Hybrid Mutual Funds and Market Timing Performance

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Abstract

I examine the stock market timing ability of two samples of hybrid mutual funds. I find that the inclusion of bond indices and a bond timing variable in a multi-factor Treynor and Mazuy model framework leads to substantially different conclusions concerning the stock market timing performance of these funds relative to the traditional Treynor Mazuy model. Coefficients from the traditional model are biased due to a strong correlation between various bond indices and the quadratic term used to measure timing ability in the model. Results from the multi-factor Treynor Mazuy model find less stock timing ability over the 1981-1991 time period than the Treynor Mazuy model and provide evidence of significant stock timing ability across the fund sample covering the 1992-2000 time period. A test designed to estimate stock portfolio changes during up and down stock markets provides some evidence that the results from the multi-factor Treynor Mazuy model are not spurious.

I. Introduction

This study examines the stock market timing ability of hybrid mutual funds. Hybrid funds include balanced, asset allocation, and flexible mutual funds that hold a combination of stocks, bonds, and cash in their portfolios. Many studies of mutual fund performance and market timing skill include these funds as part of their overall fund sample.[1] However, the traditional market timing models employed in these studies analyze funds as if they are composed of only stocks and Treasury bills and evaluate fund performance by focusing on the choice between stocks and cash. As a result, most of the studies either ignore the portion of the hybrid fund's portfolio that is invested in bonds or include a limited number of bond indices that do not span the wide selection of bonds in which these funds invest.

This paper focuses on improving the measurement of the stock market timing ability of hybrid mutual funds. Over the last ten years, there has been a tremendous growth in the number of hybrid funds in existence. Less than 70 hybrid funds were in existence in 1992. That number has grown to over 850 as of 2002. These funds are distinct from traditional mutual funds in that they claim to use investment strategies that allow the investor to receive high returns with less volatility than traditional funds. The funds generate these returns by engaging in sophisticated market timing or tactical asset allocation techniques in an attempt to generate high returns. Thus, these funds are more likely to engage in market timing than traditional equity funds. From an academic viewpoint, accurately measuring the timing ability of these funds has implications for the efficient market hypothesis. From an individual investor's perspective, identifying superior investment managers is an important objective.

[1] Among the papers that empirically examine market timing ability and include hybrid funds as a part of their overall fund sample are Treynor and Mazuy (1966), Kon (1983), Chang and Lewellen (1984), Henriksson (1984), Lee and Rahman (1990), Chan and Chen (1992), Ferson and Schadt (1996), Bello and Janjigian (1997), Volkman (1999), Becker, Ferson, Myers, and Schill (1999), Edelen (1999), Goetzmann, Ingersoll, and Ivkovic (2000), and Kosowski (2002).

I address this issue by comparing the estimated stock timing coefficients from the traditional Treynor and Mazuy (1966) model (hereafter referred to as TM) to the coefficients from a multi-factor version of the model first suggested by Lehmann and Modest (1987). The empirical literature has not fully exploited multi-factor timing model methodologies when it comes to examining hybrid mutual funds. The multi-factor version (hereafter referred to as MFTM) used in this paper differs from the traditional TM model in two ways. First, the MFTM model includes an assumed return generating process for the bond portion of the fund that more fully accounts for the wide variety of bonds in which these funds invest. Second, the model incorporates timing variables for both the stock and bond portion of the fund since the fund shifts assets across multiple asset categories.

The TM and MFTM models are based on examining a fund's return series. The focus on these models is due to their extensive use in the market timing literature. With rare exceptions (e.g. Graham and Harvey (1996) and Chance and Hemler (2001)), researchers do not have access to the actual forecasts of market timers. Changes in fund portfolio holdings and complete fund composition data are available at most on a quarterly basis (e.g. Daniel, Grinblatt, Titman, and Wermers (1997) and Wermers (2000)). Thus, the majority of market timing research must infer timing performance from the realized return series of the actively managed portfolio. The TM model and its extension are intuitively appealing, are relatively easy to implement, and have minimal data requirements.

In this paper, I focus on the following issues. First, I estimate the potential impact that the exclusion of the bond indices may have on the estimated stock timing coefficients from the TM model. I then compare the stock timing coefficients from the TM and MFTM models to examine whether the estimated coefficients are sensitive to the exclusion of the various bond indices and whether inferences concerning stock timing ability change when the bond indices are included. Finally, I examine the results from the MFTM model using a technique which combines the Henriksson and Merton (1981) model with the quadratic programming technique of Sharpe (1992) to determine if the model accurately measures the stock timing ability of the funds or if the results are spurious.

I examine two samples of hybrid mutual funds. The more recent sample is composed of both asset allocation and balanced funds and covers the time period from 1992-2000. The second sample is composed of balanced and flexible funds and covers the period 1981-1991. I find that the inclusion of the bond indices and bond timing variables in the MFTM model leads to substantially different conclusions about the stock market timing performance of these funds relative to the TM model. This is due to a strong correlation between various categories of bonds and the quadratic term used to measure timing ability in the TM model. The results show that the TM model overestimates positive stock timing ability in the older sample and underestimates ability in the more recent sample. Results from the MFTM model indicate that there is significant timing ability among the 1992 sample of funds. Additional tests suggest that the results from the MFTM model reflect actual and not spurious timing ability.

This paper is organized as follows: Section II provides a brief description of hybrid funds. Section III introduces the TM and MFTM models. Section IV discusses the construction of the fund sample. Section V describes the return generating process for hybrid funds and the timing model specification used in this paper. Section VI presents empirical results. Section VII concludes.

II. Description of Hybrid Mutual Funds

This paper exclusively examines various types of hybrid mutual funds.[2] There are three main categories of hybrid funds: balanced, asset allocation, and flexible funds. Each type of fund holds a combination of stocks, bonds, and cash securities within the fund portfolio. The differences across fund categories involve investment objectives and aggressiveness in market timing.

According to Weisenberger's Mutual Fund Panorama, the objective of a balanced fund is to minimize investment risks without unduly sacrificing possibilities for long term growth and current income. Balanced funds seek a balance between income, growth, and safety by investing in a combination of stocks, bonds, and cash investments. Traditionally, these funds have sought to achieve these goals by maintaining a fairly steady proportion of their portfolios in both equity and fixed income securities. However, contrary to popular belief, many of these funds actively engage in market timing and generate high portfolio turnover. Balanced funds often shift up to 15 percent of assets based on their forecast of the future returns from the major asset classes. In order to be classified as balanced funds, the funds must be committed to maintaining at least 25 percent of their assets in bonds and/or cash at all times regardless of market conditions.

As defined by Weisenberger's Mutual Fund Panorama, asset allocation funds are funds that seek total return by allocating the fund's portfolio among the combination of asset classes best believed to represent the most efficient tradeoff between rate of return and risk. In many cases, these funds have portfolios that appear to be indistinguishable from those of balanced funds. The difference lies in the fact that asset allocation funds are more aggressive in their attempt to market time, and most of these funds can invest in asset classes in any proportion in

[2] Given that hedge funds invest in multiple asset classes and engage in various market timing techniques, they can be thought of as a type of hybrid fund. However, I do not include them as part of this analysis. Unlike hybrid funds, hedge funds use derivatives extensively and often hold substantial short positions within their portfolios. The methodologies implemented in this paper are not designed to measure the performance of funds that hold leveraged positions.

pursuit of achieving the highest possible return. Depending on the fund, these funds tend to change their target asset allocations on a monthly basis in an attempt to time the market although they do have the freedom to make more frequent changes in allocation.

A third group of hybrid funds are flexible funds which are also referred to as flexible income funds. Most have the appearance of balanced funds but tend to focus more on generating income than on long term growth. Like balanced and asset allocation funds, they vary investments between stocks and bonds as management sees fit. The relative importance of flexible funds has declined as the number of asset allocation funds has increased.

III. Modeling Market Timing

The main goal of this paper is to determine if hybrid funds have the ability to anticipate changes in asset market conditions and appropriately shift assets into or out of stocks. This section discusses the models I use to test for this market timing ability.

To examine the stock market timing ability of hybrid funds, I employ the Treynor Mazuy (TM) timing model and a multi-factor extension of the model. Introduced in 1966, the TM model is widely used to measure the timing ability of mutual funds. In their paper, TM assume that if a mutual fund is not engaged in market timing and maintains a constant fund beta, the relationship between the fund return and the return on the benchmark will be linear. However, if the fund is successful at market timing, the fund return will be higher than the benchmark return for low or high market returns and near the market for market returns close to zero.

They test for timing ability by testing for this nonlinearity. They measure the following relationship between the excess return of the fund and the excess return of the market by estimating the following regression:

$$r_i = \alpha_i + \beta_i r_m + c_i r_m^2 + e_i \qquad (1)$$

where

r_i = excess return of the fund

r_m = excess return on the market benchmark

$c_i > 0$ is evidence of the fund having market timing ability.

Because this quadratic regression approach is easy to implement, several variations of the model have been used to test for timing ability. Lee and Rahman (1990), Grinblatt and Titman (1994), Bello and Janjigian (1997), and Volkman (1999) employ the quadratic approach with various benchmark factors to quantify both a manager's selectivity ability and timing ability. Ferson and Schadt (1996) and Becker, Ferson, Myers, and Schill (1999) develop conditional versions of the TM model which separate a manager's response to public and private information. Edelen (1999) uses the quadratic approach to examine the impact that fund cash flows have on estimated timing coefficients from the TM model. More recently, Kosowski (2002) employs a state dependent TM measure which examines performance of funds during recessionary and expansionary periods.

There are two potential problems with applying the various models used in the literature to hybrid funds. First, none of the previous work includes a set of benchmark indices that spans the set of bond investments made by these funds. At most, the models include two bond indices or factors. Second, all of the models measure timing ability only with respect to a market portfolio of stocks. However, hybrid funds are known to time across multiple categories of assets. To properly measure timing skill, a model should include all asset groups in which the fund invests and timing variables for each of the asset categories.

Lehmann and Modest (1987) provide the foundation for a multi-factor extension of the quadratic regression approach. They illustrate that a multi-factor extension of the TM model would include quadratic terms and cross terms of all the factors from the assumed return generating process. The coefficients on each quadratic term reflect the manager's ability to time movements of the specific factor. Thus, a two factor TM model where the factors are a stock and a bond index takes the form

$$r_i = a_i + b_i r_s + \lambda_{i,s} r_s^2 + c_i r_b + \lambda_{i,b} r_b^2 + d_i r_s r_b + e_i \qquad (2)$$

where

r_s = excess return on the stock market benchmark

r_b = excess return on the bond market benchmark

If a manager is successful at timing, $\lambda_{i,j}$ for any benchmark j will be positive and significant.

The empirical literature has not exploited the potential of this model in examining the timing ability of funds known to invest in multiple asset classes. Using various factors, Lehmann and Modest employ the MFTM model to test for the presence of factor timing activity and its influence on estimated fund selectivity ability. They find evidence of factor timing activity, but they do not quantify the activity as positive or perverse timing. Grinblatt and Titman (1994) use a similar regression to calculate a total performance measure that sums up a fund's timing and selectivity ability. But they do not report timing ability separately. The goal of this paper is to determine whether there are significant differences in the inferences concerning hybrid fund timing ability from the TM and MFTM timing tests. In section V, I describe the MFTM model specification used in this paper. In section VI, I use both the TM and MFTM model to examine the stock timing ability of a sample of hybrid funds.

IV. Fund Sample

I examine two hybrid fund samples covering two distinct time periods. By constructing two samples over separate time periods, I can test the robustness of the results and see whether the results derived from one fund sample are applicable to the other fund sample.

The first sample is composed of balanced and flexible income funds in existence as of December 31, 1980 as listed by Weisenberger's Mutual Funds Panorama. This sample covers the time period 1981-1991. I choose January 1981 as the beginning of the sample period in order to have a sufficient number of hybrid funds in the sample. The only requirement for a fund to be included in the sample is that the fund survives for a minimum of five years as a hybrid mutual fund. This allows a long enough time series to examine stock timing ability. Once the five year criteria is attained, this sample does not suffer from survivorship bias as mentioned in Brown, Goetzmann, Ibbotson, and Ross (1992). All funds that meet the criteria are followed until the end of the time period or until they cease operations. This sample covers the time period 1981-1991 and is composed of 56 hybrid funds.

A drawback of the first sample is that it does not include asset allocation funds which are likely to be the most aggressive market timers. To the best of my knowledge, a separate mutual fund classification for asset allocation funds did not exist until 1992. Previous to 1992, if an asset allocation fund existed, it was often classified as a balanced fund or as a stock fund if its asset allocation mix was heavily weighted toward stock. Thus, I construct a second fund sample that is composed of asset allocation and balanced funds in existence as of December 31, 1991 when Weisenberger began a separate classification for asset allocation funds. This second sample covers the time period 1992-2000 and is composed of 58 hybrid funds. Criteria for inclusion are the same as that for the 1981 sample.

It should be noted that although neither fund sample is subject to survivorship bias, both potentially suffer from look-ahead bias. Typically, some amount of look-ahead bias is inherent in tests of market timing ability where a minimum survival period is necessary in order to have sufficient data to estimate the model parameters. Carhart, Carpenter, Lynch, and Musto (2002) discuss look-ahead bias within the context of tests of performance persistence. They provide evidence that funds tend to disappear following poor multiyear performance, and this can impact inferences drawn from mutual fund performance studies.

Although look-ahead bias does exist in my sample, the bias not appear to play a major role given the results to be presented in Section VI. The percentage of affected funds is virtually identical across both fund samples, yet the results across the samples are significantly different. 16% of existing hybrid funds in 1981 and 17% of existing hybrids funds in 1992 do not survive the minimum five years. However, I find that including bond variables in the traditional model causes a decline in estimated timing ability for the 1981 sample and improves estimated timing ability for the 1992 sample. It is unlikely that look-ahead bias can explain these results.

Table 1a lists the 56 funds in the 1981 sample and Table 1b lists the 58 funds that compose the 1992 sample. Both tables list the fund name and the range of reported portfolio weights over the time period. The range of portfolio weights represents the minimum and maximum percentage of assets invested in each asset class over the entire time period by each fund. For the 1981 sample, the range of portfolio weights is based on annual fund weights as reported by CRSP. For the 1992 sample, the range is based on the quarterly weights reported by the funds to Morningstar.[3] Two points are clear from the tables. First, bonds play a large role in the portfolios of these funds. Second, as evident by the wide range of portfolio weights for each asset class, these funds actively engage in moving assets across asset classes.

V. Return Generating Process and Timing Model Specification

It is clear from the tables in the previous section that stocks, bonds, and cash assets play a large role in the portfolios of hybrid funds. Since the goal is to measure the stock market timing ability of these funds, I need to capture the various investment choices that these managers face. In this section, I discuss the model used for the return generating process of hybrid funds and the model specification used to test for timing ability.

A. A Model of Stock Portfolio Returns

Much work has been done examining an appropriate model for stock returns. Many researchers use a multifactor approach in examining stocks and stock portfolios (e.g. Jagannathan and Korajczyk (1986), Lehmann and Modest (1987), Grinblatt and Titman (1991), and Fama and French (1993, 1996)). For my purposes however, there is a disadvantage to this approach. The factors used to represent the return generating process are not actively traded in the financial markets. I want to see if managers are timing better than a passive investment strategy. Thus, I follow the portfolio approach used by Elton, Grbuer, Das, Hlvaka (1993), Elton, Gruber, and Blake (1996), and Ferson and Schadt (1996).

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[3] Funds report these weights to Morningstar on a voluntary basis. Occasionally, some funds choose not to report and some only report once a year. The weights in the table reflect the range of weights as reported to Morningstar by the funds.

Elton, Gruber, and Blake (1996) recommend a four index model to measure the performance of common stock funds. They include the S&P 500 index, a size index, a growth versus value index, and one bond index. In Elton, Gruber, and Blake (1999), they use the difference between the large cap and the small cap portfolios and the difference between the growth and value portfolios in addition to the S&P 500 index. These portfolios are correlated with the Fama and French (1993) size and book to market factors and capture the major anomalies of the single factor CAPM model. In addition, these portfolios span the major groups of stocks in which hybrid funds invest. Thus, for the return generating process for the stock portion of the fund, I use four indices that include portfolios which represent the S&P 500, small stocks, value stocks, and growth stocks.[4]

B. A Model of Bond Portfolio Returns

Much less work has been done on appropriate index models to measure the performance of bond funds. Sharpe (1992) includes various government and corporate bond indices in the factor model that he uses for style analysis. Fama and French (1993) illustrate that a bond model should include factors related to bond maturity risk and bond default risk. Blake, Elton, and Gruber (1993) propose various bond fund models. Their six factor model includes corporate and government bond indices that represent various maturities, a high yield corporate bond index, and a mortgage backed securities index.

Since these studies, there has been a tremendous growth in the number of available bond indices. In addition, when using the Blake et al. model, several of the funds in the sample do not

[4] I do not include an index or factor related to the momentum effect documented by Jegadeesh and Titman (1993) and Carhart (1997) in the interest of maintaining a relatively parsimonious model. Because I need to include multiple portfolios to model both the stock and bond portion of the fund (and quadratic terms representing these portfolios), parsimony becomes important. I provide some evidence in the following section that the exclusion of this factor and other potential stock and bond factors is not a major concern.

show sensitivity to any of the bond indices used in the model. Thus, I develop a new bond model to measure the bond portion of the funds. Bond classifications are often based on maturity and quality. When analyzing the performance of these various categories over time, it is clear that the performance of these groups is not always strongly correlated. As a result, I develop a four index bond model which includes indices that represent high quality bonds, low quality bonds, long maturity bonds, and short maturity bonds. Further research is needed concerning the validity of this model, but I do provide evidence in the next section that these indices are a valid representation of the return generating process of the bond portion of hybrid funds.

C. A Model of Hybrid Fund Returns

Based on the previous sections, I define an eight factor model that represents the expected excess return for a hybrid fund.

$$r_i = a_i + b_{i,sp} r_{sp} + b_{i,sm} r_{sm} + b_{i,gr} r_{gr} + b_{i,v} r_v + b_{i,l} r_l + b_{i,sh} r_{sh} + b_{i,hq} r_{hq} + b_{i,lq} r_{lq} + e_i \tag{3}$$

where

r_i = excess return for fund *i*

r_{sp} = excess return on the S&P 500 index

r_{sm} = excess return on a small stock portfolio

r_{gr} = excess return on a growth stock portfolio

r_v = excess return on a value stock portfolio

r_l = excess return on a long maturity bond portfolio

r_{sh} = excess return on a short maturity bond portfolio

r_{hq} = excess return on a high quality bond portfolio

r_{lq} = excess return on a low quality bond portfolio

For the stock portion of the fund, the S&P 500 index is represented by the CRSP value weighted S&P 500 index. The remaining stock portfolios are based on the benchmark portfolios created by Fama and French (1993). The small stock portfolio is the average of the small value, small neutral, and small growth portfolios. The growth stock portfolio is the average of the small growth and big growth portfolios. The value stock portfolio is the average of the small value and big value portfolios.

For the bond portion of the fund, all bond portfolios are based on bond indices available from Lehman Brothers. The long maturity bond portfolio is represented by the long maturity government/credit bond index. The short maturity bond portfolio is represented by the 1-3 year short term government index. The high quality bond portfolio is represented by the aggregate government/credit bond index. The low quality bond index is represented by the high yield bond index. All portfolios for both the stock and bond portions of the model are total return portfolios.

The main issue is whether this model effectively represents the return generating process of hybrid funds. To test the effectiveness of this model, I employ Sharpe's (1992) quadratic programming technique. The technique is used to determine the average exposure of a portfolio to movement in the returns of various asset classes. To consider equation (3) to be an appropriate model, the results of the style analysis should show that the hybrid funds have significant exposure to the portfolios defined in the equation. In addition, the equation should have substantial explanatory power.

For each fund sample, I average the fund returns for all funds in existence during a given month. Using this time series of average returns, I solve the following quadratic program:

$$\min \quad \left[\operatorname{var}\left(tr_i - \sum_{i=1}^{k} b_{i,k} tr_k \right) \right] \qquad (4)$$

subject to

$$0 \le b_{i,k} \le 1 \quad \forall\, i$$

$$\sum_{i=1}^{k} b_{i,k} = 1$$

where tr_i represents the total return as opposed to excess return. k represents the eight portfolios from the index model plus a cash portfolio that is represented by the 30 day Treasury bill return obtained from CRSP.

Results from the quadratic program are reported in Table 2.[5] Several points are clear from the table. First, the model works well across both fund samples. As indicated by the high r-squared coefficients, the model has strong explanatory power despite the constraints imposed by the quadratic programming method. The method explains 99% of the variation in average returns in the 1981 sample and 97% of the variation in returns for the 1992 sample. Second, the results show that the average hybrid fund return has non-zero exposure to all of the portfolios used in the model with the growth portfolio being the only exception.[6] Third, the results emphasize the importance of modeling the bond portion of a hybrid fund. The average total investment weight in bonds is 49.2% over the 1981-1991 period and 41.3% for the 1992-2000 period. Across both samples, all four bond categories have non-zero investment weights ranging

[5] The Gauss-Newton method is used to obtain parameter estimates that minimize the objective function. Statistical significance of the estimates is based on t-tests which use the estimated standard error of the coefficient estimates. These t-tests are valid asymptotically.

[6] However, it is still important to include the growth portfolio in the model. When the quadratic program is estimated for individual funds, several funds have significant coefficients for the growth portfolio.

from 5.0% to 21.5%, and all estimated bond portfolio weights are statistically significant except for the high quality bond category. The short maturity bond portfolio has the largest investment weights (21.5% and 17.2% in 1981 and 1992 respectively).

D) The MFTM Model Specification

Using the eight factor model from the previous section and the Lehmann and Modest (1987) methodology in section III, I can derive an appropriate MFTM model to measure the timing ability of hybrid funds. A complete multi-factor timing model specification of the eight factor model requires the estimation of a large number of quadratic and cross product terms. Thus, having a parsimonious timing model becomes an important issue.

My focus is on measuring the stock market timing ability of hybrid funds. Based on the quadratic programming solution in the previous section, the S&P 500 is the predominant stock portfolio in which hybrid funds invest. Thus, I include a quadratic term in the model for the S&P 500 which will serve to represent stock timing ability. The hybrid funds also engage in shifting assets into and out of bonds, and a quadratic term representing bond timing ability should be included in the model. The short maturity bond index is the predominant bond portfolio in which hybrid funds invest. I include a quadratic term in the model for the short maturity bond portfolio which will serve to represent bond timing ability. I exclude all other quadratic and cross terms in the interest of maintaining a relatively parsimonious model.[7]

Thus, the MFTM timing model specification used to test for timing ability is represented by

[7] Although not reported, empirical results are virtually identical when a quadratic term for the long maturity bond portfolio is substituted for the short maturity bond portfolio.

$$r_i = a_i + b_{i,sp} r_{sp} + b_{i,sm} r_{sm} + b_{i,gr} r_{gr} + b_{i,v} r_v + b_{i,l} r_l + b_{i,sh} r_{sh} + b_{i,hq} r_{hq} + b_{i,lq} r_{lq} +$$
$$\lambda i_{i,sp} r_{sp}^2 + \lambda_{i,sh} r_{sh}^2 + e_i \qquad (5)$$

where $\lambda_{i,sp}$ and $\lambda_{i,sh}$ represent stock and bond timing ability respectively.

I use monthly fund and index returns to test for stock timing ability. The use of monthly data implicitly assumes that hybrid fund managers are using a one month horizon in making allocation decisions. Chance and Hemler (1999), Goetzmann, Ingersoll, and Ivkovic (2000), and Bollen and Busse (2001) all provide evidence that the use of monthly data may fail to detect timing ability if timing decisions occur at a more frequent interval. Thus, they suggest that researchers do not find timing ability because they are using monthly data to measure the timing skill of daily timers. However, my use of monthly data is not of great concern. First, I am comparing the results from two separate models to see if the stock timing coefficient is sensitive to the inclusion of various bond portfolios. Second, as will be presented in the empirical section, I do detect evidence of stock timing ability in one of my fund samples.

VI. Empirical Results

In this section, I present empirical results. First, I examine the potential impact the exclusion of the bond indices has on estimated stock timing ability from the traditional TM model. Next, using the TM and MFTM models, I compare the stock timing coefficients from the two models to examine whether the estimated stock timing coefficients are sensitive to the exclusion of the various bond indices and whether inferences concerning stock timing ability change when the bond indices are included. Third, I examine the results from both models using a technique which combines the Henriksson and Merton (1981) model with the quadratic programming technique of Sharpe (1992) to determine if the MFTM model accurately measures the stock timing ability of the funds or if the results are spurious. Finally, I do an additional test of the data where I separate the 1992 sample into asset allocation and balanced funds and compare their performance.

A. Estimated Impact of Bond Indices

The first issue I address is how the exclusion of the bond portfolios and bond timing variable may affect the estimated timing coefficients from the traditional TM model relative to the MFTM model.

I examine the relationship between the excluded bond portfolios and the quadratic term in the TM model that is used to measure timing. It is often believed that equity and debt have a nonlinear relationship.[8] Such a relationship could directly impact the estimated stock timing coefficient. The funds in the sample hold at least one category of bonds. If the bond portfolio is positively correlated with the timing variable in the TM model, then the timing coefficient in the TM model will be upward biased. Likewise, if the bond portfolio is negatively correlated with the timing variable, then the timing coefficient in the TM model will be downward biased.

The traditional TM model I use for comparison only includes the stock portfolios from the MFTM model and is represented by

$$r_i = a_i + b_{i,sp} r_{sp} + b_{i,sm} r_{sm} + b_{i,gr} r_{gr} + b_{i,v} r_v + \lambda_{i,sp} r_{sp}^2 + e_i \qquad (6)$$

$\lambda_{i,sp}$ represents stock market timing ability.

[8] Often, this relationship is expressed by the fact that stock holders own a put where they can sell the assets of the firm to the bondholders for the face value of the debt.

To determine the relationship between the bond portfolios and bond timing variable from the MFTM model and the stock timing variable, I regress each of the bond portfolios against the variables in the TM model. I estimate the following regression:

$$r_{bond} = a_i + g_{i,sp} r_{sp} + g_{i,sm} r_{sm} + g_{i,gr} r_{gr} + g_{i,v} r_v + h_{i,sp} r_{sp}^2 + e_i \qquad (7)$$

The value for *h* represents the correlation between the bond portfolio and the timing variable of the TM model.

Table 3 presents the results of the regressions. I find that over the period 1981-1991, the correlations between the bond portfolios and the TM timing variable are all positive and statistically significant. Across the four bond portfolios, the values for *h* range from 0.390 to 1.193. The quadratic term for the short maturity bond portfolio also has a positive correlation with the TM timing variable. The value for *h* is 0.005, and the coefficient is significant at the 10% level. On the other hand, over the time period 1992-2000, the correlations are all negative. The values for *h* range from -0.269 to -0.907. The correlations for the short maturity, long maturity, and high quality bond portfolios are statistically significant at the 10% level.

Regardless of the reasons for the change in the relationship, the results highlight the importance of the bond portfolios and the bond timing variables. Suppose a fund has no stock timing ability. The results illustrate that the traditional TM model is biased toward signaling positive timing ability over the time period 1981-1991 when no timing ability exists. The opposite situation occurs for the 1992 sample where the model is biased toward detecting negative timing ability. The impact is likely to be stronger in the 1981 sample than in the 1992 sample given the stronger degree of the correlation between the bond portfolios, the bond timing variable, and the stock timing variable.

B. Stock Timing Ability: TM vs. MFTM Timing Models

Given the results in the previous section, I turn to comparing the stock timing coefficients estimated by the TM and MFTM models. My goal is to examine the extent to which the assessment of timing skill differs between the two models.

To measure the overall stock timing ability of each fund sample, I calculate the time series of returns from an equal weighted portfolio of all funds in existence on a given date *t*. Using these returns, I estimate the stock timing coefficient across both models. Because I am also interested in inferences drawn for individual funds, I estimate individual fund coefficients using both models. All statistical inferences are based on heteroskedasticity-consistent standard errors obtained from using the standard White correction.

Regression results are presented in Table 4.[9] The results highlight that inferences concerning the estimated stock timing ability of hybrid funds are sensitive to the inclusion of bond indices. First, I examine the results from the 1981 sample. There is evidence consistent with the hypothesis from the previous section that the TM model overestimates the stock timing performance of the 1981 sample. Based on the results of the TM model, hybrid funds as a group have timing ability. The stock timing coefficient of an equally weighted portfolio of hybrid funds is 0.391 which is positive and statistically significant. Individually, 79% of the funds have

[9] Since the focus of this paper is the sensitivity of the stock timing measure to two different timing specifications, I do not report the results for the bond timing variable in the table. There is no evidence of positive or perverse bond timing ability by these funds. Only four funds out of the 114 across both samples have significant bond timing coefficients. Results for the equal weighted portfolios also do not indicate any bond timing ability. But, as shown in the previous section, the inclusion of a bond timing variable is important due to its potential correlation with the stock timing variable.

a positive timing coefficient, and for 39% of the funds, the timing coefficient is positive and significant.

The results from the MFTM for this sample tell a completely different story. As a group, the stock timing coefficient for the funds is -0.091. Using a matched-pairs *t* test, I test for a significant difference between the average TM and MFTM stock timing coefficients. The *t* value for the test is 7.31 indicating that the difference from zero between the two coefficients is significant at the one percent level. The average coefficient from the MFTM model indicates no timing skill on the part of the funds as a group. At the individual level, only 42% of the funds have positive timing coefficients. Only 7% of the funds have positive and significant timing coefficients. These results provide strong evidence that the inclusion of bond indices has resulted in a decline in the estimated stock timing ability of these funds.

The regression results for the 1992 sample are also consistent with the hypothesis that the TM model underestimates the stock timing performance of this sample. The stock timing coefficient of an equally weighted portfolio of the funds increases from 0.188 to 0.401 when the MFTM model is used. Using the matched-pairs *t* test, the t value of 7.764 indicates a significant difference between the coefficients at the one percent level. The average MFTM model coefficient is statistically significant indicating timing skill. At the individual fund level, eight more funds have positive timing coefficients, and eight more funds have significant positive timing coefficients. Overall, 76% of the funds have positive timing coefficients, and for 26% of the funds, the timing coefficient is positive and significant.

These results highlight the importance of modeling the bond portion of hybrid funds when one is examining performance and timing ability. As expected, the results are more dramatic in the 1981 sample given the stronger correlation between the TM model timing variable and the various bond indices and bond timing variable. The results are also intuitively appealing. The 1990s featured a great bull market where stock market timing would be less difficult given the steady upward march in stock returns over the time period. Thus, it is not surprising that 1992 sample of hybrid funds exhibits greater stock timing ability relative to the 1981 sample.

In addition, the 1981 sample results are consistent with results from other work that use the quadratic regression approach to examine timing performance over a similar time period. None of these works exclusively examine hybrid funds, but they include hybrid funds as part of their mutual fund sample. None of these works provide a full specification for the bond portion of the fund. Lee and Rahman (1990) estimate timing skill over the period 1977-1984 and find that the average timing coefficient for the hybrid funds in their sample is positive. Ferson and Schadt (1996) find that the average timing coefficient on an equally weighted portfolio of balanced and income funds in their sample is positive and significant at the 10% level. The sample covers the time period 1968-1990. Volkman (1999) not only finds a positive average timing coefficient but estimates that 50% of the balanced funds in his sample have significant timing ability over the period 1980-1990. These results likely are due to the absence of various bond indices than to actual timing skill by the hybrid fund managers.

C. A Test of Model Accuracy – Portfolio Allocation Analysis

The results in the previous section illustrate that the MFTM model provides significantly different inferences concerning the stock timing ability of hybrid funds. In addition, the results indicate that hybrid funds exhibit timing skill over the time period 1992-2000. An issue to address is whether these inferences accurately reflect the actual timing ability of these funds.

Previous research suggests there are several potential problems with using the quadratic regression approach to extract timing skill from a time series of monthly fund returns.

First, Chance and Hemler (1999), Goetzmann, Ingersoll, and Ivkovic (2000), and Bollen and Busse (2001) provide evidence that the use of monthly data may fail to detect timing ability if timing decisions occur at a more frequent interval. They argue that researchers do not find timing ability because they are using monthly data to extract timing skill when managers are engaged in daily timing decisions. Information concerning the frequency of hybrid fund timing decisions is not publicly available, and there is no means of verifying the number of timing decisions made over a given time interval. However, this does not appear to be a major issue since I do detect significant evidence of stock timing ability in the 1992 fund sample.

Second, Jagannathan and Korajczyk (1986) demonstrate that the relationship between portfolio skewness and benchmark skewness may impact estimated timing ability. Specifically, they illustrate that if the average stock in a mutual fund is more option-like than the average stock in the market proxy, a quadratic regression can result in a significant positive timing coefficient even in the absence of any market timing skill. Thus, it may be difficult to distinguish between inherent coskewness created by the timing skill of the manager and coskewness created strictly by the composition of the portfolio relative to the benchmark. Some of the results in the previous section could reflect spurious rather than actual timing ability.

Third, Edelen (1999) describes another potential source of spurious timing. He documents a statistically significant negative relation between a fund’s abnormal return and investor flows. A fund tends to receive large cash inflows when market returns are high. This increases the portfolio weight on cash and causes the timing coefficients to be biased downward.

His results show that funds experience significant negative market timing coefficients from a quadratic model when that fund experiences cash inflows.

Fourth, Bollen and Busse (2001) suggest that the significance of a fund's timing coefficient is complicated by the possibility of misspecification of the timing function or of time-varying timing strategies. Thus, if funds are timing the market according to a specification other than the MFTM model, using the MFTM model causes violations of various regression assumptions. Thus standard corrections for the standard errors of the regression coefficients may not be sufficient.

All of these issues call into question the accuracy of the MFTM model results. It is not possible to determine the full extent to which each problem affects the results without having detailed information on fund portfolios, cash flows, and timing functions. But I design a test which combines the methodology designed by Henriksson and Merton (1981) (hereafter referred to as HM) with the quadratic programming analysis of Sharpe (1992) to see if I reach similar inferences concerning the estimated timing ability of the hybrid funds. Similar results will suggest that the MFTM model is detecting actual fund timing ability. I refer to this procedure as portfolio allocation analysis.

The intuition behind portfolio allocation analysis is that a fund which demonstrates stock timing ability will have a higher percentage of the portfolio allocated to stocks during the months in which stock returns are higher than bond and cash returns. Likewise, the fund should have a lower portfolio allocation to stocks during the months in which stocks underperform bonds and cash. By estimating portfolio allocations during up and down stock markets I can examine whether differences in stock allocations are correlated with the stock timing ability estimated by the MFTM model.

HM use a dummy variable approach where they test to see if a fund's target level of systematic risk is higher when the market is outperforming cash and lower otherwise. To implement the portfolio allocation analysis, I partition the data within each sample. One set of data includes all observations where the minimum total return on any of the four stock portfolios defined in equation (3) is greater than the maximum total return from any of the four bond portfolios and cash portfolio. A second set of data includes all observations where the maximum total return from any of the four stock portfolios is less than the minimum total return from any of the bond portfolios and cash. Thus, for each sample, I have two data sets in which the first set includes only observations where stocks are the best performing asset and the second set includes only observations where stocks are the worst performing asset. The 1981 sample is composed of 42 observations when stocks are the best performing asset class and 22 observations when stocks are the worst performing asset class. The 1992 sample is composed of 33 observations when stocks are the best and 19 observations when stocks are the worst.

For each set of observations, I employ Sharpe's quadratic program as previously defined in equation (4) to estimate the fund's exposure to each of the nine portfolios. I interpret these exposures as estimates of the average fund portfolio weights.[10] I then sum the coefficients for the four stock portfolios to obtain an approximation of the average stock portfolio weight of the fund when stocks are the best performing asset. I repeat the process for the set of observations when stocks are the worst performing asset. I calculate the difference between the average stock allocation when stocks are the best performing asset and the average allocation when stocks are the worst performing asset. I refer to this variable as the fund stock adjustment.

[10] Sharpe's methodology has been previously used to estimate portfolio weights. Sharpe (1992) uses this methodology to examine fund manager's average exposure to asset classes over time. Elton, Gruber, and Blake (1993) use this methodology to successfully compare the weights from the quadratic program to actual composition data for bond funds. Brown, Goetzmann, and Park (2000) adopt this methodology to examine hedge fund exposure to various currencies during the Asian currency crisis.

To see if there is a strong correlation between the results from this test and the results from the MFTM model, I group the funds into four categories based on their MFTM model timing coefficients: 1) positive and significant, 2) positive and not significant, 3) negative and not significant, and 4) negative and significant. I calculate the mean fund stock adjustment for funds within each of the four groupings. If I fail to detect a relationship between the portfolio analysis results and the MFTM model results, then it is likely that the MFTM model is detecting spurious rather than actual timing ability.

The results from the portfolio allocation analysis are presented in Table 5. The results suggest that the timing skill I detect from the MFTM model is not completely spurious and is directly related to estimated changes in stock allocations on the part of hybrid funds. Funds that are classified as having significant timing ability are the funds with the largest mean stock adjustment. For the 1981 sample, the four funds classified as having significant positive timing ability have an average stock adjustment of 16.8%. This result is partially driven by one fund that has a stock adjustment of over 30%. When excluding this fund, the average stock adjustment is still 9.8%. For the 1992 sample, the 14 funds with significant timing ability have an average stock adjustment of 6.2%.

The stock adjustment variable falls monotonically as estimated stock timing ability declines. Funds that have positive but insignificant MFTM timing model coefficients have mean stock adjustments that are positive but small (0.7% and 2.5% for the 1981 and 1992 samples respectively). The mean stock adjustment then becomes negative when examining the negative but insignificant timing ability classification. The adjustment is -2.8% for the 1981 sample and -5.5% for the 1992 sample.

Finally, the results for the negative and significant classification indicate that funds in this grouping are indeed perverse timers. In the 1981 sample, the 12 funds with negative timing ability have a mean stock adjustment of -5.4%. Only one fund has negative timing ability in the 1992 sample, and its stock adjustment is -25.8%.

Thus, the evidence suggests that the timing results from the MFTM model are related to estimated changes in stock allocations during up and down markets and are not completely spurious. On average, positive (negative) timing coefficients are associated with positive (negative) stock adjustments. But it is important to note that the reported standard deviations for each classification indicate that a few funds in the positive and significant category have very small or negative stock adjustments. Likewise, a few funds in the negative and significant category have positive stock adjustments. This could be due to two potential factors.

One, the portfolio allocation analysis is limited to observations when all stock portfolios outperform or underperform all bond and cash portfolios. A fund may be classified by the MFTM model as having significant positive timing ability because it is effective at timing a subset of stocks and bonds. The portfolio allocation analysis test is not designed to detect timing skill across subsets of stocks and bonds. Implementing the portfolio allocation analysis for subsets of stock and bond portfolios is difficult without more detailed portfolio information concerning the specific investment choices of individual funds.

Second, the timing coefficient from the MFTM model may capture more than a manager's ability to shift assets into stocks during up stock markets. Work by Comer (2002) suggests that quadratic regression models reward a fund manager if he only has marginal timing skill but is able to increase his allocation to stocks during the months when stocks outperform the other assets by the greatest amount. Likewise, the manager will be punished for incorrectly timing the "worst" months. The estimated allocation changes from the portfolio allocation analysis during up and down markets may be an incomplete measure of a manager's timing skill.

Thus, the portfolio allocation analysis may not completely eliminate concerns that some MFTM model results are spurious. But the strong correlation between fund classification from the MFTM model and changes in stock allocation does give confidence in the results from the model and suggests that the inferences related to timing skill from the MFTM model are more accurate than inferences drawn from the TM model test.

D. Balanced vs Asset Allocation Funds

The results from the previous sections indicate that there is some timing skill present in the 1992 sample of funds. The 1992 fund sample is composed of both asset allocation and balanced funds. As mentioned in section II, asset allocation funds are different from balanced funds in that they have more flexibility in reallocating assets and are more aggressive in timing the stock market. A final issue I examine is the relative performance of asset allocation and balanced funds. Given the different characteristics of the two groups, it is of interest to determine whether the significant timing skill detected by the MFTM model is consistent across both classifications of hybrid funds, or if the skill is confined to one of the two groups.

There is no single objective standard used to classify asset allocation and balanced funds. To separate the funds into two groups, I collect the fund's annual ICDI objectives as reported by CRSP.[11] Some funds that are classified as balanced funds early in the sample period change classifications as the manager became more aggressive in his asset allocation decisions. I

[11] I use the CRSP classification instead of the Weisenberger classification because Weisenberger's Mutual Fund Panorama is no longer available in 2000. CRSP classifies asset allocation funds as having a total return objective. Morningstar is another potential source for fund classification. I compare the CRSP classifications to the Morningstar Principia classifications and find them to be virtually identical.

classify any fund that had changes to its objective as an asset allocation fund. By doing so, I ensure that the sample of balanced funds reflects only those funds which face some restrictions in their asset allocation decisions. The separation results in a sample of 34 balanced funds and 24 asset allocation funds.

Table 6 provides descriptive statistics of the two groups of funds and highlights the similarities and differences between the two groups. The statistics are calculated by first averaging the annual time series data of each fund and then calculating the cross section mean for all funds. The average stock portfolio weights are nearly identical (56.2% and 56.7% for the asset allocation and balanced funds respectively). Both groups hold a substantial amount of bonds and cash. The main difference is the aggressiveness with which the two fund categories engage in stock market timing. The range of assets held in stocks for the asset allocation funds is much greater than that for balanced funds. The difference between the minimum and maximum percentage of assets held in stocks for asset allocation funds averages 28.9% but is only 16.7% for balanced funds. Asset allocation funds also average higher expense ratios (1.36% to 1.01%) and slightly higher portfolio turnover (101% to 83%).

To test for timing skill, I calculate an equal weighted average of returns for all funds in existence within each group. I then use the MFTM model from equation (5). Results are presented in Panel A of Table 7. The results illustrate that the timing skill detected in the 1992 sample of funds is due to the performance of the balanced funds in the sample. The timing coefficient for the balanced funds is 0.429 and the timing coefficient for the asset allocation funds is 0.204. As a group, the balanced funds have a statistically significant stock timing coefficient. Although the coefficient for the asset allocation funds is also positive, it is not statistically significant. The results indicate that the additional flexibility that asset allocation funds have does not result in greater performance relative to balanced funds.

An additional issue is whether the above result is directly related to fund expenses or turnover. As seen from the descriptive statistics, asset allocation funds have higher expenses and turnover than balanced funds. Since all fund returns are net of expenses, the higher expense ratio of asset allocation funds may impact estimated timing skill. To test for a relationship between timing skill and expenses or turnover, I rank the entire fund sample by each of these two characteristics. I break the sample up into quartiles with the first quartile representing the highest average expense (turnover) ratio. I then estimate the stock timing coefficients for each quartile.

Panel B of Table 7 presents the results for the expense ratio regressions. Group 4 which contains funds with the lowest average expense ratios has a timing coefficient of 0.419 which is the only statistically significant coefficient of the four groups. The timing coefficients are all positive for the other three groups, and in terms of absolute value, Group 1 has the greatest coefficient. But none of these coefficients are significantly different from zero. There are no statistically significant relationships between turnover and stock timing performance. Better timing performance is directly related to lower expenses.

Thus, according to the results of the MFTM model, the hybrid funds that displayed significant timing skill during the bull market of the 1990's were most likely to be balanced funds with low expense ratios and not asset allocation funds that have greater portfolio flexibility. This result is not surprising because it is difficult to consistently excel at market timing. Balanced funds make fewer portfolio changes and those changes tend to be small in magnitude. This is the type of strategy that would most likely succeed during the bull market.

Balanced funds were not nearly as successful over the 1981 to 1991 time period when stock market performance was not nearly as dramatic.

VII. Conclusion

This paper examines the stock market timing ability of hybrid mutual funds. Previous market timing studies that include hybrid funds as part of their fund sample either ignore the portion of the hybrid fund's portfolio that is invested in bonds or include a limited number of bond indices that do not span the wide selection of bonds in which these funds invest. This study addresses the problem by using a multi-factor extension of the Treynor and Mazuy model which includes an assumed return generating process for the bond portion of the fund.

I examine two samples of hybrid mutual funds. I find that the inclusion of bond indices and a bond timing variable in a multi-factor Treynor Mazuy (MFTM) model leads to substantially different conclusions concerning the stock market timing performance of these funds relative to the Treynor-Mazuy (TM) model. The TM model coefficients are biased due to a strong correlation between various bond categories and the quadratic term used to measure timing ability in the TM model. Results from the MFTM model find less stock timing ability over the 1981-1991 time period than the TM model and provide evidence of significant stock timing ability across the fund sample over the 1992-2000 time period. A test designed to estimate stock portfolio changes during up and down stock markets provides evidence that the results from the MFTM are not spurious. The significant timing ability detected in the 1992 sample is driven by the subset of balanced funds.

The results highlight the importance of using multi-index models to measure the stock timing ability of funds that are known to invest in multiple asset classes. A next step for future research may be to use this type of model to focus on various aspects of fund performance. This study focuses on stock market timing. Various attempts have been made in the literature to distinguish security selection ability and market timing ability. Additionally, much recent work has focused on conditional performance evaluation and distinguishing performance based on public and private information (e.g. Farnsworth, Ferson, Jackson, and Todd (2002)). As more hybrid funds come into existence and engage in various market timing and tactical asset allocation strategies, it will be important for researchers to continue to identify models that can accurately measure various aspects of fund performance.

References

Admati, Anat, Sudipto Bhattacharya, Paul Pfleiderer, and Stephen Ross, 1986, "On Timing and Selectivity," *Journal of Finance* 41, 715-732.

Becker, Connie, Wayne Ferson, David Myers, and Michael Schill, 1999, "Conditional Market Timing with Benchmark Investors," *Journal of Financial Economics*, 52, 119-148.

Bello, Yakri and Vahan Janjigian, 1997, "A Reexamination of the Market-Timing and Security-Selection Performance of Mutual Funds," *Financial Analysts Journal*, 24-30.

Blake, Christopher, Edwin Elton, and Martin Gruber, 1993, "The Performance of Bond Mutual Funds," *Journal of Business*, 66, 371-403.

Bollen, Nicolas and Jeffrey Busse, 2001, "On the Timing Ability of Mutual Fund Managers," *Journal of Finance* 56, 1075-1094.

Brown, Stephen and William Goetzmann, 1997, "Mutual Fund Styles," *Journal of Financial Economics* 43, 373-399.

Brown, Stephen, William Goetzmann, Roger Ibbotson, and Stephen Ross, 1992, "Surviorship Bias in Performance Studies," *Review of Financial Studies* 5, 553-580.

Brown, Stephen, William Goetzmann, and James Park, 2000, "Hedge Funds and the Asian Currency Crisis," *Journal of Portfolio Management*, 61-77.

Carhart, Mark, 1997, "On Persistence in Mutual Fund Performance," *Journal of Finance* 52, 57-82.

Carhart, Mark, Jennifer Carpenter, Anthony Lynch, and David Musto, 2002, "Mutual Fund Survivorship," *Review of Financial Studies*, 15, 1439-1463.

Chan, Anthony and Carl Chen, 1992, "How Well Do Asset Allocation Mutual Fund Managers Allocate Assets?" *Journal of Portfolio Management*, 81-91.

Chance, Don and Michael Hemler, 2001, "The Performance of Professional Market Timers: Daily Evidence from Executed Strategies," *Journal of Financial Economics* 62, 377-411.

Chang, Eric and Wilbur Lewellen, 1984, "Market Timing and Mutual Fund Investment Performance," *Journal of Business* 57, 57-72.

Comer, George, 2002, "Measuring the Market Timing Ability of Hybrid Mutual Funds," working paper, Georgetown University.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks," *Journal of Finance* 52, 1035-1058.

Edelen, Roger, 1999, "Investor Flows and the Assessed Performance of Open-Ended Mutual Funds," *Journal of Financial Economics* 53, 439-466.

Elton, Edwin, Martin Gruber, and Christopher Blake, 1996, "The Persistence of Risk-Adjusted Mutual Fund Performance," *Journal of Business* 69, 133-157.

Elton, Edwin, Martin Gruber, and Christopher Blake, 1999, "Common Factors in Active and Passive Portfolios," *European Finance Review* 3, 53-78.

Elton, Edwin, Martin Gruber, Sanjiv Das, and Matthew Hlavka, 1993, "Efficiency with Costly Information: A Reinterpretation of Evidence from Managed Portfolios," *Review of Financial Studies* 6, 1-22.

Fama, Eugene and Kenneth French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* 33, 3-56.

Fama, Eugene and Kenneth French, 1996, "Multifactor Explanations of Asset Pricing Anomalies," *Journal of Finance* 51, 55-84.

Farnsworth, Heber, Wayne Ferson, David Jackson, and Steven Todd, 2002, "Performance Evaluation with Stochastic Discount Factors," *Journal of Business* 75, 473-503.

Ferson, Wayne and Rudi Schadt, 1996, "Measuring Fund Strategy and Performance in Changing Economic Conditions," *Journal of Finance* 51, 425-461.

Goetzmann, William, Jonathan Ingersoll, and Zoran Ivkovic, 2000, "Monthly Measurement of Daily Timers," *Journal of Financial and Quantitative Analysis* 35, 257-290.

Grinblatt, Mark and Sheridan Titman, 1994, "A Study of Monthly Mutual Fund Returns and Performance Evaluation Techniques," *Journal of Financial and Quantitative Analysis* 29, 419-444.

Henriksson, Roy, 1984, "Market Timing and Mutual Fund Performance: An Empirical Investigation," *Journal of Business* 57, 73-96.

Henriksson, Roy and Robert Merton, 1981, "On Market Timing and Investment Performance," *Journal of Business* 54, 513-533.

Jagannathan, Ravi and Robert Korajczyk, 1986, "Assessing the Market Timing Performance of Managed Portfolios," *Journal of Business* 59, 217-235.

Jegadeesh, Narasimhan and Sheridan Titman, 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance* 48, 65-91.

Kon, Stanley, 1983, "The Market-Timing Performance of Mutual Fund Managers," *Journal of Business* 56, 323-347.

Kosowski, Robert, 2002, "Do Mutual Funds Perform When It Matters Most to Investors? US Mutual Fund Performance and Risk in Recessions and Booms 1962-2000," working paper, INSEAD.

Lee, Cheng-few and Shafiqur Rahman, 1990, "Market Timing, Selectivity, and Mutual Fund Performance: An Empirical Investigation," *Journal of Business* 63, 261-278.

Lehmann, Bruce and David Modest, 1987, "Mutual Fund Performance Evaluation: A Comparison of Benchmarks and Benchmark Comparisons," *Journal of Finance* 42, 233-265.

Sharpe, William, 1992, "Asset Allocation: Management Style and Performance Measurement," *Journal of Portfolio Management*, 7-19.

Treynor, Jack and Kay Mazuy, 1966, "Can Mutual Funds Outguess the Market?" *Harvard Business Review*, 131-136.

Volkman, David, 1999, "Market Volatility and Perverse Timing Performance of Mutual Fund Managers," *Journal of Financial Research* 22, 449-470.

Wermers, Russ, 2000, "Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses," *Journal of Finance* 55, 1655-1695.

Table 1a

1981 Sample of Balanced and Flexible Funds

The table presents the fund names and range of portfolio weights for the 56 balanced and flexible funds in the 1981 fund sample. The list of funds is obtained from Weisenberger's Annual Investment Companies. The range of portfolio weights reflect the minimum and maximum percentage invested in each asset class over the time period 1981-1991 based on the annual weights reported by the CRSP. A complete time series of weights is not available for all funds.

	Range of Portfolio Weights		
Name of Fund as of 1981	**Stocks**	**Bonds**	**Cash**
Boston Foundation Fund	41-51%	22-50%	9-35%
Vance Sanders Investors Fund	45-68%	22-43%	1-22%
Investors Mutual	36-64%	28-58%	4-22%
Putnam (George) Fund of Boston	45-66%	16-37%	2-21%
American Balanced Fund	48-69%	24-45%	6-14%
Loomis-Sayles Mutual Fund	49-76%	20-47%	1-27%
Wellington Fund	60-69%	30-38%	0-3%
Composite Bond & Stock Fund	41-67%	27-46%	1-32%
National Security Balanced Fund		No annual weights reported	
Nation-Wide Securities	46-69%	20-42%	1-26%
Sigma Trust Shares	49-65%	14-48%	3-30%
Dodge & Cox Balanced Fund	54-69%	23-36%	5-23%
Sentinel Balanced Fund	48-63%	11-44%	8-35%
Stein Roe & Farnham Balanced Fund	31-63%	22-53%	6-29%
Lindner Fund for Income	13-97%	0-83%	(-1)-41%
United Continental Income Fund	43-68%	14-43%	3-41%
Pax World Fund	40-75%	0-38%	3-60%
Axe-Houghton Fund B	52-60%	37-40%	1-10%
Lord Abbett Income Fund	1-15%	76-97%	2-23%
Keystone K-1	36-64%	31-61%	2-12%
National Sec. Income Fund	38-55%	6-55%	7-49%
National Sec. Dividend Fund	51-86%	2-28%	4-46%
Security Investment Fund	30-63%	28-60%	2-17%
Franklin Income Series	22-54%	33-73%	1-25%
Mutual Shares Corp.	30-70%	11-29%	4-55%
Value Line Income Fund	39-73%	5-50%	1-53%
Puritan Fund	39-61%	23-50%	2-16%
Financial Industrial Income Fund	61-89%	3-28%	2-34%
Provident Fund for Income	44-71%	21-34%	3-34%
Founders Income Fund		No annual weights reported	
Kemper Total Return Fund	51-78%	13-43%	6-29%
Fidelity Equity Income Fund	51-77%	14-40%	2-10%
Hamilton Income Fund	51-76%	15-36%	1-29%
State Farm Balanced Fund	53-74%	6-30%	(-4)-41%
Mutual of Omaha Income Fund	10-32%	26-76%	4-54%
Wellesley Income Fund	35-41%	55-62%	1-5%
Income Fund of America	43-59%	23-52%	5-27%
Mass. Income Development Fund	45-62%	27-50%	4-14%
Dreyfus Special Income Fund	35-40%	53-56%	5-12%
Axe Houghton Income Fund	0%	67-93%	7-33%
First Investors Natural Resources		No annual weights reported	
Liberty Fund		No annual weights reported	
Decator Income Fund	53.0-93.0%	1-38%	0-9%
ISI Income Fund		No annual weights reported	
AGE High Income Fund	0%	91-98%	2-9%
Colonial Income Fund	0%	68-98%	2-32%
First Investors Fund for Income	1-7%	88-94%	4-5%

Lutheran Brotherhood Income	1-8%	28-97%	3-67%
Convertible Yield Securities	2-32%	66-94%	0-13%
United Income Fund	70-90%	0-12%	5-29%
Northeast Investors Trust	0-2%	93-116%	(-16)-6%
Putnam Income Fund	0%	58-78%	22-42%
Newton Income Fund		No annual weights reported	
Monthly Income Shares	0-3%	36-100%	0-64%
PRO Income Fund	0-3%	35-72%	25-62%
Qualified Dividend Portfolio I	59-100%	0-40%	(-5)-23%

Table 1b

1992 Sample of Balanced and Asset Allocation Funds

The table presents the fund names and range of portfolio weights for the 58 balanced and asset allocation funds in the 1992 fund sample. The list of funds is obtained from Weisenberger's Annual Investment Companies. The range of portfolio weights reflect the minimum and maximum percentage invested in each asset class over the time period 1992-2000 based on quarterly weights reported by the funds to Morningstar. A complete time series of weights is not available for all funds.

	Range of Portfolio Weights		
Name of Fund as of 1992	**Stocks**	**Bonds**	**Cash**
Alliance Balanced Shares	50.7-65.3%	15.0-43.8%	0.0-29.0%
American Balanced Fund	44.9-59.0%	22.2-49.0%	3.0-21.5%
Axe Houghton Fund B	45.4-61.1%	11.3-40.1%	1.0-41.3%
Bascom Hill Balanced	26.0-70.3%	19.9-42.0%	1.9-46.0%
CGM Mutual	55.8-75.0%	1.9-42.3%	0.0-24.4%
Composite Bond and Stock	53.0-61.8%	20.5-40.9%	0.0-7.3%
Connecticut Mutual Total Return	37.8-65.0%	31.0-49.2%	3.0-25.8%
Crabbe Huson Asset Allocation	37.8-58.7%	32.5-46.6%	1.3-18.5%
Dean Witter Strategist Fund	50.0-77.0%	0.0-42.6%	0.5-23.0%
Delaware Group Delaware	55.4-71.4%	22.4-36.7%	0.0-9.9%
Dodge and Cox Balanced	55.3-59.8%	32.8-40.5%	0.0-9.4%
Eclipse Balanced	52.0-62.7%	31.6-48.0%	0.0-8.6%
Equitable Balanced	37.4-78.7%	0.0-44.9%	(-0.3)-43.0%
Evergreen American Retirement	40.7-81.3%	0.0-48.2%	(-1.9)-19.3%
Federated Stock and Bond	36.9-59.5%	32.0-52.6%	1.8-21.7%
Fidelity Asset Manager	31.8-61.7%	23.9-39.2%	5.2-40.3%
Fidelity Balanced	17.4-62.0%	33.8-57.9%	0.0-27.5%
Fiduciary Total Return	46.4-94.2%	0.0-40.6%	0.0-27.0%
Fortis Advantage Asset Allocation	30.8-65.7%	0.8-60.2%	0.0-24.8%
IAA Trust Asset Allocation	41.7-56.2%	15.9-47.5%	0.0-17.3%
IDS Mutual Fund	53.9-63.4%	27.0-41.5%	0.0-14.6%
Landmark Balanced	49.4-64.1%	21.7-48.0%	(-3.1)-18.5%
Mass Financial Total Return	41.9-57.0%	17.7-39.8%	1.9-22.7%
Merriman Asset Allocation	0.0-77.5%	0.0-30.0%	0.4-75.0%
MetLife-State St. Managed Assets	38.9-69.1%	15.1-55.4%	3.2-12.0%
MIMLIC Asset Allocation	41.0-69.6%	26.4-53.0%	0.0-16.0%
New England Balanced Fund	55.7-73.6%	25.2-42.7%	0.2-6.0%
New York Life Instl Multi Asset	31.8-74.3%	8.3-50.8%	6.2-42.4%
Olympic Trust Balanced Income	37.3-56.3%	31.8-59.0%	0.0-14.2%
Oppenheimer Asset Allocation	42.9-58.8%	30.5-47.3%	(-1.0)-17.0%
Overland Express Asset Allocation	33.2-100%	0.0-63.9%	0.0-4.1%
Pacifica Balanced Fund	45.0-61.3%	33.5-50.0%	0.0-13.0%
Paine Webber Asset Allocation	47.3-78.7%	0.0-43.2%	0.9-34.2%
Pasadena Balanced Return Fund	49.1-72.9%	11.4-40.1%	0.0-21.0%
Pax World Fund	46.0-72.5%	15.2-45.0%	1.3-32.5%
Permanent Portfolio	25.7-56.2%	20.0-41.6%	2.3-37.3%
Phoenix Balanced	34.0-62.1%	26.9-37.6%	(-1.8)-7.8%
Piper Jaffray Balanced	45.1-64.1%	33.1-57.3%	(-10.3)-3.7%
Prudential Flexi-Conserve A	40.0-62.6%	12.0-56.5%	1.5-33.0%
Prudential Flexi-Strategy B	40.8-94.0%	0.0-45.2%	0.0-50.4%
Putnam George	55.6-66.4%	29.4-37.6%	(-1.8)-7.8%
RBB Balanced Portfolio	30.7-69.1%	27.0-52.6%	0.0-16.7%
Rea Graham Balanced Portfolio	17.0-61.9%	5.2-36.0%	15.1-61.0%
RIT Balanced	46.3-57.6%	37.5-48.3%	0.0-10.2%
Seafirst Asset Allocation	49.0-60.0%	35.2-47.0%	1.0-12.5%
Sentinel Balanced	44.4-61.0%	30.0-44.5%	3.5-33.0%
Sherson Equity Strategic Invest	41.0-79.7%	0.0-40.5%	0.5-42.0%
Stagecoach Asset Allocation	27.0-73.0%	19.7-72.3%	0.0-30.0%

State Farm Balanced	59.8-67.9%	20.2-33.2%	4.3-16.5%
Strong Investment	27.4-70.0%	24.0-70.1%	0.8-37.0%
Thompson Unger & Plumb Balanced	69.1-74.2%	17.3-29.6%	0.3-13.5%
Triflex	52.3-65.0%	0.0-40.0%	1.4-12.0%
Twentieth Century Balanced	51.4-60.7%	34.2-41.1%	0.3-12.0%
United Continental Income	41.2-68.3%	10.6-43.8%	1.6-17.1%
USAA Balanced Portfolio	40.0-49.7%	30.0-52.0%	1.3-28.0%
USAA Cornerstone	73.0-82.0%	10.0-24.5%	0.0-1.3%
Vanguard Asset Allocation	32.2-70.0%	10.0-57.0%	0.0-48.3%
Wellington Fund	57.0-66.0%	32.0-40.0%	0.1-5.0%

Table 2
Sharpe Quadratic Programming Technique

The table presents the results from the Sharpe quadratic portfolio technique that is used to estimate the average percentage of assets that each fund sample has allocated to various asset categories. For each fund sample, the return on an equally weighted portfolio of all funds in existence is calculated. This return is regressed against the returns of the nine stock, bond, and cash portfolios listed in the table. In the estimation, each coefficient for each portfolio is constrained to be between zero and one, and the sum of all nine coefficients is constrained to equal one. Each coefficient estimate represents the average percentage of assets allocated to the specific asset category. The r-squared reflects the explanatory power of the constrained regression. * denotes portfolio percentages that are significantly different from zero at the 5% level

	Estimated Portfolio Percentage	
Portfolio	**1981 Sample**	**1992 Sample**
SP 500	29.1*	46.0*
Small stock	8.0*	3.4*
Growth stock	0.0	0.0
Value stock	11.6*	9.0*
Long maturity bond	12.2*	10.2*
Short maturity bond	21.5*	17.2*
High quality bond	5.7	5.0
Low quality bond	9.8*	8.9*
Cash	1.8	0.0
R – squared	.987	.968

Table 3
Correlation of Bond Portfolios with Treynor-Mazuy Timing Variable

The table presents the results of the regression of each of four bond portfolios and the squared term for the short bond portfolio against the variables included in the Treynor Mazuy (TM) model. The excess return on the bond portfolio is regressed against 1) the excess return of the S&P 500, 2) the excess return of a small stock portfolio, 3) the excess return of a growth stock portfolio, 4) the excess return of a value stock portfolio, and 5) the squared excess return of the S&P 500. The value *h* represents the coefficient on the squared excess return of the S&P 500 index which is the variable used to measure stock timing ability in the TM model. A statistically significant value for *h* represents a significant correlation between the bond variable and the stock timing variable in the TM model. * denotes values significant at the five percent level. ** denotes value significant at the ten percent level.

1981-1991	
Bond Portfolio	**Value of h**
Short bond portfolio	0.390*
Long bond portfolio	1.697*
High quality bond portfolio	1.081*
Low quality bond portfolio	1.193*
Short bond portfolio squared	0.005**

1992-2000	
Bond Portfolio	**Value of h**
Short bond portfolio	-0.269**
Long bond portfolio	-0.907**
High quality bond portfolio	-0.370**
Low quality bond portfolio	-0.383
Short bond portfolio squared	-0.001

Table 4
Stock Timing Coefficients from Treynor-Mazuy and Multi-Factor Treynor Mazuy Model

The table reports the cross section of results for the stock timing coefficients for both fund samples. For the Treynor Mazuy (TM) model, each fund's excess return is regressed against 1) the excess return of the S&P 500, 2) the excess return of a small stock portfolio, 3) the excess return of a growth stock portfolio, 4) the excess return of a value stock portfolio, and 5) the squared excess return of the S&P 500. For the multi-factor Treynor Mazuy (MFTM) model, each fund's excess return is regressed against the variables from the TM model plus 1) the excess return of a short bond portfolio, 2) the excess return of a long bond portfolio, 3) the excess return of a high quality bond portfolio, 4) the excess return of a low quality bond portfolio, and 5) the squared excess return on the short bond portfolio. For both models, the stock timing coefficient is represented by the coefficient on the squared excess return of the S&P 500. The average stock timing coefficient and its standard deviation are based on the regression of the excess returns of an equal weighted portfolio of all funds within the sample. The statistical significance of individual fund timing coefficients is based on heteroskedasticity-consistent standard errors.

	1981 Sample		**1992 Sample**	
	TM	**MFTM**	**TM**	**MFTM**
Average stock timing coefficient	0.391*	-0.091	0.188	0.401*
Standard deviation	0.151	0.059	0.141	0.192
# positive coefficients	44	24	36	44
# negative coefficients	12	32	22	14
# positive and significant coefficients	22	4	6	14
# negative and significant coefficients	4	12	3	1

Table 5
Portfolio Allocation Analysis

The table reports results for the portfolio allocation analysis performed on both fund samples. I partition the observations within each dataset. One partition includes all observations where the minimum total return of the four stock portfolios defined in equation (3) is greater than the maximum total return from any of the four bond portfolios and cash portfolio. A second partition of data includes all observations where the maximum total return from any of the four stock portfolios is less than the minimum total return from any of the bond portfolios and cash. For each set of observations, I employ Sharpe's quadratic program as previously defined in equation (4) to estimate the fund's exposure to each of the nine portfolios. These exposures represent estimates of the average fund portfolio weights. I sum the coefficients for the four stock categories to get an approximate average stock portfolio weight when stocks are the best performing asset class. I repeat when stocks are the worst performing asset. I calculate the difference between the average stock allocation when stocks are the best performing asset and the average allocation when stocks are the worst performing asset. I refer to this variable as the stock adjustment. I group the funds into four categories based on their MFTM model timing coefficients classification: 1) positive and significant, 2) positive and not significant, 3) negative and not significant, and 4) negative and significant and report the mean stock adjustment for each classification.

Classification	# of Funds	Mean Stock Adjustment	Std. Dev.
1981 Sample			
Positive and significant	4	0.168	0.149
Positive and not significant	20	0.007	0.052
Negative and not significant	20	-0.028	0.068
Negative and significant	12	-0.054	0.058
1992 Sample			
Positive and significant	14	0.062	0.061
Positive and not significant	30	0.025	0.095
Negative and not significant	13	-0.055	0.076
Negative and significant	1	-0.258	na

Table 6
Descriptive Statistics for Asset Allocation and Balanced Funds

The table presents descriptive statistics for the period 1992-2000 for the asset allocation and balanced funds in the 1992 sample. Averages are calculated by first calculating the average value for each individual fund over the time period and then calculating the cross sectional mean. All data is from CRSP.

	Asset Allocation	**Balanced**
Number of funds	24	34
Average stock portfolio weight	56.2%	56.7%
Average bond portfolio weight	32.3%	37.3%
Average cash portfolio weight	11.4%	6.0%
Average range of stock weights	39.0%-67.9%	47.5%-64.2%
Average portfolio turnover	101%	82.8%
Average expense ratio	1.36%	1.01%

Table 7
Stock Timing Coefficients for Two Partitions of 1992 Sample of Funds

The table reports stock timing coefficient results for two partitions of the 1992 sample of funds. In Panel A, the partition is by fund objective. Funds are classified as either asset allocation or balanced funds based on the fund objective as reported by CRSP. In Panel B, the partition is based on fund expense ratio. The sample is sorted by expense ratio and divided into quartiles with the first quartile representing funds with the highest expense ratio. Within each category, I compute the return on an equal weighted portfolio of all funds within the group. The stock timing coefficient is estimated using the excess returns and the multi-factor Treynor Mazuy model where the coefficient of the square of the S&P 500 index represents the stock timing coefficient. * represents statistical significance at the five percent level. Statistical significance of timing coefficients is based on heteroskedasticity-consistent standard errors.

Panel A-Fund Objective

	Number of Funds	Stock Timing	Standard Deviation
Asset allocation funds	24	0.204	0.249
Balanced funds	34	0.429*	0.203

Panel B-Expense Ratio

	Average Expense Ratio	Stock Timing	Standard Deviation
Group 1	1.72%	0.462	0.294
Group 2	1.23%	0.112	0.206
Group 3	0.99%	0.365	0.225
Group 4	0.69%	0.419*	0.189