of the comparison of the models provides insights into the working characteristics of mutual fund timing and selectivity models.

Chapter 2

REVIEW OF LITERATURE

Earlier studies on investment performance evaluation concentrated on techniques which identified a portfolio's return on a risk-adjusted basis. These performance measures were designed to rank portfolios according to their risk and return characteristics.

In portfolio analysis, the part of the risk that can nearly be eliminated by holding a widely diversified portfolio is called non-systematic risk, sometimes referred to as firm-specific. As the alternative name implies, this risk is born out of factors which affect any company on an individual basis, based on its particular operating environment. However, the risk factors which affect firms in isolation can be greatly reduced if a large number of these companies' securities are held in a portfolio. As a result, rational investors will hold diversified portfolios to eliminate firm-specific risk.

The systematic risk (or market risk), portfolio beta (β_p), is the part of the total risk, in the portfolio context, which can not be eliminated. Systematic risk, β_p, explains how the portfolio's return is affected by the market, which is in turn influenced by general economic conditions. This relationship can be expressed in terms of the portfolio return, R_p, and market return, R_m, covariance and the variance of the market return, σ^2_{Rm}:

$$\beta_p = COV(R_p, R_m) / \sigma^2_{Rm}. \tag{2.1}$$

The original performance measures as developed by Sharpe (1966), Treynor (1965), and Jensen (1968), were all formulated under the assumption of constant portfolio risk. The findings of these classical works, as well as most of the recent studies, indicate that after accounting for fund expenses, most of the mutual funds have not been able to outperform the market.

Next, an overview of mutual fund performance models is presented and the findings of the empirical studies based on these models are discussed.

Treynor's Reward-to-Volatility Ratio

The CAPM based reward-to-volatility ratio introduced by Treynor (1965) uses systematic risk as its risk adjustment factor. This relationship is of the form:

$$(R_p - R_f) / \beta_p. \tag{2.2}$$

The numerator, the excess return, is the difference between the portfolio return, R_p, and the risk-free interest rate, R_f, which is the reward for the risk-bearing investor, while the denominator, portfolio beta, β_p, is the adjustment factor for risk. Since the Treynor measure only considers the systematic risk portion of the total risk, it ignores the portfolio's diversification, and the implicit assumption is that the portfolio is relatively well-diversified.

Sharpe's Reward-to-Variability Ratio

Sharpe's (1966) reward-to-variability ratio is also CAPM based. It adjusts the portfolio's return based on its total risk, namely systematic and non-systematic risk. The total risk is measured by the standard deviation of the portfolio. This relationship is of the form:

$$(R_p-R_f)/\sigma_p. \tag{2.3}$$

The numerator is the risk premium earned by the portfolio, R_p-R_f, and the variability in the portfolio's returns is expressed as the standard deviation of the portfolio, σ_p. As a result, the reward-to-variability index is, in effect, the excess return per unit of total risk. The Sharpe ratio is an appropriate measure for nearly perfectly diversified portfolios, since the standard deviation is a good measure of the total risk. Sharpe (1966) found that using his model and taking into account the fund expenses, a sample of 34 mutual funds underperformed the Dow-Jones portfolio.

The Sharpe and Treynor ratios would have identical results if the portfolio under consideration is perfectly diversified, as the portfolio risk is represented either by the portfolio beta factor (market risk) or its standard deviation. A set of portfolios can be ranked on the basis of risk-adjusted returns using these methods.

The Sharpe and Treynor performance statistics can be classified as measures that are based on return per unit of risk. The next performance measure, the Jensen model, can be described in terms of return differential expressed as a function of portfolio return and benchmark portfolio (market proxy).

Jensen Measure

Jensen (1968) proposed a measure of performance which also relies on CAPM assumptions. It was shown that portfolio or security returns can be expressed in risk premium form, $R_{pft}=R_{pt}-R_{ft}$, as:

$$R_{pft} = \beta_p R_{mft} + e_{pt}, \tag{2.4}$$

which defines a linear relationship among the effects portfolio beta, β_p, market return in risk premium form, $R_{mft}=R_m-R_f$, and random error, e_{pt}, where $E(e_{pt})=0$, and R_{ft} is the risk free rate. Jensen showed that a manager with superior forecasting ability will show $\hat{e}_{pt}>0$. In other words, this excess return is a new added term to what is already realized as the premium due to portfolio risk. The proposed performance measure, α_p, was formulated by using expression (2.4) without the constraint of a zero intercept:

$$R_{pft} = \alpha_p + \beta_p R_{mft} + u_{pt}, \tag{2.5}$$

where u_{pt} is the error term which has an expectation of zero.

According to this formulation he suggested that portfolios with better than average returns will have a positive α_p, or a positive regression intercept. Therefore, α_p is considered as the specific return of a particular portfolio over the market return. In an efficient market under equilibrium conditions, this intercept will equal zero, which is consistent with the assumptions of the Capital Asset Pricing Model. Jensen claims that when a manager possesses timing ability, his model will show a portfolio risk, β_p, which is biased downward and an α_p, which is biased upward. However, the model's results would be unbiased if the manager is an unsuccessful market timer. Jensen (1968) found that his sample of 115 mutual funds over the period 1945-1964 did not outperform the passive policy known as buy-the-market-and-hold.

McDonald (1974) investigated the risk and return characteristics of 123 mutual funds and their consistency with the stated objectives. The study used monthly returns over the period 1960-1969. The findings suggested that funds with more aggressive objectives (higher risk) produced better results, in terms of Sharpe's and Treynor's measures, than the average funds (lower risk). Only 5% of the funds showed a significant α_p at the 5% level using Jensen's performance measure, which could be explained in terms of mere chance.

Murphy (1980), using risk-adjusted (Jensen's α_p) and absolute returns, conducted a simulation study to measure the performance of 100 portfolio managers over 10 years. He claimed that the abnormal returns reported by most of the mutual fund studies are rarely large enough to be reported as significant, given their measurement errors. The results of the study show that over the period of 10 years, underperformers (outperformers) occasionally had superior (inferior) performance, an outcome explained by chance. However, one would expect that over longer time periods, the true skill of the managers could be correctly identified.

French and Henderson (1985) examined the Sharpe, Treynor, and Jensen measures for 50 simulated portfolios, over a 5 year period, using monthly returns. The study considers the accuracy of these performance measures given the amount of random noise in the stock returns. The rankings are accurate and consistent with the designed portfolios. However, the authors found that their results were similar to those of Murphy (1980), that the estimates for portfolios' abnormal returns are only significant when the resulting alphas are very large. The study claimed that the monthly portfolio excess returns were approximately 1% or greater before they appeared to be significant at the 5% level. Murphy also proposed a similar figure.

In a recent study, Grinblatt and Titman (1989) used quarterly portfolio returns over the period 1975-1984 to test for abnormal performance as modeled by Jensen's α_p. They found evidence of superior performance among funds classified as aggressive-growth and growth, and among funds with small net asset value. However, due to the high expense of this particular group of funds, their returns did not show abnormal performance after adjusting for the fund expense.

Ippolito (1989) conducted a similar study over the period 1965-1984 using the Jensen measure to evaluate the mutual fund industry, and examined its implications on market efficiency. He claimed that the absence of superior returns by mutual fund managers are consistent with the efficient market hypothesis, given the cost of acquired information.

The performance models discussed above assume the portfolio systematic risk (beta), β_p, to be stationary over time. The possibility that β_p may vary over time is not considered. A market timer will attempt to adjust the portfolio's riskiness according to market conditions. In anticipation of a rising (bull) market, the portfolio will consist of high risk securities, and in a declining (bear) market, the portfolio holdings will be shifted to low risk securities. Therefore, in market timing environments, the portfolio beta, β_p, will no longer be stationary, and the results of previously discussed risk-adjusted performance measures will not be valid.

Even if the portfolio manager is not attempting to engage in market timing, the systematic risk of the individual securities held in the portfolio might be changing through time. Another factor influencing the portfolio beta could be the changing market value of the securities. These changes in turn cause the portfolio beta to be nonstationary, which would be evidence to invalidate the studies that are based on the assumption of constant beta. Furthermore, there are other factors that also might affect the portfolios' rankings using the traditional performance measures. Some of these findings are briefly discussed in the following section.

Grant (1977) showed that the performance and risk measures defined by Treynor and Jensen are biased if the market timer possesses skill in macroforecasting activities. Furthermore, his study's results indicate that in the presence of market timing ability, the Jensen performance measure, α_p, will be biased downward, which is contradictory to Jensen's findings.

Miller and Gehr (1978) found the Sharpe measure to be biased when the sample size was varied. Through analytical derivation, the magnitude of the bias for various sample sizes was presented. For N=3, the bias in the Sharpe measure was approximately 77% upward, and for N=50, the upward bias was 1.6%. The study suggested that for equal sample sizes, the rankings of the portfolios will not change. However, the results will vary if unequal sample sizes are used. Chen and Lee (1986) claimed that, using the Sharpe measure, the portfolio rankings are a function of sample size, the investment horizon, and market conditions. To compensate for the observed bias, they suggest that a shorter investment horizon and a large sample size be used.

The previous measures presented by Jensen, Sharpe, and Treynor focus on the overall portfolio return on a risk-adjusted basis. Next, the performance measures which make distinctions between managerial timing and selectivity abilities are discussed.

Treynor and Mazuy's Timing Model

Treynor and Mazuy (1966) used a sample of 57 mutual funds over the period 1953-1962 to test for market timing ability. They claimed that a fund with successful market timing will have a concave characteristic line, which they account for by adding a quadratic term to the market model expression, $R_{pft}=\alpha_p+\beta_p R_{mft}+e_{pt}$:

$$R_{pft} = \alpha_p + \beta_p R_{mft} + \gamma_p R^2_{mft} + \epsilon_{pt}, \tag{2.6}$$

where a test of market timing is equivalent to the test of the null hypothesis $H_o{:}\gamma_p=0$. The study found no evidence of market timing ability on the part of mutual fund managers. Williamson (1972), using Treynor and Mazuy's method, tested a sample of 180 mutual funds for the period 1961-1970, and his results also indicate that the fund managers were not successful in forecasting the market.

Fama's Timing and Selectivity Model

Fama (1972) offered a more specific breakdown of the total portfolio return. The study was one of the original contributors which made distinctions between selectivity and timing components of the portfolio return. Selectivity (microforecasting) was defined as the return differential between a managed portfolio and a naively selected portfolio with similar risk characteristics, and timing was referred to as the part of the portfolio return that is due to the movements of the market as a whole. The study proposed the following model:

$$R_{pft} = [R_{pt} - R_{pt}(\beta_p)] + [R_{mt}(\beta_p) - R_{ft}], \tag{2.7}$$

where $R_{pft}=R_{pt}-R_{ft}$ is portfolio's overall performance component in risk premium form consisting of the portfolio return, R_p, and the risk free rate, R_f; $[R_{pt}-R_{pt}(\beta_p)]$ is the selectivity component which is expressed in terms of portfolio return, R_p, market return, R_m, and the portfolio beta, β_p; and the portfolio risk (timing) component is captured by the term $[R_{mt}(\beta_p)-R_{ft}]$.

There have been attempts to develop models which take into account the nonstationarity of the portfolio beta. In the following paragraphs, the empirical evidence on the stationarity of the portfolio beta is presented and the models which account for a nonstationary portfolio beta are discussed. This next section consists of a review of the studies that deal with mutual fund portfolios rather than individual stocks.

The test for mutual fund selectivity and systematic risk parameters' stability during bear and bull markets was undertaken by Fabozzi and Francis (1979). The authors employed the following modification of the single-index market model, $R_{pt}=\alpha_p+\beta_p R_{mt}+e_{pt}$, to test for the nonstationarity of the mutual fund performance parameters:

$$r_{pt} = A_{1p} + A_{2p}D_t + B_{1p}r_{mt} + B_{2p}D_t r_{mt} + e_{pt}, \qquad (2.8)$$

where r_{pt} and r_{mt} are the portfolio and market returns, D_t is a binary variable which equals one for a bull market and takes a value of zero for a bear market, and A_{2p} and B_{2p} are coefficients that show the effects of a bull market on selectivity (alpha), A_{1p}, and timing (beta), B_{1p}, measures. To examine the stationarity of the performance parameters, the hypotheses $H_o: A_{2p}=0$ and $H_o: B_{2p}=0$ are tested for significance using the t-test. The authors conducted the study for a sample of 85 mutual funds over the period 1965-1971. The alphas were found to be stable and not sensitive to market conditions. The results of the study for market timing ability are essentially the same as in the work conducted by Treynor and Mazuy (1966), that mutual fund portfolio managers do not alter the portfolio beta to account for changing market conditions. Alexander and Stover (1980) also used the indicator variable regression model which, in addition, accounted for leads and lags. The study found no evidence that mutual fund managers are successful market timers.

Kon and Jen (1978,1979) and Kon (1983) used switching regression to test for beta stationarity for a sample of 49 mutual funds over the period 1960-1971. They found substantial evidence in favor of the nonstationarity of mutual fund systematic risk. The authors claimed that the observed beta nonstationarity was due to managerial timing activities. The study did not report consistent patterns of selectivity and timing performance of the selected mutual funds.

Miller and Gressis (1980) also showed that mutual fund portfolio beta nonstationarity exists, and their study proposed a partition regression method to estimate the performance parameters. The study used the weekly returns of a sample of 28 mutual funds over the period 1973-1974.

Francis and Fabozzi (1980) used the random coefficient model (RCM) and reached the same conclusions, that portfolio beta for some funds is best described by a random process. The RCM estimation procedure relies on the residuals, e_{pt}, of the market model, $R_{pt}=\alpha_p+\beta_p R_{mt}+e_{pt}$, and on the variances of the residual and the fund's beta for each period around the mean beta. The study used a sample of 85 funds' monthly returns over the period 1965-1972. Furthermore, the investment objectives of the funds were classified as Growth, Growth-Income, Balanced, and Income.

It is possible that the mutual fund portfolio betas are not stationary, but this evidence should not always lead to the conclusion that fund managers are engaged in market timing. As previously discussed, the portfolio beta nonstationarity could be attributed to the changing market value or betas of the individual securities held in the portfolio. This argument was discussed by Alexander, Benson, and Eger (1982), who also concluded that mutual fund portfolio betas are nonstationary. Following the previously proposed models of beta nonstationarity, namely switching and partition regression models, the authors used a technique based on the first-order Markov process. The data consisted of monthly returns for a sample of 67 mutual funds over the period 1965-1973.

In a recent study, Kane and Marks (1988) examined the validity of the Sharpe measure when market timing exists. They have shown that the Sharpe measure will fail to rank market timers correctly according to their ability if quarterly or longer time periods of return data are used. The study finds that using monthly or daily fund return data is much more accurate in ranking the fund managers who are successful market timers, which could be explained in terms of parameter stationarity (stability) in shorter time intervals.

To predict market movements, a portfolio manager has to forecast bear and bull markets. The accuracy of the market predictions depends on a manager's forecasting ability and on how frequently (s)he is correct. The level of predictive accuracy required to justify timing activities is one of the main issues addressed in the timing studies dealing with potential benefits and limitations of market timing.

Sharpe (1975) showed the likely gains from market timing using the historical data on an annual basis for the period 1929-1972. The gains from perfect timing are shown to be approximately 4% per year, and it is suggested that only managers who possess truly superior timing skills, stated at a minimum of 70% accuracy, should engage in timing to beat a buy-and-hold strategy. The study classified each year as a bull or bear market, depending on whether stocks or cash equivalent returns exceeded each other on an annual basis. Because of the drastic market conditions experienced during The Great Depression and in the two decades immediately after World War II, the study also investigated the more conservative years, those during the periods 1934-1972 and 1946-1972, and the previously mentioned results remained intact. The proportion of the bull markets in all the three periods had a range of 0.60-0.70.

In a similar study conducted by Jeffrey (1984) over the period 1926-1982, he stressed that the risks from market timing outweigh its rewards. The study suggests that to engage in successful market timing is to take a "contrarian view" to the market consensus, which would be in conflict with the objectives of the trustees of the funds. Jeffrey concluded that, because of an unfavorable potential loss-gain relationship in market timing activities, fund managers should follow the established policies and guidelines of the trustees, and avoid the costly and risky task of forecasting market movements.

Chua and Woodward (1986) extended Sharpe's (1975) work in a more detailed analysis. Their study differentiated between the ability to forecast bear and bull markets, and it considered various combinations of forecasting abilities for rising and declining markets. Furthermore, the study considered assets such as long-term corporate bonds and real estate in addition to Treasury bills for portfolio switchings. The study found that to beat a buy-and-hold strategy, it is necessary to have, at the minimum, the following accuracies: 80% bull and 50% bear; 70% bull and 80% bear; or 60% bull and 90% bear. The results for corporate bonds and real estate as alternative investment assets indicated that even higher predictive accuracies are required to surpass a buy-and-hold strategy. These results indicate the importance of being in a bull market versus a bear market, as predicting rising markets requires higher accuracy. For example, a portfolio manager with less than a 60% bull market predictive accuracy should not attempt to time the market. The authors confirm Jeffrey's (1984) results that, historically, the years in which the stock market has shown high returns are not frequent and have happened over short time periods. They also suggest that the market can be characterized as having had average or subaverage years, which is an argument in favor of a passive buy-and-hold strategy if managers do not possess superior timing skills, particularly for bull markets. Chua and Woodward (1986) reported large standard deviations in returns resulting from the timing activities. The study suggested that with such large variations, it would be difficult to have "consistently positive gains," while it would be possible for some fund managers to have superior returns and outperform others.

Droms' (1989) main contribution to the body of timing studies was that, in addition to the yearly switchings, he also considered quarterly and monthly portfolio timing revisions between bear and bull markets. The study showed that managers can attain higher returns if they engage in more frequent switchings, and as a consequence, the accuracies required to beat a buy-and-hold strategy would be lower. However, as was discussed in the other studies, transaction costs affect portfolio returns more dramatically as timing activities increase. In other words, it becomes less advantageous to engage in market timing as transaction costs increase. It is possible that the trade-off between portfolio switchings and transaction costs does not produce returns large enough to justify market timing in real world portfolio management activities.

All the studies discussed have formulated the degree of accuracy required to beat a buy-and-hold strategy portfolio during up and down markets. However, it should be emphasized that the results of the majority of the time studies discussed are based on historical data. If the market would have taken a different path, the results might favor market timing. For example, Vandell and Stevens (1989) show that during the period 1973-1984, it was more important to time bear markets than to time bull markets, which contradicts the findings of the previous studies. As a result, in this case, the rewards of timing would have outweighed its risks.

Clarke, FitzGerald, Berent, and Statman (1989) argued that market timers' returns depend on the level of information they possess. He claimed that even with moderate information, a market forecaster can beat a buy-and-hold strategy. According to the study, a market timer who does not possess any information follows the passive strategy of buy-and-hold. Clarke proposed a simple model based on GNP, which aids in forecasting market movements. The information about future stock trends is gathered by analyzing the correlation cceffficient between the GNP number and the stock returns. According to this model, in the case of a buy-and-hold strategy, the market timer is correct 66% of time, which corresponds to a correlation of 0.1 between the GNP and stock returns. The 66% rate of accuracy is period specific and represents the proportion of bull markets (versus bear) in the time period during which the study was conducted. Furthermore, a 67% rate of accuracy corresponds to a correlation of 0.3 between the GNP and stock returns. However, with transaction costs included, higher levels of accuracy are required to surpass a buy-and-hold strategy.

Sy (1990) confirmed Vandell's (1989) and Dorms' (1989) results that, because of the stock market's recent behavior, it would be easier to beat a buy-and-hold strategy than had been implied in the previous timing studies. The study suggested that gains from market timing are period specific, and the influencing factor was mentioned as the return differential between stock and cash returns. Furthermore, it was stressed that the advantage of the market timers in recent years is due to the narrowing of the gap between stock and cash returns. According to Sy, small investors will be less successful in market timing than professional investors, because small investors must pay large transaction costs and do not hold the skills. Next, the mutual fund performance models which distinguish between timing and selectivity measures are discussed.

Jensen's Timing and Selectivity Model

Jensen (1972) formulated a model of timing and selectivity, where the input variables include the *ex post* returns of the portfolio, R_{pft}, the market return, R_{mft}, the expected return on the market, $E(R_{mf})$, the portfolio target beta in time t, β_{pt}, and the manager's response to the market information, θ. This relationship is expressed as:

$$R_{pft} = \eta_0 + \eta_1\pi_{pt} + \eta_2\pi^2_{pt} + \upsilon_{pt}, \qquad (2.9)$$

where $\pi_{pt}=R_{mft}-E(R_{mf})$. Jensen (1972) specified the large sample least-squares estimates, or probability limits, of the coefficients as:

$$plim\ \hat{\eta}_0 = \alpha_p + \beta_{pt}E(R_{mf}) + \theta(\rho^2_{TIM} - 1)\sigma^2\pi, \qquad (2.10)$$

$$plim\ \hat{\eta}_1 = \rho^2_{TIM}\theta E(R_{mf}) + \beta_{pt}, \tag{2.11}$$

and

$$plim\ \hat{\eta}_2 = \theta, \tag{2.12}$$

where the manager's market timing ability measure is estimated by ρ_{TIM}, which is the correlation between the manager's forecast and the outcome of π_{pt}. The parameters of managerial selectivity measure, α_p, and timing ability, ρ_{TIM}, cannot be computed unless the estimates of the market's expected return, $E(R_{mf})$, and details about the market forecast and the corresponding portfolio adjustments, are known.

Henriksson-Merton Bivariate Regression Model

Based on the value of macroforecasting skills, Merton (1981) formulated an equilibrium theory which is based on two possible market conditions, namely whether stocks or riskless securities provide a greater return. This approach to the prediction of market conditions does not rely on the magnitude of the forecasts as does Jensen (1972). However, the procedure requires forecasts by the fund manager whether stocks or riskless securities will outperform each other.

According to the manager's belief about the direction of the market, the funds will be appropriately invested in stocks or riskless securities. Therefore, the portfolio beta will be adjusted depending on the forecast of a bear or a bull market. And as expected, a rational market timer will design a higher portfolio beta for a bull market than for a bear market. A brief explanation of the model follows.

If γ_t is denoted as the market timer's forecast variable predicted at time $t-1$ for time period t, then the conditional probabilities of γ_t given the outcome of the market return are:

$$p_{1t} = prob[\gamma_t=0 \mid R_{mt} \leq R_{ft}], \tag{2.13}$$

$$1 - p_{1t} = prob[\gamma_t=1 \mid R_{mt} \leq R_{ft}],$$

and

$$p_{2t} = prob[\gamma_t=1 \mid R_{mt} > R_{ft}], \tag{2.14}$$

$$1 - p_{2t} = prob[\gamma_t=0 \mid R_{mt} > R_{ft}],$$

where p_{1t} and p_{2t} are the conditional probabilities of a correct forecast given a bear market, $R_{mt} \leq R_{ft}$, and a bull market, $R_{mt} > R_{ft}$. HM showed that $p_{1t}+p_{2t}$ is a necessary and sufficient statistic for evaluating the manager's timing skill. A greater than one summation of probabilities indicates that the manager possesses macroforecasting (timing) ability. Furthermore, $p_{1t}=1$ and $p_{2t}=1$ are the necessary conditions for perfect foresight. The situation where the manager fails to predict the market directions correctly is represented by the condition $p_{1t}+p_{2t}=1$. In addition, η_1 is denoted as the portfolio target beta during a bear market, $R_{mt} \leq R_{ft}$, and in the presence of a bull market, $R_{mt} > R_{ft}$, the portfolio beta is represented by η_2. Therefore, at time t, depending on a bear or a bull market, the fund manager will adjust the portfolio beta between η_1 and η_2. A rational manager is expected to have $\eta_1 < \eta_2$. Using these concepts, Henriksson and Merton (1981) derived the following timing and selectivity model:

$$R_{pft} = \alpha_p + \beta_1 X_t + \beta_2 Y_t + \epsilon_{pt}, \tag{2.15}$$

where

$$X_t = R_{mt} - R_{ft},$$

and

$$Y_t = max[0, -X_t].$$

The large sample estimates of the regression coefficients are shown as:

$$plim\ \beta_1 = p_1\eta_2 + (1-p_2)\eta_1, \tag{2.16}$$

$$plim\ \beta_2 = (p_1 + p_2 - 1)(\eta_2 - \eta_1), \tag{2.17}$$

where p_1 and p_2 are the proportions of successful predictions for bear, $R_{mt} \leq R_{ft}$, and bull markets, $R_{mt} \succ R_{ft}$.

A measure of the manager's macroforecasting skill is provided by testing the null hypothesis $H_o: \beta_2 = 0$. If $\beta_2 = 0$, two conditions arise: 1) $p_{1t} + p_{2t} = 1$ indicates lack of timing ability; and 2) $\eta_1 = \eta_2$ represents an identical bull and bear market portfolio beta, which shows that the fund manager does not engage in portfolio risk adjustments. Furthermore, α_p provides a consistent estimate of the managerial selectivity ability, which is tested by the null hypothesis $H_o: \alpha_p = 0$.

Henriksson and Merton (1981) have also derived a nonparametric procedure which relies on the predictions of the forecaster. This study uses the described CAPM-based parametric test which relies on the observed market and portfolio returns to test for managerial timing and selectivity abilities.

Henriksson and Merton (1981) showed that the derived performance model is heteroskedastic and the error term ϵ_{pt} has nonconstant variance. This study uses the White method (see p. 71) to correct for heteroskedasticity to obtain efficient estimates.

Chang and Lewellen (1984) tested a sample of 67 mutual funds for the period 1971-1979 using monthly data. The authors used the Henriksson-Merton model to test for the presence of market timing and stock selectivity abilities. They found no evidence of superior market timing, nor did the managers show any microforecasting abilities. Another study performed by Henriksson (1984) reached the same conclusions using a sample of 116 mutual funds over the period 1968-1980.

Bhattacharya-Pfleiderer Time-Varying Beta Model

The shortcomings of the Jensen's timing and selectivity model were corrected by Bhattacharya and Pfleiderer (1983). The authors substitute R_{mft} for π_{pt}, and through their formulation, the portfolio's timing and selectivity measures rely on return data from the fund, R_{pft}, and the market, R_{mft}. The model does not require any forecast data as in Jensen's case. The Bhattacharya and Pfleiderer's (BP) modification of Jensen's model is expressed as:

$$R_{pft} = \alpha_p + \theta E(R_{mf})(1-\varphi)R_{mft} + \theta\varphi(R^2_{mft}) + \omega_{pt}, \tag{2.18}$$

where

$$\varphi = \sigma^2_\pi/(\sigma^2_\pi + \sigma^2_\epsilon).$$

The term ϵ is the error associated with the fund manager's forecast, and σ^2_π and σ^2_ϵ are the variances of the terms π_{pt} and ϵ_{pt}. Furthermore, α_p is shown to be the proper consistent estimator for managerial selectivity skill. To test for the fund's macroforecasting (timing) skill, the components of the error term, ω_{pt}, are considered:

$$\omega_{pt} = \theta\varphi\epsilon_{pt}R_{mft} + u_{pt}. \tag{2.19}$$

BP showed that the manager's timing ability can be estimated by running a no-intercept regression of ω^2_{pt} on R^2_{mft}:

$$(\omega_{pt})^2 = \theta^2\varphi^2\sigma^2_\epsilon(R_{mft})^2 + \zeta_{pt}, \tag{2.20}$$

where

$$\zeta_{pt} = \theta^2\varphi^2(R_{mft})^2(\epsilon^2_{pt}-\sigma^2_\epsilon) + (u_{pt})^2 + 2\theta\varphi R_{mft}\epsilon_{pt}u_{pt}. \tag{2.21}$$

Merton (1980) proposed the following estimator for $\sigma^2\pi$:

$$\sigma^2_\pi = \{\sum_{t=1}^{n} [\ln(1 + R_{mft})]^2\}/n, \tag{2.22}$$

which requires only the market risk premium return, R_{mft}, as the input variable.

Using expressions (2.18), (2.19), and (2.22), BP showed that the manager's timing ability can be measured by investigating the correlation between the portfolio beta, β_p, and the market return, R_{mf}:

$$\rho_{TIM} = \sqrt{\sigma^2_\pi \,/\, (\sigma^2_\pi + \sigma^2_\epsilon)}. \tag{2.23}$$

To test for the manager's timing ability, the null hypothesis $H_o: \rho_{TIM}=0$ is tested. The managerial selectivity ability is tested by the null hypothesis $H_o{:}\alpha_p=0$.

Correction for Heteroskedasticity

The BP timing and selectivity model specified in expressions (2.18) and (2.20) is heteroskedastic and does not provide the most efficient estimates of the managerial timing and selectivity parameters due to the nonconstancy of the error terms' variance. The efficient estimates of the timing and selectivity measures can be computed using a generalized least squares method (GLS) which relies on the variances of the error terms ω_{pt} and ζ_{pt}. Lee and Rahman (1990) offered the following derivations for the variances of the error terms:

$$\sigma^2_\omega = \theta^2\varphi^2\sigma^2_\epsilon(R_{mft})^2 + \sigma^2_u, \tag{2.24}$$

and

$$\sigma^2_\zeta = 2\theta^4\varphi^4(R_{mft})^4\sigma^4_\epsilon + 2\sigma^4_u + 4\theta^2\varphi^2\sigma^2_\epsilon(R_{mft})^2\sigma^2_u, \tag{2.25}$$

where σ^2_ϵ is the estimate derived from expressions (2.18) and (2.20), and σ^2_u is estimated using expression (2.5): $R_{pft}=\alpha_p+\beta_p R_{mft}+u_{pt}$. Furthermore, the variables in expression (2.18), including the intercept term, α_p, are divided by σ_ω. This forms the following expression:

$$R_{pft}/\sigma_\omega = \alpha_p/\sigma_\omega + \theta E(R_{mf})(1-\varphi)R_{mft}/\sigma_\omega + \theta\varphi(R^2_{mft})/\sigma_\omega + \omega'_{pt}, \tag{2.26}$$

which is a no-intercept regression estimation procedure. Similarly, the variables in expression (2.19) are divided by σ_ζ:

$$\omega^2_{pt}/\sigma_\zeta = \theta^2\varphi^2\sigma^2_\epsilon(R_{mft})^2/\sigma_\zeta + \zeta'_{pt}, \tag{2.27}$$

where ω^2_{pt} is the original disturbance term of the expression

(2.18), and the computation procedure is continued as before. These new approximations provide the most efficient estimates for the managerial selectivity and timing ability measures.

Lee and Rahman (1990), using the BP model, tested for microforecasting and macroforecasting abilities of a sample of 93 mutual funds. The study used monthly returns over the period 1977-1984. The results show that 15% of the funds had significant positive stock selectivity, and 10% showed significant negative selectivity. Furthermore, 17% of the funds show that the managers were successful market timers, as evidenced by the significance of the results at the 5% level. The authors concluded that there is "some evidence" of superior performance among the individual mutual funds, and suggested that their results have implications for managers on how to formulate timing and selectivity strategies.

Lockwood-Kadiyala Stochastic Regression Model

Lockwood and Kadiyala (1988) (LK) proposed a time varying beta model to test for managerial timing and selectivity ability. The LK model avoids the shortcomings of the Jensen model (1968), which assumes a constant portfolio beta, and of the Henriksson-Merton model (1981) which relies on the assumption that the portfolio beta, β_p, be altered only when the market's condition is changed, i.e., when the sign of $R_{mft}=R_{mt}-R_{ft}$ is switched between bear and bull markets.

The LK model treats the portfolio beta as a stochastic parameter, β_{pt}. The model is formulated such that the portfolio beta is a time varying parameter:

$$\beta_{pt} = \delta_{p1} + \delta_{p2}\pi_{mt} + \phi_{pt}, \tag{2.28}$$

where

$$\pi_{mt} = R_{mft} - E(R_{mf}),$$

and

$$\phi_{pt} = \textit{random error}.$$

The expected market return, $E(R_{mf})$, is approximated using the sample market risk premium returns, R_{mft}. Under the LK's formulation, the time varying portfolio beta market model, $R_{pft}=\alpha_p+\beta_{pt}R_{mft}+\epsilon_{pt}$, is combined with the expression (2.28) to form the following timing and selectivity model:

$$R_{pft} = \alpha_p + \delta_{p1}R_{mft} + \delta_{p2}Q_{mt} + v_{pt}, \tag{2.29}$$

where

$$Q_{mt} = R_{mft}\pi_{mt},$$

$$v_{pt} = R_{mft}\phi_{pt} + \epsilon_{pt},$$

and

$$corr(\phi, \epsilon) = 0.$$

In addition, the mean of expression (2.29) is expressed as:

$$E(R_{pf}) = \alpha_p + \delta_{p1}E(R_{mf}) + \delta_{p2}\sigma^2_{Rmf}, \tag{2.30}$$

which shows that the outcome of the manager's portfolio timing activities are related to the market risk premium return volatility.

To test for the manager's timing ability, the null hypothesis $H_o{:}\,\delta_2=0$ is tested. Furthermore, α_p provides a consistent estimator of the managerial selectivity ability, which is a test of the null hypothesis $H_o: \alpha_p = 0$.

Due to the heteroskedasticity of the error term:

$$\sigma^2_v = \sigma^2_\epsilon + \sigma^2_\phi R^2_{mft}, \tag{2.31}$$

the derived timing and selectivity model requires correction to account for nonconstant error term variance. This study uses White's method (see p. 71) to correct for the model's heteroskedasticity.

The Lee and Chen (1982) variable mean response regression model and Chen and Stockum's (1986) generalized random beta model are similar to the LK model with minor differences in interpretation of the parameters and formulation of the methodology. However, all of these models are based on the pioneering work of Treynor and Mazuy (1966) which introduced the quadratic regression model to test for managerial timing ability. Treynor and Mazuy did not consider the heteroskedasticity of the error term.

Using the stochastic regression performance model, Lockwood and Kadiyala (1988), tested a sample of 47 mutual funds over the period 1964-1979 using monthly returns. The results reported show that the majority of funds do not demonstrate any managerial skill in macroforecasting and microforecasting abilities.

The BP timing and selectivity model specification is similar to the LK methodology. The estimation procedures for measuring the managerial selectivity ability, α_p, are identical. However, the BP model uses the error term, ω_{pt}, to measure the managerial timing ability, whereas the LK methodology relies on the significance of the coefficient of R^2_{mft} in their quadratic regression model. This study uses the generalized least squares (GLS) for the BP model and White's method (see p. 71) for the LK model to correct for the models' heteroskedasticity to account for nonconstant error terms variance. The White method is not applicable to the BP methodology because of the model's specification.

Using the JN, HM, LK, and BP performance models, we tested our sample of mutual funds for the period 1984-1989 using monthly data. This study uses the funds data from the Weisenberger and Standard and Poor's (1984-1989) "Security Owner Stock Guide" reports. The return data is based on selected mutual funds over the period 1984-1989 (6 years) which are invested primarily in U.S. stocks and satisfy the following criteria:

1) the fund existed for the entire 1984-1989 period;
2) at most, 15% of assets in cash majority of the time;
3) at most, 2% in bonds;
and
4) short selling, investments in options, and calls are not permitted.

Using the above criteria, a sample of 31 mutual funds qualified. Appendix A provides a list of the selected funds and their investment objective. The fund size distribution is shown in Table 1.

Table 1

Selected Mutual Funds' (31) Size Distribution

Total Assets ($mil)	Frequency
< 100	6
100 - 250	4
250 - 500	4
500 - 750	6
750 - 1000	5
> 1000	6

The Wiesenberger report (1989) classifies the selected funds as Maximum Capital Gains, Long-Term Growth, and Growth and Current Income.

The market proxy is represented by the S&P 500 value-weighted index, which includes capital appreciation, dividends, and their reinvestment. The risk-free rate is represented by one-month T-bills. The performance results are summarized in Table 2. The individual fund performance results are included in Appendix B. As the results indicate, we also confirm the previous studies that, on average, fund managers do not possess superior timing and selectivity abilities.

Table 2
Summary of Sample Mutual Funds' (31) Performance Using Various Models

Model	$\alpha_p{}^a$	$\beta_p{}^a$
Jensen	(1^{**})	(24^{**})
Henriksson-Merton[b]	2^{*}	$3^{*}(1^{**})$
Lockwood-Kadiyala[b]	2^{*}	$1^{*}(5^{**})$
Bhattacharya-Pfleiderer[b]	1^{*}	(2^{**})

[a]Number of funds with significant performance parameter.
[b]Models corrected for heteroskedasticity.
*Significant at the 5% level.
(**)Significant at the 1% level.

Roll (1978) has criticized the performance evaluation studies suggesting that a true market portfolio is not observable, which in turn affects the computation of the portfolio beta. Mayers and Rice (1979) acknowledge the problems with the proper identification of the benchmark portfolio. However, in response to Roll, the study argues that the widely used market proxies as the benchmark portfolio are the "best available" and that the results of CAPM-based portfolio studies are valid.

As discussed by Grinblatt and Titman (1989), the set of assets that comprise the benchmark portfolio and the portfolio being evaluated should be consistent. This argument is applicable to our study and a further discussion is provided in Section (4.2.2).

Cornell (1979) proposed a model which uses the portfolio composition data to arrive at an overall performance measure.

The model avoids the claimed shortcomings of the CAPM-based performance measures by Roll (1978). The Cornell measure does not distinguish between managerial selectivity and timing abilities. Elton and Gruber (EG) (1986) also proposed a timing and selectivity model which requires knowledge about the portfolio composition. The EG timing measure relies on the covariance, $COV(\gamma(s),X_m)$, between the proportion of the portfolio invested in stocks, $\gamma(s)$, and the market return, X_m. The selectivity parameter is based on the covariance between the proportion of the portfolio invested in individual securities and on their returns.

Using portfolio composition data, Ferri, Oberhelman, and Roenfeldt (1984) tested a sample of 69 mutual funds for market timing ability. The study employed the quarterly data for funds which were classified as Maximum Capital Gains or Long-Term Growth, over the period 1975-1980. The funds' asset sizes were categorized as small (less than $100M), medium ($100M-$250M), and large (greater than $250M). The study's approach did not consider the change in portfolio beta using the timing and selectivity models as did other studies, and their methodology was based on whether or not the percentage of the total assets in common stocks changed during bull and bear markets. Regardless of the type and size of the fund, the evidence found was against successful market timing.

Hwang (1988) examined the robustness of various performance measures for their accuracy in ranking portfolios and in the identification of positive performance. The study's results indicated that the Elton-Gruber measure is the most robust in detecting managerial timing performance. The Henriksson-Merton methodology was chosen as the best model to reveal managerial selectivity ability, and the Cornell measure was recommended as the most appropriate for capturing total performance.

Another recent development in the area of performance measurement is investment evaluation using the Arbitrage Pricing Theory (APT) proposed by Ross (1976). In the APT model context, the portfolio (security) returns are expressed in terms of a linear relationship between multiple factor shocks. The difficulty in identification of these factors has been suggested as one of the shortcomings of the APT. Some of the popular economic (factor) shocks include market portfolio return, real economic growth, inflation, unemployment, and interest rates. Chang and Lewellen (1985), Connor and Korajczyk (1986), and Lehman and Modest (1987), among others, have proposed performance models based on the APT. Because of the data requirement constraints of the Cornell, Elton and Gruber, and APT performance models, we will not address them further in this study.

The previous discussion has provided ample evidence of mutual funds' performances using various methodologies with different specifications. The majority of the results indicate that fund managers are unable to produce returns above the benchmark portfolio, often represented by various market indices. Occasional evidence of superior performance in prior work has been regarded as mere chance. One argument to explain the poor performance of mutual funds has been the incurring fund expenses and transaction fees. Furthermore, this has given an opportunity for proponents of the efficient market hypothesis to defend their position, that "beating the market" is not possible. However, a review of mutual funds' performance records indicates that some of the funds have been able to beat the market during extended periods of time, i.e., five or ten years, in absolute returns.

These arguments point to several possible explanations. As one group of researchers has discussed, it is possible that fund managers are not able to produce superior returns due to their inability to correctly forecast future economic events. One could also perceive the problem from the widely-used models' perspective that the performance models are weak and misspecified in detecting managerial skills. Yet, the common data problems including noise, measurement errors, and misspecified variables also contribute to the biases in inferences drawn from the performance studies. The amount of variability that exists in the return data due to known and unknown factors plays a major role in what the output of the performance models means.

If the input to the model is controlled, it would be possible to understand the mechanism (or working characteristic) of the model. One way to approach this is by means of a simulation. A reasonable question is how great a manager's return needs to be before it is recognized as skillful. The only studies to date that have addressed this point are those of Murphy (1980) and French and Henderson (1985). Utilizing the Jensen measure, both studies proposed that funds should have monthly excess returns of at least 1% before being shown statistically significant by the Jensen model. However, Jensen's measure is only adequate for specific portfolio management environments. For example, the model breaks down in the presence of managerial timing activities. However, the more sophisticated models that account for managerial timing and selectivity activities have not yet been tested using a simulation procedure. Furthermore, the form of input return data that is constructed after the real mutual fund portfolios has not been discussed.

Given the amount of noise that is characteristic of the mutual fund return data, how skillful do managers need to be before being identified as superior? In other words, in managerial timing and selectivity environments, what magnitude of portfolio returns are required before the various mutual fund performance models show a manager as having superior ability in market timing and stock selection. In this study, these skills will be considered both in isolation and in combination.

The literature review shows an absence of adequate simulation studies to test the power of various timing and selectivity models. The selected models represent a complete set when the available data includes the portfolio returns and relevant market data. This study will examine the following timing and selectivity models: 1) Jensen (JN); 2) Henriksson-Merton (HM); 3) Lockwood-Kadiyala (LK); and 4) Bhattacharya-Pfleiderer (BP). Furthermore, the models chosen for our study have been used on an extensive basis to test mutual fund performance. The simulation design in this study is unique as it considers realistic portfolio environments. This study proposes a variety of skill environments in timing and selectivity abilities, which is a realistic assumption in classifying the mutual fund portfolio managers as underperformers (no-skill), average (semi-skilled), and outperformers (skilled). Using these skill environments, the designed simulation examines the power of mutual fund performance models.

Chapter 3

DESIGN OF SIMULATION MODEL

The objective of the designed simulation is to examine the power of various timing and selectivity models. The models considered treat the portfolio beta with varying degrees of stationarity. The findings of the study will show whether the stochastic beta models result in significant improvements over the simpler models, those which treat the portfolio beta as constant or bivariate. The experiments are conducted in environments in which there are diverse portfolio management skill levels. The generated portfolios depict varying degrees of skill in market timing and stock selectivity. After having designed several different portfolio structures, the study conducts tests to examine the effectiveness of various timing and selectivity models to detect macroforecasting and microforecasting skills.

The important question being addressed is how different timing and selectivity models perform when varying degrees of managerial skill exist. Therefore, it is necessary to devise a simulation procedure to introduce timing and selectivity ability into portfolio returns in a realistic manner.

The expertise of the portfolio manager in market timing (macroforecasting) and stock selectivity (microforecasting) is based on how frequently (s)he can correctly predict market direction and stocks with superior returns. We assume that the skills of macroforecasting and microforecasting are independent events, as it is possible for a portfolio manager to be a successful market timer, yet have holdings in stocks that give merely average or subaverage returns.

We employ a simulation procedure that compares the power of selected timing and selectivity models by examining their errors in testing the null hypotheses of no market timing and no selectivity abilities. Errors are committed by rejecting the null hypotheses that no market timing and no selectivity forecasting abilities (independent events) exist when, in actuality, they do (managers lack ability). Similarly, after having introduced timing and selectivity abilities into the data, errors will be committed when the test fails to reject the null hypotheses, that no timing and no selectivity abilities exist, when it is false (managers possess skill).

In this chapter, the time series behavior and distributional properties of monthly market returns over the period 1975-1989 (15 years) are investigated. Then, the modelling procedure for the market returns is discussed. This forms the basis for the proposed design of timing and selectivity portfolios. The design of portfolio returns is based on the simulated series of market returns and on the portfolio cash composition.

The monthly portfolio and market returns in the risk premium form and the portfolio's monthly percentage of assets in cash will be generated according to a ten year period

(N=120). The market risk premium returns are modelled using the distributional characteristics of the series over the period 1975-1989. The portfolio's monthly cash composition, expressed in percentage, will be generated according to the empirical distribution of the series for our sample of mutual funds over the period 1984-1989 (6 years). Our choice of these particular periods is consistent with most of the recent mutual fund timing and selectivity studies' data.

3.1 BEAR AND BULL MARKET CLASSIFICATION

Various mutual fund timing and selectivity studies have defined bull and bear markets according to the parameters of the market and their trends. Some of the most common definitions found in mutual fund performance studies performed by Fabozzi and Francis (1979), Kim and Zumwalt (1979), and Veit and Cheney (1982) are the following:

1) a bull market is distinguished from a bear market according to the magnitude of the market return, R_m. A bull (up) market is defined where:

   a) the market return, R_m, exceeds the average market return, $E(R_m)$; or

   b) the market return, R_m, exceeds the risk-free rate, R_f; or

   c) the market return, R_m, exceeds zero.

2) some of the popular definitions taking into account the market trend are:

   a) a period is defined as an up or down market depending on whether the absolute value of the market return, $|R_m|$, is larger than one half of one standard deviation of the market return, $\sigma_{Rm}/2$. The periods which do not qualify are not used and are defined as neither up nor down market.

b) another trend-based definition by Cohen, Zinbarg, and Zeikel (1973) considers a period as bearish or bullish depending on whether the markets in surrounding periods are rising or declining. For example, a rising period surrounded by declining periods is classified as a bearish period.

There are still other definitions which are variations of the above classifications. Some of the mutual fund studies have examined the sensitivity of the results to the different bull/bear market definitions. For example, Veit (1982) used four different definitions of up and down markets to test if mutual funds over the period 1944-1978 were successful timers. His study results did not change with different up and down market definitions. Similarly, Alexander and Stover (1980), Fabozzi and Francis (1979), and Kim and Zumwalt (1979) used different definitions to test for the stability of mutual fund performance parameters, i.e., alpha and beta, and found that their studies' results were not sensitive to different bull/bear market classifications.

To test for required predictive accuracies in bear and bull markets, the timing studies conducted by Sharpe (1975), Jeffrey (1984), Chua (1986), Clarke (1989), Droms (1989), Sy (1990), and Kester (1990) define the bull/bear market based on whether the market return, R_m, or the risk-free rate, R_f, exceed each other in each period, i.e., $R_m > R_f$ is classified as a bull period, and $R_m \leq R_f$ indicates a bear period. We will use this definition for our study. Given our intention to examine the relative power among the mutual fund performance models, the validity of our results should not be jeopardized by our choice of bear/bull market definition.

To be consistent with our sample mutual fund return data, the generated portfolio returns will be on a monthly basis. Furthermore, monthly switchings, or portfolio revisions, will be introduced into the data to reflect timing and selectivity skills. The mutual fund performance models chosen for our study for the purpose of relative power comparison have been empirically tested in most of the recent studies that have used monthly switchings. Kon (1983), Chang and Lewellen (1984), Henriksson (1984), Lockwood and Kadiyala (1988), and Lee and Rahman (1990) have assumed monthly switchings to test for the presence of managerial timing and selectivity skills.

Other mutual fund timing studies, dealing with predictive accuracy, undertaken by Droms (1989), Clarke (1989), Sy (1990), and Kester (1990) have also considered portfolio revisions on a monthly basis. The trade-off between transaction costs and more frequent switchings is dependent upon variables which are specific to each fund manager, i.e., portfolio size and funds' established guidelines. Our choice of bear/bull market definition and monthly switchings, or portfolio revisions, is consistent with the other recent mutual fund performance studies and will thus allow us to compare our results with the work of others and improve upon the previous work.

3.2 DATA GENERATION OF MARKET RETURNS

The focus of our study is equity mutual fund portfolios and their measures of timing and selectivity. As was previously discussed, we are assuming monthly switchings between common stocks and Treasury bills for the purpose of managerial timing activities, or portfolio revisions. The timing and selectivity models used in our study are all expressed in terms of risk premium, i.e., $R_{pf}=R_p-R_f$ and $R_{mf}=R_m-R_f$. The risk premium can be explained in terms of the premium (expected return) that investors receive from taking risk in their investments; in other words, the expected return from investments in risky assets.

To generate the simulated market and portfolio returns in the risk premium form, the time series behavior and distribution of market risk premium, R_{mf}, are investigated. To accomplish this, it is also necessary to explore the relationship between the proxies for the market return, R_m, and the risk-free rate, R_f, through time. Furthermore, this study is concerned with the behavior of assets in the aggregate, i.e., portfolios, rather than individual stocks.

3.2.1 Time Series Behavior of Market Risk Premium

The time series behavior of security prices and their distribution have been investigated extensively in the financial literature. In one of the original studies, Granger and Morgenstern (1963) showed that during the period 1875-1956, U.S. stock indices including S&P, Dow Jones, and other stock prices indices in manufacturing, transportation, utilities, mining, and trade and finance closely followed a random walk. The authors used spectral analysis with weekly and monthly returns to investigate the presence of any cycles that could be used for forecasting the price movements. The study's conclusion was that, "the evidence of 'cycles' obtained" was not significant and that any attempts to exploit the stock price trends would be, "at best only marginally worthwhile."

The majority of the random walk studies in the financial literature have considered individual stock returns on a daily basis and some even used annual data. Fama (1965) examined the daily prices of stocks on the Dow Jones Industrial Average over the period 1957-1962 to test for dependence. The results for daily, four-day, nine-day, and sixteen-day price changes indicated a strong independence in the data. The three methods used to test for dependance were serial correlation, runs test, and Alexander's filters test.

Fama and French (1988) studied the permanent and temporary components of stock prices. The data consisted of the monthly returns of all stocks listed on the New York Stock Exchange. The study considered value-weighted and equal-weighted portfolios, together with a grouping of stocks based on a specific industry and size. The authors reported a predictable variation of less than three percent of the total variation for small time horizons. For longer time horizons, those of 3-5 years, the predictability increases. The results of this study confirmed the previous random walk studies' results that the reported autocorrelations are not substantial for time horizons that could provide any meaningful results for portfolio management practices.

Jegadeesh (1990) claimed that individual stock returns are predictable. The study employed monthly return data from the Center for Research in Security Prices (CRSP) file. The author reported that patterns of serial correlation are seasonal, and in particular, the month of January was found to be different from the other months. The dependence in data was reported as significant at the 5% level for negative first-order and positive higher-order serial correlations. It is suggested that these results are due to an inefficient market or variations in expected stock returns.

The issue of random walk in the capital markets will continue to be debated in the financial literature. It is certain that no study has shown an absolute random walk or departure among the share prices on an individual or an aggregate basis. Whatever the form of the market "walk", it is possible that, occasionally, patterns might exist that could offer insight into the direction of this debate. However, it is possible that period-specific social, economical, and political factors influence the share prices as well. The studies that have identified a trend in security prices point to patterns which are not economically significant. On the other hand, the statistical models used to examine the behavior of security prices could also be inadequate or lacking in power. The upcoming discussion regarding the distribution of stock prices also shares such shortcomings.

The argument of inadequate models was considered by Peters (1989,1991) who applied the Chaos theory to test for patterns and trends in capital market returns. This relatively new technique relies on modelling systems based on non-linear dynamics. The preliminary work of Peters has not produced results that could be economically implemented in practice, i.e., for forecasting purposes. However, if the capital markets and the economical systems have properties that can be explained in terms of a fractal structure, then there is promise in developing financial models that are based on non-linear dynamic systems.

For this study's modelling purposes, the S&P 500 monthly risk premium returns over the period 1975-1989 (15 years, N=180) are investigated. Our proxy for the risk-free rate, R_f, is the one-month Treasury bill rate. This particular choice of risk-free rate is consistent with mutual fund timing and selectivity studies. The market return, R_m, is estimated using the S&P 500 value-weighted index. The monthly returns for R_m and R_f were obtained from the Ibbotson and Sinquefield annual year book (1990).

Ibbotson and Sinquefield (1989) used annual return data over the time period 1926-1989 to investigate the time series behavior of equity risk premium composed of value-weighted S&P 500 index (including capital appreciation, dividends, and their reinvestments), and Treasury bills having the shortest maturity (not less than one month). They suggested that the equity risk premium closely follows a random walk pattern. The study reports a first-order autocorrelation of .02. Since our study employs models which are in terms of equity risk premia, we would extend Ibbotson and Sinquefield's work in a more detailed way using monthly data over the period 1975-1989.

First, the results of the serial correlation analysis with various lags are reported. The cross correlation between the market return, R_m, and risk-free rate, R_f, is also investigated. The behavior of the S&P 500 risk premium, $ln(1+R_{mf})$, over the 15 year period 1975-1989 using monthly data is presented in Figure 1. The time pattern does not show any observed trends. The estimated autocorrelations up to lag fifty are depicted in Figure 2. The significance of autocorrelation estimates is investigated using the test statistic offered by Box and Jenkins (1976):

$$Q = N \sum_{k=1}^{M} r_k^2, \tag{3.1}$$

where r^2_k is the autocorrelation estimate at lag k, M is the number of lags, and N represents the number of observations (N=120). Q is approximately distributed as χ^2 with M degrees of freedom. The results, at the 5% significance level, indicate that the hypothesis of random walk is not rejected for our market risk premium, R_{mf}, monthly data. In other words, the series does not present any significant dependance among its elements. The cross correlation analysis between the market return, R_m, and risk-free rate, R_f, using a similar test statistic, offered by Box and Jenkins (1976):

$$S = N \sum_{k=1}^{M} r_k^2, \tag{3.2}$$

also shows a lack of significant cross correlation among the market risk premium, R_{mf}, components, R_m *and* R_f, at the 5% significance level. For the S statistic, r^2_k represents the cross correlation estimate at lag k between R_m *and* R_f . The test for significant cross correlation between the market return, R_m, and the risk-free rate, R_f, is conducted using leads and lags of ±48 periods. The estimated cross correlations are shown in Figure 3. These results confirm the hypothesis of random walk for the monthly market risk premium data, $ln(1+R_{mf})$, over the period 1975-1989.

Figure 1. Time Pattern of ln(1+Rmft), Monthly Returns 1975-1989

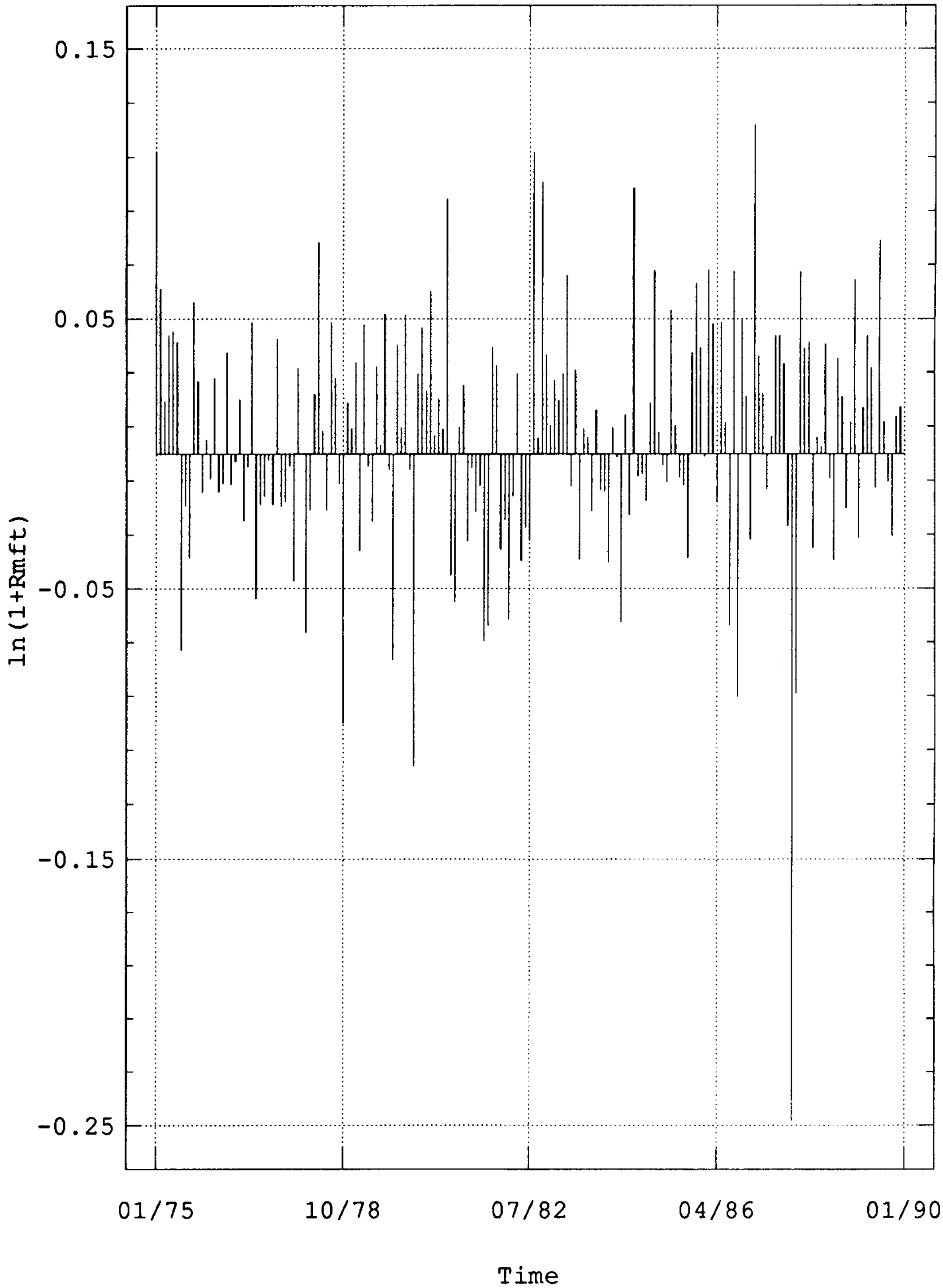
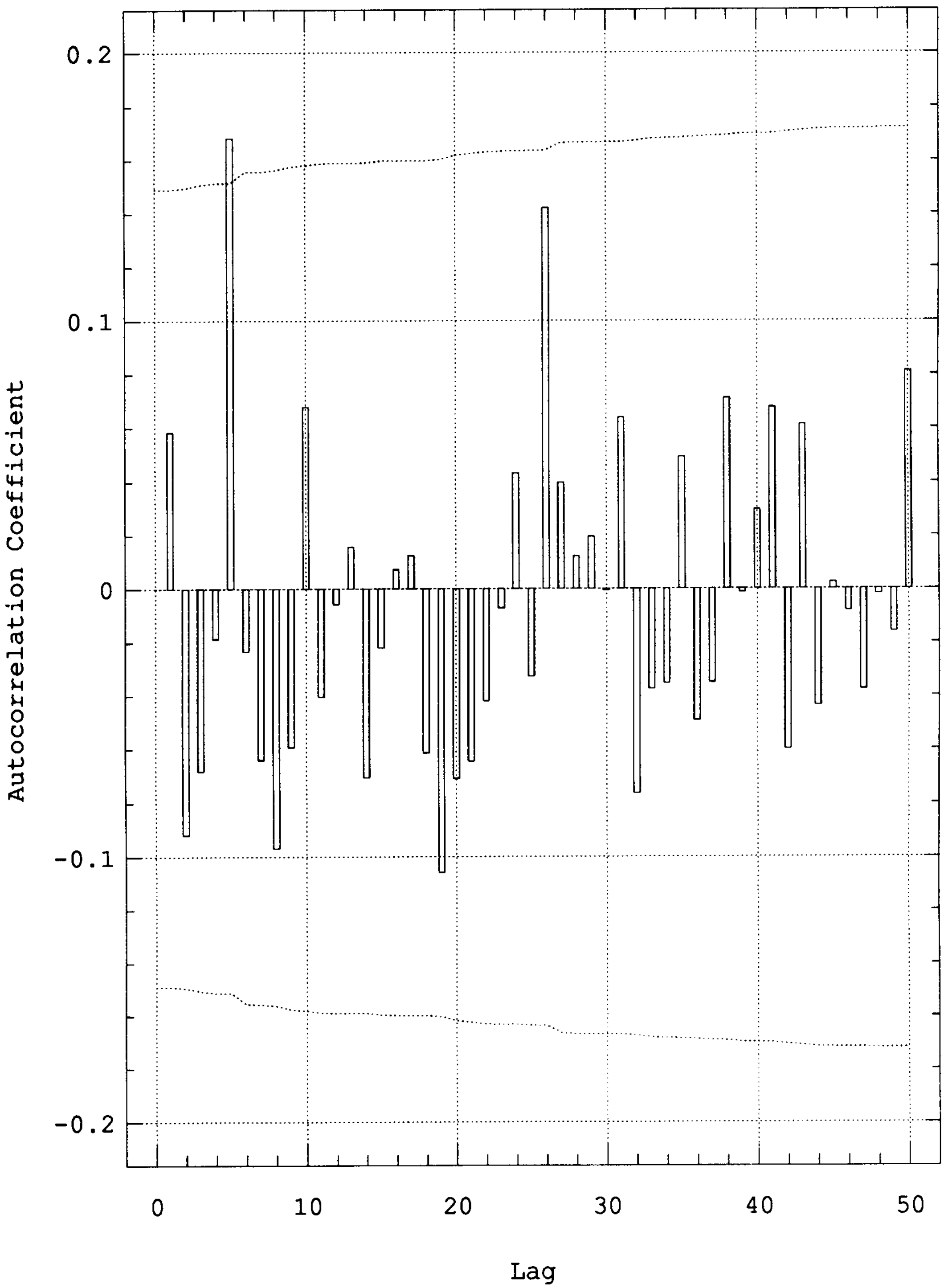


Figure 2. Estimated Autocorrelations of ln(1+Rmft), Monthly Returns 1975-1989



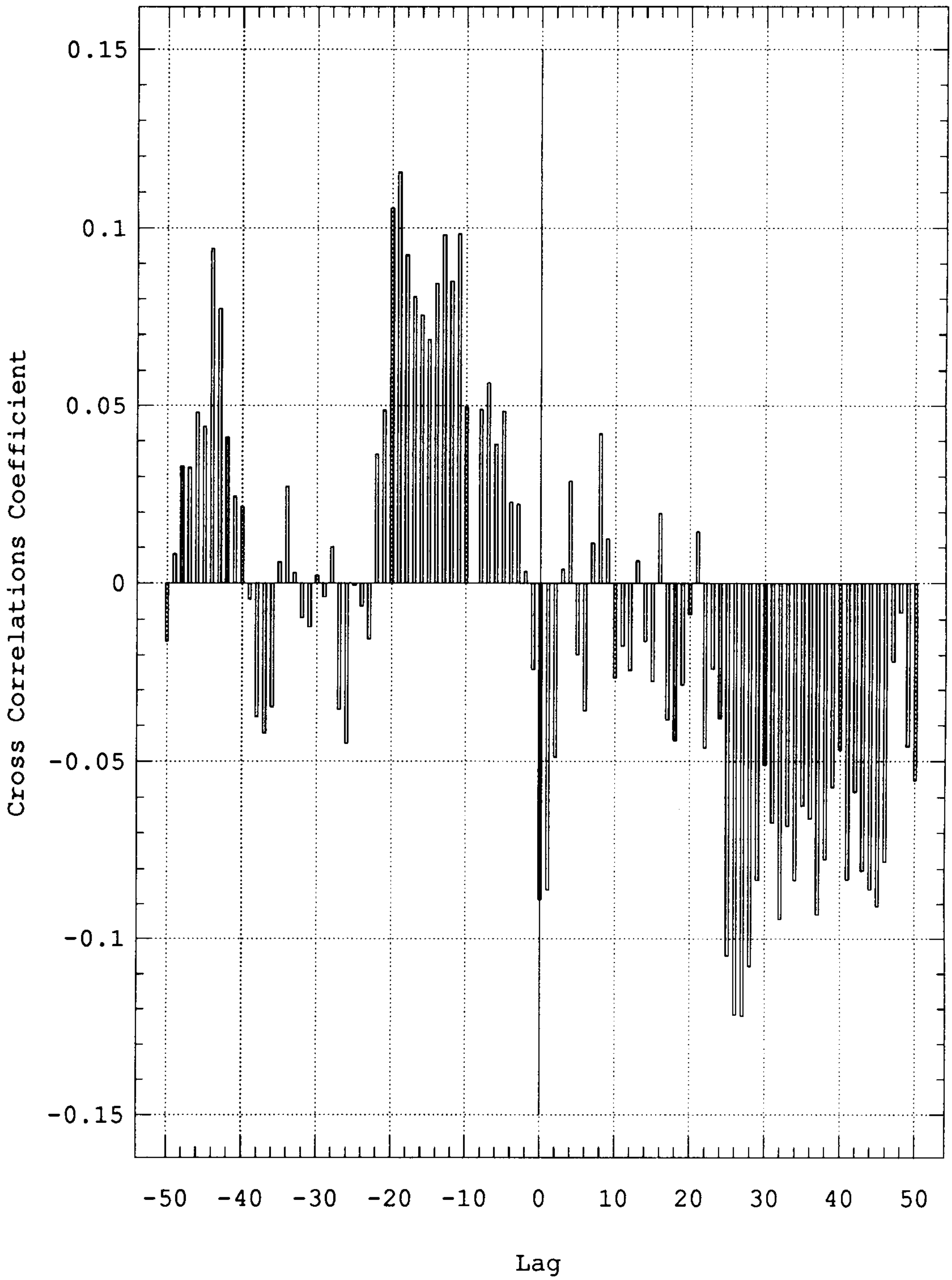
3.2.2 Distributional Properties of Market Risk Premium

In addition to the time series behavior, the underlying distribution of asset returns has also been widely investigated. The common practice in the field of finance is to assume a lognormal distribution for the stock returns. Part of the research, performed by Officer (1972), Fieltz and Smith (1972), Leitch and Paulson (1975), and Simkowitz and Beedles (1980), among others, has emphasized stable paretian (SP) distributions as alternatives in explaining the population model of the returns. The normal and lognormal distributions are among the family of SP distributions, which are identified by four parameters. A particular distribution is differentiated by the first parameter α, i.e., α=2 for the normal distribution. The mean, variance, and symmetry of the distribution are characterized by the second, third, and fourth parameters.

Next, the empirical studies dealing with the distribution of stocks are discussed, and then for this study's modelling purposes, the distributional properties of the sample market risk premium return series, R_{mf}, are explored and the results are presented.

Most of the studies investigating the distribution of stock returns have dealt with individual securities, but recently the underlying distribution of stocks in the aggregate has also been investigated. Press (1967) proposed that the distributions of individual stocks are generally

Figure 3. Estimated Cross Correlations Between ln(1+Rmft) and ln(1+Rft)



skewed and leptokurtic, a distribution which is peaked higher and has denser tails than a normal variate. The author used the monthly data of the Dow Jones Industrial Average stocks over the period 1926-1960. Officer (1972), Fieltz and Smith (1972), Leitch and Paulson (1975), and Simkowitz and Beedles (1980) using daily and monthly stock returns, concluded that the observed distributions deviate from a normal variate and can be characterized as leptokurtic. Furthermore, kurtosis and skewness representative of a asymmetric stable distribution were present.

Blattberg and Gonedes (1974) used daily rates of return for 30 securities of the Dow Jones Industrial Average over the period 1957-1962 to show that the student (or t) distribution presented a better fit than the symmetric stable distributions. Hsu, Miller, and Wichern (1974) challenged the notion of variance nonstationarity and heavy-tailed distributions. Using the daily closing prices of four stocks over the period 1963-1970, the study concluded that during "subperiods of homogenous activities," stock returns can be modeled using a normal family of distributions. Furthermore, in the periods of time during which the capital markets are characterized by constant changes, it is suggested that the parameters of the assumed distributions are subject to nonstationarity.

Using the daily returns of individual stocks on the Dow Jones Industrial Average, and the S&P 500 equal-weighted and value-weighted indices, over the period 1962-1980, Kon (1984) showed that the stocks' underlying distribution can be better represented by a discrete mixture of normal distributions than the student model. Bookstaber and McDonald (1987) used the daily returns of 21 randomly chosen stocks from the Center of Research in Security Prices (CRSP) files to introduce a generalized distribution which accounts for different degrees of fat tails in the observed stock distributions. The individual stocks' returns were also examined for longer holding periods. The study suggested that the proposed distribution is viable for explaining the behavior of option pricing models.

Other studies have considered the distribution of stock returns on an aggregate basis, which is consistent with our study. Upton and Shannon (1979), using monthly returns over the period 1956-1975, investigated how the portfolios of fifty stocks, randomly chosen from the New York Stock Exchange, were distributed. The authors used the Kolmogorov-Smirnov (KS) test to examine the goodness-of-fit, and their findings indicate that monthly portfolio returns follow a lognormal distribution. The results for individual assets showed a departure from lognormality. Furthermore, the portfolio strategies, rebalanced verses buy-and-hold, did not alter the study's findings.

Tehranian and Helms (1982) conducted a similar study using monthly returns over the period 1961-1976. The distribution of NYSE stocks were investigated by examining 500 portfolios of 20 stocks randomly selected from the set of 685 stocks listed on the Exchange. This study, also using the KS test, concluded that portfolio returns fall under a lognormal distribution. Next, the empirical distribution of the market risk premium series, R_{mft}, over the period 1975-1989 is explored.

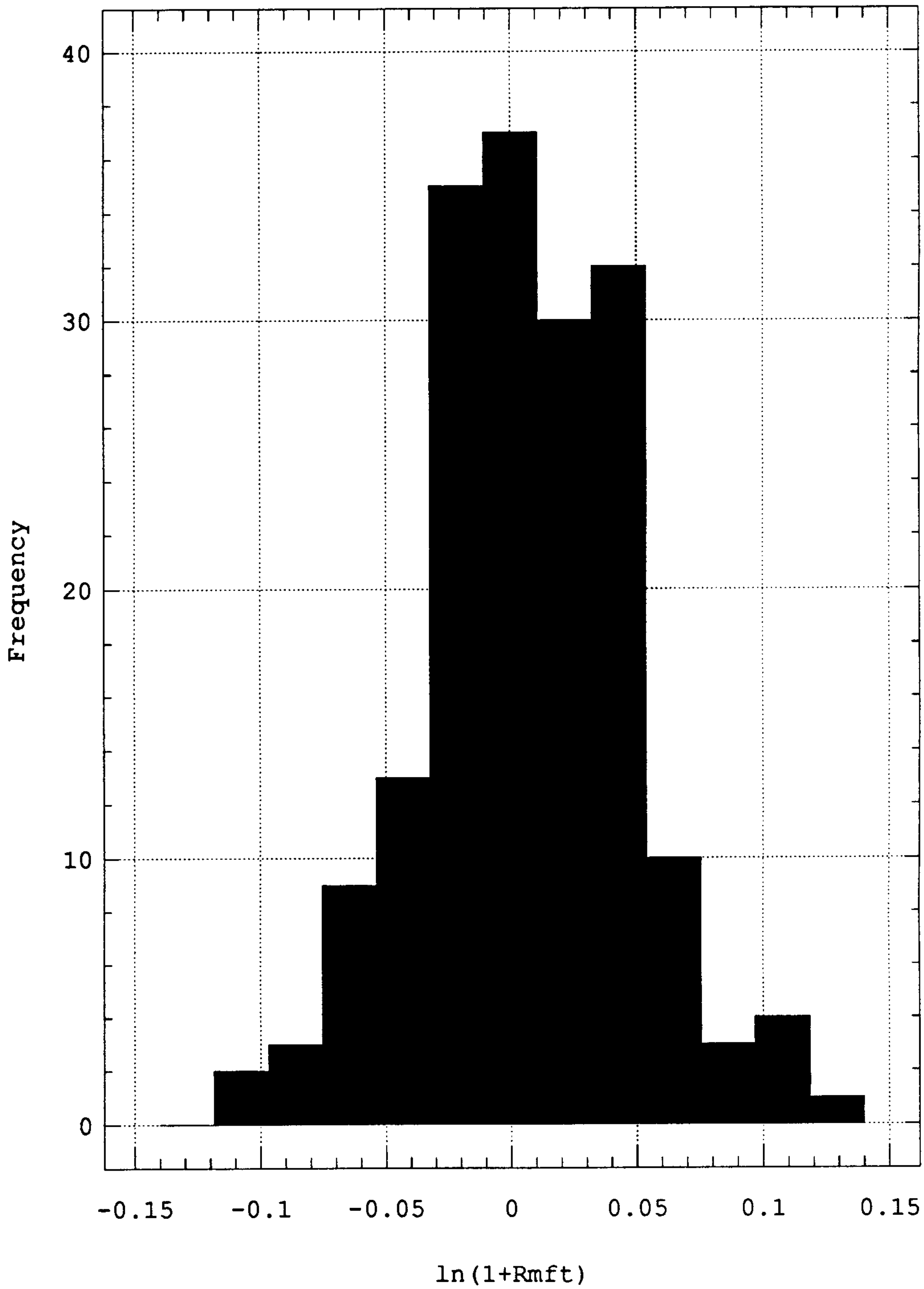
The market risk premium monthly returns are calculated by subtracting the risk-free rate (one-month T-bills) from the market return (S&P 500), $R_{mft}=R_{mt}-R_{ft}$. This study uses the natural logarithm of asset return relatives, $ln(1+R_{mft})$, to investigate the distributional properties of this time series. The frequency distribution of the monthly market risk premium return relatives, $ln(1+R_{mft})$, over the period 1975-1989 (15 years) is shown in Figure 4. The mean and standard deviation of the period 1975-1989 and various subperiods are summarized in Table 3.

Table 3

Mean and Standard Deviation of Monthly Market Risk Premium Series Return Relatives, $ln(1+R_{mft})$

Period	1975-1989	1975-1979	1980-1984	1985-1989
$\mu_{ln(1+Rmf)}$	0.005699	0.004348	0.002767	0.009983
$\sigma_{ln(1+Rmf)}$	0.045369	0.039163	0.043675	0.052672

Figure 4. Distribution of ln(1+Rmft),
Monthly Returns 1975-1989



The results of the goodness-of-fit test using the Kolmogorov-Smirnov (KS) test is overwhelmingly in favor of the lognormal distribution at the 5% significance level *(KS=0.0684, Sig. level=0.37)*. In other words, the assumption of a normal distribution for the time series $ln(1+R_{mft})$ is confirmed.

The studies that have investigated the volatility, or variability in returns, of the stock market also provide insights into the behavior of security prices. Poterba and Summers (1986) claimed that volatility shocks, or periods of higher uncertainty, to the stock market are temporary and will dissipate over long periods. The authors used the S&P 500 composite stock index data over the period 1926-1984. They showed that the volatility shocks last for less than six months, sometimes lasting only a month.

Jones and Wilson (1989) undertook a similar study which considered volatility between months over the period 1885-1989 using S&P 500 and other indices existing before the formation of S&P. The authors investigated the within-decade volatility over the past 100 years and reported that the highest volatility was observed during the Great Depression of the 1930's. Based on month-to-month percentage changes within decades, the volatility in the 1980's is shown to be comparable to other decades.

Bookstaber and Pomerantz (1989) suggested that volatility tends to be mean-reverting: above-average volatility declines and below-average volatility increases. The study claimed that volatility is expected to be stable over long time periods and should not deviate from the mean level significantly.

Harris (1989) studied the volatility of S&P 500 stocks and the factors that might influence it. Causes of relative increased volatility in the S&P 500 stock index were listed as: the origin of trade in index futures and index options, growth in foreign ownership of American equities, and the growth in index funds. The magnitude of increase was less significant over bi-weekly and longer return time intervals.

Schwert (1990) confirmed the results of previous studies which had shown that growth in computerized trading and in stock index futures and options did not increase stock market volatility. The volatility of monthly returns on the S&P 500 and NYSE stock indices over the period 1885-1989 is shown to be stable. The significant increases in volatility were observed only during times of uncertainty, such as throughout the Great Depression, 1929-1939, and following Black Monday, October 1987. The study cites several economic factors that cause long-term volatility: financial leverage, operating leverage, personal leverage, and the condition of the economy.

In our study, the stationarity of the market risk premium return relatives' distribution over various subperiods, as was shown in Table 3 (p. 59), was tested. At the 5% significance level, the mean and variance of the underlying distributions over the three five-year subperiods were not statistically different, which implies strict stationarity for the series $ln(1+R_{mft})$. These results validate our assumption of a normal distribution model for the market risk premium return relatives, $ln(1+R_{mft})$.

In the previous discussion, the time series properties and the distributional characteristics of the market return series in the risk premium form, $ln(1+R_{mft})$, were examined. It was shown that the series, $ln(1+R_{mft})$, can be approximated using a normal distribution with parameters $N(0.0057, 0.0454)$. Using a sequence of generated standard normal variates, $ZRMF$, the simulated monthly market returns are computed as follows:

$$R_{mft} = EXP(ZRMF_t \sigma_{ln(1+Rmf)} + \mu_{ln(1+Rmf)}) - 1 \qquad t=1,120. \qquad (3.3)$$

The procedures for the design of timing and selectivity portfolios are presented in the following sections. This part of the study also includes a discussion of how to account for noise. The latter part of Chapter 3 presents a summary of the simulation procedure and the model validation.

3.3 DESIGN OF TIMING PORTFOLIOS

Market timing is the ability to predict major market movements. A manager with superior timing skills is ideally fully invested in common stocks when the share prices are rising; yet when the share prices are declining, the skilled timer will invest in assets which are not affected by the down-turn of the market, such as cash equivalents or short-term securities. If bear markets did not exist, there would be no need to forecast the market movements, as the investors' primary research activities would be directed toward stock selection. Therefore, the main objective of market timing is to stay out of declining stock markets for as long as they last.

From the above discussion, one can conclude that a fund manager will ideally invest a higher proportion of assets in stocks when a bull market is present, and while a bear market is present, the proportion of the portfolio invested in stocks will be lowered. Such portfolio adjustments during market movements can also be explained in terms of changing the risk of the portfolio. As an upward-moving market warrants a higher risk portfolio to capitalize on the increasing share prices, and a declining market will require a partial divestment in stocks to control for the falling share prices. A manager, given the fund's objectives and guidelines, can control the portfolio risk in three ways. If a manager is to be invested in stocks at all times, the portfolio management timing activities will be directed primarily toward the identification of high and low risk stocks. However, a manager whose guidelines permit a varying degree of investments in other assets has the advantage of switching the portfolio holdings to alternate assets during up and down markets, which could be thought of as an asset allocation strategy. Finally, the manager could engage in a combination of the two stated strategies. This study's timing model is based on fund managers whose portfolio management activities are primarily focused on switchings between stocks and cash equivalent/short term Treasury securities, with the majority of the assets being invested in the stock market portfolio.

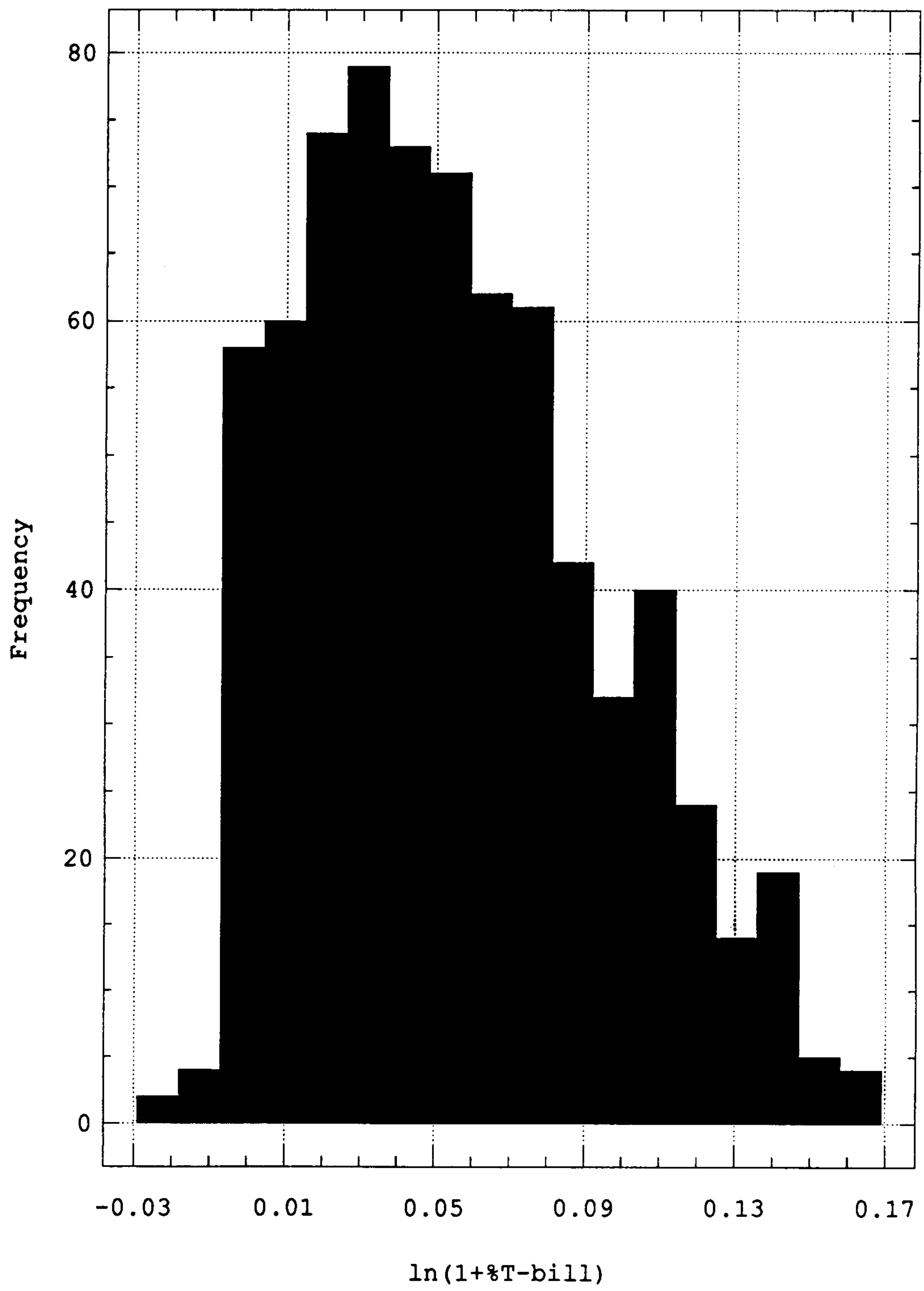
This study's model of managers' timing behavior is formulated based on the assumption that there is a correlation between the market movements and the proportion of portfolio assets being invested in common stocks and cash. A successful market timer will decrease the cash portion during up (bull) markets, and in declining markets, will lower portfolio holdings in common stocks. This strategy will enhance portfolio returns during market fluctuations.

This study uses the sample mutual fund data to model the fund managers' timing behavior. The percentage of total assets in cash, bonds, and common stocks are reported on a quarterly basis. These funds have the majority of their portfolio holdings in common stocks at all times. The funds' major shifts in portfolio composition are indicative of the designed strategy to predict the market fluctuations in an attempt to time such movements. This study's model of fund manager's timing behavior is based on the empirical distribution of the percentage of assets invested in cash during the 1984-1989 period. The selected funds, as previously discussed (p. 34), have a wide range of asset sizes and objectives, which provide a suitable representation of the universe of the mutual funds that behave in accordance to this study's model.

The distribution of our sample of mutual funds' percent investments in cash equivalents/short-term T-bills denoted by π_t, is shown in Figure 5. Similar to the R_{mft} series, the observed percentages of investments in T-bills, π_t, cannot theoretically fall below 100%, and the series distribution is positively skewed. These properties can be modeled using a lognormal distribution. The data is transformed to the natural logarithm of one plus the observed percentage of assets in T-bills, $ln(1+\pi_t)$. Using the Box-Jenkins Q statistic for the series $ln(1+\pi_t)$, the autocorrelation estimates and their significance indicate that the hypothesis of a random walk is a reasonable assumption.

Although the results of the KS test *(KS=0.081, Sig. level=1.16E-4)* show that the observations of $ln(1+\pi_t)$ do not closely conform to a normal distribution, for the purposes of this study, a normal distribution assumption with parameters $N \sim (0.05640, 0.04799)$ is reasonable. Furthermore, this assumption facilitates the use of a bivariate lognormal timing model which is discussed in the following paragraph. The results of the KS test and autocorrelation analysis for market risk premium returns, $ln(1+R_{mft})$, showed that this series can be accurately modelled using a normal distribution

Figure 5. Distribution of ln(1+%T-bill),
Monthly Composition 1984-1989



with parameters $N\sim(0.0057,0.0454)$.

This study's timing model is based on the assumption that the monthly market risk premium returns, $ln(1+R_{mft})$, and the percentage of assets invested in cash (T-bills), $ln(1+\pi_t)$, follow a joint bivariate normal distribution. This particular specification is advantageous in that it allows for the correlation, ρ_{TIM}, between the two variables. In other words, the degree of relationship between the market risk premium and percentage of assets in cash can be accurately modeled by varying the value of ρ_{TIM}. A manager with perfect skill in forecasting the market movements is assigned a correlation coefficient of ρ_{TIM}=-1, indicating that at least 100 percent of the total portfolio's assets were invested in common stocks during up markets, ideally fully divested in cash. This study's timing model allows for borrowing against cash (risk-free rate) to invest in stocks (greater than 100% portfolio composition in stocks), which is consistent with the real mutual fund portfolios and portfolio theory. Perfect foresight will also show an increasing percentage of portfolio switchings to cash during bear markets. Another advantage of the bivariate distribution model is the control for the magnitude of such shifts during extreme market environments, as a severe bear market warrants maximum allowable shift to cash. In other words, the noise factor is controlled, as insignificant fluctuations will prevent managerial overreaction to switch the fund's holdings between stocks and cash. The bivariate lognormal model is a reliable assumption as it accounts for the stochastic nature of the market fluctuations and the proportionate magnitude of the shifts to cash during bull and bear markets. The timing model using a bivariate normal distribution has the following specification, i.e., $N{\sim}(\mu,\sigma^2)$:

$$\{\mu_{ln(1+Rmf)}+\rho_{TIM}(\sigma_{ln(1+\pi)}/\sigma_{ln(1+Rmf)})(X_{Rmf}-\mu_{ln(1+Rmf)}),\sigma^2_{ln(1+\pi)}(1-\rho^2_{TIM})\},\qquad(3.4)$$

where ρ_{TIM} is the correlation coefficient between market risk premium, R_{mft}, and the percentage of the assets in cash, π_t. The marginal distribution of $ln(1+R_{mft})$ is $N{\sim}(\mu_{ln(1+Rmf)},\sigma_{ln(1+Rmf)})$. The parameters of the bivariate lognormal distribution model are estimated using the mean and standard deviation of historical observations of the market risk premium, R_{mft}, and the percentage of assets in cash, π_t. However, these observations are converted to the natural logarithmic form, i.e., $ln(1+R_{mft})$ and $ln(1+\pi_t)$, to follow the model specification. Using two sequences of generated standard normal random variates, *ZRMF* and *ZPCT*, the simulated monthly percentage of assets in cash, portfolio composition in T-bills, is computed as follows (for t=1,120):

$$\pi_t=EXP[\mu_{\ln(1+\pi)}+\rho_{TIM}\sigma_{\ln(1+\pi)}ZRMF+ZPCT\sigma_{\ln(1+\pi)}\sqrt{(1-\rho^2_{TIM})}]-1.\qquad(3.5)$$

By adjusting the correlation coefficient, ρ_{TIM}, between the market risk premium, R_{mft}, and the percentage of assets in cash, π_t, it is possible to simulate managers with varying degrees of skill in macroforecasting. A manager with perfect foresight is assigned a $\rho_{TIM}=-1$. As the market accelerates upward, the portfolio holdings in cash will be proportionately decreased, and in down markets, the percentage of portfolio assets in cash will be raised to compensate for declining share prices. Once the monthly percentage of assets in T-bills, π_t, are generated, the monthly portfolio return can be expressed by the following timing model:

$$R_{pt} = (1 - \pi_t)R_{mt} + \pi_t R_{ft} \qquad t=1,120, \tag{3.6}$$

and by subtracting R_{ft} from both sides, expression (3.6) in risk premium form is:

$$R_{pft} = (1 - \pi_t)R_{mft} \qquad t=1,120, \tag{3.7}$$

where $R_{pft}=R_{pt}-R_{ft}$ and $R_{mft}=R_{mt}-R_{ft}$.

The portfolio's monthly T-Bill composition is computed according to the expression (3.5). The corresponding simulation parameters for the monthly T-bill percentage, $ln(1+\pi_t)$, depend on the series distribution, which is specified as $N\sim(0.0564,0.0480)$. However, in environments in which the manager's timing ability is classified as skilled, $\rho_{TIM}=-1$, the constructed portfolio returns are not large enough for models to have a perfect or nearly perfect timing ability detection rate, i.e., 95% or greater. The specified parameters of the T-bill distribution, $N\sim(0.0564,0.0480)$, affect the timing portfolio's return. One way to resolve this issue is to permit a higher proportion of the portfolio to be invested in cash. This can be accomplished by varying the standard deviation of the T-bill distribution until the models can detect the timing ability with an approximate probability of 0.95 or greater. Using the described procedure, the models attain an approximate detection rate of 95% or greater, when the T-bill distribution, $ln(1+\pi_t)$, is specified as $N{\sim}(0.0564, 0.240)$. The newly specified standard deviation is five times the magnitude of the previous parameter.

Heteroskedasticity and Tests of Market Timing

The models of market timing thus far discussed have been shown to be heteroskedastic or to have nonconstant residual variance when market timing is present in portfolio returns. Henriksson and Merton (1981) and Huang and Jo (1988) have offered the nonstationarity of the portfolio systematic risk, β_p, as the cause of heteroskedasticity. Although some studies in the financial literature have assumed homoskedastic (constant) error term variance, the results of timing studies will be substantially different if heteroskedasticity is present. This incorrect assumption would lead to erroneous statistical inferences regarding the significance of the parameters. Nonconstant error variance produces inefficient but consistent selectivity and timing parameter estimates; however, the covariance matrix estimates affecting the standard errors would be inconsistent.

White (1980) proposed a covariance matrix estimator which is heteroskedastic-consistent and does not require knowledge of the heteroskedasticity structure. In other words, White's method is applicable when the variables that cause the nonconstant error variance in the model are not known. The study offered the following covariance matrix estimator to allow for the nonconstant error term variance:

$$(X'X)^{-1}(X'diag(e_i^2)X)(X'X)^{-1}, \tag{3.8}$$

where X is the matrix of the model's independent variables and $diag(e_i^2)$ is the diagonal matrix of the squared residuals of the model. White (1980) showed that the proposed covariance matrix estimator provides reliable inferences and confidence intervals in analyzing the parameter estimates, and when testing hypotheses on their accuracy.

Henriksson and Merton (1981) were among the original contributors to have observed the heteroskedasticity of the error term variances in portfolio timing studies. They offered generalized weighted least squares estimation to correct for the heteroskedasticity.

Chang and Lewellen (1984) and Henriksson (1984) reported that their studies' results using the HM timing model were almost identical before and after the correction for the heteroskedasticity. To correct for the nonconstant error term variance, the authors applied the weighted least squares to a sample of mutual funds' monthly returns over the period 1968-1980. However, despite Henriksson's (1984) assertion that the results were not affected by the heteroskedasticity correction, its presence in the data was confirmed.

Jagannathan and Korajczyk (1986) claimed that the corrected standard errors for the heteroskedasticity can be as much as two or three times the size of uncorrected standard errors. This amount of error would be substantial when testing for the presence of timing ability, and the results would present a completely different picture of a manager's ability to time market movements. Breen and Jagannathan, and Ofer (1986), using the HM timing model, undertook a simulation study to investigate the significance of correction made for heteroskedasticity when testing for the timing ability of portfolio managers. By building hypothetical portfolios for managers who had varying degrees of timing skill, it was shown that correction for heteroskedasticity can significantly affect the results of tests for market timing ability. The authors employed both the White and the generalized least squares methods for the treatment of nonconstant error term variance. Another important finding was that the importance of correction for heteroskedasticity in market timing studies is dependent upon the specific asset samples and their distributional properties.

Lockwood and Kadiyala (1988) also used the weighted least squares procedure to correct for the heteroskedasticity in their time varying beta model. Lee and Rahman (1990) employed the BP model to investigate the market timing and selectivity of selected mutual funds. Similar to previously conducted performance studies, generalized least squares (GLS) was applied to account for the nonconstancy of the error term variance.

We will test the effect of correction for heteroskedasticity in our designed timing and selectivity portfolios. White's heteroskedasticity-consistent covariance matrix estimator is applied to the HM and LK mutual fund performance models. For the BP model, the statistical inferences do not directly rely on the standard errors of the model. Therefore, the White method is not applicable. This study uses the generalized least squares estimator for the BP model, as described by Lee and Rahman (1990), to test for the effects of heteroskedasticity.

3.4 DESIGN OF SELECTIVITY PORTFOLIOS

To model managerial selectivity behavior, different levels of excess returns are added to the market risk premium series, R_{mf}. Excess return is the return component, denoted by Δ_t, that represents a manager's ability to invest in superior stocks. With T-bills included in the portfolio, π_t, the monthly portfolio returns in risk premium form can be expressed by the following timing and selectivity model:

$$R_{pft} = (1 - \pi_t) R_{mft} + (1 - \pi_t) \Delta_t \qquad t=1,120, \qquad (3.9)$$

the first term, $(1 - \pi_t) R_{mft}$, captures the timing effect of the portfolio, and the second term, $(1 - \pi_t)\Delta_t$, represents the selectivity effect of the managed fund.

Our study's approach is consistent with the previous studies, Brown and Warner (1980) and French (1985), among others, that assumed excess returns to be constant over time. This specification does not consider the stochasticity of the monthly excess returns due to managerial selectivity activities. However, the results of the study will be more tractable when examining the power of the models to detect microforecasting skill.

The level of excess return is the controlling factor for the degree of the manager's expertise in superior stock selection. To design portfolios with selectivity skill, constant levels of excess return, Δ_t, due to superior stock selection, are introduced into the monthly portfolio returns. The introduced levels of excess return due to selectivity skill are 0% (no-skill), 1% (semi-skilled), and 2% (skilled). With this formulation, regardless of the market conditions, i.e., bull or bear periods, the simulated fund manager's abilities for superior (inferior) stock selection will be reflected by their decision to invest in undervalued (overvalued) stocks.

3.5 MODEL OF NOISE

The designed model of managerial timing and selectivity behavior does not account for noise (error), e_t. The models' power to detect managerial selectivity and timing abilities would be overestimated if the parameter variability and the amount of noise for the process is underestimated. On the other hand, in the presence of excessive amounts of variability, the power of the models would be underestimated. The variability of the parameters in the simulation model, R_{mft} and π_t, are accounted for using the historical distributional properties of these variables, i.e., σ_{Rmf} and σ_π.

To introduce noise into the constructed timing and selectivity portfolio returns, the observed distribution of the error terms for various performance models using our sample of the mutual funds' return data is considered. The summary statistics of the error terms for the group of mutual funds using the four performance models are shown in Table 4.

Using these results, the noise (error) term is added to the monthly portfolio returns in the following manner:

$$R_{pft} = (1 - \pi_t)R_{mft} + (1 - \pi_t)\Delta_t + e_t \qquad t=1,120, \qquad (3.10)$$

where e_t is generated according to the distribution $N{\sim}(0,0.044)$.

Table 4
Summary Statistics of Error Terms For Sample Mutual Fund Data Using Various Performance Models

Model	σ^2_e[a]
Jensen	0.0451
Henriksson-Merton	0.0447
Lockwood-Kadiyala	0.0442
Bhattacharya-Pfleiderer	0.0442

[a]Average of 31 funds.

3.6 SIMULATION FLOWCHART

With three levels of timing ability, $\rho_{TIM}=0,-0.50,-1$, and three levels of selectivity ability, $\Delta_{SEL}=0\%,1\%,2\%$, nine combinations of portfolio environments are possible as shown in Figure 6.

Figure 6. Timing and Selectivity Environments

Timing Skill, ρ_{TIM}

Selectivity Skill, Δ_{SEL}	0.0	-0.50	-1
0%			
1%			
2%			

In each timing and selectivity environment, 1000 sets of 120 monthly (10 years) observations of market returns, R_{mft}, portfolio composition in T-bills, π_t, and portfolio returns, R_{pft}, are generated. The randomly generated market returns, R_{mft}, and portfolio composition in T-bill, π_t, are used to construct portfolio returns, R_{pft}. Furthermore, three sets of random number seeds are used to replicate the experiment in each of the nine timing and selectivity environments.

The choice of 1000 iterations and three replications insures high precision in the designed simulation results. More specifically, with 1000 iterations, the 95% confidence interval about the expected rejection rate, using a binomial distribution, will be approximately within 30% of the nominal significance level. Furthermore, it is necessary to have a minimum of two replications in order to have an estimate of the error variance between the treatments in the analysis of variance, which is discussed in detail in Section 3.8. In our study, a total of three replications are performed to conduct the experimental design to achieve higher accuracy.

The steps in the simulation procedure are summarized and a flowchart of the model is shown in Figure 7.

STEP 1: Initialize random number seeds: *IRMF* (used for generation of R_{mft}), *JPCT* (used for generation of π_t), and KERR (used for generation of e_t). Three sets of random numbers are used to replicate the experiment three times in each timing and selectivity environment.

STEP 2: Select timing, $\rho_{TIM}=0,-0.50,-1$, and selectivity, $\Delta_{SEL}=0\%,1\%,2\%$ environments; nine possible combinations.

STEP 3: Using the random number seeds in step 1, generate 120 standard normal variates, $N(0,1)$, for generating market returns, $ZRMF_t$, portfolio composition in T-bills, $ZPCT_t$, and error terms, $ZERR_t$.

STEP 4: Generate market risk premium returns, R_{mft}, and portfolio composition in T-bills, π_t (for $t=1,120$):

$$R_{mft} = EXP(ZRMF_t\sigma_{ln(1+Rmf)} + \mu_{ln(1+Rmf)}) - 1$$

$$\pi_t = EXP[\mu_{\ln(1+\pi)} + \rho_{TIM}\sigma_{\ln(1+\pi)}ZRMF + ZPCT\sigma_{\ln(1+\pi)}\sqrt{(1-\rho_{TIM}^2)}] - 1$$

STEP 5: Generate timing and selectivity portfolio returns:
$R_{pft} = (1 - \pi_t)R_{mft} + (1 - \pi_t)\Delta_t + e_t \qquad t=1,120$

STEP 6: Collect summary statistics on the generated series, R_{mft}, π_t, and R_{pft}.

STEP 7: Apply timing and selectivity models:

1) Jensen (JN);
2) Henriksson-Merton (HM), both with and without correction for heteroskedasticity using White's method;
3) Lockwood-Kadiyala (LK), both with and without correction for heteroskedasticity using White's method;

and

4) Bhattacharya-Pfleiderer (BP), both with and without correction for heteroskedasticity using the GLS method.

STEP 8: Return to Step 3 (1000 iterations).

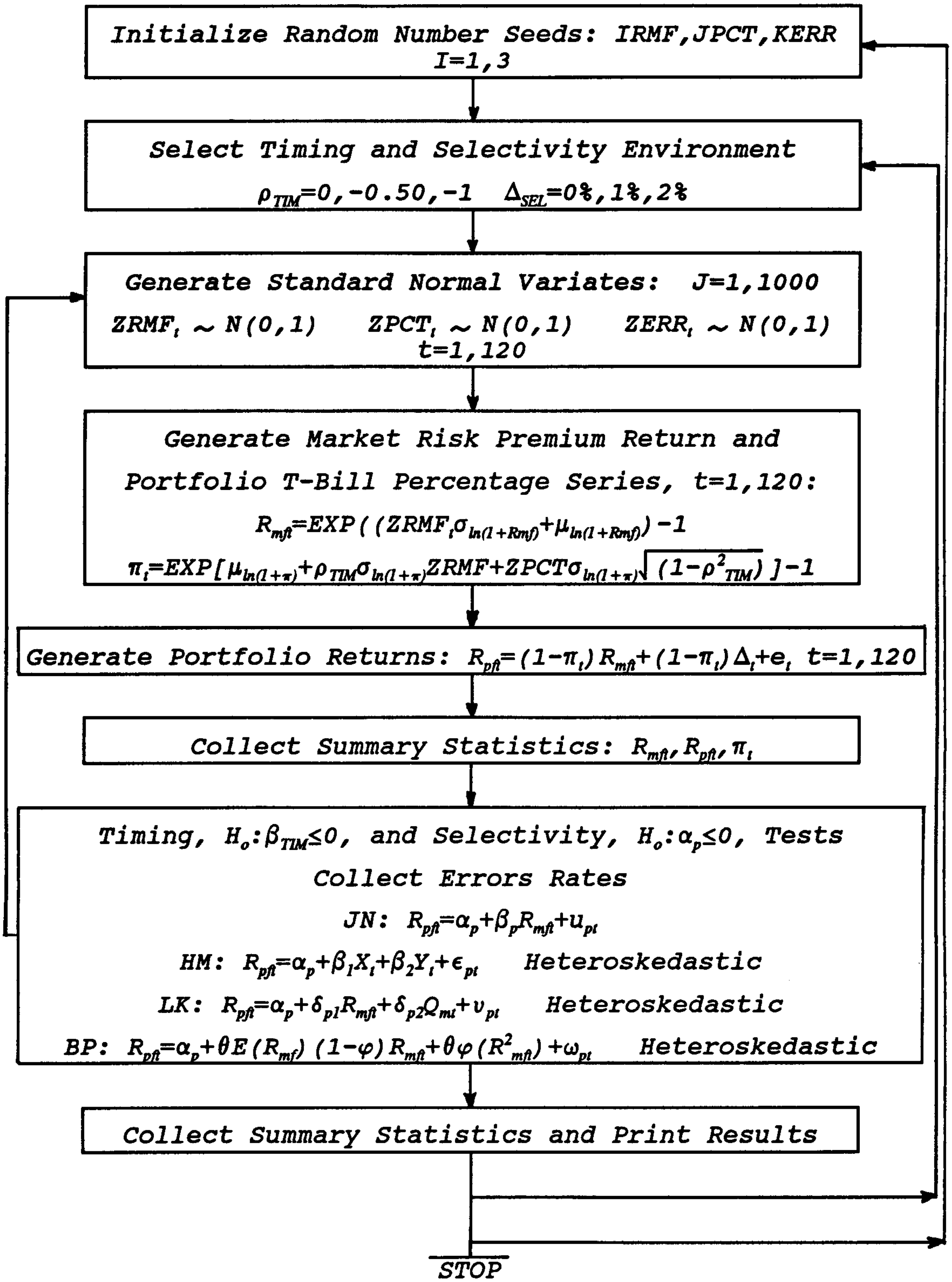
STEP 9: Collect summary statistics and print results.

STEP 10: Return to Step 2, select the next timing and selectivity environment (9 possible environments).

STEP 11: Return to Step 1, reinitialize the random number seeds, *IRMF*, *ZPCT*, *KERR* (3 iterations).

The computer program, coded in Fortran77, is presented in Appendix C.

Figure 7. Simulation Flowchart



3.7 MODEL VALIDATION

To validate the designed simulation model, we investigate the distributional properties and the time series behavior of the generated market risk premium returns, R_{mft}, percent allocation to T-bills, π_t, and the timing and selectivity portfolio returns, R_{pft}. The specification of the timing model in the following expression:

$$\pi_t = EXP[\mu_{\ln(1+\pi)} + \rho_{TIM}\sigma_{\ln(1+\pi)}ZRMF + ZPCT\sigma_{\ln(1+\pi)}\sqrt{(1-\rho^2_{TIM})}] - 1$$

is validated using the input and output values of the timing parameter, ρ_{TIM}. The structure and specification of the simulation model is tested for its adequacy using the described procedure. The simulated series of the model, R_{mft}, R_{pft}, π_t, are compared to the market's actual performance in order to measure their accuracy.

3.7.1 Time Series Behavior of the Generated Series

The hypothesis of random walk for historical patterns of market risk premium series, $ln(1+R_{mft})$, and percent allocation to T-bills, $ln(1+\pi_t)$, in their natural logarithmic form was previously confirmed. Similarly, the simulated series are tested for their time independence in order to validate the random walk hypothesis. The time pattern of the generated portfolio returns, $ln(1+R_{pft})$, is also investigated. Randomly selected samples from the nine managerial timing and selectivity environments were chosen and tested for trends, and the estimated autocorrelations up to lag fifty were estimated. The results using the Box and Jenkins (1976) Q statistic, at the 5% significance level, indicate that the hypothesis of random walk is not rejected for the market risk premium series, $ln(1+R_{mft})$, percent allocation to T-bills, $ln(1+\pi_t)$, and for the generated portfolio returns, $ln(1+R_{pft})$. These findings indicate that the simulated series do not present any significant dependence among their elements. Thus, the mirror behavior of the designed model's output and input validates the simulation procedure.

The designed timing model is validated by investigating the cross correlation, ρ_{TIM}, between the generated market risk premium returns, R_{mft}, and the percent allocation to T-bills, π_t. The accuracy of the timing model is measured by comparing the input (actual) values of the timing parameter, ρ_{TIM}, with its output (simulated) values. The results, as shown in Table 5, confirm the accuracy of the designed timing model. The correlation between the generated portfolio returns, R_{pft}, and the portfolio composition in T-bills, π_t, in various timing and selectivity environments are shown in Table 6.

Table 5

Actual vs. Simulated Values of Timing Parameter, ρ_{TIM}

Cross Correlation Coefficient, ρ_{TIM} Actual	Simulated[a]	(95% Conf. Inter.)
-1.00	-0.9809	(not defined)[b]
-0.50	-0.4908	(-0.37,-0.73)
0.00	-0.0027	(-0.18,0.18)

[a]Averages of three experiments each with 1000 replications.

[b]Failure in log transformation on the mean: $z'=(1/2)\log_e((1+\rho_{TIM})/(1-\rho_{TIM}))$.

3.7.2 Distributional Properties of the Generated Series

Similar to the analysis of the time series behavior of the generated series, the input and output values of the distributional parameters of the generated series are compared. To achieve this, the mean and standard deviation of the generated series (output), market risk premium returns, R_{mft}, and percent allocation to T-bills, π_t, are compared with their input values. The input values were chosen according to the distributional characteristics of the historical patterns of these series. These results are shown in Tables 7 and 8. These results indicate that the characteristics of the generated distributions are identical to their historical patterns, validating the model.

Table 6

Correlation Between Portfolio Returns, R_{pft}, and Portfolio Composition in T-bills, π_t, in Various Timing and Selectivity Environments

	TIMING SKILL		
	$\rho_{TIM} = 0$	$\rho_{TIM} = -0.50$	$\rho_{TIM} = -1$
$\Delta_{SEL} = 0\%$	-0.0288	-0.3097	-0.5874
SELECTIVITY			
$\Delta_{SEL} = 1\%$	-0.0727	-0.3470	-0.6142
SKILL			
$\Delta_{SEL} = 2\%$	-0.1123	-0.3814	-0.6397

Table 7

Mean and Standard Deviation of Monthly Market Risk Premium Return Series, R_{mf}, Actual vs. Simulated

	Actual 1975-1989	Simulated[a]	(95% Conf. Interval)
μ_{Rmf}	0.0067	0.0069	(-0.0013,0.0147)
σ_{Rmf}	0.0448	0.0458	(0.0407,0.0526)

[a]Averages of three experiments each with 1000 replications.

Table 8

Mean and Standard Deviation of Monthly Percent Allocation to T-bills, π_t, Actual vs. Simulated

	Actual	Simulated[a]		
	1975-1989	$\rho_{TIM}=0$	$\rho_{TIM}=-0.50$	$\rho_{TIM}=-1$
$\mu_{\pi t}{}^{b}$	0.0593	0.0897	0.0893	0.0884
$\sigma_{\pi t}{}^{b}$	0.2614	0.2657	0.2658	0.2653

[a]Averages of three experiments each with 1000 replications.

[b]95% confidence intervals: $\mu_{\pi t}$: (0.0125,0.1061) and $\sigma_{\pi t}$: (0.2362,0.3051).

3.8 EXPERIMENTAL DESIGN

The degree of a manager's expertise in market timing (macroforecasting) is simulated according to the percent of assets in Treasury bills indicating the manager's ability to forecast the market movements. Similarly, the selectivity model (microforecasting) is designed by introducing various levels of excess returns into the designed selectivity portfolios' returns.

We assume that the timing and selectivity abilities for both bear and bull markets are equal. The values of the timing skill parameter, designated by the correlation coefficient between the market risk premium and the distribution of the Treasury bills, ρ_{TIM}, considered are 0 (no skill), -0.50 (semi-skilled), and -1 (skilled). This choice of values gives us the extremes and the average skill level of the fund managers, which is a suitable representation of the range of managerial skill level. Similarly, the selectivity skill parameters are chosen at 0% (no skill), 1% (semi-skilled), and 2% (skilled) levels. With this specification, nine combinations of portfolio environments are possible, as was shown in Figure 6 (p. 77).

For every cell, we will generate portfolio returns which are transformed to show various levels of market timing and selectivity skills. The monthly market risk premium return, R_{mft}, will be randomly generated for a ten year period (N=120) according to its empirical distribution over the period 1975-1989 (15 years). This is the period in which most of the state of the art mutual fund performance studies were conducted. Given this return data, we construct portfolio returns that would have been realized, *ex post*, if the managers would have had a variety of skill levels in market timing and stock selection. In other words, various combinations of managerial abilities in predicting market movements and superior stock selection are examined. We test the mutual fund performance models for their ability to detect managerial timing and selectivity skills.

According to a manager's expertise on forecasting the market direction and superior stock returns, the generated portfolios are transformed to show investments in the market portfolio or in Treasury bills to account for market timing. With this specification, we introduce timing ability by switching between the stock market portfolio and Treasury bills.

Regardless of market conditions, i.e., bear or bull periods, the hypothetical fund managers' abilities for superior stock selection will be reflected by the level of excess return added to the portfolio returns.

Each of the nine environments for generating portfolio returns will be used to construct 1000 samples of 120 monthly observations (over 10 years) that are consistent with the mutual funds studies. The tests for statistical significance of market timing and selectivity parameters under different models will provide the means for comparing the error rates across a variety of skill environments. The results of this power analysis will show how different models perform under a variety of managerial timing and selectivity skills under changing market and portfolio conditions.

In the no-skill environments, we examine the performance models by testing how frequently the null hypotheses of no market timing and no selectivity abilities are rejected when the null is true. Concurrently, in skilled environments, the error rates for failing to reject the null hypotheses of no managerial skills in timing and selectivity environments will be examined when the null is false. However, for the purpose of power curve analyses, in skilled environments, we will be interested in the decision rule that leads to the acceptance of the alternative hypotheses, i.e., one minus the observed error rate.

The specified experimental study is a three-factor *(3X3X4)* complete randomized design. These analyses define two experimental studies to be conducted for tests of market timing and of selectivity abilities. The designed experiment will provide answers on how the three factors of model, timing, and selectivity, and their interactions affect the models' power to detect managerial skills in market timing and selectivity abilities. Furthermore, since the study's results are reported in proportion form, *p*, i.e., the error

rates are reported in terms of the number of times that they occur out of 1000 trials, the analyses of variance are conducted using the transformation $p'=2\arcsin\sqrt{p}$.

Chapter 4

ANALYSIS OF RESULTS

For each specific level of microforecasting and macroforecasting abilities and their combinations, each model is tested for statistically significant timing and selectivity parameters at the 5% level. In other words, the power of various timing and selectivity models is analyzed. A model's power can be explained in terms of the rate of errors committed.

The experiments are conducted to collect the number of times out of 1000 repetitions where the null hypothesis of no selectivity ability, $H_o\!:\alpha_p\leq 0$, is rejected for each model. Similarly, the null hypothesis of no market timing ability, $H_o\!:\beta_{TIM}\leq 0$, is tested across the performance models.

The results of the simulation in the test of market timing are presented in Appendix D, and the results for the test of selectivity ability are included in Appendix E. The probabilities in these tables are the proportion of times that the null hypotheses of no timing ability, $H_o\!:\beta_{TIM}\leq 0$, and no selectivity ability, $H_o\!:\alpha_p\leq 0$, are rejected at the 5% (1%) level in each of the nine microforecasting and macroforecasting environments. The proportions are averages of three experiments, each consisting of 1000 trials. The experiments are replicated using three different sets of random number seeds.

Chapter 4 is organized as follows. First, the effects of heteroskedasticity correction are investigated. Then, the results of analyses on the power of models in tests of market timing and selectivity performance are presented. In this chapter, significance at the 5% level refers to the inferences drawn on the analyses of variance, i.e., not on the tests of null hypotheses $H_o: \beta_{TIM} \leq 0$ and $H_o: \alpha_p \leq 0$.

4.1 EFFECTS OF HETEROSKEDASTICITY CORRECTION

Breen, Jagannathan, and Ofer (BJO) (1986) showed that correction for heteroskedasticity in tests of market timing ability can be important. Using the Henriksson-Merton (HM) model, the study concluded that when testing for market timing ability, the adjustments for heteroskedasticity have minimal effects in the case of normally distributed asset returns. However, the effects of correction for nonconstant error term variance were not investigated in tests of managerial selectivity skill. Our study's results confirm BJO's (1986) study when testing for timing ability using the HM model. Furthermore, there is no observed pattern in the differences, and the model's results, using analysis of variance, before and after correction for heteroskedasticity are not statistically significant at the 5% level. These results are shown in Table 9. The factors of model and timing, and model and selectivity do not interact in a significant way at the 5% level.

Table 9

ANOVA Table for Testing Henriksson-Merton Model's Results Before and After Correction for Heteroskedasticity, Using White's Method, in Test of Market Timing

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:HM Hetrosk.	0.0	1	0.0	0.0	.99
B:Timing	148785.3	2	74392.6	9521.1	.00
C:Selectivity	39.8	2	19.9	2.5	.09
INTERACTIONS					
AB	0.7	2	0.4	0.0	.95
AC	0.9	2	0.4	0.0	.94
BC	21.1	4	5.3	0.7	.61
ABC	1.1	4	0.3	0.0	.99
RESIDUAL	281.3	36	7.8		
TOTAL	149130.2	53			

In tests of selectivity ability when a manager does not possess skill, $\Delta_{SEL}=0\%$, the uncorrected heteroskedastic HM model tends to underreject (cause fewer errors) the null hypothesis of no selectivity ability, $H_o:\alpha_p \leq 0$. In the presence of managerial selectivity skill, $\Delta_{SEL}=1\%,2\%$, when the HM model is not corrected for the nonconstant error term variance, the model's response is characterized by an overrejection tendency (increased errors) in testing the null hypothesis $H_o:\alpha_p \leq 0$. However, as shown in Table 10, the analysis of variance indicates that these observed differences in results are not significant at the 5% level.

Furthermore, the interaction between the factors of model and timing, and model and selectivity, are not significant at the 5% level.

Table 10

ANOVA Table for Testing Henriksson-Merton Model's Results Before and After Correction for Heteroskedasticity, Using White's Method, in Test of Selectivity Ability

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:HM Hetrosk.	5.9	1	5.9	0.7	.41
B:Timing	13207.5	2	6603.7	819.4	.00
C:Selectivity	72006.2	2	36003.1	4467.6	.00
INTERACTIONS					
AB	7.8	2	3.9	0.5	.62
AC	8.2	2	4.1	0.5	.60
BC	1113.1	4	278.3	34.5	.00
ABC	9.0	4	2.2	0.3	.89
RESIDUAL	290.1	36	8.1		
TOTAL	86647.8	53			

This study uses the White method to correct for HM's nonconstant error term variance, and it should be emphasized that these original findings are based on the assumption of normally distributed asset returns.

In the case of the Lockwood-Kadiyala (LK) model, the test of null hypotheses of no market timing ability, $H_o:\beta_{TIM}\leq 0$, and no selectivity ability, $H_o:\alpha_p\leq 0$, are characterized by fewer errors (underrejection) in no-skill environments and by increased errors (overrejection) in skilled environments, when ignoring heteroskedasticity. Furthermore, as shown in Tables 11 and 12, the analyses of variance indicate that these differences are significant at the 5% level. In addition, the factors of model and timing, and model and selectivity, when testing for timing and selectivity abilities (H_o:β_{TIM}≤0 and H_o:α_p≤0) do not exhibit significant interactions at the 5% level.

Table 11

ANOVA Table for Testing Lockwood-Kadiyala Model's Results Before and After Correction for Heteroskedasticity, Using White's Method, in Test of Market Timing

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:LK Hetrosk.	40.9	1	40.9	4.7	.04
B:Timing	25.5	2	12.7	1.5	.24
C:Selectivity	150402.3	2	75201.1	8616.2	.00
INTERACTIONS					
AB	0.2	2	0.1	0.0	.99
AC	3.6	2	1.8	0.2	.81
BC	44.2	4	11.0	1.3	.30
ABC	1.6	4	0.4	0.0	.99
RESIDUAL	314.2	36	8.7		
TOTAL	150832.7	53			

Table 12

ANOVA Table for Testing Lockwood-Kadiyala Model's Results Before and After Correction for Heteroskedasticity, Using White's Method, in Test of Selectivity Ability

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:LK Hetrosk.	17.8	1	17.8	5.7	.02
B:Timing	162278.3	2	81139.1	25884.7	.00
C:Selectivity	104.1	2	52.0	16.6	.00
INTERACTIONS					
AB	1.7	2	0.8	0.3	.76
AC	2.8	2	1.4	0.4	.64
BC	38.3	4	9.6	3.0	.03
ABC	1.6	4	0.4	0.1	.97
RESIDUAL	112.8	36	3.1		
TOTAL	162557.4	53			

Similar to the LK model, the Bhattacharya-Pfleiderer (BP) model tends to underreject (fewer errors) the null hypothesis of no selectivity ability, $H_o:\alpha_p \leq 0$, when a manager does not possess microforecasting skill, $\Delta_{SEL}=0\%$. In the presence of selectivity ability, $\Delta_{SEL}=1\%,2\%$, this is characterized by an increase in errors (overrejection). The analysis of variance, shown in Table 13, indicates that these differences are significant at the 5% level, and that the factors of model and selectivity and model and timing do not exhibit significant interaction in testing the hypothesis $H_o:\alpha_p \leq 0$.

Table 13

ANOVA Table for Testing Bhattacharya-Pfleiderer Model's Results Before and After Correction for Heteroskedasticity, Using GLS Method, in Test of Selectivity Ability

Source of Variation	*SS*	*df*	*MS*	*F*[*]	*Sig. level*
MAIN EFFECTS					
A:BP Hetrosk.	12.9	1	12.9	5.4	.03
B:Timing	161950.1	2	80975.1	33852.9	.00
C:Selectivity	84.9	2	42.4	17.7	.00
INTERACTIONS					
AB	2.2	2	1.1	0.4	.64
AC	7.2	2	3.6	1.5	.23
BC	18.8	4	4.7	2.0	.12
ABC	2.9	4	0.7	0.3	.88
RESIDUAL	86.1	36	2.4		
TOTAL	162165.1	53			

The patterns of errors for the BP model are completely different than for other models when testing for managerial timing ability. This is characterized by more errors (overrejection) in no-skill environments and by fewer errors (underrejection) in skilled environments when the model is not corrected for heteroskedasticity. Furthermore, the analysis of variance, as summarized in Table 14, indicates that these differences are significant at the 5% level. In addition, the interaction between the model and timing factors is significant at the 5% level, but the factors of model and selectivity do not interact in a significant way.

Table 14

ANOVA Table for Testing Bhattacharya-Pfleiderer Model's Results Before and After Correction for Heteroskedasticity, Using GLS Method, in Test of Timing Ability

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:BP Hetrosk.	1347.2	1	1347.2	128.4	.00
B:Timing	148396.0	2	74198.0	7072.1	.00
C:Selectivity	27.2	2	13.6	1.3	.28
INTERACTIONS					
AB	110.9	2	55.5	5.3	.01
AC	4.0	2	2.0	0.2	.83
BC	21.2	4	5.3	0.5	.73
ABC	1.0	4	0.2	0.0	.99
RESIDUAL	377.7	36	10.5		
TOTAL	150285.2	53			

In this study, the LK model is corrected for heteroskedasticity using White's method, and the BP model accounts for the nonconstancy of error term variance using the generalized least squares (GLS) method. The effects of correction for heteroskedasticity using the Lockwood-Kadiyala and Bhattacharya-Pfleiderer models, under the assumption of normally distributed asset returns, have not previously been investigated.

The Jensen (JN) model does not present any heteroskedasticity-related biases and, therefore, is not modified to account for nonconstant error term variance. In comparing the power of models in tests for managerial selectivity and timing abilities, we rely on results of corrected models (except Jensen) for heteroskedasticity in order to avoid the biases of nonconstant error term variance.

4.2 POWER COMPARISON AMONG THE MODELS

In this Section, the power of the performance models is examined at each timing and selectivity environment, when they are applied to each sample of randomly generated market and portfolio returns. As previously mentioned, the analyses of variance for the HM, LK, and BP models are conducted using the heteroskedasticity-corrected results. Furthermore, the analyses are undertaken using the *arcsin* transformed simulation results. However, the analyses of variance graphs will be presented in proportion form, i.e., without the *arcsin* transformation, in order to facilitate a better understanding and discussion of the models' comparison in terms of their power.

4.2.1 Power of Models in Test of Market Timing Ability

A three-factor experimental design is performed to explore the relationship among the timing, selectivity, and model factors. Furthermore, this study explores whether the interactions among these factors have an effect on various models' ability to show true managerial timing skill. These results, as shown in the ANOVA Table 15, indicate that the main effects of all the factors are highly significant at the 5% level. The interactions among the three factors are also highly significant.

Table 15

ANOVA Table for Testing No Timing Ability, $H_o: \beta_{TIM} \leq 0$; All Models Included

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:Model	31690.6	3	10563.5	1233.2	.00
B:Timing	225953.2	2	112976.6	13189.3	.00
C:Selectivity	10589.7	2	5294.8	618.1	.00
INTERACTIONS					
AB	15300.5	6	2550.1	297.7	.00
AC	36755.4	6	6125.9	715.2	.00
BC	2592.4	4	648.1	75.7	.00
ABC	5989.2	12	499.1	58.3	.00
RESIDUAL	616.7	72	8.6		
TOTAL	329487.9	107			

The Jensen index is often used as a selectivity model to test for managerial microforecasting ability. This model assumes that the portfolio beta, β_p, is constant through time and it does not consider market timing. However, as Lockwood and Kadiyala (1988), among others, have discussed, and as our results indicate, Jensen's model can be considered as an overall performance model. In the presence of both market timing and selectivity abilities, the model's performance parameter, α_p, tends to absorb both skills as a combination. In other words, in the presence of a given level of market selectivity (timing) and with added levels of timing (selectivity) skill, the model's power is increased.

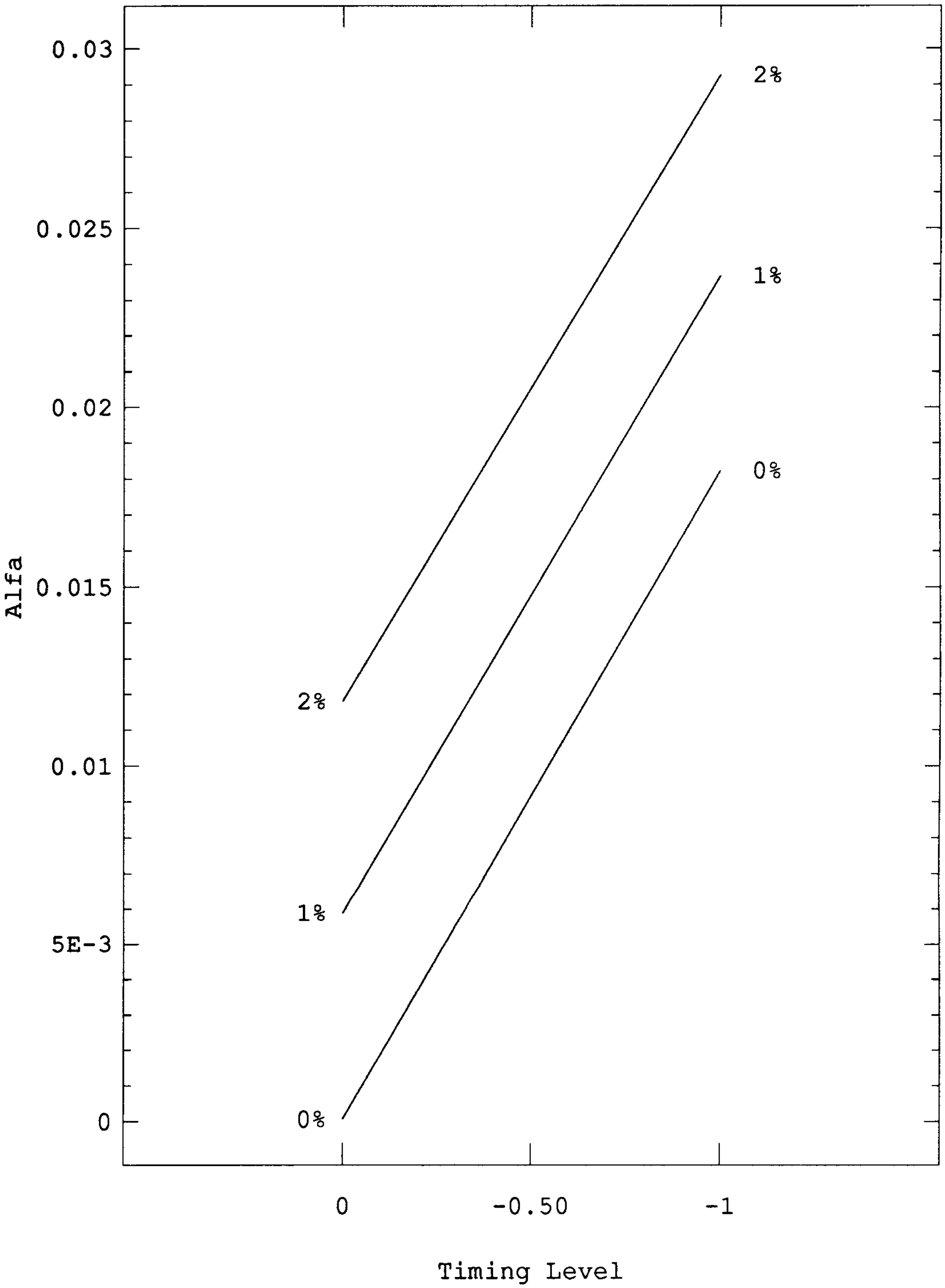
The behavior of the Jensen performance parameter, α_p, in the nine timing and selectivity environments is shown in Figure 8. Our results confirm Jensen's (1968) contention that in the presence of market timing ability, the model's estimated selectivity parameter, α_p, is biased upward. Furthermore, as shown in Table 16, the differences in alfas, α_p, in the various timing environments, $\rho_{TIM}=0,-0.50,-1$, are statistically significant at the 5% level, i.e., Sig. level for the Timing factor = .00. These results are in contradiction to Grant's (1977) study that predicted α_p would be biased downward when a manager possesses market timing ability. The behavior of the selectivity parameters of the HM, LK, and BP models will be discussed when comparing the

Table 16

ANOVA Table for Differences in JN's Alfas, α_p, in Various Timing and Selectivity Environments

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:Selectivity	0.001427	2	7.14E-04	2.748E5	.00
B:Timing	0.000584	2	2.92E-04	1.124E5	.00
INTERACTIONS					
AB	3.79E-07	4	9.49E-08	3.654E1	.00
RESIDUAL	4.68E-06	18	2.60E-09		
TOTAL	0.002012	26			

Figure 8. Behavior of Jensen's Alfa in Timing and Selectivity Environments



power of the models in tests for managerial selectivity abilities (see section 4.2.2).

The Jensen model is a single parameter performance model which is used to test for managerial selectivity ability. The Henriksson-Merton (HM), Lockwood-Kadiyala (LK), and Bhattacharya-Pfleiderer (BP) are two parameter performance models which have been formulated to differentiate between managerial selectivity and timing abilities.

The Jensen model is included in this part of the analysis only for the purpose of comparing statistical power among the performance models to uncover managerial timing ability. However, it will not be formally discussed as it is used only as a selectivity model. A formal analysis of this model is presented when the study examines statistical power among models to test for managerial selectivity ability (Section 4.2.2).

The analysis of variance using the HM, LK, and BP models when testing for timing ability are presented in Table 17. The main effects of the factor model are highly significant at the 5% level, however, the interaction between the model and timing factors is not significant.

A pairwise comparison among the factor level means for various models indicates that models LK and BP behave similarly, and are both significantly different from the HM model at the 5% level. This is depicted in Figure 9 which exhibits the 95% confidence intervals for the models' means.

Table 17

ANOVA Table for Testing No Timing Ability, $H_0:\beta_{TIM}\leq 0$; All Models Included (Except Jensen)

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:Model	319.2	2	159.6	17.12	.00
B:Timing	224034.8	2	112017.4	12.02E3	.00
C:Selectivity	49.7	2	24.9	2.67	.08
INTERACTIONS					
AB	42.6	4	10.6	1.14	.35
AC	4.1	4	1.0	0.11	.98
BC	36.0	4	9.0	0.97	.43
ABC	1.5	8	0.2	0.02	1.0
RESIDUAL	503.3	54	9.3		
TOTAL	224991.2	80			

As shown in Figure 10, the HM model has more power to demonstrate no timing ability when the manager possesses no skill, i.e., $\rho_{TIM}=0$. In other words, the HM model has fewer errors. However, in environments that are classified as semi-skilled and skilled in timing ability, $\rho_{TIM}=-0.50,-1$, the LK and BP models have more power. This argument is also depicted in Figure 10, as the time varying beta models of LK and BP show fewer errors.

In the skilled timing environment, $\rho_{TIM}=-1$, all the models have almost perfect detection rates, i.e., > 95%. Although all of the models are highly powerful, models LK and BP commit fewer errors than the HM model in skilled

Figure 9. 95% Confidence Intervals for Models' Means in Test of Market Timing

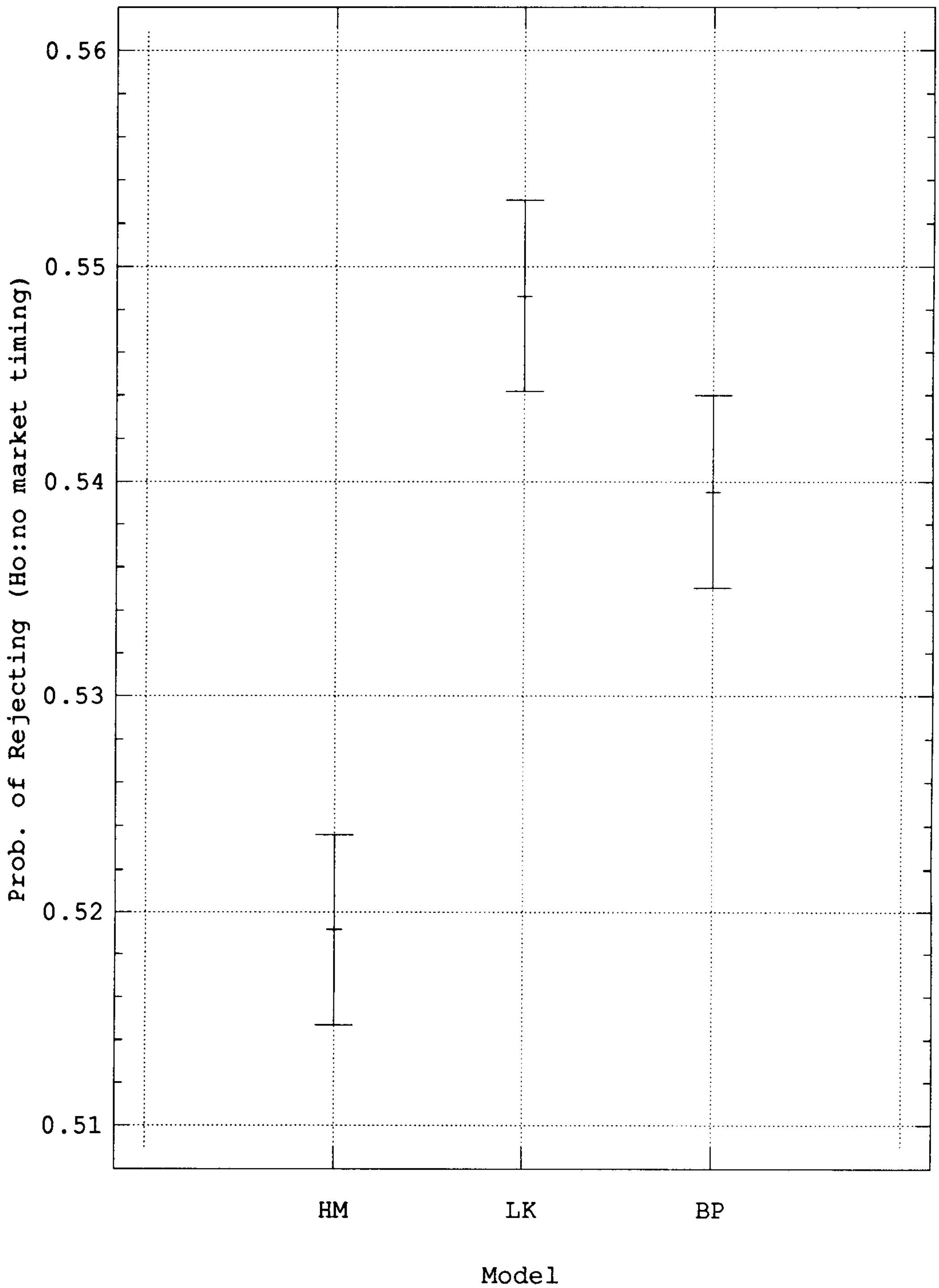
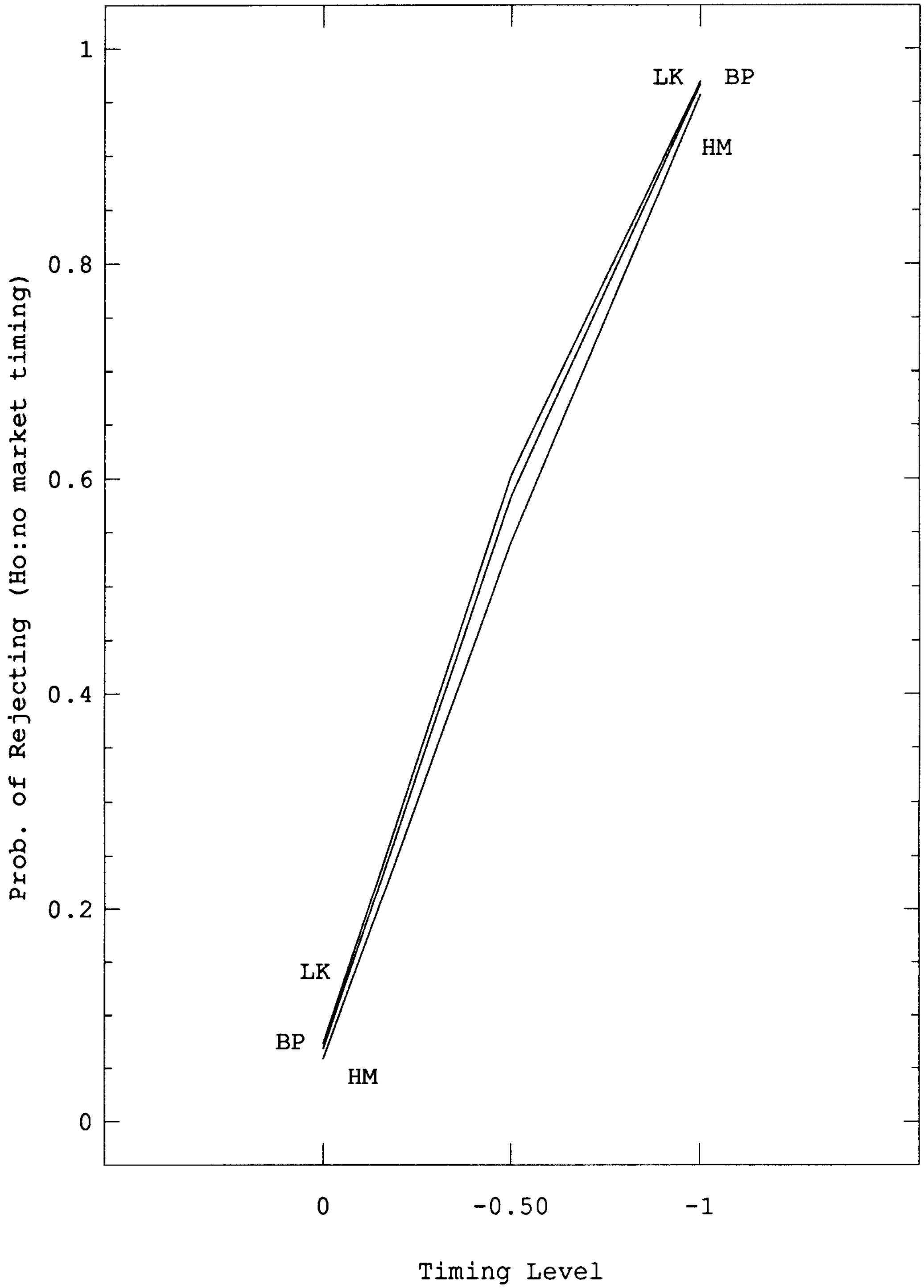


Figure 10. Plot of Interactions for
Model by Timing Level in Test of Timing



environments. The analysis of variance showed that the interaction among the factors model and timing is not significant at the 5% level. In other words, the models in the specific timing environments: ρ_{TIM}=*0,-0.50,-1*, respond similarly, which can be seen as almost parallel lines in Figure 10.

The same model behavior is repeated in the specific selectivity environments: Δ_{SEL}=*0%,1%,2%*. The selectivity levels affect the models' responses in the same way, meaning that the model and selectivity factors do not interact. All the models sacrifice power or have higher error rates across the selectivity environments. These models' behavior are shown in Figure 11. In other words, the models' responses are not significant at the 5% level. The rankings of the models in tests of market timing are summarized in Table 18.

The portfolio returns associated with the nine timing and selectivity environments are summarized in Table 19. The portfolio returns, R_p, associated with the nine skill environments are shown in the form of a response surface in Figure 12. A manager with no skill in timing and selectivity activities, ρ_{TIM}=*0* and Δ_{SEL}=*0%*, on average, shows an annual return of 16.43%. The market return under the same simulated conditions was 17.43%.

In the semi-skilled managerial timing environment, ρ_{TIM} =*-0.50*, the minimum realized portfolio return equals 24.99% annually when the manager possess no selectivity ability,

Figure 11. Plot of Interactions for
Model by Selectivity Level in Test of Timing

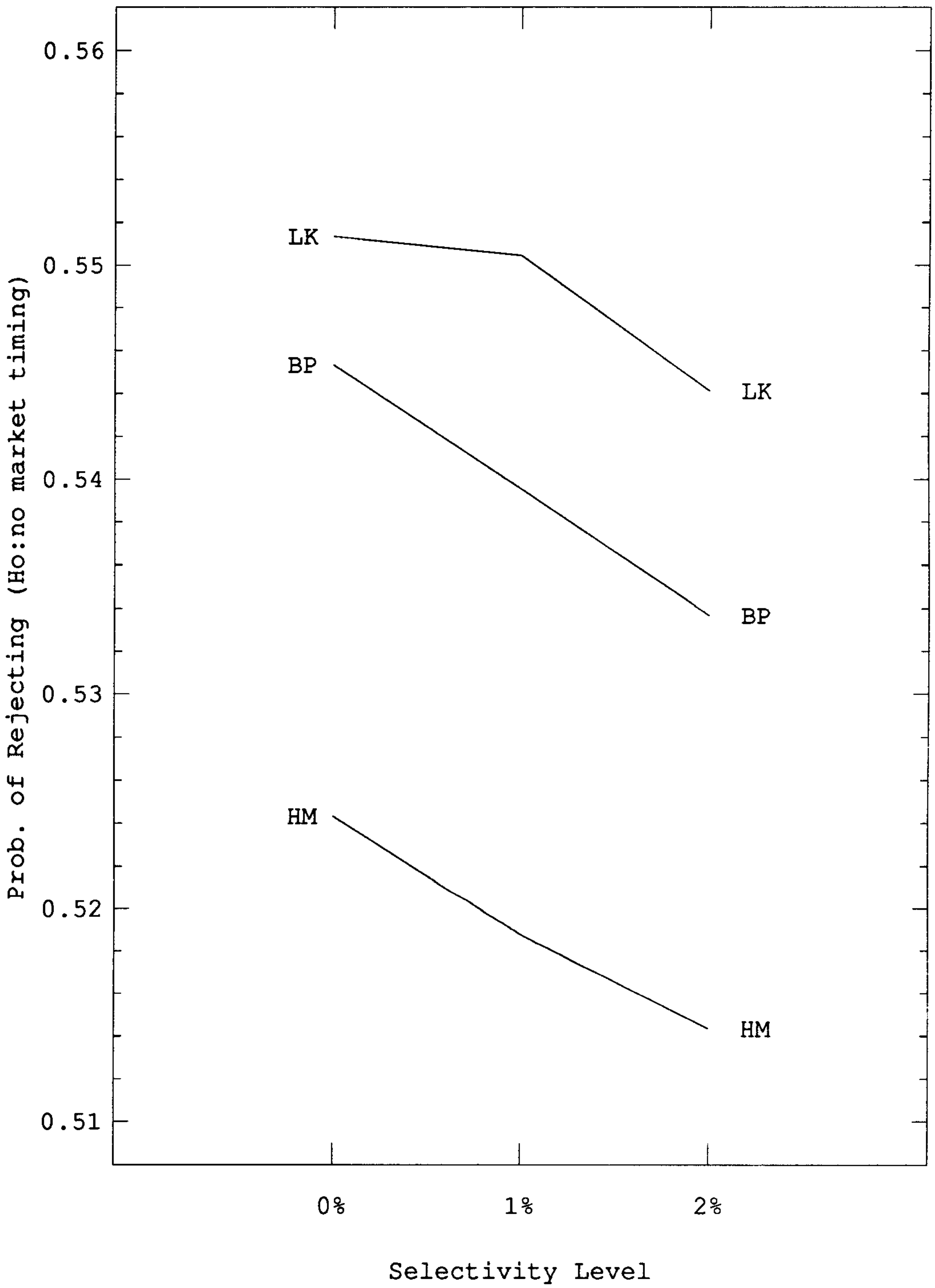


Table 18

Rankings of Mutual Fund Performance Models in Test of Market Timing Ability, $H_o: \beta_{TIM} \leq 0$, in Various Timing and Selectivity Environments

	TIMING SKILL		
	$\rho_{TIM} = 0$	$\rho_{TIM} = -0.50$	$\rho_{TIM} = -1$
$\Delta_{SEL} = 0\%$	1. HM 2. LK,BP	1. LK,BP 2. HM	1. LK,BP 2. HM
SELECTIVITY			
$\Delta_{SEL} = 1\%$	1. HM 2. LK,BP	1. LK,BP 2. HM	1. LK,BP 2. HM
SKILL			
$\Delta_{SEL} = 2\%$	1. HM 2. LK,BP	1. LK,BP 2. HM	1. LK,BP 2. HM

Table 19

Portfolio Annual Returns[a] in Absolute, R_p, and Risk-Premium, R_{pf}, Forms, and Standard Deviation[b], σ_{Rpf}, in Various Timing and Selectivity Environments[c]

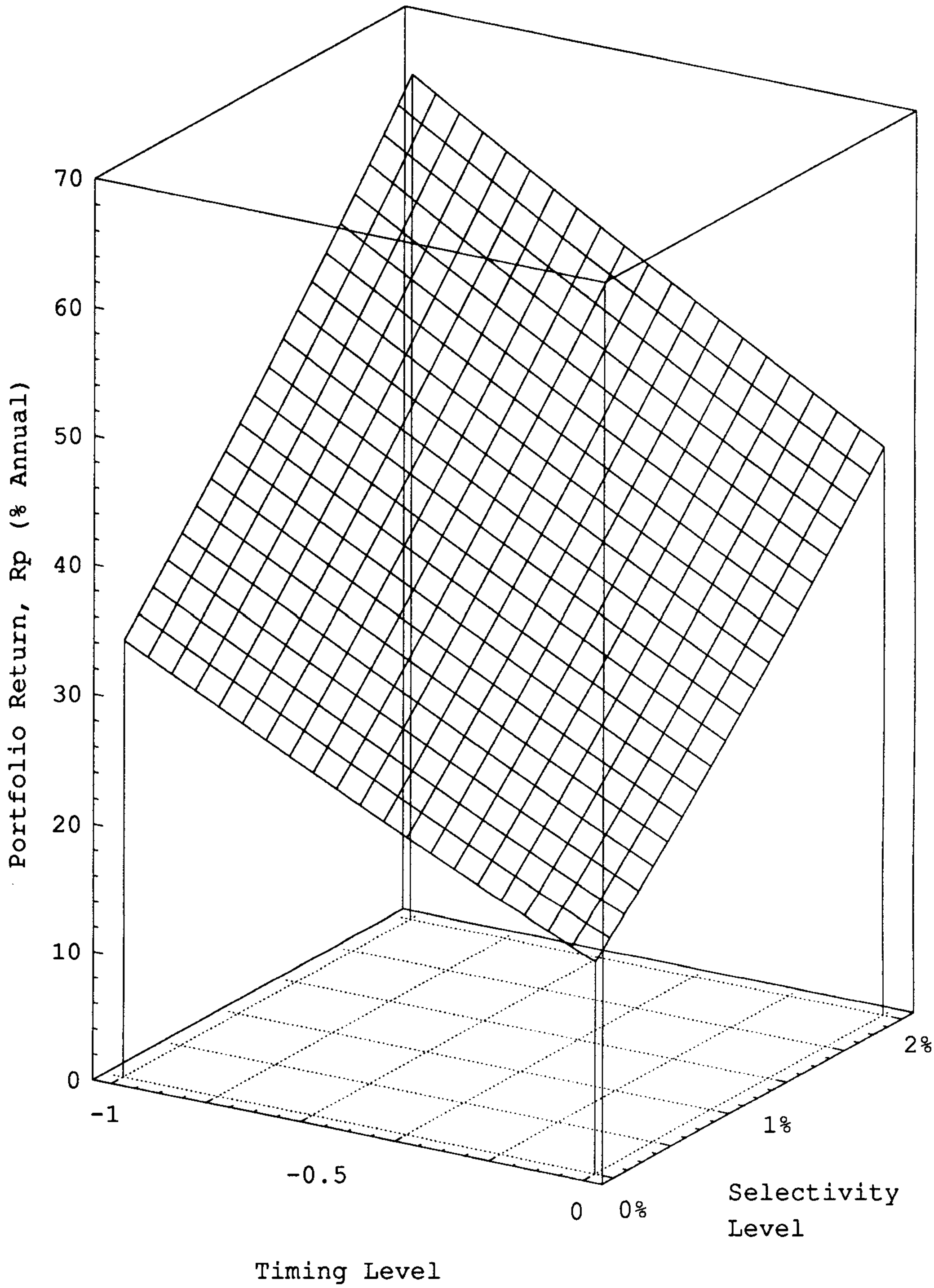
		TIMING SKILL $\rho_{TIM} = 0$	$\rho_{TIM} = -0.50$	$\rho_{TIM} = -1$
$\Delta_{SEL} = 0\%$	R_p Annual:	16.43%	24.99%	33.99%
	R_{pf} Annual:	5.61%	13.45%	21.70%
	σ_{Rpf}:	6.23%	6.31%	6.35%
SELECTIVITY				
$\Delta_{SEL} = 1\%$	R_p Annual:	29.63%	39.00%	48.86%
	R_{pf} Annual:	17.71%	26.25%	35.28%
	σ_{Rpf}:	6.25%	6.39%	6.51%
SKILL				
$\Delta_{SEL} = 2\%$	R_p Annual:	44.05%	54.52%	65.58%
	R_{pf} Annual:	30.94%	40.38%	50.38%
	σ_{Rpf}:	6.28%	6.49%	6.68%

[a]Averages of three experiments, each with 1000 trials. Experiments are replicated using three different sets of random number seeds.

[b]Standard deviation of returns in the risk-premium form, R_{pf}.

[c]Market performance statistics: R_m annual=17.43%, R_{mf} annual=7.40%, and σ_{Rmf}=4.58%.

Figure 12. Timing and Selectivity
Portfolio Return Environments, Rp (% Annual)

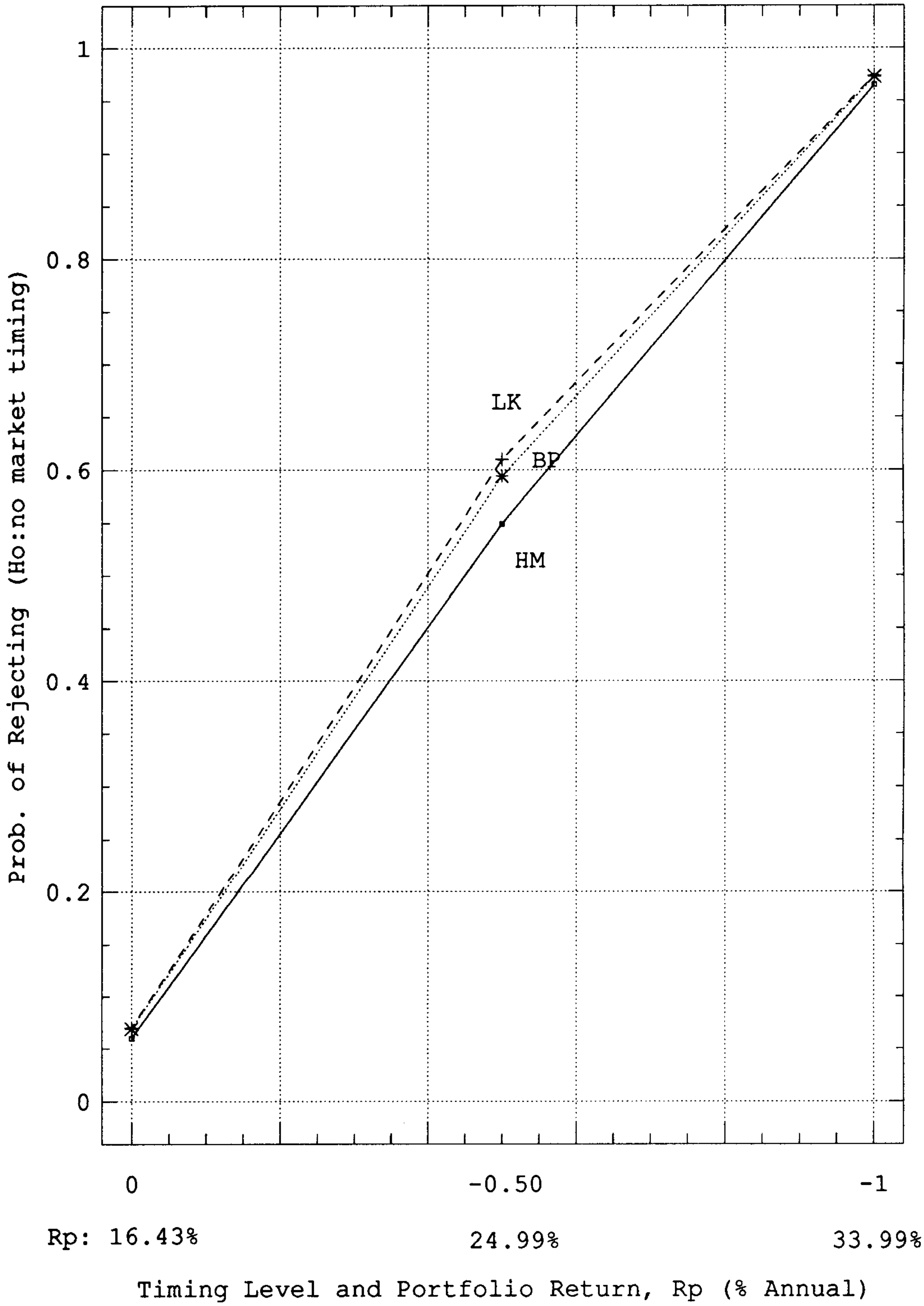


$\Delta_{SEL}=0\%$. In this case, the HM, LK, and BP models all detect managerial timing ability with probabilities of 0.50 or greater. The power of models in the test of market timing and the corresponding timing skill and portfolio returns are shown in Figure 13.

In skilled environments, $\rho_{TIM}=-1$, the minimum portfolio annual return equals 33.99% when the manager is not successful in superior stock selection, $\Delta_{SEL}=0\%$. Given this return environment, all of the models detect managerial timing ability with probabilities of 0.95 or greater as is shown in Figure 13.

When the managed fund and the market have approximately the same performance, R_p=16.43% and R_m=17.43%, the Henriksson-Merton model exhibits the highest power in detecting lack of managerial timing skill. The LK and BP models also perform well in exposing lack of ability. On the other hand, when the manager is skillful in forecasting the market direction, $\rho_{TIM}=-1$, with a minimum realized return of 33.93% annually, the LK and BP models perform better than the HM model. This model behavior is also repeated in semi-skilled timing environment, $\rho_{TIM}=-0.50$. A graphical representation of these results is presented in Figure 13.

Figure 13. Power of Models in Test of
Timing When Selectivity Level = 0%



4.2.2 Power of Models in Test of Selectivity Ability

The tests for managerial selectivity ability to investigate the power of the models are conducted in a similar fashion to the tests for market timing ability. Appendix E summarizes the three-factor experimental design study to explore the relationship among the factors of model, selectivity, and timing. The proportions in Appendix E are the probabilities that the null hypothesis of no selectivity ability, $H_o{:}\alpha \leq 0$, is rejected by selectivity parameters that are statistically significant at the 5% level. The results of analysis of variance are summarized in Table 20. The main effects of all the factors and interactions between them are highly significant.

A closer investigation of Appendix E reveals that with timing skill added to the constructed portfolio returns, the Henriksson-Merton model tends to sacrifice power. Given the selectivity skill environments, $\Delta_{SEL}=0\%,1\%,2\%$, the probability of rejecting the null hypothesis of no selectivity ability, $H_o{:}\alpha \leq 0$, tends to decrease across all timing environments, $\rho_{TIM}=0,-0.50,-1$. This is characterized by fewer errors in no-skill environments and by increased errors in skilled environments. This particular model's behavior can be explained in terms of a negative correlation between timing and selectivity skills. Figure 14 depicts the behavior of the model's selectivity parameter, α_p, in the presence of

Table 20

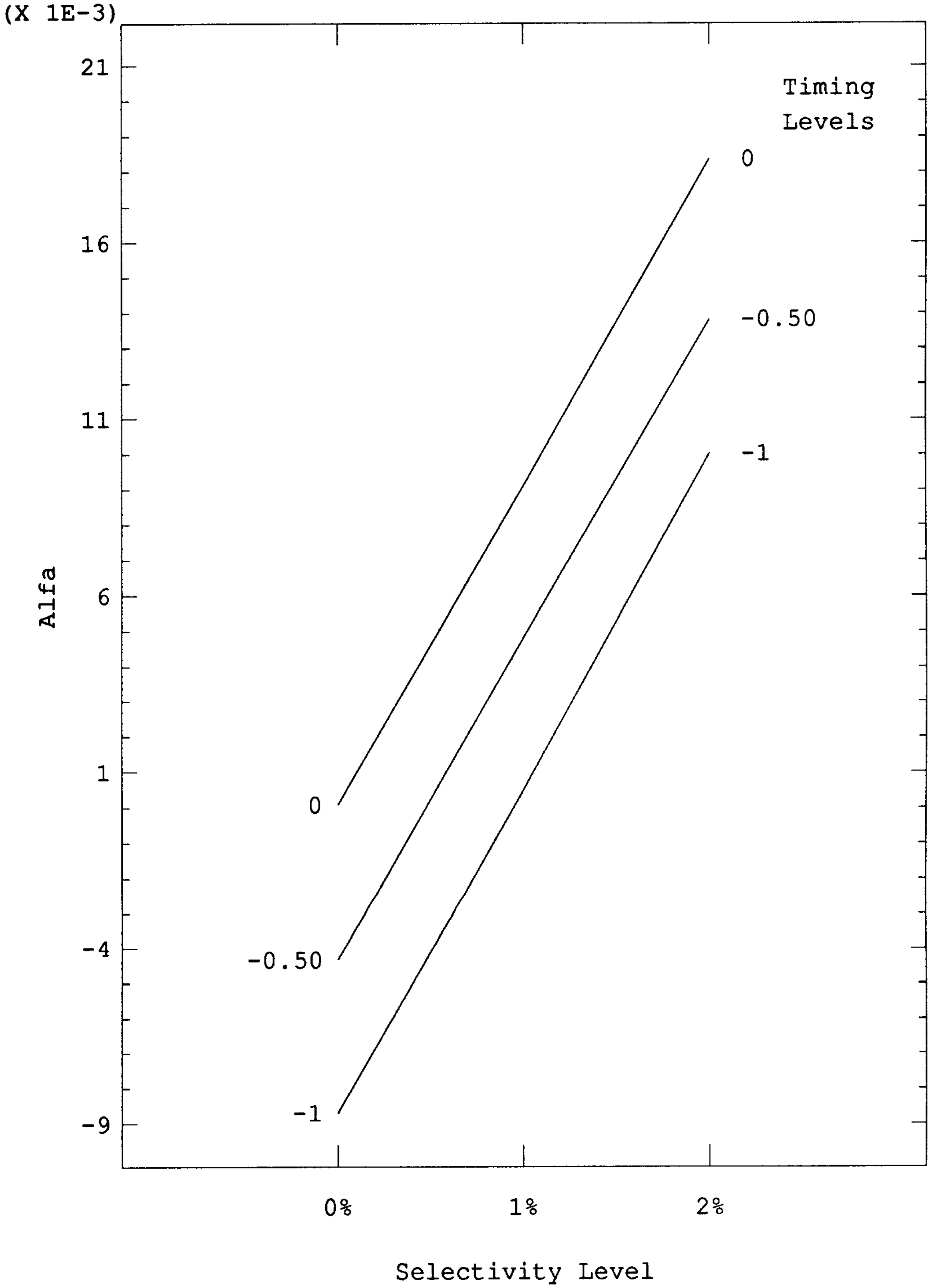
ANOVA Table for Testing No Selectivity Ability, $H_0:\alpha_p \leq 0$; All Models Included

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:Model	82084.9	3	27361.6	5525.0	.00
B:Timing	233140.0	2	116570.0	23538.3	.00
C:Selectivity	871.1	2	435.5	87.9	.00
INTERACTIONS					
AB	10556.2	6	1759.4	355.3	.00
AC	23105.9	6	3851.0	777.6	.00
BC	3104.5	4	776.1	156.7	.00
ABC	6075.3	12	506.3	102.2	.00
RESIDUAL	356.6	72	4.9		
TOTAL	359294.6	107			

market timing ability. With the added managerial timing skill, the model tends to break down as it becomes biased in showing the true selectivity ability of the manager. As shown in Table 21, the differences in alfas, α_p, in the various timing environments, $\rho_{TIM}=0,-0.50,-1$, are statistically significant at the 5% level, i.e., Sig. level for the Timing factor = .00.

Various empirical mutual fund studies, Kon (1983), Chang and Lewellen (1984), Henriksson (1984), and more recently Connor and Korajczyk (1991) have confirmed this characteristic of the HM model. The mutual funds with significant timing parameter have most often demonstrated a

Figure 14. Behavior of HM's Alfa in
Timing and Selectivity Environments, Test of Selectivity



negative selectivity performance. Henriksson (1984) has offered possible explanations, including market portfolio proxy and errors-in-variables biases, and model misspecification.

Table 21

ANOVA Table for Differences in HM's Alfas, α_p, in Various Timing and Selectivity Environments

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:Selectivity	.001523	2	7.61E-4	7917.1	.00
B:Timing	.000331	2	1.65E-4	1721.9	.00
INTERACTIONS					
AB	3.36E-7	4	8.40E-8	0.9	.50
RESIDUAL	1.73E-6	18	9.61E-8		
TOTAL	.001856	26			

Jagannathan and Korajczyk (1986) also pursued this problem and their study suggested that the HM model tends to break down due to the nature of the constructed portfolios. The existence of options or option-like securities in mutual fund portfolios have been offered as possible directions to explain the negative correlation among the timing and selectivity measures observed when using the HM model. This particular behavior of the HM model, negative correlation between α_p and added managerial timing abilities, ρ_{TIM}=*0,-0.50, -1*, is also confirmed in our study. Furthermore, given the investment objectives of our sample fund data, our results are applicable in environments where the mutual funds are classified as Maximum Capital Gains (MCG), Growth and Current Income (GCI), and Long-Term Growth (LTG). In addition, the constructed fund portfolios in this study can be categorized as investments in companies with high-capitalization stocks.

The LK and BP models' selectivity parameters tend to be robust in the various levels of timing environments. Figures 15 and 16 show the behavior of these models' alfa, α_p, in timing, $\rho_{TIM}=0,-0.50,-1$, and selectivity, $\Delta_{SEL}=0\%,1\%,2\%$, environments. Furthermore, as Table 22 shows, the timing (selectivity) environments do not affect the models' alfas, α_p, i.e., the timing (selectivity) and model factors do not interact: Sig. level = 0.99 (.28). In addition, the models' alfas, α_p, behave similarly, as the main effect of the factor model is not statistically significant at the 5% level, i.e., Sig. level = .07.

The inadequacy of the Jensen model in tests for managerial timing ability was mentioned in the previous section. Therefore, to investigate the power of these models in testing for managerial selectivity ability, we examine all of the models in the no-skill managerial timing environment, $\rho_{TIM}=0$. The JN and HM models tend to be robust in environments where the portfolio manager possesses no timing ability. However, when testing for models' power in environments where managerial timing (macroforecasting)

Figure 15. Behavior of BP and LK's Alfa in Timing Environments, Test of Selectivity

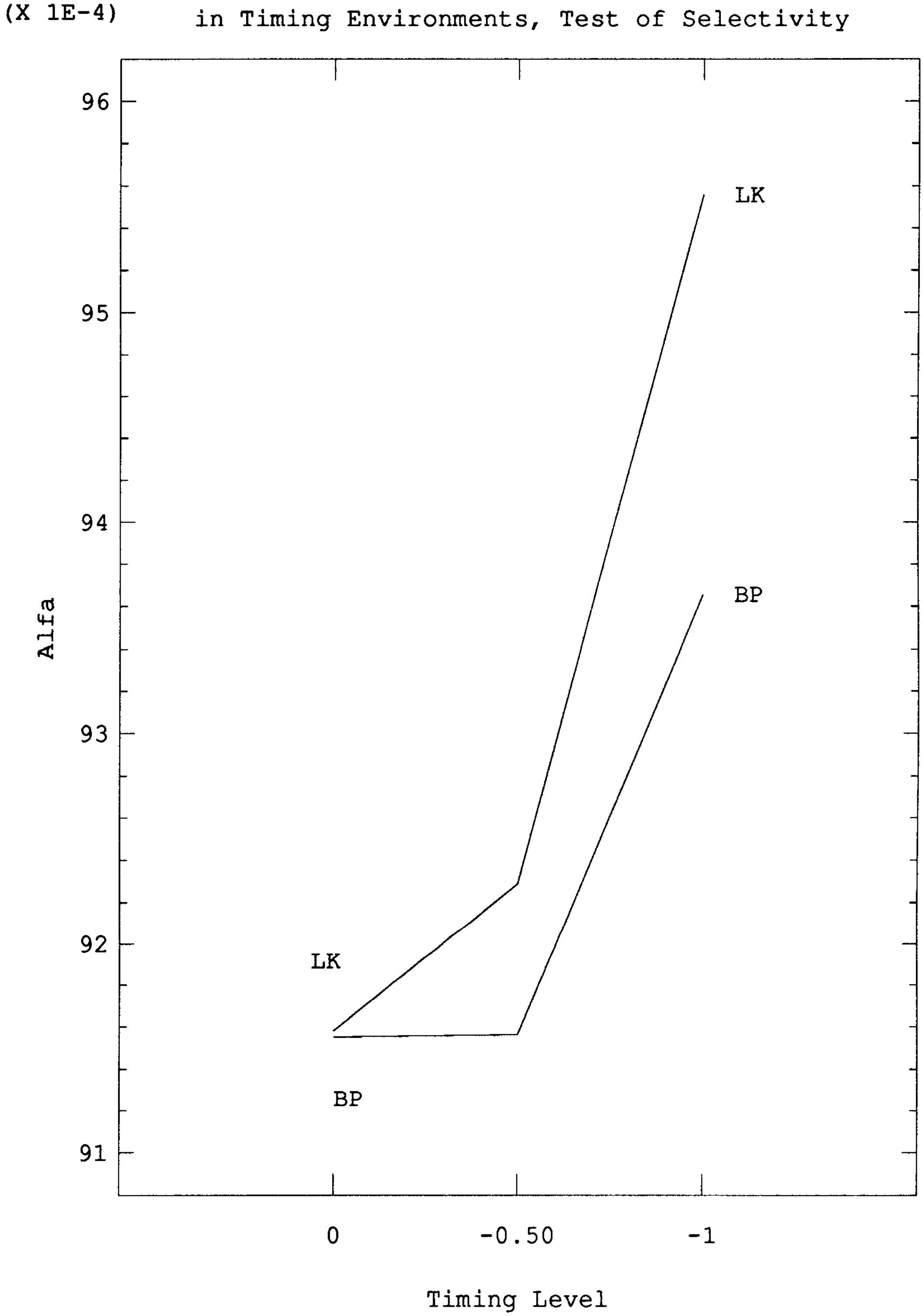
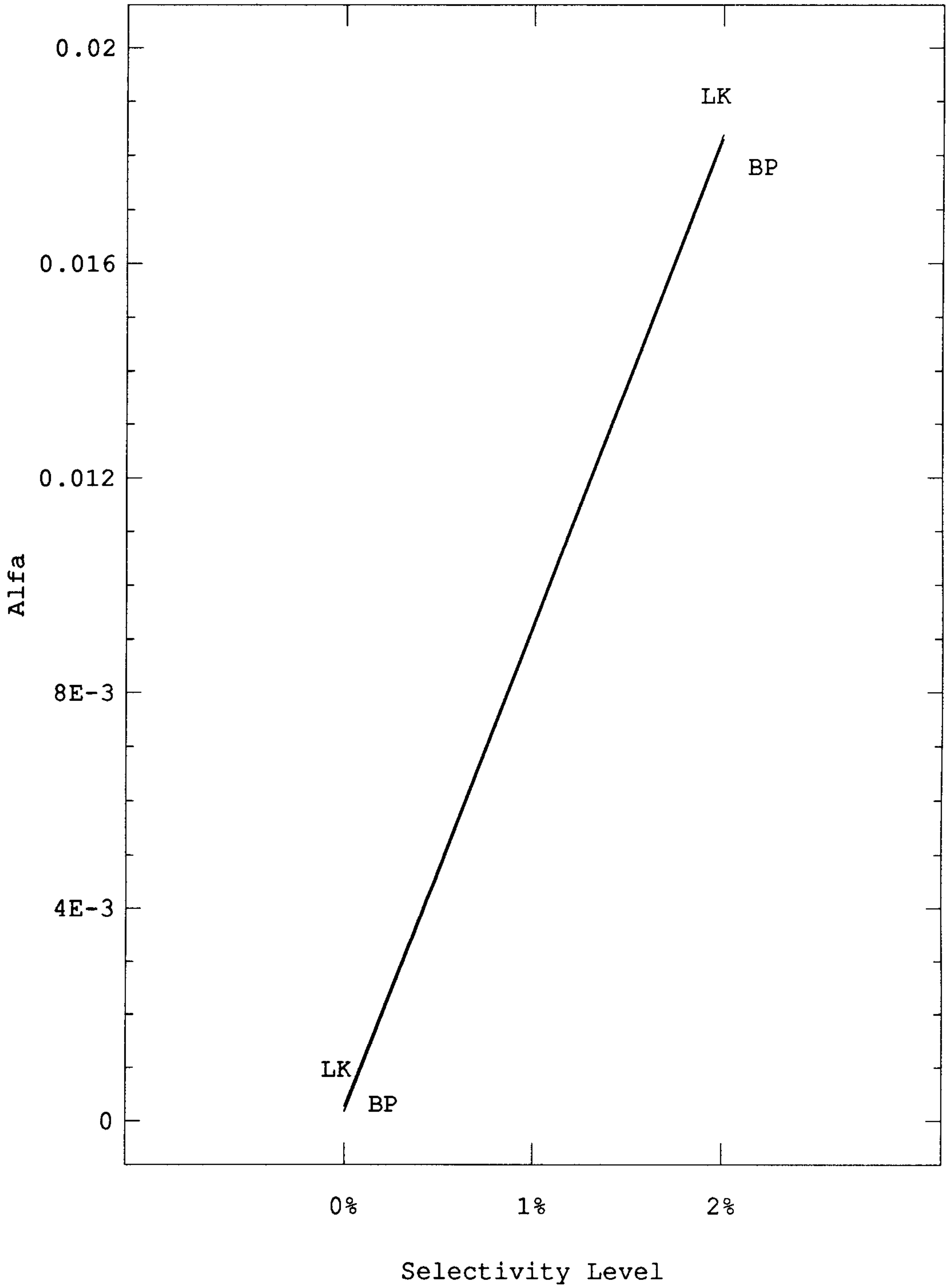


Figure 16. Behavior of BP and LK's Alfa
in Selectivity Environments, Test of Selectivity



ability exists, the JN and HM models tend to break down. Therefore, we only investigate the LK and BP models in these environments, i.e., $\rho_{TIM}=0,-0.50,-1$.

Table 22

ANOVA Table for Differences in LK and BP's Alfas, α_p, in Various Timing and Selectivity Environments

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:Model	1.00E-07	1	1.00E-07	3.5	.07
B:Timing	0.002956	2	0.001478	48821.4	.00
C:Selectivity	1.00E-06	2	5.00E-07	16.4	.00
INTERACTIONS					
AB	8.47E-10	2	4.23E-10	1.40E02	.99
AC	8.07E-08	2	4.03E-08	1.3	.28
BC	1.07E-07	4	2.67E-08	0.9	.48
ABC	1.10E-09	4	2.76E-10	0.90E-2	.99
RESIDUAL	1.09E-06	36	3.03E-08		
TOTAL	0.002959	53			

Analysis of variance was conducted for all the models when testing for the null hypothesis of no selectivity ability in the presence of no macroforecasting (timing) skill, $\rho_{TIM}=0$. These results are summarized in Table 23. The main effects and interactions between the model and selectivity factors are highly significant at the 5% level.

Table 23

ANOVA Table for Testing No Selectivity Ability, H_o:$\alpha_p \leq 0$; When $\rho_{TIM}=0$, All Models Included

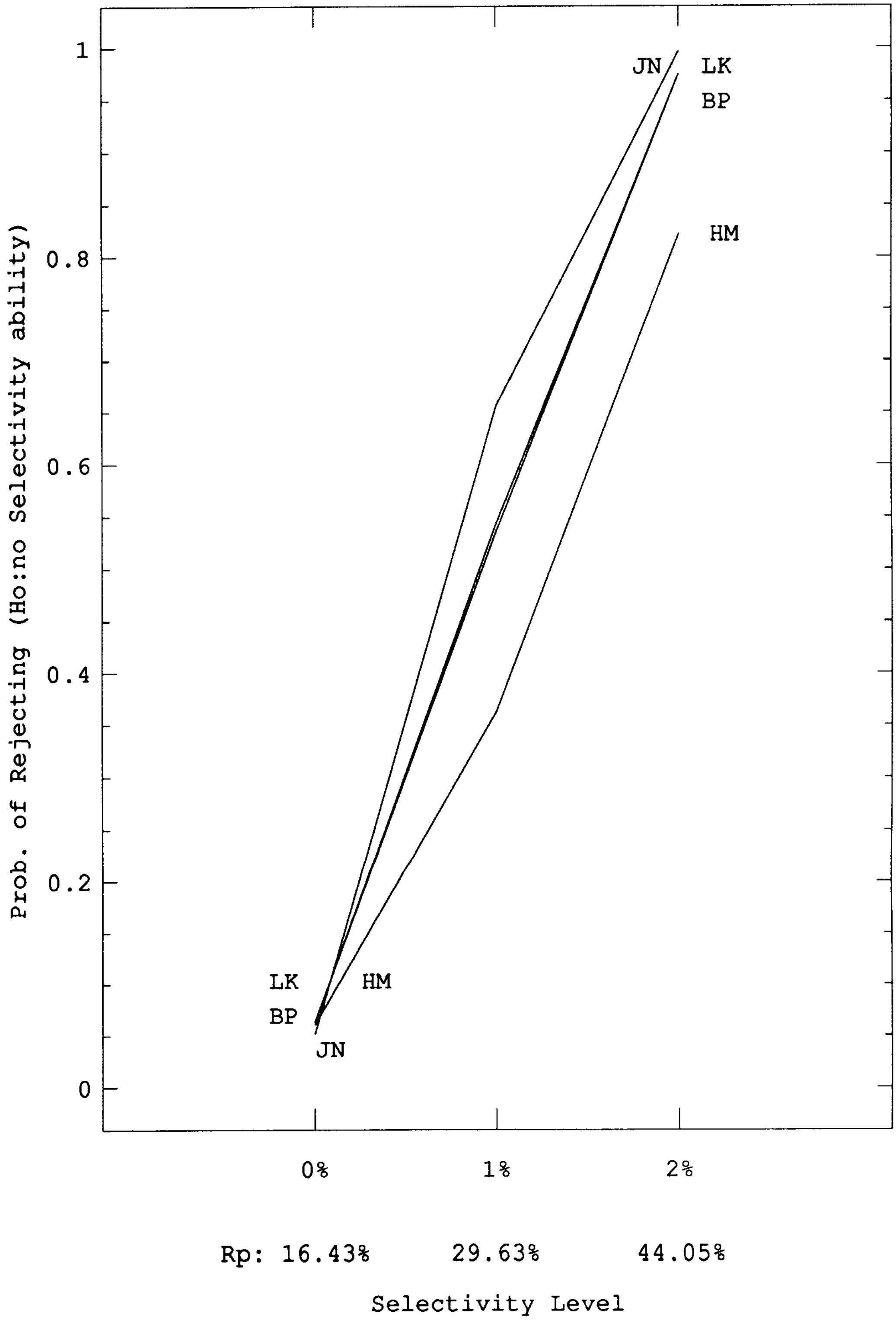
Source of Variation	*SS*	*df*	*MS*	*F*[*]	*Sig. level*
MAIN EFFECTS					
A:Model	3043.3	3	1014.4	291.8	.00
B:Selectivity	99021.9	2	49511.0	14241.1	.00
INTERACTIONS					
AB	1853.4	6	308.9	88.8	.00
RESIDUAL	83.4	24	3.5		
TOTAL	104002.1	35			

The treatment means are used to conduct a pairwise comparison among the models. Figure 17 demonstrates how these models behave in various managerial selectivity environments, $\Delta_{SEL}=0\%,1\%,2\%$, when managerial timing ability does not exist, $\rho_{TIM}=0$.

The error rates for the environment in which no managerial selectivity ability exists, $\Delta_{SEL}=0\%$, do not differ significantly, hence, all of the models exhibit similar power. However, in the presence of managerial selectivity ability, $\Delta_{SEL}=1\%,2\%$, error rates differ significantly. As is shown in Figure 17, the Jensen model is significantly different at the 5% level and exhibits the highest power, i.e., commits the least number of errors, when $\Delta_{SEL}=1\%,2\%$.

The LK and BP models show the next highest performance,

Figure 17. Plot of Interactions for Model by Selectivity Level, Test of Selectivity

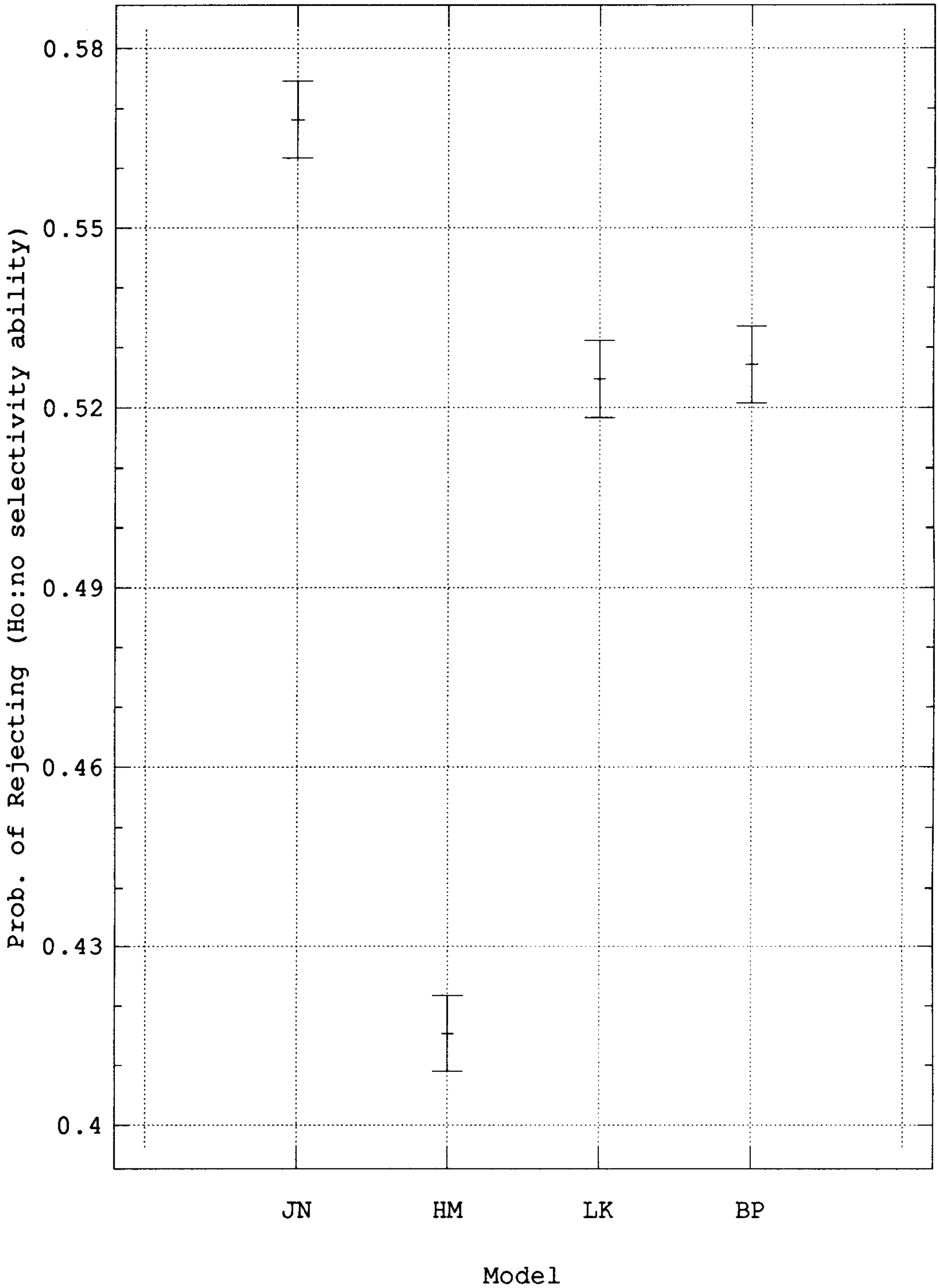


and behave very similarly in both managerial selectivity environments where the added levels of skill are 1% and 2%. The HM methodology has the least power as it commits the most errors in skilled environments, and the model is significantly different from other models at the 5% level. These results, together with the selectivity environments and the associated portfolio returns, R_p, when the manager does not possess timing ability, $\rho_{TIM}=0$, are depicted in Figure 17.

An overall comparison, using multiple range analysis, among the models' means showed that the JN model has the highest discriminatory power when testing for the null hypothesis of no selectivity ability, and the HM model is most inferior. The 95% confidence intervals for models' means are shown in Figure 18. It can be seen that models LK and BP are very similar and the results indicate that both models are significantly different from the JN and HM models at the 5% level.

These results are only applicable when the managerial timing ability does not exist, $\rho_{TIM}=0$. Next, the LK and BP models are explored in terms of their power across macroforecasting (timing) skill environments, $\rho_{TIM}=0,-0.50,-1$. The results of the analysis of variance when testing for selectivity ability for the LK and BP models is shown in Table 24. Due to the biases of the JN and HM models, these methodologies are not included. The main effects and interactions between the model and selectivity factors, and

Figure 18. 95% Confidence Intervals for Models' Means, Test of Selectivity



model and timing, are not statistically significant at the 5% level. The results of range analysis showed that there is no significant difference among the LK and BP models at the 5% level. The 95% confidence intervals for models' means, shown in Figure 19, confirm these results.

Table 24

ANOVA Table for Testing No Selectivity Ability, $H_0:\alpha_p \le 0$; Across All Timing Environments Using LK and BP Models

Source of Variation	*SS*	*df*	*MS*	F^*	*Sig. level*
MAIN EFFECTS					
A:Model	0.4	1	0.39	0.17	.69
B:Timing	161161.3	2	80580.67	3.439E4	.00
C:Selectivity	57.0	2	28.50	12.16	.00
INTERACTIONS					
AB	2.0	2	1.01	0.43	.65
AC	1.3	2	0.65	0.28	.76
BC	20.8	4	5.19	2.22	.09
ABC	5.3	4	1.32	0.56	.69
RESIDUAL	84.3	36	2.34		
TOTAL	161332.5	53			

Figure 20 shows the effect of various managerial selectivity abilities, $\Delta_{SEL}=0\%,1\%,2\%$, on these models' power. The models are virtually identical and do not exhibit statistically significant differences in various levels of microforecasting skill. The interactions between the factors of model and timing is depicted in Figure 21. The LK model

Figure 19. 95% Confidence Intervals for Models' Means, Test of Selectivity

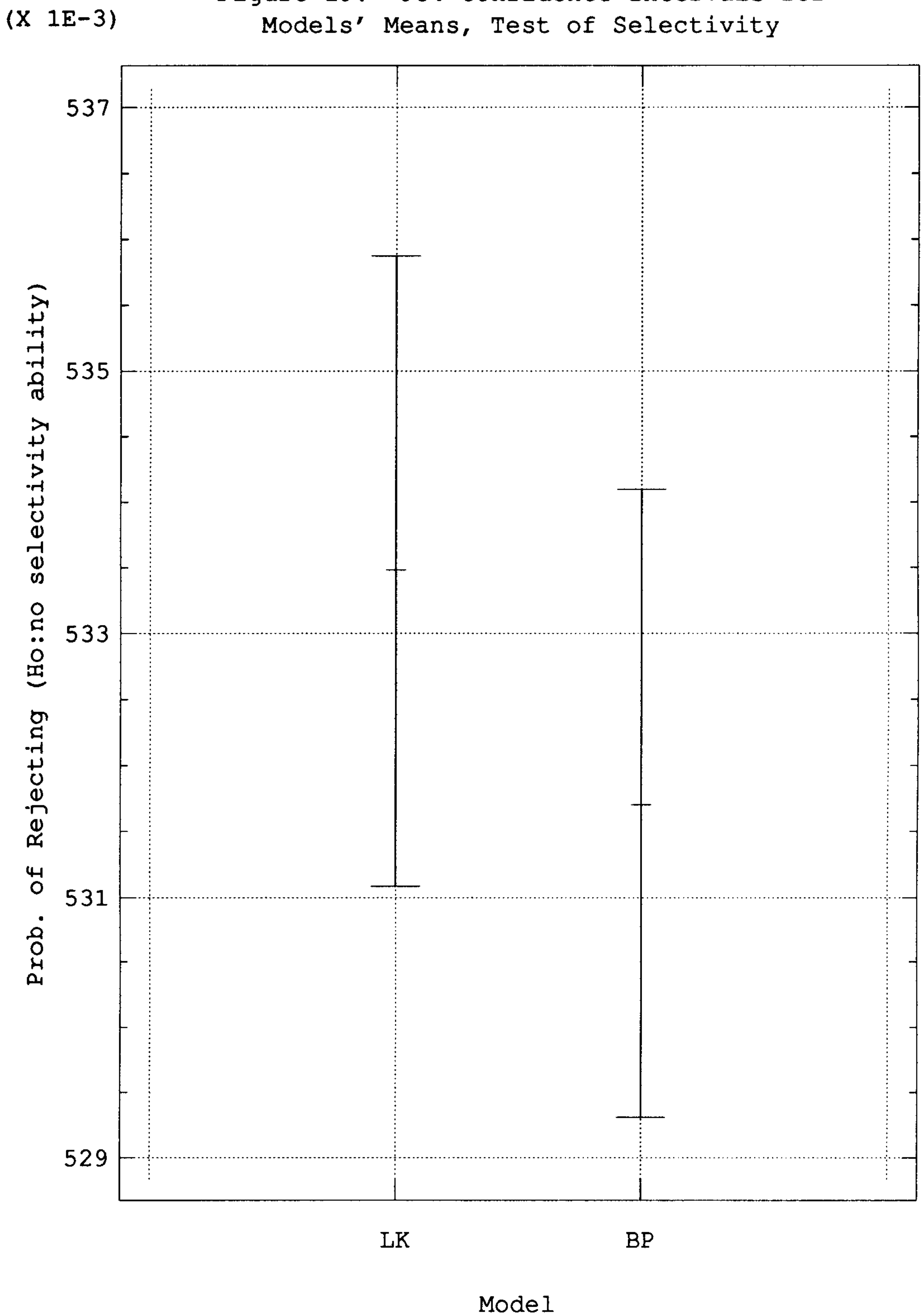


Figure 20. Plot of Interactions for
Model by Selectivity Level, Test of Selectivity

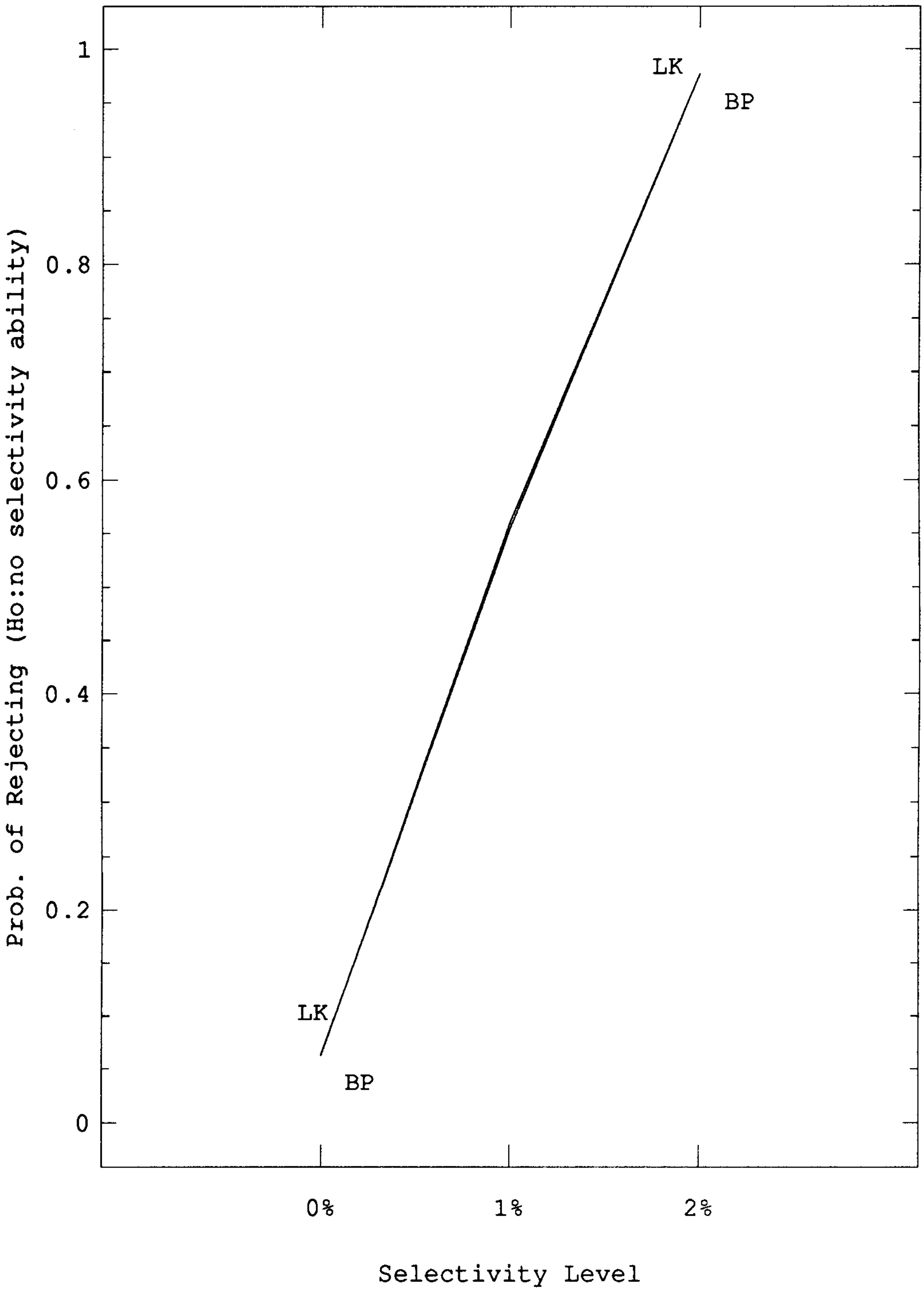
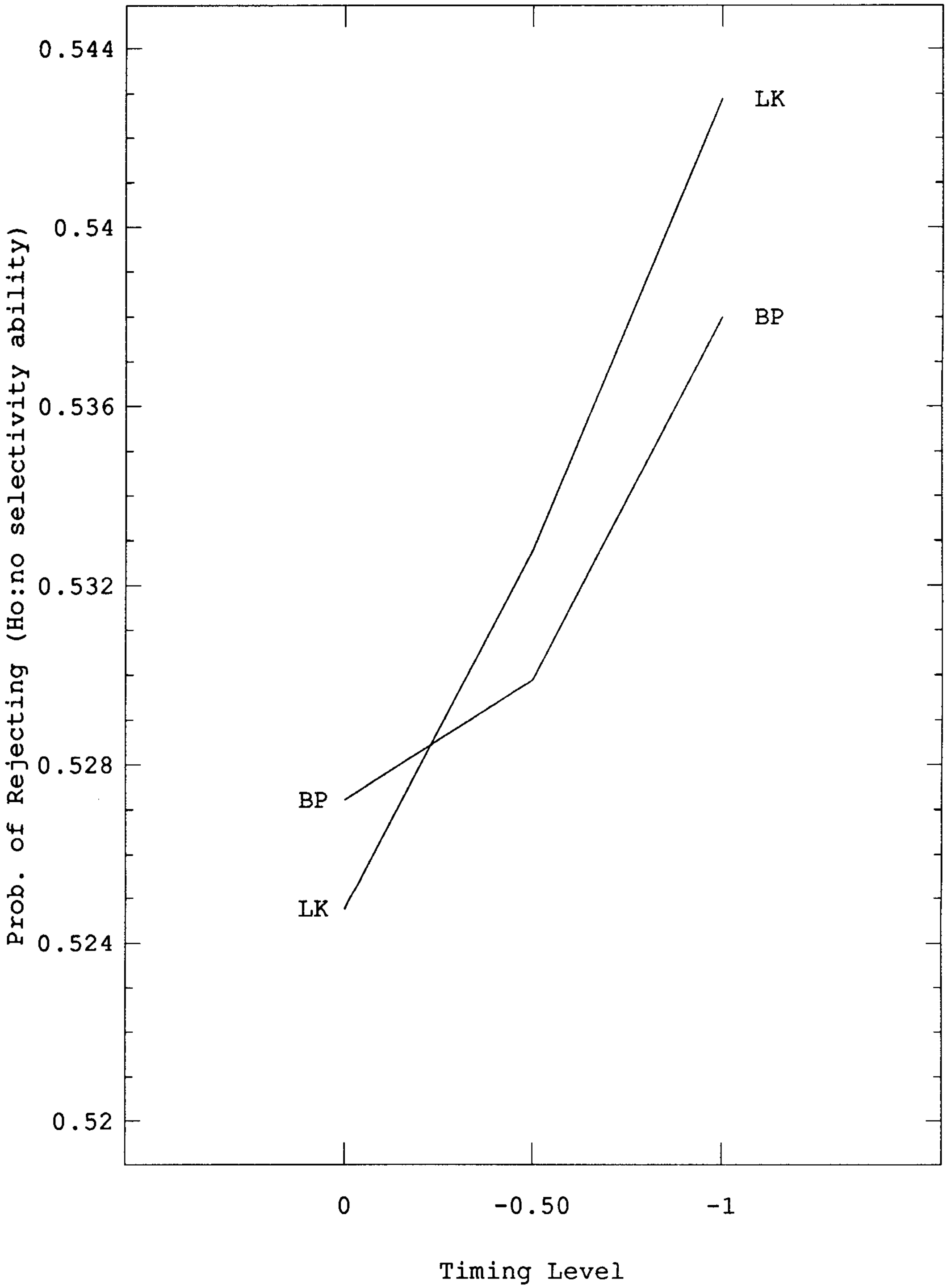


Figure 21. Plot of Interactions for Model by Timing Level, Test of Selectivity



has fewer errors in the no-skill environment, $\rho_{TIM}=0$; therefore, it has more power than the BP model in showing lack of managerial selectivity ability. This specific behavior is also repeated in environments in which the manager possesses timing ability, $\rho_{TIM}=-0.50,-1$, as is shown in Figure 21. Although the LK model exhibits higher power in revealing managerial selectivity ability, these differences are marginal and the models are not statistically significant at the 5% level. Furthermore, this leads us to the conclusion that the heteroskedasticity correction methods of White and GLS, in this case, perform equally. The rankings of the models in tests of managerial selectivity ability are summarized in Table 25.

The selectivity portfolio returns are summarized in Table 21, as are the timing portfolios. With a minimum portfolio return of 16.43% annually, when managers have no-skill in both timing and selectivity abilities, $\rho_{TIM}=0$ and $\Delta_{SEL}=0\%$, all of the models perform well in detecting no selectivity ability with the probability of errors approaching 0.05.

When the manager is semi-skilled in selectivity ability, $\Delta_{SEL}=1\%$, and possess no timing ability, $\rho_{TIM}=0$, the realized portfolio return equals 29.63%. In this return environment, all the models except the HM detect managerial selectivity ability with probabilities of 0.50 or greater, with the JN showing the highest power.

Table 25

Rankings of Mutual Fund Performance Models in Test of Managerial Selectivity Ability, $H_o: \alpha_p \leq 0$, for Various Timing and Selectivity Environments

	TIMING SKILL		
	$\rho_{TIM} = 0$	$\rho_{TIM} = -0.50$	$\rho_{TIM} = -1$
$\Delta_{sel} = 0\%$	1. JN 2. LK,BP 3. HM	1. LK,BP	1. LK,BP
SELECTIVITY			
$\Delta_{sel} = 1\%$	1. JN 2. LK,BP 3. HM	1. LK,BP	1. LK,BP
SKILL			
$\Delta_{sel} = 2\%$	1. JN 2. LK,BP 3. HM	1. LK,BP	1. LK,BP

The models exhibit the same behavior when the manager has superior skills in selectivity and has no-skill in market timing, $\Delta_{SEL}=2\%$ and $\rho_{TIM}=0$. With a realized portfolio return of 44.05% annually, the JN, LK, and BP models detect managerial ability with probabilities of 0.95 or greater. The HM model exhibits minimum power when the manager is skilled in stock selectivity, $\Delta_{SEL}=2\%$. With the increased timing skill and improved portfolio return, the LK and BP models show the same power in tests of managerial selectivity ability, whereas the JN and HM models break down.

The LK and BP methodologies provide identical model specifications in testing for managerial selectivity ability. However, when the models are corrected for the heteroskedasticity due to nonconstant error term variance, the LK model is modified using the White method and the BP model is corrected using the GLS formulation. Our study examines the power of these models in testing for managerial selectivity ability to explore the differences among the two methods.

Chapter 5

SUMMARY AND CONCLUSIONS

The results of this study provide evidence on the statistical power of various mutual fund timing and selectivity models. However, the results are subject to a set of constraints. The simulated portfolio returns were constructed under a set of assumptions. The market risk premium monthly returns were generated according to the distribution of the series during the period 1975-1989. The timing portfolios were constructed using the T-bill distribution of mutual fund sample data over the period 1984-1989. The investment objectives of these funds were classified as Maximum Capital Gain (MCG), Growth and Current Income (GCI), and Long-Term Growth (LTG). The amount of noise in the constructed portfolio returns was modeled according to the observed distribution of the error terms when the performance models were applied to the mutual fund return data. The market risk premium returns and portfolio composition in T-bills were modeled using a lognormal distribution. In addition, the timing portfolio returns were simulated, according to a bivariate lognormal distribution, using the market returns and the sample mutual fund T-bill distribution. Furthermore, the selectivity portfolios were simulated by adding constant levels of excess returns to the monthly generated returns.

Mutual fund portfolio management activities are very complex and diverse. Therefore, the results of our study are applicable only under the specified conditions. The outlined assumptions were an attempt to capture and model mutual fund portfolio managers' behavior in specific timing and selectivity environments.

The observed error rates for the Henriksson-Merton model were not affected by correction for heteroskedasticity. The results indicate that this condition holds true both in tests of market timing and managerial selectivity abilities, $H_o: \beta_{TIM} \leq 0$ and $H_o: \alpha_p \leq 0$. However, in the case of the Lockwood-Kadiyala model, the observed differences in error rates are significantly different at the 5% level after correction for heteroskedasticity. This pattern is observed in both tests of managerial timing and selectivity abilities. Similar to the LK model, the Bhattacharya-Pfleiderer model's results for tests of managerial timing and selectivity abilities are significantly different at the 5% level after accounting for nonconstant error term variance.

In tests of market timing, the LK and BP models exhibited more power to reveal managerial ability in macroforecasting than the HM model. However, in environments where managers do not possess timing ability, the HM model was more powerful in demonstrating lack of skill.

The power of performance models were also examined when testing for managerial selectivity ability. In the no-skill timing environment, the models had the following ranking: 1) Jensen; 2) Lockwood-Kadiyala and Bhattacharya-Pfleiderer (tied); and 3) Henriksson-Merton. However, when managers possess timing skill, the LK and BP models performed identically in revealing managerial skill in testing for selectivity ability. Furthermore, in selectivity environments where managers possess timing ability, the Jensen and Henriksson-Merton models were not robust, as the models broke down in detecting managerial ability. According to the described rankings, the time-varying beta models of Lockwood-Kadiyala and Bhattacharya-Pfleiderer overall showed the highest power in tests of both market timing and selectivity abilities.

Most of the recent mutual fund studies have concluded that, on average, the fund managers do not possess timing and selectivity skills. Attempts have been made to provide answers to this pattern of results. From this study's perspective, a simulation procedure was designed to model the managerial timing and selectivity skills. According to the amount of noise which is characteristic of equity mutual funds, together with this study's assumptions, a fund manager would be identified as a market timer when the realized portfolio return exceeds the market return by at least 17% annually. More specifically, the corresponding accuracies of detection rate for managerial timing ability were as follows: HM: 96.5%, LK: 97.4%, and BP: 97.3%. In tests of selectivity ability, the minimum portfolio return in excess of market return was at least 27% annually before the fund manager could be identified as skillful in superior stock selection. Furthermore, the models achieved the following levels of accuracy in detecting the managerial selectivity ability: JN: 99.6%, HM: 82.2%, and LK and BP: 97.5%.

This partly explains the results of previous mutual fund studies that managers, on average, cannot "beat the market." This may be discussed in terms of the noise that is present in the return data. The models selected in this study did not provide reliable results given the characteristics of the data used in current performance studies. The models lack power in detecting ability, unless the fund managers are extremely skillful in forecasting market directions and selecting superior stocks.

Aside from the results of the performance models, if the fund returns are not superior compared to the benchmark portfolios, it is possible that managers do not engage in active management due to the excessive transaction costs incurred in trading securities. It is also possible that managers do not attempt to time the market, simply because the down-side risk is not tolerable. One interesting explanation could be that fund managers engage in "herd behavior", as discussed by Scharfstein and Stein (1990). Under this behavioral theory, the manager acts according to "group psychology", and ignores quality information that might be available. Furthermore, the asset allocation activities of fund managers can also be analyzed under this theory. If mutual fund managers behave according to the "herd" model, then it is possible that, on average, they will not be able to outperform the market.

Given a portfolio management environment where money managers engage in timing and selectivity activities, more powerful models that account for noise need to be formulated. In addition, the state of the art performance models require further examination. The designed timing and selectivity portfolios could be expanded to include investments in small stocks and fixed-income securities. Another possibility is the inclusion of non-cash securities as a timing medium. Further examination of mutual fund timing and selectivity models under diverse portfolio and market conditions would provide more in-depth insight into the working characteristics (power) of these models.

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APPENDICES

APPENDIX A

LIST OF SELECTED MUTUAL FUNDS (AS OF 1989)

GCI: Growth and Current Income
LTG: Long-term Growth
MCG: Maximum Capital Gains

	Fund	Objective	Total Assets($mil)
1.	Aim Eq. - Aim Const.	MCG	83.58
2.	Alliance (Chemical)	LTG	837.42
3.	American Capital Entr.	MCG	601.24
4.	David L. Babson (Gr.)	LTG	273.39
5.	Bull & Bear Cap. Gr.	LTG	65.43
6.	Colonial Gr.	GCI	124.76
7.	Eaton Vance Gr.	LTG	92.12
8.	Eaton Vance Sp. Eq.	LTG	53.49
9.	Evergreen	MCG	792.37
10.	Fidelity Destiny	LTG	1753.30
11.	Fidelity Magellan	MCG	12699.60
12.	Fidelity Trend	LTG	883.64
13.	Financial Ind.	LTG	369.49
14.	Franklin Equity	MCG	412.45
15.	Franklin Gr. Series	LTG	144.14
16.	Lord Abbett Dev. Gr.	MCG	135.79
17.	M. Lynch Sp. Value	LTG	66.44
18.	Morgan (W.L.) Gr.	LTG	732.80
19.	Pioneer II	GCI	4382.59
20.	Price T. Rowe Gr. Stock	LTG	1516.04
21.	Price T. Row New Era	LTG	826.58
22.	Putnam Hlth. Sci.	LTG	293.80
23.	Putnam Investors	LTG	691.68
24.	Putnam Voyager	MCG	731.36
25.	Scudder Cap. Gr.	MCG	993.11
26.	Seligman Cap.	MCG	124.62
27.	Seligman Gr.	LTG	554.36
28.	State Str. Investments	GCI	575.11
29.	Strategic Investments	LTG	59.40
30.	20th Cent. Select	LTG	2858.68
31.	Vanguard Index Trust	GCI	1803.84

APPENDIX B

PERFORMANCE MODELS' STATISTICS FOR SELECTED MUTUAL FUNDS (HETEROSKEDASTICITY-CORRECTED)

		Fund 1	Fund 2	Fund 3	Fund 4
Size	($mil)	83.58	837.42	601.24	273.39
R_{pf}^{1}	Ann. %	20.37	6.94	4.32	6.61
σ_{Rpf}	Mon. %	9.81	7.64	12.62	6.03
JN:	α	0.017	-0.002	0.003	-0.001
	β	0.324	1.125**	0.832**	0.956
	R^2	0.027	0.530	0.106	0.616
	σ_ϵ	0.097	0.053	0.120	0.038
HM:	α	0.039*	-0.005	0.011	-0.004
	β_{TIM}	3.031*	0.200	0.424	0.132
	R^2	0.309	0.532	0.110	0.617
	σ_ϵ	0.083	0.053	0.121	0.038
LK:	α	-0.015	-0.002	0.007	-0.001
	β_{TIM}	11.099**	0.066	1.377	-0.310
	R^2	0.465	0.530	0.110	0.617
	σ_ϵ	0.073	0.053	0.121	0.038
BP:	α	-0.013	-0.003	0.008	-0.002
	ρ_{TIM}	0.475**	0.029	-0.071	0.045
	R^2	0.465	0.530	0.110	0.617
	σ_ϵ	0.073	0.053	0.121	0.038

*Significant at the 5% level.

**Significant at the 1% level.

[1]Returns are in risk premium form, $R_{pf} = R_p - R_f$. For the same period, 1984-1989, Market Return: $R_{mf} = 0.92\%$ and $\sigma_{Rmf} = 4.95\%$.

Appendix B (cont.)

Performance Models' Statistics for Selected Mutual Funds

		Fund 5	Fund 6	Fund 7	Fund 8
Size	($mil)	65.43	124.76	92.12	53.49
R_{pf}^{1}	Ann. %	-5.37	8.20	7.34	0.00
σ_{Rpf}	Mon. %	7.61	6.09	5.71	6.23
JN:	α	-0.011	-0.001	-0.001	-0.007
	β	1.045**	1.006	0.993	1.020
	R^2	0.461	0.666	0.739	0.653
	σ_ϵ	0.056	0.035	0.029	0.037
HM:	α	-0.003	-0.003	0.002	-0.009
	β_{TIM}	-0.042	0.120	-0.203	0.092
	R^2	0.470	0.667	0.743	0.654
	σ_ϵ	0.056	0.036	0.029	0.037
LK:	α	-0.008	-0.001	0.000	-0.008
	β_{TIM}	-0.967	0.058	-0.391	0.079
	R^2	0.467	0.666	0.741	0.653
	σ_ϵ	0.056	0.036	0.029	0.037
BP:	α	-0.008	-0.001	0.000	-0.008
	ρ_{TIM}	-0.102	0.049	-0.085	0.035
	R^2	0.467	0.666	0.741	0.653
	σ_ϵ	0.056	0.036	0.029	0.037

*Significant at the 1% level.

**Significant at the 5% level.

[1]Returns are in risk premium form, $R_{pf} = R_p - R_f$. For the same period, 1984-1989, Market Return: $R_{mf} = 0.92\%$ and $\sigma_{Rmf} = 4.95\%$.

Appendix B (cont.)

Performance Models' Statistics for Selected Mutual Funds

		Fund 9	Fund 10	Fund 11	Fund 12
Size	($mil)	792.37	1753.30	12699.60	883.64
R_{pf}^{1}	Ann. %	4.69	8.80	11.73	5.77
σ_{pf}	Mon. %	5.32	6.68	6.04	6.18
JN:	α	-0.002	0.000	0.002	-0.003
	β	0.819**	0.979**	1.038**	1.050**
	R^2	0.580	0.526	0.722	0.705
	σ_ϵ	0.035	0.046	0.032	0.034
HM:	α	0.000	0.003	0.006	0.003
	β_{TIM}	-0.143	-0.132	-0.242	-0.310
	R^2	0.582	0.527	0.727	0.713
	σ_ϵ	0.035	0.046	0.032	0.034
LK:	α	0.000	0.001	0.003	0.000
	β_{TIM}	-0.656	-0.436	-0.550	-1.115
	R^2	0.586	0.530	0.725	0.717
	σ_ϵ	0.035	0.046	0.032	0.033
BP:	α	-0.001	0.001	0.004	0.000
	ρ_{TIM}	-0.066	-0.030	-0.083	-0.103
	R^2	0.586	0.530	0.725	0.717
	σ_ϵ	0.035	0.046	0.032	0.033

*Significant at the 1% level.

**Significant at the 5% level.

[1]Returns are in risk premium form, $R_{pf} = R_p - R_f$. For the same period, 1984-1989, Market Return: $R_{mf} = 0.92\%$ and $\sigma_{Rmf} = 4.95\%$.

Appendix B (cont.)

Performance Models' Statistics for Selected Mutual Funds

		Fund 13	Fund 14	Fund 15	Fund 16
Size	($mil)	369.49	412.45	144.14	135.79
R_{pf}^{1}	Ann. %	4.01	8.37	7.50	-6.27
σ_{Rpf}	Mon. %	6.33	6.06	3.96	6.14
JN:	α	-0.005	0.001	0.000	-0.013**
	β	1.105**	0.840**	0.716**	1.012**
	R^2	0.746	0.470	0.801	0.664
	σ_ϵ	0.032	0.044	0.018	0.036
HM:	α	-0.003	0.016*	-0.006	-0.011
	β_{TIM}	-0.084	-0.817	0.347**	-0.081
	R^2	0.746	0.524	0.824	0.665
	σ_ϵ	0.032	0.042	0.016	0.036
LK:	α	-0.005	0.008*	-0.003	-0.012*
	β_{TIM}	-0.019	-2.606	1.160**	-0.385
	R^2	0.746	0.534	0.831	0.666
	σ_ϵ	0.032	0.042	0.016	0.036
BP:	α	-0.004	0.008	-0.003	-0.012*
	ρ_{TIM}	-0.036	-0.168	0.403**	-0.033
	R^2	0.746	0.534	0.831	0.666
	σ_ϵ	0.032	0.042	0.016	0.036

*Significant at the 1% level.

**Significant at the 5% level.

[1]Returns are in risk premium form, $R_{pf} = R_p - R_f$. For the same period, 1984-1989, Market Return: R_{mf} = 0.92% and σ_{Rmf} = 4.95%.

Appendix B (cont.)

Performance Models' Statistics for Selected Mutual Funds

		Fund 17	Fund 18	Fund 19	Fund 20
Size	($mil)	66.44	732.80	4382.59	1516.04
R_{pf}^{1}	Ann. %	-4.07	4.46	5.14	5.82
σ_{Rpf}	Mon. %	5.49	6.51	6.73	5.52
JN:	α	-0.010**	-0.003	-0.004	-0.002
	β	0.938**	0.965**	1.114**	0.879**
	R^2	0.716	0.540	0.670	0.621
	σ_ϵ	0.029	0.044	0.039	0.034
HM:	α	-0.002	0.000	0.004	0.000
	β_{TIM}	-0.481*	-0.145	-0.405	-0.078
	R^2	0.738	0.539	0.681	0.622
	σ_ϵ	0.028	0.045	0.039	0.034
LK:	α	-0.006	0.000	0.002	0.000
	β_{TIM}	-1.648**	-0.960	-1.861**	-0.672
	R^2	0.747	0.545	0.696	0.626
	σ_ϵ	0.028	0.044	0.038	0.034
BP:	α	-0.006	-0.001	0.001	-0.001
	ρ_{TIM}	-0.222	-0.036	-0.151	-0.046
	R^2	0.747	0.545	0.696	0.626
	σ_ϵ	0.028	0.044	0.038	0.034

*Significant at the 1% level.

**Significant at the 5% level.

[1]Returns are in risk premium form, $R_{pf} = R_p - R_f$. For the same period, 1984-1989, Market Return: $R_{mf} = 0.92\%$ and $\sigma_{Rmf} = 4.95\%$.

Appendix B (cont.)

Performance Models' Statistics for Selected Mutual Funds

		Fund 21	Fund 22	Fund 23	Fund 24
Size	($mil)	826.58	293.80	691.68	731.36
R_{pf}^{1}	Ann. %	7.56	9.06	6.27	9.30
σ_{Rpf}	Mon. %	5.27	6.70	6.21	7.00
JN:	α	0.000	0.000	-0.001	-0.001
	β	0.848**	1.092**	0.841**	1.200**
	R^2	0.632	0.650	0.448	0.720
	σ_ϵ	0.032	0.040	0.046	0.037
HM:	α	0.003	0.001	0.001	-0.001
	β_{TIM}	-0.157	-0.076	-0.070	-0.009
	R^2	0.635	0.650	0.448	0.720
	σ_ϵ	0.032	0.040	0.047	0.038
LK:	α	0.002	0.000	-0.001	-0.002
	β_{TIM}	-0.951*	-0.337	0.217	0.202
	R^2	0.644	0.651	0.448	0.720
	σ_ϵ	0.032	0.040	0.047	0.038
BP:	α	0.001	0.000	0.000	-0.001
	ρ_{TIM}	-0.063	-0.026	-0.002	-0.006
	R^2	0.644	0.651	0.448	0.720
	σ_ϵ	0.032	0.040	0.047	0.038

*Significant at the 1% level.

**Significant at the 5% level.

[1]Returns are in risk premium form, $R_{pf} = R_p - R_f$. For the same period, 1984-1989, Market Return: $R_{mf} = 0.92\%$ and $\sigma_{Rmf} = 4.95\%$.

Appendix B (cont.)

Performance Models' Statistics for Selected Mutual Funds

		Fund 25	Fund 26	Fund 27	Fund 28
Size	($mil)	993.11	124.62	554.36	575.11
R_{pf}^{1}	Ann. %	10.40	-1.11	4.63	7.15
σ_{Rpf}	Mon. %	5.89	6.67	7.40	5.13
JN:	α	0.002	-0.009	-0.001	-0.001
	β	0.920	1.098**	0.822**	0.900**
	R^2	0.595	0.663	0.302	0.754
	σ_ϵ	0.038	0.039	0.062	0.026
HM:	α	0.010	-0.008	-0.002	-0.001
	β_{TIM}	-0.462*	-0.027	0.072	-0.001
	R^2	0.613	0.663	0.302	0.754
	σ_ϵ	0.037	0.039	0.063	0.026
LK:	α	0.006	-0.008	0.000	-0.001
	β_{TIM}	-1.650**	-0.296	-0.252	0.048
	R^2	0.622	0.664	0.302	0.754
	σ_ϵ	0.037	0.039	0.063	0.026
BP:	α	0.006	-0.008	-0.002	-0.001
	ρ_{TIM}	-0.173	-0.021	0.022	0.006
	R^2	0.622	0.664	0.302	0.754
	σ_ϵ	0.037	0.039	0.063	0.026

*Significant at the 1% level.

**Significant at the 5% level.

[1]Returns are in risk premium form, $R_{pf} = R_p - R_f$. For the same period, 1984-1989, Market Return: R_{mf} = 0.92% and σ_{Rmf} = 4.95%.

Appendix B (cont.)

Performance Models' Statistics for Selected Mutual Funds

		Fund 29	Fund 30	Fund 31
Size	($mil)	59.40	2858.68	1803.84
R_{pf}^{1}	Ann. %	-13.19	6.54	9.70
σ_{Rpf}	Mon. %	13.69	6.94	5.11
JN:	α	-0.003	-0.003	0.000
	β	0.037	1.241**	0.972**
	R^2	0.000	0.782	0.887
	σ_ϵ	0.138	0.032	0.017
HM:	α	0.005	-0.003	0.000
	β_{TIM}	-0.437	-0.042	-0.017
	R^2	0.003	0.782	0.887
	σ_ϵ	0.139	0.033	0.017
LK:	α	0.005	-0.005	0.000
	β_{TIM}	-2.894	0.392	-0.042
	R^2	0.015	0.783	0.887
	σ_ϵ	0.138	0.033	0.017
BP:	α	0.001	-0.003	0.000
	ρ_{TIM}	-0.028	-0.035	0.000
	R^2	0.015	0.783	0.887
	σ_ϵ	0.138	0.033	0.017

*Significant at the 1% level.

**Significant at the 5% level.

[1]Returns are in risk premium form, $R_{pf} = R_p - R_f$. For the same period, 1984-1989, Market Return: R_{mf} = 0.92% and σ_{Rmf} = 4.95%.

APPENDIX C

COMPUTER PROGRAM

The subroutines for the least squares estimation using singular value decomposition and random number generation have been adapted from Press, Flannery, Teukolsky, and Vetterling (1989).

```
      PROGRAM PORTMGT
C
      PARAMETER(M=120,NJ=2,N=3,LIM=1000)
C
      DOUBLE PRECISION DIV,EXRET,AB(N),VAR(N,N),AX(M,N),
     *     AY(N,N),AZ(N),UU(M,N),X(N),B(M),PAR(N),DEL(M),
     *     PAR1(N),SIG(N),BEAR,BULL
      DOUBLE PRECISION ABJ(NJ),VARJ(NJ,NJ),AXJ(M,NJ),
     *     AYJ(NJ,NJ),AZJ(NJ),UUJ(M,NJ),XJ(NJ), PARJ(NJ),
     *     PAR1J(NJ),SIGJ(NJ)
      DOUBLE PRECISION ERROR(M),ZERR(M),ERRMN,ERRSIG
      DOUBLE PRECISION RPF(M),RMF(M),ZRMF(M),PCTBILL(M),
     *     ZPCT(M),RHM(M),RMFSQ(M),QMF(M),PIMF(M),TVAL(N),
     *     TVALJ(NJ),RES(M),RESQ(M),DIAG(M,N),PP(N,N),
     *     SS(N,N),HETMAT(N,N),HETT(N),XB(M)
      DOUBLE PRECISION QMSE,RSQ,RSQJN,QMSEJN,RSQHM,QMSEHM,
     *     RSQLK,QMSELK,RSQBP,QMSEBP
      DOUBLE PRECISION ALFJN,ALFHM,ALFHMK,ALFLK,ALFLKK,ALFBP,
     *     ALFBPK
      DOUBLE PRECISION BETJN,UPBET,DNBET,UPBETK,DNBETK
      DOUBLE PRECISION RMFMN,RMFSIG,PCTMN,PCTSIG,TIMRHO
      DOUBLE PRECISION GEORMF,AVGRMF,SDRMF,GEORPF,AVGRPF,SDRPF
      DOUBLE PRECISION RMFGEO,RMFAVG,RMFSD,RPFGEO,RPFAVG,RPFSD
      DOUBLE PRECISION RMFSKW,RMFKUR,RPFSKW,RPFKUR,RPFANN,
     *     ANNRPF
      DOUBLE PRECISION SKWRMF,RKURMF,SKWRPF,RKURPF,RMFANN,
     *     ANNRMF
C
      DOUBLE PRECISION RMMON,RMANN,RMGEO,
     *                 RPMON,RPANN,RPGEO,
     *                 SMMON,SMANN,SMGEO
C
      DOUBLE PRECISION ZSMF(M),SMF(M),SMFMN,SMFSIG,GEOSMF,
     *     AVGSMF,SDSMF
      DOUBLE PRECISION SMFGEO,SMFAVG,SMFSD,SMFANN,ANNSMF,
     *     SMFRHO
      DOUBLE PRECISION SMFSKW,SMFKUR,SKWSMF,RKUSMF
C
```

```
      DOUBLE PRECISION AVGPCT,SDPCT,SKWPCT,RKUPCT,GEOPCT,
     *     PCTGEO

      DOUBLE PRECISION PCTAVG,PCTSD,PCTSKW,PCTKUR,ANNPCT,
     *     PCTANN
      DOUBLE PRECISION TJNS,HMS,HMT,HMKS,HMKT,TLKS,TLKT,TLKKS,
     *     TLKKT
      DOUBLE PRECISION DELFI,BPS,DEFISQ,SIGESQ,DLORMF,SIGPIS,
     *     BPRHO,BPT,VARWSQ(M),VARGSQ(M),BHRPF(M),BHRMF(M),
     *     BHRMFS(M),BPKS,GLSWSQ(M),GLRMFS(M),BPKT,VARU,
     *     XM,WSQ(M),ABPRHO,HBPRHO,WRMFSQ,RMFQUA
      DOUBLE PRECISION AVGRES,SDRES,RESSKW,RESKUR
      DOUBLE PRECISION TRAVJN,TRSDJN,TRSKJN,TRKUJN
      DOUBLE PRECISION TRAVHM,TRSDHM,TRSKHM,TRKUHM
      DOUBLE PRECISION TRAVLK,TRSDLK,TRSKLK,TRKULK
      DOUBLE PRECISION TRAVBP,TRSDBP,TRSKBP,TRKUBP
      DOUBLE PRECISION TRAVHT,TRSDHT,TRSKHT,TRKUHT
      DOUBLE PRECISION SUMCOR,SUMRMF,SUMPCT,SUMSMF,AVGCOR,
     *     SMCORR,AVCORR
C
C
      OPEN(UNIT=6,FILE='SIM1',STATUS='NEW')
C
C
      DO 2 IJ=1,11,5
           TIMRHO=-(IJ-1.)/10.
C
           DO 3 IJK=1,21,10
                EXRET=(IJK-1.)/1000.
C
                IRMF=-35249
                JPCT=-36247
                KERR=-72055
                LSMF=-35553
C
C               IRMF=-74815
C               JPCT=-76509
C               KERR=-19689
C               LSMF=-42751
C
C               IRMF=-39737
C               JPCT=-97025
C               KERR=-68763
C               LSMF=-99083
C
                WRITE(6,180) IRMF,JPCT,KERR
 180            FORMAT(//,2X,'IRMF = ',I10,2X,'JPCT = ',I10,
     *              2X,'KERR= ',I10)
C
                BULL=0.
                BEAR=0.
```

```
C
      RMFGEO=0.
      RMFANN=0.
      RMFAVG=0.
      RMFSD=0.
      RMFSKW=0.
      RMFKUR=0.
C
      SMFGEO=0.
      SMFANN=0.
      SMFAVG=0.
      SMFSD=0.
      SMFSKW=0.
      SMFKUR=0.
C
      RPFGEO=0.
      RPFANN=0.
      RPFAVG=0.
      RPFSD=0.
      RPFSKW=0.
      RPFKUR=0.
C
      PCTGEO=0.
      PCTANN=0.
      PCTAVG=0.
      PCTSD=0.
      PCTSKW=0.
      PCTKUR=0.
C
      AVGCOR=0.
      AVCORR=0.
C
      KNTJN=0
      ALFJN=0.
      BETJN=0.
      TRAVJN=0.
      TRSDJN=0.
      TRSKJN=0.
      TRKUJN=0.
      JASP5=0
      JBSN5=0
      JCSP1=0
      JDSN1=0
C
      RSQJN=0.
      QMSEJN=0.
C
      KNTHM=0
      ALFHM=0.
      ALFHMK=0.
      UPBET=0.
```

```
      DNBET=0.
      UPBETK=0.
      DNBETK=0.
      TRAVHM=0.
      TRSDHM=0.
      TRSKHM=0.
      TRKUHM=0.
      KAHSP5=0
      KBHSN5=0
      KCHSP1=0
      KDHSN1=0
      KEHTP5=0
      KFHTN5=0
      KGHTP1=0
      KHHTN1=0
C
      RSQHM=0.
      QMSEHM=0.
C
      KPHSP5=0
      KQHSN5=0
      KRHSP1=0
      KSHSN1=0
      KTHTP5=0
      KUHTN5=0
      KVHTP1=0
      KWHTN1=0
C
      KNTLK=0
      ALFLK=0.
      ALFLKK=0.
      TRAVLK=0.
      TRSDLK=0.
      TRSKLK=0.
      TRKULK=0.
      LASP5=0
      LBSN5=0
      LCSP1=0
      LDSN1=0
      LETP5=0
      LFTN5=0
      LGTP1=0
      LHTN1=0
C
      RSQLK=0.
      QMSELK=0.
C
      LPKSP5=0
      LQKSN5=0
      LRKSP1=0
      LSKSN1=0
```

```
      LTKTP5=0
      LUKTN5=0
      LVKTP1=0
      LWKTN1=0
C
C
      KNTBP=0
      ALFBP=0.
      ALFBPK=0.
      ABPRHO=0.
      HBPRHO=0.
      TRAVBP=0.
      TRSDBP=0.
      TRSKBP=0.
      TRKUBP=0.
      TRAVHT=0.
      TRSDHT=0.
      TRSKHT=0.
      TRKUHT=0.
      KABSP5=0
      KBBSN5=0
      KCBSP1=0
      KDBSN1=0
      KEBTP5=0
      KFBTN5=0
      KGBTP1=0
      KHBTN1=0
C
      RSQBP=0.
      QMSEBP=0.
C
      KPBSP5=0
      KQBSN5=0
      KRBSP1=0
      KSBSN1=0
      KTBTP5=0
      KUBTN5=0
      KVBTP1=0
      KWBTN1=0
C
C
C
```

```
C                        *******************
C                        Collect Error Rates
C                        *******************
C
              DO 4 IREP=1,LIM
C
C**************************************************************
C  Generate Normally distributed Random Variables, N(0,1),
C  For Market Risk-Premium Returns, RMF:ZRMF, and Timing
C            Skill, PCTBILL:ZPCT, Parameters
C
C**************************************************************
C
C
                   CALL STDNOR(ZRMF,M,IRMF)
C
                   CALL STDNOR(ZPCT,M,JPCT)
C
                   CALL STDNOR(ZERR,M,KERR)
C
                   CALL STDNOR(ZSMF,M,LSMF)
C
C
C*****************************************************
C  Generate RMF, PCTBILL, and SUPRET Based on the
C            Simulation Parameters
C*****************************************************
C
                   RMFMN=0.0056995
                   RMFSIG=0.0453691
                   SMFMN=.01097
                   SMFSIG=.0649738
                   SMFRHO=0.75899
                   PCTMN=0.0564033
                   PCTSIG=0.0479906*5.
                   ERRMN=0.0
                   ERRSIG=0.0446604
C
C
                   DO 14 I=1,M
                        RMF(I)=EXP((ZRMF(I)*RMFSIG)+RMFMN)
     *                       -1.
C
                        IF (RMF(I).GT.0.) BULL=BULL+1.
                        IF (RMF(I).LE.0.) BEAR=BEAR+1.
C
                        PCTBILL(I)=EXP(PCTMN+(TIMRHO*PCTSIG*
     *                       ZRMF(I))+(ZPCT(I)*PCTSIG*
     *                       DSQRT(1.-(TIMRHO**2))))-1.
C
```

```
                    SMF(I)=EXP(SMFMN+(SMFRHO*SMFSIG
     *                   ZRMF(I))+(ZSMF(I)*SMFSIG*DSQRT
     *                   (1.-(SMFRHO**2)))) -1.
C
                    ERROR(I)=ERRMN+(ZERR(I)*ERRSIG)
C
   14               CONTINUE
C
C
C
C
C*********************************************************
C  Generate Portfolio Returns With Timing and Selectivity
C                   Skills
C*********************************************************
C
C
               DO 16 I=1,M
C
                    RPF(I)=((1.-PCTBILL(I))*RMF(I))+
C     *                  ((1.-PCTBILL(I))*SMF(I)*0.20)+
      *                  ((1.-PCTBILL(I))*EXRET)+
      *                  ERROR(I)
C
   16               CONTINUE
C
C
C          ******************************************
C          Calculate Summary Statistics for RMF and RPF
C          ******************************************
C
           CALL STATS(M,RMF,GEORMF,ANNRMF,AVGRMF,SDRMF,
     *          SKWRMF,RKURMF)
           CALL STATS(M,SMF,GEOSMF,ANNSMF,AVGSMF,SDSMF,
     *          SKWSMF,RKUSMF)
           CALL STATS(M,RPF,GEORPF,ANNRPF,AVGRPF,SDRPF,
     *          SKWRPF,RKURPF)
           CALL STATS(M,PCTBILL,GEOPCT,ANNPCT,AVGPCT,
     *          SDPCT,SKWPCT,RKUPCT)
C
           SUMCOR=0.
           SUMRMF=0.
           SUMPCT=0.
           DO 17 I=1,M
                SUMCOR=SUMCOR+((RMF(I)-AVGRMF)*
     *               (PCTBILL(I)-AVGPCT))
                SUMRMF=SUMRMF+((RMF(I)-AVGRMF)*
     *               (RMF(I)-AVGRMF))
                SUMPCT=SUMPCT+((PCTBILL(I)-AVGPCT)*
     *               (PCTBILL(I)-AVGPCT))
  17            CONTINUE
```

```
              AVGCOR=AVGCOR+(SUMCOR/(DSQRT(SUMRMF)
     *             *DSQRT(SUMPCT)))
C
              SMCORR=0.
              SUMRMF=0.
              SUMSMF=0.
C
              DO 20 I=1,M
                   SMCORR=SMCORR+((RMF(I)-AVGRMF)*
     *                  (SMF(I)-AVGSMF))
                   SUMRMF=SUMRMF+((RMF(I)-AVGRMF)*
     *                  (RMF(I)-AVGRMF))
                   SUMSMF=SUMSMF+((SMF(I)-AVGSMF)*
     *                  (SMF(I)-AVGSMF))
   20              CONTINUE
C
              AVCORR=AVCORR+(SMCORR/(DSQRT(SUMRMF)*
     *             DSQRT(SUMSMF)))
C
              RMFGEO=RMFGEO+GEORMF
              RMFANN=RMFANN+ANNRMF
              RMFAVG=RMFAVG+AVGRMF
              RMFSD=RMFSD+SDRMF
              RMFSKW=RMFSKW+SKWRMF
              RMFKUR=RMFKUR+RKURMF
C
              SMFGEO=SMFGEO+GEOSMF
              SMFANN=SMFANN+ANNSMF
              SMFAVG=SMFAVG+AVGSMF
              SMFSD=SMFSD+SDSMF
              SMFSKW=SMFSKW+SKWSMF
              SMFKUR=SMFKUR+RKUSMF
C
              RPFGEO=RPFGEO+GEORPF
              RPFANN=RPFANN+ANNRPF
              RPFAVG=RPFAVG+AVGRPF
              RPFSD=RPFSD+SDRPF
              RPFSKW=RPFSKW+SKWRPF
              RPFKUR=RPFKUR+RKURPF
C
              PCTGEO=PCTGEO+GEOPCT
              PCTANN=PCTANN+ANNPCT
              PCTAVG=PCTAVG+AVGPCT
              PCTSD=PCTSD+SDPCT
              PCTSKW=PCTSKW+SKWPCT
              PCTKUR=PCTKUR+RKUPCT
C
C
C
```

```
C         ************************************
C         *                                  *
C         *           JENSEN MODEL           *
C         *                                  *
C         ************************************
C
               KNTJN=KNTJN+1
C
               CALL JENSEN(M,NJ,AXJ,RMF,B,RPF)
C
               CALL LSTSQR(M,NJ,AXJ,AYJ,AZJ,ABJ,B,XJ,UUJ,
     *              PARJ,DEL,PAR1J)
C
               CALL STDERR(NJ,AYJ,AZJ,VARJ,SIGJ)
C
               CALL REGSTA(M,NJ,UUJ,RPF,ABJ,QMSE,RSQ,VARJ,
     *              TVALJ,XB,RES,RESQ)
C
               CALL RESID(M,NJ,RES,RESQ,AVGRES,SDRES,
     *              RESSKW,RESKUR)
C
               VARU=SDRES*SDRES
C
               TRAVJN=TRAVJN+AVGRES
               TRSDJN=TRSDJN+SDRES
               TRSKJN=TRSKJN+RESSKW
               TRKUJN=TRKUJN+RESKUR
C
               TJNS=TVALJ(1)
               ALFJN=ALFJN+ABJ(1)
               BETJN=BETJN+ABJ(2)
C
               IF (TJNS.GE.1.658) JASP5=JASP5+1
               IF (TJNS.LE.-1.658) JBSN5=JBSN5+1
               IF (TJNS.GE.2.358) JCSP1=JCSP1+1
               IF (TJNS.LE.-2.358) JDSN1=JDSN1+1
C
               RSQJN=RSQJN+RSQ
               QMSEJN=QMSEJN+QMSE
C
C
C         **********************************
C         *                                *
C         *     HENRIKSSON-MERTON MODEL    *
C         *                                *
C         **********************************
C
               KNTHM=KNTHM+1
C
               CALL HENMER(M,N,AX,RMF,RHM,B,RPF)
C
```

```
            CALL LSTSQR(M,N,AX,AY,AZ,AB,B,X,UU,PAR,
     *           DEL,PAR1)
C
            CALL STDERR(N,AY,AZ,VAR,SIG)
C
            CALL REGSTA(M,N,UU,RPF,AB,QMSE,RSQ,VAR,
     *           TVAL,XB,RES,RESQ)
C
            CALL RESID(M,N,RES,RESQ,AVGRES,SDRES,
     *           RESSKW,RESKUR)
C
            TRAVHM=TRAVHM+AVGRES
            TRSDHM=TRSDHM+SDRES
            TRSKHM=TRSKHM+RESSKW
            TRKUHM=TRKUHM+RESKUR
C
            ALFHM=ALFHM+AB(1)
            UPBET=UPBET+AB(2)
            DNBET=DNBET+(AB(2)-AB(3))
C
            HMS=TVAL(1)
            HMT=TVAL(3)
C
            IF (HMS.GE.1.658) KAHSP5=KAHSP5+1
            IF (HMS.LE.-1.658) KBHSN5=KBHSN5+1
            IF (HMS.GE.2.358) KCHSP1=KCHSP1+1
            IF (HMS.LE.-2.358) KDHSN1=KDHSN1+1
C
            IF (HMT.GE.1.658) KEHTP5=KEHTP5+1
            IF (HMT.LE.-1.658) KFHTN5=KFHTN5+1
            IF (HMT.GE.2.358) KGHTP1=KGHTP1+1
            IF (HMT.LE.-2.358) KHHTN1=KHHTN1+1
C
            RSQHM=RSQHM+RSQ
            QMSEHM=QMSEHM+QMSE
C
C       *****************************************
C       Hansen-White Heteroscedasticity Correction
C       *****************************************
C
            CALL HETRSC(M,N,DIAG,UU,AB,RESQ,PP,SS,VAR,
     *           HETMAT,HETT)
C
            ALFHMK=ALFHMK+AB(1)
            UPBETK=UPBETK+AB(2)
            DNBETK=DNBETK+(AB(2)-AB(3))
C
            HMKS=HETT(1)
            HMKT=HETT(3)
C
            IF (HMKS.GE.1.658) KPHSP5=KPHSP5+1
```

```
            IF (HMKS.LE.-1.658) KQHSN5=KQHSN5+1
            IF (HMKS.GE.2.358) KRHSP1=KRHSP1+1
            IF (HMKS.LE.-2.358) KSHSN1=KSHSN1+1
C
            IF (HMKT.GE.1.658) KTHTP5=KTHTP5+1
            IF (HMKT.LE.-1.658) KUHTN5=KUHTN5+1
            IF (HMKT.GE.2.358) KVHTP1=KVHTP1+1
            IF (HMKT.LE.-2.358) KWHTN1=KWHTN1+1
C
C       ************************************
C       *                                  *
C       *     LOCKWOOD-KADIYALA MODEL      *
C       *                                  *
C       ************************************
C
            KNTLK=KNTLK+1
C
            CALL LOCKAD(M,N,AX,RMF,AVGRMF,QMF,PIMF,B,
     *          RPF)
C
            CALL LSTSQR(M,N,AX,AY,AZ,AB,B,X,UU,PAR, DEL,
     *          PAR1)
C
            CALL STDERR(N,AY,AZ,VAR,SIG)
C
            CALL REGSTA(M,N,UU,RPF,AB,QMSE,RSQ,VAR,
     *          TVAL,XB,RES,RESQ)
C
            CALL RESID(M,N,RES,RESQ,AVGRES,SDRES,
     *          RESSKW,RESKUR)
C
            TRAVLK=TRAVLK+AVGRES
            TRSDLK=TRSDLK+SDRES
            TRSKLK=TRSKLK+RESKUR
            TRKULK=TRKULK+RESSKW
C
            ALFLK=ALFLK+AB(1)
C
            TLKS=TVAL(1)
            TLKT=TVAL(3)
C
            IF (TLKS.GE.1.658) LASP5=LASP5+1
            IF (TLKS.LE.-1.658) LBSN5=LBSN5+1
            IF (TLKS.GE.2.358) LCSP1=LCSP1+1
            IF (TLKS.LE.-2.358) LDSN1=LDSN1+1
C
            IF (TLKT.GE.1.658) LETP5=LETP5+1
            IF (TLKT.LE.-1.658) LFTN5=LFTN5+1
            IF (TLKT.GE.2.358) LGTP1=LGTP1+1
            IF (TLKT.LE.-2.358) LHTN1=LHTN1+1
C
```

```
          RSQLK=RSQLK+RSQ
          QMSELK=QMSELK+QMSE
C
C     *****************************************
C     Hansen-White Heteroscedasticity Correction
C     *****************************************
C
          CALL HETRSC(M,N,DIAG,UU,AB,RESQ,PP,SS,VAR,
     *          HETMAT,HETT)
C
          ALFLKK=ALFLKK+AB(1)
C
          TLKKS=HETT(1)
          TLKKT=HETT(3)
C
          IF (TLKKS.GE.1.658) LPKSP5=LPKSP5+1
          IF (TLKKS.LE.-1.658) LQKSN5=LQKSN5+1
          IF (TLKKS.GE.2.358) LRKSP1=LRKSP1+1
          IF (TLKKS.LE.-2.358) LSKSN1=LSKSN1+1
C
          IF (TLKKT.GE.1.658) LTKTP5=LTKTP5+1
          IF (TLKKT.LE.-1.658) LUKTN5=LUKTN5+1
          IF (TLKKT.GE.2.358) LVKTP1=LVKTP1+1
          IF (TLKKT.LE.-2.358) LWKTN1=LWKTN1+1
C
C     *************************************
C     *                                   *
C     *    BHATTACHARYA-PFLEIDERER MODEL  *
C     *                                   *
C     *************************************
C
          KNTBP=KNTBP+1
C
          CALL BP(M,N,AX,RMF,RMFSQ,B,RPF)
C
          CALL LSTSQR(M,N,AX,AY,AZ,AB,B,X,UU,PAR,
     *          DEL,PAR1)
C
          DELFI=AB(3)
C
          CALL STDERR(N,AY,AZ,VAR,SIG)
C
          CALL REGSTA(M,N,UU,RPF,AB,QMSE,RSQ,VAR,
     *          TVAL,XB,RES,WSQ)
C
          CALL RESID(M,N,RES,WSQ,AVGRES,SDRES,
     *          RESSKW,RESKUR)
C
          TRAVBP=TRAVBP+AVGRES
          TRSDBP=TRSDBP+SDRES
          TRSKBP=TRSKBP+RESSKW
```

```
              TRKUBP=TRKUBP+RESKUR
C
              ALFBP=ALFBP+AB(1)
C
              BPS=TVAL(1)
C
              IF (BPS.GE.1.658) KABSP5=KABSP5+1
              IF (BPS.LE.-1.658) KBBSN5=KBBSN5+1
              IF (BPS.GE.2.358) KCBSP1=KCBSP1+1
              IF (BPS.LE.-2.358) KDBSN1=KDBSN1+1
C
              RSQBP=RSQBP+RSQ
              QMSEBP=QMSEBP+QMSE
C
              WRMFSQ=0.
              RMFQUA=0.
              DO 18 I=1,M
                   WRMFSQ=WRMFSQ+(WSQ(I)*RMFSQ(I))
                   RMFQUA=RMFQUA+(RMFSQ(I)*RMFSQ(I))
  18          CONTINUE
C
              DEFISQ=WRMFSQ/RMFQUA
C
              SIGESQ=DEFISQ/(DELFI*DELFI)
C
              SIGPIS=0.
              DO 19 I=1,M
                   DLORMF=(DLOG(1+RMF(I)))**2
                   SIGPIS=SIGPIS+DLORMF
  19               CONTINUE
              SIGPIS=SIGPIS/(M-0.)
C
              XM=M
              BPRHO=DSQRT(SIGPIS/(SIGPIS+SIGESQ))
              IF (DELFI.LT.0.0) BPRHO=-BPRHO
              BPT=(BPRHO*DSQRT(XM-2.))/DSQRT(1.-(BPRHO
     *             *BPRHO))
              ABPRHO=ABPRHO+BPRHO
C
              IF (BPT.GE.1.658) KEBTP5=KEBTP5+1
              IF (BPT.LE.-1.658) KFBTN5=KFBTN5+1
              IF (BPT.GE.2.358) KGBTP1=KGBTP1+1
              IF (BPT.LE.-2.358) KHBTN1=KHBTN1+1
C
C         **********************************
C         GLS Heteroscedasticity Correction
C         **********************************
C
              DO 25 I=1,M
                   VARWSQ(I)=DSQRT((DEFISQ*RMFSQ(I))+VARU)
                   BHRPF(I)=RPF(I)/VARWSQ(I)
```

```
                    BHRMF(I)=RMF(I)/VARWSQ(I)
                    BHRMFS(I)=RMFSQ(I)/VARWSQ(I)
C                   VARGSQ(I)=(2*((DABS(DEFISQ))**2)*
     *                   (RMFSQ(I)**2))+(2*(VARU**2))+
     *                   (4*DEFISQ*RMFSQ(I)*VARU)
                    GLSWSQ(I)=WSQ(I)/DSQRT(VARGSQ(I))
                    GLRMFS(I)=RMFSQ(I)/DSQRT(VARGSQ(I))
   25          CONTINUE
C
               CALL BPTWO(M,N,AX,BHRMF,BHRMFS,B,BHRPF,VARWSQ)
C
               CALL LSTSQR(M,N,AX,AY,AZ,AB,B,X,UU,PAR,
     *              DEL,PAR1)
C
               DELFI=AB(3)
C
               CALL STDERR(N,AY,AZ,VAR,SIG)
C
               CALL REGSTA(M,N,UU,BHRPF,AB,QMSE,RSQ,VAR,
     *              TVAL,XB,RES,RESQ)
C
               CALL RESID(M,N,RES,RESQ,AVGRES,SDRES,
     *              RESSKW,RESKUR)
C
               TRAVHT=TRAVHT+AVGRES
               TRSDHT=TRSDHT+SDRES
               TRSKHT=TRSKHT+RESSKW
               TRKUHT=TRKUHT+RESKUR
C
               ALFBPK=ALFBPK+AB(1)
C
               BPKS=TVAL(1)
C
               IF (BPKS.GE.1.658) KPBSP5=KPBSP5+1
               IF (BPKS.LE.-1.658) KQBSN5=KQBSN5+1
               IF (BPKS.GE.2.358) KRBSP1=KRBSP1+1
               IF (BPKS.LE.-2.358) KSBSN1=KSBSN1+1
C
               WRMFSQ=0.
               RMFQUA=0.
               DO 29 I=1,M
                    WRMFSQ=WRMFSQ+(GLSWSQ(I)*GLRMFS(I))
                    RMFQUA=RMFQUA+(GLRMFS(I)*GLRMFS(I))
   29               CONTINUE
C
               DEFISQ=WRMFSQ/RMFQUA
C
               SIGESQ=DEFISQ/(DELFI*DELFI)
C
               BPRHO=DSQRT(SIGPIS/(SIGPIS+SIGESQ))
               IF (DELFI.LT.0.0) BPRHO=-BPRHO
```

```
              BPKT=(BPRHO*DSQRT(XM-2.))/DSQRT(1.-(BPRHO*
     *             BPRHO))
              HBPRHO=HBPRHO+BPRHO
C
              IF (BPKT.GE.1.658) KTBTP5=KTBTP5+1
              IF (BPKT.LE.-1.658) KUBTN5=KUBTN5+1
              IF (BPKT.GE.2.358) KVBTP1=KVBTP1+1
              IF (BPKT.LE.-2.358) KWBTN1=KWBTN1+1
C
C        ******************************
C        Continue Simulation Iterations
C        ******************************
C
    4         CONTINUE
C
         DIV=LIM
C
         BULL=BULL/DIV
         BEAR=BEAR/DIV
C
         RMFGEO=RMFGEO/DIV
         RMFANN=RMFANN/DIV
         RMFAVG=RMFAVG/DIV
         RMFSD=RMFSD/DIV
         RMFSKW=RMFSKW/DIV
         RMFKUR=RMFKUR/DIV
C
         SMFGEO=SMFGEO/DIV
         SMFANN=SMFANN/DIV
         SMFAVG=SMFAVG/DIV
         SMFSD=SMFSD/DIV
         SMFSKW=SMFSKW/DIV
         SMFKUR=SMFKUR/DIV
C
         RPFGEO=RPFGEO/DIV
         RPFANN=RPFANN/DIV
         RPFAVG=RPFAVG/DIV
         RPFSD=RPFSD/DIV
         RPFSKW=RPFSKW/DIV
         RPFKUR=RPFKUR/DIV
C
         PCTAVG=PCTAVG/DIV
         PCTSD=PCTSD/DIV
         PCTSKW=PCTSKW/DIV
         PCTKUR=PCTKUR/DIV
C
         AVGCOR=AVGCOR/DIV
         AVCORR=AVCORR/DIV
C
         ALFJN=ALFJN/DIV
         BETJN=BETJN/DIV
```

```
      TRAVJN=TRAVJN/DIV
      TRSDJN=TRSDJN/DIV
      TRSKJN=TRSKJN/DIV
      TRKUJN=TRKUJN/DIV
      RSQJN=RSQJN/DIV
      QMSEJN=QMSEJN/DIV
C
      ALFHM=ALFHM/DIV
      ALFHMK=ALFHMK/DIV
      UPBET=UPBET/DIV
      DNBET=DNBET/DIV
      UPBETK=UPBETK/DIV
      DNBETK=DNBETK/DIV
      TRAVHM=TRAVHM/DIV
      TRSDHM=TRSDHM/DIV
      TRSKHM=TRSKHM/DIV
      TRKUHM=TRKUHM/DIV
      RSQHM=RSQHM/DIV
      QMSEHM=QMSEHM/DIV
C
      ALFLK=ALFLK/DIV
      ALFLKK=ALFLKK/DIV
      TRAVLK=TRAVLK/DIV
      TRSDLK=TRSDLK/DIV
      TRSKLK=TRSKLK/DIV
      TRKULK=TRKULK/DIV
      RSQLK=RSQLK/DIV
      QMSELK=QMSELK/DIV
C
      ALFBP=ALFBP/DIV
      ALFBPK=ALFBPK/DIV
      ABPRHO=ABPRHO/DIV
      HBPRHO=HBPRHO/DIV
      TRAVBP=TRAVBP/DIV
      TRSDBP=TRSDBP/DIV
      TRSKBP=TRSKBP/DIV
      TRKUBP=TRKUBP/DIV
      TRAVHT=TRAVHT/DIV
      TRSDHT=TRSDHT/DIV
      TRSKHT=TRSKHT/DIV
      TRKUHT=TRKUHT/DIV
      RSQBP=RSQBP/DIV
      QMSEBP=QMSEBP/DIV
C
C
      CALL STATMON(M,RMFGEO,RMMON,RMANN,RMGEO)
      CALL STATMON(M,RPFGEO,RPMON,RPANN,RPGEO)
      CALL STATMON(M,SMFGEO,SMMON,SMANN,SMGEO)
C
C
C
```

```
      WRITE(6,125) TIMRHO,EXRET
  125 FORMAT(/,2X,'TIMRHO = ',F8.5,2X,'EXC. RET. = ',F8.5)
C
      WRITE(6,103) BULL,BEAR
  103 FORMAT(/,2X,'NO. BULL = ',F7.2,2X,'NO. BEAR = ',F7.2)
C
C
      WRITE(6,104) RMGEO,RMANN,RMMON
  104 FORMAT(//,2X,'RM GEO = ',F9.6,3X,'RM ANN = ',F9.6,
     *          3X,'RM MON = ',F9.6)
C
      WRITE(6,105) RMFGEO,RMFANN,RMFAVG
  105 FORMAT(/,2X,'RMF GEO = ',F9.6,3X,'RMF ANN = ',F9.6,
     *          3X,'RMF AVG = ',F9.6)
C
      WRITE(6,107) RMFSD,RMFSKW,RMFKUR
  107 FORMAT(/,2X,'RMF SD = ',F9.6,3X,'RMF SKW = ',F9.6,
     *          3X,'RMF KUR = ',F9.6)
C
C
      WRITE(6,102) SMGEO,SMANN,SMMON
  102 FORMAT(//,2X,'SM GEO = ',F9.6,3X,'SM ANN = ',F9.6,
     *          3X,'SM MON = ',F9.6)
C
      WRITE(6,250) SMFGEO,SMFANN,SMFAVG
  250 FORMAT(/,2X,'SMF GEO = ',F9.6,3X,'SMF ANN = ',F9.6,
     *          3X,'SMF AVG = ',F9.6)
C
      WRITE(6,252) SMFSD,SMFSKW,SMFKUR
  252 FORMAT(/,2X,'SMF SD = ',F9.6,3X,'SMF SKW = ',F9.6,
     *          3X,'SMF KUR = ',F9.6)
C
      WRITE(6,108) PCTAVG
  108 FORMAT(//,2X,'PCT AVG = ',F9.6)
C
      WRITE(6,109) PCTSD,PCTSKW,PCTKUR
  109 FORMAT(/,2X,'PCT SD = ',F9.6,3X,'PCT SKW = ',F9.6,
     *          3X,'PCT KUR = ',F9.6)
C
C
      WRITE(6,101) RPGEO,RPANN,RPMON
  101 FORMAT(//,2X,'RP GEO = ',F9.3,3X,'RP ANN = ',F9.6,
     *          3X,'RP MON = ',F9.6)
C
      WRITE(6,110) RPFGEO,RPFANN,RPFAVG
  110 FORMAT(/,2X,'RPF GEO = ',F9.3,3X,'RPF ANN = ',F9.6,
     *          3X,'RPF AVG = ',F9.6)
C
      WRITE(6,112) RPFSD,RPFSKW,RPFKUR
  112 FORMAT(/,2X,'RPF SD = ',F9.6,3X,'RPF SKW = ',F9.6,
     *          3X,'RPF KUR = ',F9.6)
```

```
C
C
      WRITE(6,114) AVGCOR
  114 FORMAT(/,2X,'AVG COR(RMF,PCTBILL) = ',F9.6)
C
      WRITE(6,115) AVCORR
  115 FORMAT(/,2X,'AVG COR(RMF,SMF) = ',F9.6)
C
C
      WRITE(6,130)
  130 FORMAT(//,2X,'JN CNT',2X,'JN SP5',2X,'JN SN5',2X,
     *          'JN SP1',2X,'JN SN1')
C
      WRITE(6,134) KNTJN,JASP5,JBSN5,JCSP1,JDSN1
  134 FORMAT(2X,I6,2X,I6,2X,I6,2X,I6,2X,I6)
C
      WRITE(6,135) ALFJN,BETJN
  135 FORMAT(/,2X,'JN ALFA = ',F9.6,3X,'JN BETA = ',F9.6)
C
      WRITE(6,182) TRAVJN,TRSDJN
  182 FORMAT(/,2X,'JN RES AV = ',F9.6,3X,'JN RES SD = ',F9.6)
C
      WRITE(6,184) TRSKJN,TRKUJN
  184 FORMAT(/,2X,'JN RES SKW = ',F9.6,3X,'JN RES KUR =',F9.6)
C
      WRITE(6,137) RSQJN,QMSEJN
  137 FORMAT(/,2X,'RSQ JN = ',F9.6,3X,'MSE JN = ',F9.6)
C
C
C
      WRITE(6,140)
  140 FORMAT(//,2X,'HM CNT',2X,'HM SP5',2X,'HM SN5',2X,
     *          'HM SP1',2X,'HM SN1')
C
      WRITE(6,142) KNTHM,KAHSP5,KBHSN5,KCHSP1,KDHSN1
  142 FORMAT(2X,I6,2X,I6,2X,I6,2X,I6,2X,I6)
C
      WRITE(6,148)
  148 FORMAT(/,2X,'HM TP5',2X,'HM TN5',2X,'HM TP1',2X,
     *          'HM TN1')
C
      WRITE(6,149) KEHTP5,KFHTN5,KGHTP1,KHHTN1
  149 FORMAT(2X,I6,2X,I6,2X,I6,2X,I6)
C
      WRITE(6,172) ALFHM,ALFHMK
  172 FORMAT(/,2X,'HM ALF = ',F9.6,3X,'HM ALF H = ',F9.6)
C
      WRITE(6,141) UPBET,DNBET
  141 FORMAT(/,2X,'UP BETA = ',F9.6,3X,'DN BETA = ',F9.6)
C
      WRITE(6,170) UPBETK,DNBETK
```

```
 170 FORMAT(/,2X,'UP BETA H = ',F9.6,3X,'DN BETA H = ',F9.6)
C
     WRITE(6,190) TRAVHM,TRSDHM
 190 FORMAT(/,2X,'HM RES AV = ',F9.6,3X,'HM RES SD = ',F9.6)
C
     WRITE(6,192) TRSKHM,TRKUHM
 192 FORMAT(/,2X,'HM RES SKW = ',F9.6,3X,'HM RES KUR =',F9.6)
C
     WRITE(6,143) RSQHM,QMSEHM
 143 FORMAT(/,2X,'RSQ HM = ',F9.6,3X,'MSE HM = ',F9.6)
C
     WRITE(6,144)
 144 FORMAT(/,2X,'HM H SP5',2X,'HM H SN5',2X,'HM H SP1',
    *          2X,'HM H SN1')
C
     WRITE(6,145) KPHSP5,KQHSN5,KRHSP1,KSHSN1
 145 FORMAT(2X,I8,2X,I8,2X,I8,2X,I8)
C
     WRITE(6,146)
 146 FORMAT(/,2X,'HM H TP5',2X,'HM H TN5',2X,'HM H TP1',
    *          2X,'HM H TN1')
C
     WRITE(6,147) KTHTP5,KUHTN5,KVHTP1,KWHTN1
 147 FORMAT(2X,I8,2X,I8,2X,I8,2X,I8)
C
C
C
     WRITE(6,150)
 150 FORMAT(//,2X,'LK CNT',2X,'LK SP5',2X,'LK SN5',2X,
    *          'LK SP1',2X,'LK SN1')
C
     WRITE(6,152) KNTLK,LASP5,LBSN5,LCSP1,LDSN1
 152 FORMAT(2X,I6,2X,I6,2X,I6,2X,I6,2X,I6)
C
     WRITE(6,159)
 159 FORMAT(/,2X,'LK TP5',2X,'LK TN5',2X,'LK TP1',2X,
    *          'LK TN1')
C
     WRITE(6,158) LETP5,LFTN5,LGTP1,LHTN1
 158 FORMAT(2X,I6,2X,I6,2X,I6,2X,I6)
C
     WRITE(6,151) ALFLK,ALFLKK
 151 FORMAT(/,2X,'LK ALF = ',F9.6,3X,'LK ALF H = ',F9.6)
C
     WRITE(6,153) RSQLK,QMSELK
 153 FORMAT(/,2X,'RSQ LK = ',F9.6,3X,'MSE LK = ',F9.6)
C
     WRITE(6,203) TRAVLK,TRSDLK
 203 FORMAT(/,2X,'LK RES AV = ',F9.6,3X,'LK RES SD = ',F9.6)
C
     WRITE(6,202) TRSKLK,TRKULK
```

```
 202 FORMAT(/,2X,'LK RES SKW = ',F9.6,3X,
    *           'LK RES KUR = ',F9.6)
C
     WRITE(6,154)
 154 FORMAT(/,2X,'LK H SP5',2X,'LK H SN5',2X,'LK H SP1',
    *          2X,'LK H SN1')
C
     WRITE(6,155) LPKSP5,LQKSN5,LRKSP1,LSKSN1
 155 FORMAT(2X,I8,2X,I8,2X,I8,2X,I8)
C
     WRITE(6,156)
 156 FORMAT(/,2X,'LK H TP5',2X,'LK H TN5',2X,'LK H TP1',
    *          2X,'LK H TN1')
C
     WRITE(6,157) LTKTP5,LUKTN5,LVKTP1,LWKTN1
 157 FORMAT(2X,I8,2X,I8,2X,I8,2X,I8)
C
C
C
     WRITE(6,160)
 160 FORMAT(//,2X,'BP KNT',2X,'BP SP5',2X,'BP SN5',2X,
    *           'BP SP1',2X,'BP SN1')
C
     WRITE(6,162) KNTBP,KABSP5,KBBSN5,KCBSP1,KDBSN1
 162 FORMAT(2X,I6,2X,I6,2X,I6,2X,I6,2X,I6)
C
     WRITE(6,168)
 168 FORMAT(/,2X,'BP TP5',2X,'BP TN5',2X,
    *           'BP TP1',2X,'BP TN1')
C
     WRITE(6,169) KEBTP5,KFBTN5,KGBTP1,KHBTN1
 169 FORMAT(2X,I6,2X,I6,2X,I6,2X,I6)
C
     WRITE(6,161) ALFBP,ALFBPK
 161 FORMAT(/,2X,'ALF BP = ',F9.6,5X,'ALF BP H = ',F9.6)
C
     WRITE(6,175) ABPRHO,HBPRHO
 175 FORMAT(/,2X,'BP RHO = ',F9.6,5X,'BP RHO H = ',F9.6)
C
     WRITE(6,163) RSQBP,QMSEBP
 163 FORMAT(/,2X,'RSQ BP = ',F9.6,5X,'MSE BP = ',F9.6)
C
     WRITE(6,210) TRAVBP,TRSDBP
 210 FORMAT(/,2X,'BP RES AV = ',F9.6,3X,'BP RES SD = ',F9.6)
C
     WRITE(6,212) TRSKBP,TRKUBP
 212 FORMAT(/,2X,'BP RES SKW = ',F9.6,3X,
    *           'BP RES KUR = ',F9.6)
C
     WRITE(6,214) TRAVHT,TRSDHT
 214 FORMAT(/,2X,'BP RES AV HT = ',F9.6,3X,
```

```
    *           'BP RES SD HT = ',F9.6)
C
     WRITE(6,216) TRSKHT,TRKUHT
 216 FORMAT(/,2X,'BP RES SKW HT = ',F9.6,3X,
    *           'BP RES KUR HT = ',F9.6)
C
     WRITE(6,164)
 164 FORMAT(/,2X,'BP H SP5',2X,'BP H SN5',2X,'BP H SP1',
    *           2X,'BP H SN1')
C
     WRITE(6,165) KPBSP5,KQBSN5,KRBSP1,KSBSN1
 165 FORMAT(2X,I8,2X,I8,2X,I8,2X,I8)
C
     WRITE(6,166)
 166 FORMAT(/,2X,'BP H TP5',2X,'BP H TN5',2X,'BP H TP1',
    *           2X,'BP H TN1')
C
     WRITE(6,167) KTBTP5,KUBTN5,KVBTP1,KWBTN1
 167 FORMAT(2X,I8,2X,I8,2X,I8,2X,I8)
C
C
   3      CONTINUE
C
   2 CONTINUE
C
      END
C
C
C         *********************************
C              END OF MAIN PROGRAM
C         *********************************
C
C
      SUBROUTINE JENSEN(MX,NX,AXJ,RMF,B,RPF)
C
         DOUBLE PRECISION AXJ(MX,NX),B(MX),RMF(MX),RPF(MX)
C
         DO 5 I=1,MX
            AXJ(I,1)=1.
            AXJ(I,2)=RMF(I)
            B(I)=RPF(I)
   5        CONTINUE
C
      RETURN
      END
C
C
C
```

```
      SUBROUTINE HENMER(MX,NX,AX,RMF,RHM,B,RPF)
C
         DOUBLE PRECISION AX(MX,NX),RMF(MX),RHM(MX),B(MX),
     *      RPF(MX)
C
         DO 5 I=1,MX
            IF (RMF(I).LT.0.) THEN
                RHM(I)=-RMF(I)
            ELSE
               RHM(I)=0.0
            ENDIF
            AX(I,1)=1.0
            AX(I,2)=RMF(I)
            AX(I,3)=RHM(I)
            B(I)=RPF(I)
    5    CONTINUE
C
      RETURN
      END
C
C
C
      SUBROUTINE LOCKAD(MX,NX,AX,RMF,AVGRMF,QMF,PIMF,B,RPF)
C
         DOUBLE PRECISION AX(MX,NX),RMF(MX),QMF(MX),PIMF(MX),
     *      AVGRMF,B(MX),RPF(MX)
C
         DO 5 I=1,MX
            PIMF(I)=RMF(I)-AVGRMF
            QMF(I)=RMF(I)*PIMF(I)
            AX(I,1)=1.0
            AX(I,2)=RMF(I)
            AX(I,3)=QMF(I)
            B(I)=RPF(I)
    5    CONTINUE
C
      RETURN
      END
C
C
C
      SUBROUTINE BP(MX,NX,AX,RMF,RMFSQ,B,RPF)
C
         DOUBLE PRECISION AX(MX,NX),RMF(MX),RMFSQ(MX),B(MX),
     *      RPF(MX)
C
         DO 5 I=1,MX
            RMFSQ(I)=RMF(I)*RMF(I)
            AX(I,1)=1.
            AX(I,2)=RMF(I)
            AX(I,3)=RMFSQ(I)
```

```
         B(I)=RPF(I)
    5    CONTINUE
C
      RETURN
      END
C
C
C
      SUBROUTINE BPTWO(MX,NX,AX,BHRMF,BHRMFS,B,BHRPF,
     *   VARWSQ)
C
         DOUBLE PRECISION AX(MX,NX),BHRMF(MX),BHRMFS(MX),
     *      B(MX),BHRPF(MX),VARWSQ(MX)
C
         DO 5 I=1,MX
            AX(I,1)=1./VARWSQ(I)
            AX(I,2)=BHRMF(I)
            AX(I,3)=BHRMFS(I)
            B(I)=BHRPF(I)
    5    CONTINUE
C
      RETURN
      END
C
C
C
      SUBROUTINE STATS(MX,RET,GEORET,ANNRET,AVGRET,SDRET,
     *      RSKW,RKUR)
C
         DOUBLE PRECISION RET(MX),GEORET,AVGRET,SDRET,RVAR,D,
     *      D1,RETVAR,RSKW,RKUR,ANNRET
C
         GEORET=1.
         AVGRET=0.0
C
         DO 5 I=1,MX
            GEORET=GEORET*(1.+RET(I))
            AVGRET=AVGRET+RET(I)
    5    CONTINUE
C
         GEORET=GEORET-1.
         ANNRET=((GEORET+1.)**0.10)-1.
         AVGRET=AVGRET/(MX-0.)
         RVAR=0.
         RSKW=0.
         RKUR=0.
C
         DO 10 I=1,MX
            D=RET(I)-AVGRET
            D1=D*D
            RVAR=RVAR+D1
```

```
            D1=D1*D
            RSKW=RSKW+D1
            D1=D1*D
            RKUR=RKUR+D1
   10    CONTINUE
C
         RETVAR=RVAR/(MX-1.)
         SDRET=DSQRT(RETVAR)
         RSKW=RSKW/(MX*(SDRET**3))
         RKUR=(RKUR/(MX*(SDRET**4)))-3.
C
      RETURN
      END
C
C
C
      SUBROUTINE STATMON(MX,RETGEO,RTMON,RTANN,RTGEO)
C
         DOUBLE PRECISION RETGEO,RTMON,RTANN,RTGEO,DIV,RFAVG
C
         DIV=MX-0.
         RFAVG=0.00655778
C
         RTMON=((RETGEO+1.)**(1./DIV))-1.+RFAVG
         RTANN=((RTMON+1.)**(DIV/10.))-1.
         RTGEO=((RTMON+1.)**DIV)-1.
C
      RETURN
      END
C
C
C
      SUBROUTINE RESID(MX,NX,RES,RESQ,AVGRES,SDRES,RESSKW,
     *      RESKUR)
C
         DOUBLE PRECISION RES(MX),RESQ(MX),AVGRES,SDRES,
     *      RESSKW,RESKUR,VARU,D,D1
C
         AVGRES=0.0
         VARU=0.0
C
         DO 5 I=1,MX
            AVGRES=AVGRES+RES(I)
            VARU=VARU+RESQ(I)
    5    CONTINUE
C
         AVGRES=AVGRES/(MX-0.)
         SDRES=DSQRT(VARU/(MX-NX-0.))
C
         RESSKW=0.
         RESKUR=0.
```

```
C
         DO 10 I=1,MX
            D=RES(I)-AVGRES
            D1=D*D
            D1=D1*D
            RESSKW=RESSKW+D1
            D1=D1*D
            RESKUR=RESKUR+D1
   10       CONTINUE
C
         RESSKW=RESSKW/(MX*(SDRES**3))
         RESKUR=(RESKUR/(MX*(SDRES**4)))-3.
C
      RETURN
      END
C
C
C
      SUBROUTINE REGSTA(MX,NX,UU,Y,AB,QMSE,RSQ,VAR,TVAL,XB,
     *   RES,RESQ)
C
         DOUBLE PRECISION UU(MX,NX),Y(MX),AB(NX),VAR(NX,NX),
     *      TVAL(NX),QMSE,RSQ,YSUM,YTY,SSTO,SSE,XB(MX),
     *      RES(MX),RESQ(MX)
C
         YSUM=0.
         YTY=0.
         SSE=0.
C
         DO 5 I=1,MX
            YTY=YTY+(Y(I)*Y(I))
            YSUM=YSUM+Y(I)
    5    CONTINUE
C
         DO 10 I=1,MX
            XB(I)=0.
            DO 15 J=1,NX
               XB(I)=XB(I)+UU(I,J)*AB(J)
   15       CONTINUE
            RES(I)=Y(I)-XB(I)
            RESQ(I)=RES(I)*RES(I)
            SSE=SSE+(RES(I)*RES(I))
   10    CONTINUE
C
         SSTO=YTY-((YSUM*YSUM)/MX)
         QMSE=SSE/(MX-NX)
         RSQ=1.-(SSE/SSTO)
C
         DO 20 J=1,NX
            TVAL(J)=AB(J)/DSQRT(QMSE*VAR(J,J))
   20    CONTINUE
```

```
C
      RETURN
      END
C
C
C
      SUBROUTINE HETRSC(MX,NX,DIAG,UU,AB,RESQ,PP,SS,VAR,
     *   HETMAT,HETT)
C
         DOUBLE PRECISION DIAG(MX,NX),UU(MX,NX),RESQ(MX),
     *      PP(NX,NX),SS(NX,NX),VAR(NX,NX),HETMAT(NX,NX),
     *      HETT(NX),AB(NX)
C
         DO 5 J=1,NX
            DO 10 I=1,MX
               DIAG(I,J)=UU(I,J)*RESQ(I)
   10       CONTINUE
    5    CONTINUE
C
         DO 15 II=1,NX
            DO 20 J=1,NX
               PP(J,II)=0.
               DO 25 I=1,MX
                  PP(J,II)=PP(J,II)+UU(I,J)*DIAG(I,II)
   25          CONTINUE
   20       CONTINUE
   15    CONTINUE
C
         DO 30 II=1,NX
            DO 35 J=1,NX
               SS(J,II)=0.
               DO 40 I=1,NX
                  SS(J,II)=SS(J,II)+VAR(J,I)*PP(I,II)
   40          CONTINUE
   35       CONTINUE
   30    CONTINUE
C
         DO 45 II=1,NX
            DO 50 J=1,NX
               HETMAT(J,II)=0.
               DO 55 I=1,NX
                 HETMAT(J,II)=HETMAT(J,II)+SS(J,I)*VAR(I,II)
   55          CONTINUE
   50       CONTINUE
   45    CONTINUE
C
         DO 60 J=1,NX
            HETT(J)=AB(J)/DSQRT(HETMAT(J,J))
   60    CONTINUE
C
      RETURN
```

```
      END
C
C
C
      FUNCTION UNFORM(ISEED)
C
         DOUBLE PRECISION X(89),XI,XJ
C
         I=121500
         I1=2041
         I2=25673
         XI=1./I
C
         J=117128
         J1=1277
         J2=24749
         XJ=1./J
C
         K=312500
         K1=741
         K2=66037
         DATA L /0/
C
         IF (ISEED.LT.0.OR.L.EQ.0) THEN
            L=1
            N1=MOD(I2-ISEED,I)
            N1=MOD(I1*N1+I2,I)
            N2=MOD(N1,J)
            N1=MOD(I1*N1+I2,I)
            N3=MOD(N1,K)
            DO 5 II=1,89
               N1=MOD(I1*N1+I2,I)
               N2=MOD(J1*N2+J2,J)
               X(II)=(DFLOAT(N1)+DFLOAT(N2)*XJ)*XI
    5       CONTINUE
         ISEED=1
         ENDIF
         N1=MOD(I1*N1+I2,I)
         N2=MOD(J1*N2+J2,J)
         N3=MOD(K1*N3+K2,K)
         II=1+(89*N3)/K
         IF(II.GT.89.OR.II.LT.1) PAUSE 'FUNCTION UNFORM'
         UNFORM=X(II)
         X(II)=(DFLOAT(N1)+DFLOAT(N2)*XJ)*XI
C
      RETURN
      END
C
C
C
```

```
      FUNCTION XNORM(ISEED)
C
         DOUBLE PRECISION A,B,C,Y,Z
C
         DATA K /0/
C
         IF (K.EQ.0) THEN
   5        A=2.*UNFORM(ISEED)-1.
            B=2.*UNFORM(ISEED)-1.
            C=(A*A)+(B*B)
            IF (C.GE.1.) GO TO 5
            Y=DSQRT(-2.*DLOG(C)/C)
            Z=A*Y
            XNORM=B*Y
            K=1
         ELSE
            XNORM=Z
            K=0
         ENDIF
C
      RETURN
      END
C
C
C
      SUBROUTINE STDNOR(ZVAR,MX,ISEED)
C
         DOUBLE PRECISION ZVAR(MX)
C
         DO 5 I=1,MX
            ZVAR(I)=XNORM(ISEED)
    5    CONTINUE
         ITEMP=INT(ZVAR(MX)*1E7)
         ISEED=-ABS(ITEMP)
C
      RETURN
      END
C
C
C
      SUBROUTINE LSTSQR(MX,NX,AX,AY,AZ,AB,B,X,UU,PAR,
     *   DEL,PAR1)
         DOUBLE PRECISION B(MX),AB(NX),AY(NX,NX),AX(MX,NX),
     *      AZ(NX),UU(MX,NX),X(NX),PAR(NX),DEL(MX),PAR1(NX)
         DOUBLE PRECISION XAZ,XLIM
C
         PREC=1.D-12
C
         DO 5 I=1,MX
            DO 10 J=1,NX
               UU(I,J)=AX(I,J)
```

```
   10         CONTINUE
    5      CONTINUE
C
           CALL LSQALG(MX,NX,AX,AY,AZ,PAR1)
C
           XAZ=0.0
           DO 15 J=1,NX
              IF (AZ(J).GT.XAZ) XAZ=AZ(J)
   15         CONTINUE
           XLIM=PREC*XAZ
           DO 20 J=1,NX
              IF (AZ(J).LT.XLIM) AZ(J)=0.0
   20      CONTINUE
C
           CALL REGCOF(MX,NX,AX,AY,AZ,B,AB,PAR)
           CALL ITERAT(MX,NX,AX,AY,AZ,UU,AB,B,X,PAR,DEL)
C
        RETURN
        END
C
C
C
        SUBROUTINE STDERR(NX,AY,AZ,VAR,SIG)
C
           DOUBLE PRECISION AY(NX,NX),AZ(NX),VAR(NX,NX),
     *        SIG(NX),TOT
C
           DO 5 I=1,NX
              SIG(I)=0.0
              IF(AZ(I).NE.0.) SIG(I)=1./(AZ(I)*AZ(I))
    5      CONTINUE
C
           DO 10 I=1,NX
              DO 15 J=1,I
                 TOT=0.0
                 DO 20 K=1,NX
                    TOT=TOT+AY(I,K)*AY(J,K)*SIG(K)
   20            CONTINUE
                 VAR(I,J)=TOT
                 VAR(J,I)=TOT
   15         CONTINUE
   10      CONTINUE
C
        RETURN
        END
C
C
C
```

```
      SUBROUTINE REGCOF(MX,NX,AX,AY,AZ,B,X,PAR)
C
         DOUBLE PRECISION AX(MX,NX),AZ(NX),AY(NX,NX),B(MX),
     *      X(NX),PAR(NX),T
C
         DO 5 J=1,NX
            T=0.
            IF (AZ(J).NE.0.) THEN
               DO 10 I=1,MX
                  T=T+AX(I,J)*B(I)
   10          CONTINUE
               T=T/AZ(J)
            ENDIF
            PAR(J)=T
    5    CONTINUE
C
         DO 15 J=1,NX
            T=0.0
            DO 20 JJ=1,NX
               T=T+AY(J,JJ)*PAR(JJ)
   20       CONTINUE
            X(J)=T
   15    CONTINUE
C
      RETURN
      END
C
C
C
      SUBROUTINE LSQALG(MX,NX,AX,AY,AZ,PAR1)
C
         DOUBLE PRECISION AX(MX,NX),AZ(NX),AY(NX,NX),
     *      PAR1(NX),PAR2,PAR3,E1,E2,E3,E4,E5,E6,E7,E8
C
         E1=0.0
         PAR2=0.0
         PAR3=0.0
C
         DO 5 J=1,NX
            I=J+1
            PAR1(J)=PAR2*E1
            E1=0.0
            E2=0.0
            PAR2=0.0
C
            IF (J.LE.MX) THEN
               DO 10 L=J,MX
                  PAR2=PAR2+DABS(AX(L,J))
   10          CONTINUE
C
               IF (PAR2.NE.0.0) THEN
```

```
                 DO 15 L=J,MX
                    AX(L,J)=AX(L,J)/PAR2
                       E2=E2+AX(L,J)*AX(L,J)
   15            CONTINUE
C
                 E3=AX(J,J)
                 E1=-DSIGN(DSQRT(E2),E3)
                 E4=E3*E1-E2
                 AX(J,J)=E3-E1
                 IF (J.NE.NX) THEN
                    DO 20 K=I,NX
                       E2=0.0
                       DO 25 L=J,MX
                          E2=E2+AX(L,J)*AX(L,K)
   25                  CONTINUE
                       E3=E2/E4
                       DO 30 L=J,MX
                          AX(L,K)=AX(L,K)+E3*AX(L,J)
   30                  CONTINUE
   20               CONTINUE
C
                 ENDIF
                 DO 35 L=J,MX
                    AX(L,J)=PAR2*AX(L,J)
   35            CONTINUE
              ENDIF
C
           ENDIF
C
           AZ(J)=PAR2*E1
           E1=0.0
           E2=0.0
           PAR2=0.0
           IF ((J.LE.MX).AND.(J.NE.NX)) THEN
              DO 40 L=I,NX
                 PAR2=PAR2+DABS(AX(J,L))
   40         CONTINUE
              IF (PAR2.NE.0.0) THEN
                 DO 45 L=I,NX
                    AX(J,L)=AX(J,L)/PAR2
                    E2=E2+AX(J,L)*AX(J,L)
   45            CONTINUE
              E3=AX(J,I)
              E1=-DSIGN(DSQRT(E2),E3)
              E4=E3*E1-E2
              AX(J,I)=E3-E1
              DO 50 L=I,NX
                 PAR1(L)=AX(J,L)/E4
   50         CONTINUE
C
              IF (J.NE.MX) THEN
```

```
                DO 55 K=I,MX
                   E2=0.0
                   DO 60 L=I,NX
                      E2=E2+AX(K,L)*AX(J,L)
   60              CONTINUE
                   DO 65 L=I,NX
                          AX(K,L)=AX(K,L)+E2*PAR1(L)
   65              CONTINUE
   55           CONTINUE
             ENDIF
C
             DO 70 L=I,NX
                AX(J,L)=PAR2*AX(J,L)
   70        CONTINUE
          ENDIF
       ENDIF
C
       PAR3=DMAX1(PAR3,(DABS(AZ(J))+DABS(PAR1(J))))
    5  CONTINUE
C
       DO 75 J=NX,1,-1
C
          IF (J.LT.NX) THEN
C
             IF (E1.NE.0.0) THEN
C
                DO 80 K=I,NX
                   AY(K,J)=(AX(J,K)/AX(J,I))/E1
   80           CONTINUE
                DO 85 K=I,NX
                   E2=0.0
                   DO 90 L=I,NX
                      E2=E2+AX(J,L)*AY(L,K)
   90              CONTINUE
                   DO 95 L=I,NX
                      AY(L,K)=AY(L,K)+E2*AY(L,J)
   95              CONTINUE
   85           CONTINUE
              ENDIF
C
              DO 100 K=I,NX
                   AY(J,K)=0.0
                   AY(K,J)=0.0
  100         CONTINUE
           ENDIF
C
       AY(J,J)=1.0
       E1=PAR1(J)
       I=J
   75  CONTINUE
C
```

```
      DO 105 J=NX,1,-1
         I=J+1
         E1=AZ(J)
         IF (J.LT.NX) THEN
            DO 110 K=I,NX
               AX(J,K)=0.0
 110        CONTINUE
         ENDIF
         IF (E1.NE.0.0) THEN
         E1=1.0/E1
         IF (J.NE.NX) THEN
            DO 115 K=I,NX
               E2=0.0
               DO 120 L=I,MX
                  E2=E2+AX(L,J)*AX(L,K)
 120           CONTINUE
               E3=(E2/AX(J,J))*E1
               DO 125 L=J,MX
                  AX(L,K)=AX(L,K)+E3*AX(L,J)
 125           CONTINUE
 115        CONTINUE
         ENDIF
         DO 127 K=J,MX
            AX(K,J)=AX(K,J)*E1
 127     CONTINUE
      ELSE
         DO 128 K=J,MX
            AX(K,J)=0.0
 128     CONTINUE
      ENDIF
C
      AX(J,J)=AX(J,J)+1.0
 105  CONTINUE
C
      DO 130 L=NX,1,-1
         DO 135 ICNT=1,30
            DO 140 I=L,1,-1
               KR=I-1
               IF ((DABS(PAR1(I))+PAR3).EQ.PAR3) GO TO 7
               IF ((DABS(AZ(KR))+PAR3).EQ.PAR3) GO TO 17
 140        CONTINUE
  17        E5=0.0
            E2=1.0
            DO 145 J=I,L
               E3=E2*PAR1(J)
               IF ((DABS(E3)+PAR3).NE.PAR3) THEN
                  E1=AZ(J)
                  E4=DSQRT(E3*E3+E1*E1)
                  AZ(J)=E4
                  E4=1.0/E4
                  E5=(E1*E4)
```

```
              E2=-(E3*E4)
              DO 150 K=1,MX
                 E7=AX(K,KR)
                 E8=AX(K,J)
                 AX(K,KR)=(E7*E5)+(E8*E2)
                 AX(K,J)=-(E7*E2)+(E8*E5)
150           CONTINUE
           ENDIF
145        CONTINUE
  7        E8=AZ(L)
           IF (I.EQ.L) THEN
              IF (E8.LT.0.0) THEN
                 AZ(L)=-E8
                 DO 155 K=1,NX
                    AY(K,L)=-AY(K,L)
155              CONTINUE
              ENDIF
              GO TO 27
           ENDIF
           IF (ICNT.EQ.30) PAUSE 'SUBROUTINE LSQALG'
           E6=AZ(I)
           KR=L-1
           E7=AZ(KR)
           E1=PAR1(KR)
           E4=PAR1(L)
           E3=((E7-E8)*(E7+E8)+(E1-E4)*(E1+E4))/
     *        (2.0*E4*E7)
           E1=DSQRT(E3*E3+1.0)
           E3=((E6-E8)*(E6+E8)+E4*((E7/(E3+
     *        DSIGN(E1,E3)))-E4))/E6
           E5=1.0
           E2=1.0
           DO 160 K=I,KR
              J=K+1
              E1=PAR1(J)
              E7=AZ(J)
              E4=E2*E1
              E1=E5*E1
              E8=DSQRT(E3*E3+E4*E4)
              PAR1(K)=E8
              E5=E3/E8
              E2=E4/E8
              E3=(E6*E5)+(E1*E2)
              E1=-(E6*E2)+(E1*E5)
              E4=E7*E2
              E7=E7*E5
              DO 165 KK=1,NX
                 E6=AY(KK,K)
                 E8=AY(KK,J)
                 AY(KK,K)=(E6*E5)+(E8*E2)
                 AY(KK,J)=-(E6*E2)+(E8*E5)
```

```
  165                 CONTINUE
                      E8=DSQRT(E3*E3+E4*E4)
                      AZ(K)=E8
                      IF (E8.NE.0.0) THEN
                         E8=1.0/E8
                         E5=E3*E8
                         E2=E4*E8
                      ENDIF
                      E3=(E5*E1)+(E2*E7)
                      E6=-(E2*E1)+(E5*E7)
                      DO 170 KK=1,MX
                         E7=AX(KK,K)
                         E8=AX(KK,J)
                         AX(KK,K)=(E7*E5)+(E8*E2)
                         AX(KK,J)=-(E7*E2)+(E8*E5)
  170                 CONTINUE
  160              CONTINUE
                   PAR1(I)=0.0
                   PAR1(L)=E3
                   AZ(L)=E6
  135           CONTINUE
   27        CONTINUE
  130     CONTINUE
C
      RETURN
      END
C
C
C
      SUBROUTINE ITERAT(MX,NX,AX,AY,AZ,UU,AB,B,X,PAR,DEL)
C
         DOUBLE PRECISION AX(MX,NX),AY(NX),AZ(NX,NX),B(MX),
     *      AB(NX),DEL(MX),UU(MX,NX),X(NX),PAR(NX),REM
C
         DO 5 I=1,MX
            REM=-B(I)
            DO 10 J=1,NX
               REM=REM+(UU(I,J)*AB(J))
   10       CONTINUE
            DEL(I)=REM
    5    CONTINUE
C
         CALL REGCOF(MX,NX,AX,AY,AZ,DEL,X,PAR)
C
         DO 15 J=1,NX
             AB(J)=AB(J)-X(J)
   15        CONTINUE
C
      RETURN
      END
```

APPENDIX D. RESULTS OF MARKET TIMING TESTS

THE PROBABILITY[a] THAT THE NULL HYPOTHESIS OF NO MARKET TIMING ABILITY, $H_o: \beta_{TIM} \leq 0$, IS REJECTED BY TIMING PARAMETERS STATISTICALLY SIGNIFICANT AT THE 5% LEVEL.[b]

		TIMING SKILL								
		$\rho_{TIM} = 0$			$\rho_{TIM} = -0.50$			$\rho_{TIM} = -1$		
	JN:	.063	.046	.047	.357	.375	.349	.833	.852	.867
$\Delta_{SEL} = 0\%$	HM:	.057	.047	.074	.536	.532	.579	.976	.954	.964
	LK:	.073	.053	.085	.621	.584	.624	.984	.966	.972
	BP:	.068	.049	.090	.605	.566	.611	.987	.963	.969
SELECTIVITY										
	JN:	.649	.647	.672	.961	.972	.989	1.00	.999	.999
$\Delta_{SEL} = 1\%$	HM:	.056	.048	.073	.545	.518	.562	.964	.946	.957
	LK:	.082	.061	.087	.623	.580	.607	.975	.970	.969
	BP:	.070	.048	.091	.598	.554	.596	.974	.959	.966
SKILL										
	JN:	.994	.998	.997	1.00	1.00	1.00	1.00	1.00	1.00
$\Delta_{SEL} = 2\%$	HM:	.062	.054	.060	.527	.514	.558	.965	.940	.949
	LK:	.080	.066	.073	.606	.578	.604	.974	.954	.962
	BP:	.066	.056	.076	.584	.553	.586	.972	.949	.961

[a]The experiments are replicated using three different sets of random number seeds.

[b]The HM and LK performance models are corrected for heteroskedasticity using White's method. Similarly, the BP model is modified using the GLS method.

APPENDIX D

THE PROBABILITY[a] THAT THE NULL HYPOTHESIS OF NO MARKET TIMING ABILITY, $H_o: \beta_{TIM} \leq 0$, IS REJECTED BY TIMING PARAMETERS STATISTICALLY SIGNIFICANT AT THE 5% LEVEL.[b]

		TIMING SKILL								
		$\rho_{TIM} = 0$			$\rho_{TIM} = -0.50$			$\rho_{TIM} = -1$		
$\Delta_{SEL} = 0\%$	JN:	.063	.046	.047	.357	.375	.349	.833	.852	.867
	HM:	.054	.049	.074	.543	.533	.576	.975	.955	.964
	LK:	.058	.044	.081	.593	.569	.611	.986	.961	.971
	BP:	.115	.087	.128	.713	.680	.719	.994	.983	.986
SELECTIVITY										
$\Delta_{SEL} = 1\%$	JN:	.649	.647	.672	.961	.972	.989	1.00	.999	.999
	HM:	.050	.050	.074	.544	.523	.558	.971	.948	.959
	LK:	.076	.048	.084	.595	.557	.595	.974	.962	.964
	BP:	.133	.089	.129	.697	.691	.703	.991	.985	.983
SKILL										
$\Delta_{SEL} = 2\%$	JN:	.994	.998	.997	1.00	1.00	1.00	1.00	1.00	1.00
	HM:	.059	.054	.059	.528	.511	.545	.963	.941	.949
	LK:	.066	.059	.075	.583	.558	.585	.968	.949	.959
	BP:	.119	.097	.121	.691	.697	.703	.990	.976	.978

[a]The experiments are replicated using three different sets of random number seeds.

[b]The performance models are not modified to account for heteroskedasticity.

APPENDIX D

THE PROBABILITY[a] THAT THE NULL HYPOTHESIS OF NO MARKET TIMING ABILITY, $H_o: \beta_{TIM} \leq 0$, IS REJECTED BY TIMING PARAMETERS STATISTICALLY SIGNIFICANT AT THE 1% LEVEL.[b]

		TIMING SKILL								
		$\rho_{TIM} = 0$			$\rho_{TIM} = -0.50$			$\rho_{TIM} = -1$		
	JN:	.012	.006	.007	.165	.143	.155	.586	.621	.615
$\Delta_{SEL} = 0\%$	HM:	.013	.011	.019	.299	.285	.324	.918	.855	.871
	LK:	.019	.017	.037	.374	.360	.388	.928	.889	.918
	BP:	.010	.014	.027	.331	.335	.367	.927	.890	.915
SELECTIVITY										
	JN:	.395	.394	.374	.855	.864	.870	.991	.993	.995
$\Delta_{SEL} = 1\%$	HM:	.009	.009	.019	.285	.276	.330	.888	.861	.859
	LK:	.033	.016	.040	.355	.343	.389	.910	.894	.901
	BP:	.015	.015	.026	.317	.309	.368	.910	.891	.897
SKILL										
	JN:	.973	.982	.991	1.00	.999	.999	1.00	1.00	1.00
$\Delta_{SEL} = 2\%$	HM:	.011	.012	.015	.272	.282	.314	.868	.808	.834
	LK:	.026	.017	.030	.342	.350	.373	.894	.859	.888
	BP:	.011	.018	.019	.311	.303	.352	.893	.854	.878

[a]The experiments are replicated using three different sets of random number seeds.

[b]The HM and LK performance models are corrected for heteroskedasticity using White's method. Similarly, the BP model is modified using the GLS method.

APPENDIX D

THE PROBABILITY[a] THAT THE NULL HYPOTHESIS OF NO MARKET TIMING ABILITY, $H_o: \beta_{TIM} \leq 0$, IS REJECTED BY TIMING PARAMETERS STATISTICALLY SIGNIFICANT AT THE 1% LEVEL.[b]

		TIMING SKILL								
		$\rho_{TIM} = 0$			$\rho_{TIM} = -0.50$			$\rho_{TIM} = -1$		
	JN:	.012	.006	.007	.165	.143	.155	.586	.621	.615
$\Delta_{SEL} = 0\%$	HM:	.005	.009	.021	.316	.291	.330	.904	.858	.875
	LK:	.014	.012	.028	.363	.336	.359	.924	.885	.906
	BP:	.042	.031	.064	.538	.513	.557	.979	.955	.968
SELECTIVITY										
	JN:	.395	.394	.374	.855	.864	.870	.991	.993	.995
$\Delta_{SEL} = 1\%$	HM:	.006	.008	.020	.302	.275	.325	.884	.860	.856
	LK:	.016	.010	.028	.349	.316	.349	.909	.882	.895
	BP:	.055	.032	.063	.519	.504	.542	.967	.954	.959
SKILL										
	JN:	.973	.982	.991	1.00	.999	.999	1.00	1.00	1.00
$\Delta_{SEL} = 2\%$	HM:	.005	.011	.014	.290	.268	.303	.861	.811	.841
	LK:	.013	.011	.019	.335	.306	.343	.899	.840	.877
	BP:	.047	.036	.052	.506	.498	.522	.964	.936	.949

[a]The experiments are conducted using three different sets of random number seeds.

[b]The performance models are not modified to account for heteroskedasticity.

APPENDIX E. RESULTS OF SELECTIVITY TESTS

THE PROBABILITY[a] THAT THE NULL HYPOTHESIS OF NO SELECTIVITY ABILITY, $H_0: \alpha \leq 0$, IS REJECTED BY SELECTIVITY PARAMETERS STATISTICALLY SIGNIFICANT AT THE 5% LEVEL.[b]

		TIMING SKILL								
		$\rho_{TIM} = 0$			$\rho_{TIM} = -0.50$			$\rho_{TIM} = -1$		
	JN:	.063	.046	.047	.357	.375	.349	.833	.852	.867
$\Delta_{SEL} = 0\%$	HM:	.061	.056	.066	.011	.013	.022	.004	.001	.005
	LK:	.068	.062	.061	.049	.063	.064	.050	.072	.075
	BP:	.068	.059	.062	.057	.060	.064	.060	.072	.069
SELECTIVITY										
	JN:	.649	.647	.672	.961	.972	.989	1.00	.999	.999
$\Delta_{SEL} = 1\%$	HM:	.358	.401	.329	.164	.191	.164	.054	.066	.072
	LK:	.536	.551	.520	.573	.571	.546	.584	.588	.572
	BP:	.541	.555	.535	.565	.561	.534	.569	.567	.560
SKILL										
	JN:	.994	.998	.997	1.00	1.00	1.00	1.00	1.00	1.00
$\Delta_{SEL} = 2\%$	HM:	.824	.828	.815	.620	.542	.611	.427	.458	.401
	LK:	.976	.977	.972	.976	.979	.974	.977	.985	.983
	BP:	.976	.977	.972	.975	.979	.974	.977	.985	.983

[a]The experiments are replicated using three different sets of random number seeds.

[b]The HM and LK performance models are corrected for heteroskedasticity using White's method. Similarly, the BP model is modified using the GLS.

APPENDIX E

THE PROBABILITY[a] THAT THE NULL HYPOTHESIS OF NO SELECTIVITY ABILITY, $H_o: \alpha \leq 0$, IS REJECTED BY SELECTIVITY PARAMETERS STATISTICALLY SIGNIFICANT AT THE 5% LEVEL.[b]

		TIMING SKILL								
		$\rho_{TIM} = 0$			$\rho_{TIM} = -0.50$			$\rho_{TIM} = -1$		
	JN:	.063	.046	.047	.357	.375	.349	.833	.852	.867
$\Delta_{SEL} = 0\%$	HM:	.057	.047	.059	.011	.013	.017	.000	.001	.005
	LK:	.061	.053	.055	.044	.056	.061	.049	.066	.070
	BP:	.061	.053	.055	.044	.056	.061	.049	.066	.070
SELECTIVITY										
	JN:	.649	.647	.672	.961	.972	.989	1.00	.999	.999
$\Delta_{SEL} = 1\%$	HM:	.355	.379	.313	.163	.184	.156	.057	.065	.074
	LK:	.536	.537	.498	.551	.563	.528	.568	.583	.562
	BP:	.536	.537	.498	.551	.563	.528	.568	.583	.562
SKILL										
	JN:	.994	.998	.997	1.00	1.00	1.00	1.00	1.00	1.00
$\Delta_{SEL} = 2\%$	HM:	.815	.820	.809	.620	.630	.589	.422	.456	.396
	LK:	.971	.968	.973	.972	.974	.975	.980	.983	.986
	BP:	.971	.968	.973	.972	.974	.975	.980	.983	.986

[a]The experiments are replicated using three different sets of random number seeds.

[b]The performance models are not modified to account for heteroskedasticity.

APPENDIX E

THE PROBABILITY[a] THAT THE NULL HYPOTHESIS OF NO SELECTIVITY ABILITY, $H_0: \alpha \leq 0$, IS REJECTED BY SELECTIVITY PARAMETERS STATISTICALLY SIGNIFICANT AT THE 1% LEVEL.[b]

		TIMING SKILL								
		$\rho_{TIM} = 0$			$\rho_{TIM} = -0.50$			$\rho_{TIM} = -1$		
	JN:	.012	.006	.007	.165	.143	.155	.586	.621	.615
$\Delta_{SEL} = 0\%$	HM:	.023	.012	.018	.000	.001	.001	.000	.000	.000
	LK:	.020	.012	.014	.013	.009	.016	.017	.013	.020
	BP:	.023	.010	.016	.011	.007	.018	.013	.010	.021
SELECTIVITY										
	JN:	.395	.394	.374	.855	.864	.870	.991	.993	.995
$\Delta_{SEL} = 1\%$	HM:	.155	.171	.141	.043	.066	.065	.016	.019	.025
	LK:	.269	.305	.259	.319	.320	.265	.345	.322	.303
	BP:	.299	.310	.256	.310	.316	.270	.329	.317	.294
SKILL										
	JN:	.973	.982	.991	1.00	.999	.999	1.00	1.00	1.00
$\Delta_{SEL} = 2\%$	HM:	.603	.618	.588	.370	.394	.330	.193	.217	.179
	LK:	.878	.874	.881	.865	.886	.884	.897	.920	.907
	BP:	.877	.876	.886	.880	.884	.878	.904	.913	.893

[a]The experiments are replicated using three different sets of random number seeds.

[b]The HM and LK performance models are corrected for heteroskedasticity using White's method. Similarly, the BP model is modified using the GLS method.

APPENDIX E

THE PROBABILITY[a] THAT THE NULL HYPOTHESIS OF NO SELECTIVITY ABILITY, $H_0: \alpha \leq 0$, IS REJECTED BY SELECTIVITY PARAMETERS STATISTICALLY SIGNIFICANT AT THE 1% LEVEL.[b]

		TIMING SKILL								
		$\rho_{TIM} = 0$			$\rho_{TIM} = -0.50$			$\rho_{TIM} = -1$		
$\Delta_{SEL} = 0\%$	JN:	.012	.006	.007	.165	.143	.155	.586	.621	.615
	HM:	.022	.010	.016	.000	.002	.001	.000	.000	.000
	LK:	.015	.009	.010	.013	.008	.013	.015	.012	.018
	BP:	.015	.009	.010	.013	.008	.013	.015	.012	.018
SELECTIVITY										
$\Delta_{SEL} = 1\%$	JN:	.395	.394	.374	.855	.864	.870	.991	.993	.995
	HM:	.131	.161	.133	.043	.057	.061	.015	.017	.022
	LK:	.249	.273	.244	.291	.291	.256	.312	.313	.291
	BP:	.249	.273	.244	.291	.291	.256	.312	.313	.291
SKILL										
$\Delta_{SEL} = 2\%$	JN:	.973	.982	.991	1.00	.999	.999	1.00	1.00	1.00
	HM:	.579	.592	.565	.342	.366	.321	.176	.213	.186
	LK:	.865	.866	.870	.864	.880	.874	.889	.920	.898
	BP:	.865	.866	.870	.864	.880	.874	.889	.920	.898

[a]The experiments are replicated using three different sets of random number seeds.
[b]The performance models are not modified to account for heteroskedasticity.