THE BENEFITS OF TIME-VARYING ASSET ALLOCATION ACROSS HEDGE FUND INDICES

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ABSTRACT

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In this paper, the risk-adjusted performance of dynamic asset allocation strategies for hedge fund indices, based on minimum variance and maximum Sharpe ratio approaches, is examined and compared to the S&P500 index benchmark. Furthermore, the added benefits of using conditional volatility forecasting, namely an asymmetric generalized autoregressive conditionally heteroscedastic (asymmetric GARCH) process, are examined when constructing dynamic hedge fund index portfolios. The evaluation period is based on a monthly out-of-sample comparison from May 2002 to June 2006 for nine Credit Suisse First Boston / Tremont hedge fund indices. Weekly and daily rebalanced dynamic portfolios are examined on the out-of-sample data from December 2005 until the end of June 2006 for the three main sub-indices of Standard & Poor's Hedge Fund Index. A multivariate asymmetric GARCH model is also considered for portfolio construction using daily S&P Hedge Fund sub-indices data. Before transaction costs are included, results show that when hedge fund indices exhibit volatility clustering, accounting for forecasted next-period volatility generates portfolios with the best risk-return profile among all portfolios under consideration. After accounting for transaction costs, out-of-sample results indicate that all dynamic hedge fund indices portfolios largely outperform the S&P 500 index, both on a risk-adjusted and nominal basis.

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1. Introduction

Alfred Winslow Jones created the very first hedge fund in 1949 that combined short-selling, leveraging, incentive fees and shared risk strategies. However it took until the mid 1990s for hedge funds to truly emerge as a popular investment vehicle for high net-worth individuals and institutional investors. As of mid-2005, hedge fund assets overseen by single managers rose to $1.371 trillion, whereas the holdings in funds of hedge funds rose to $709 billion, according to Hedge Fund Manager Magazine. The tremendous popularity of this new investment vehicle can be explained by the highly diverse investment strategies employed by hedge fund managers and alleged heterogeneous returns with respect to other traditional asset classes.

Studies of hedge funds have faced several challenges including data availability, a survivorship bias, a reporting bias, and others, which adversely affect the efficient and the unbiased estimation of a given strategy's return. These limitations as well as concerns with regards to liquidity and front and back-load expenses need to be taken into consideration when making a decision to invest in hedge funds or "investable" hedge fund indices such as the CSFB/Tremont Sector Invest Indices.

The investable hedge fund indices which have recently appeared provide an opportunity to exploit tactical asset allocation strategies in the alternative assets space. Funds of Funds (FOF's), Pension Funds, Endowments, Family Funds and other financial asset management institutions will undoubtedly seriously examine allocating a portion of their assets under management to these new investment vehicles. FOF's will likely be the first to take advantage of the "investable" hedge fund indices universe and employ quantitative asset allocation strategies, such as the one explored in this work, on this emerging asset class. In the same fashion as they currently do with individual hedge fund managers, FOF's in the nearest future will allocate part of their capital to hedge fund indices.

Capitalizing on this new investment opportunity, this work proposes dynamic asset allocation strategies to hedge fund indices based on the minimum variance and the maximum Sharpe ratio approaches. Amenc and Martellini (2002) demonstrate the benefits of considering a minimum variance portfolio along the efficient frontier when it comes to tactical hedge fund indices asset allocation. Their results suggest the possibility of achieving a reduction in volatility with no detrimental effect on the returns.

Volatility plays a key role in controlling for and forecasting risks in various financial operations. Numerous statistical models have been proposed to describe and predict the behavior of financial asset volatility. They include: rolling variance estimates, autoregressive conditional heteroscedasticity (ARCH) models and non-parametric models. One of the most comprehensive works examining stock market volatility to-date is that of Engle and Patton (2001). It has been documented, by this and other studies, that the volatility of most financial assets exhibits persistence and is mean-reverting.

When it comes to univariate GARCH specifications, volatility is often represented by conditional variance or conditional standard deviations. The development of multivariate autoregressive conditionally heteroscedastic (MGARCH) models from the original univariate specifications represented a major step forward in the modeling of economic time series. Issues of risk assessment, asset allocation, hedging and options pricing are usually resolved in the multivariate GARCH framework. Asset allocation with the multivariate GARCH specification uses time-varying volatilities and cross-correlations between the assets to determine their optimal weights within the portfolio.

Discrete time models, GARCH, are used to examine implications of volatility on portfolio weights. Dijk and Frances (2001) find that GARCH models successfully capture excess kurtosis, which is especially relevant to hedge fund indices. Further, Engle and Patton (2001) state that even in cases when the true data generating process for assets under consideration is not GARCH, GARCH models still serve as a first-rate approximation. The distinctive feature of this work is therefore that the assets under consideration are hedge fund indices. It is believed that no other study on hedge funds to-date incorporated conditional volatility forecasting for optimal hedge fund indices asset allocation.

Several studies undertaken to examine the returns predictability of hedge fund indices find significant results. Agarwal and Naik (2003) use the set of excess returns on standard assets and options on these assets as factors to forecast hedge fund returns. Non-linear factors are proxied for by positions in derivatives. Schneeweis and Spurgin (2000) employ passive option strategies, whereas Lhabitant (2001) captures non-linearity by including hedge fund indices as factors. Amenc, Bied and Martellini (2002) examine lagged multi-factor models on hedge fund indices. Given the difficulty of forecasting expected returns, further work in the area is warranted.[1]

[1] Pioneering works by Merton (1980) and Jorion (1985, 1986) argue that the optimal estimator of the expected return is noisy with a finite sample size.

This paper is organized as follows: Section 2 provides a review of the literature on hedge funds relevant to this work and presents testable hypotheses. Section 3 gives a description of two hedge fund indices data providers used throughout this study. Section 4 introduces models used to forecast conditional volatility and correlations, and presents the methodology for constructing dynamic portfolios. Section 5 talks about transaction costs and how they are accounted for within the resulting portfolios. Section 6 discusses out-of-sample results and Section 7 concludes and presents viable directions for future research on this topic.

2. Literature Review

The hedge funds literature focuses primarily on return characteristics of this alternative asset class, which is usually explained by either fund-specific characteristics or is linked to relevant global macro factors. Significant research has been done on what drives hedge fund performance, whether it is predictable, and whether it makes sense to add this relatively new asset class to a mix of traditional asset allocations composed of stocks and bonds. Very little to-date has been written on optimal fund-of-funds portfolio construction. This section will first discusses findings related to drivers of individual hedge fund and hedge fund indices performance, followed by an examination of studies on the benefits of hedge funds within a broader portfolio, and concludes with the details on what is known and unknown about optimal hedge fund portfolio construction. In addition, it is outlined how this work contributes to that body of knowledge.

Fung and Hsieh (1997) and Schneeweis and Pescatore (1999) find that sources of expected returns differ for various hedge fund strategies and that some of those strategies provide return opportunities not typically available through traditional investment vehicles. Schneeweis and Pescatore (1999) further state that style-based performance analysis and asset allocation frameworks can be used to determine the optimal allocation to hedge funds. Factor analysis is the most popular method for explaining returns when it comes to hedge fund styles (or indices). Similar to Fung and Hsieh (1997), Schneeweis and Spurgin (1998), Schneeweis and Pescatore (1999), Agarwail and Naik (2000) and others indicate that set of factors can explain return drivers of hedge fund strategies, extending the Fama and French (1996) approach.

Since every hedge fund strategy is meant to take advantage of certain conditions prevalent in the market, researchers try to replicate the payoffs of that strategy by considering factors that the payoff is based on. Three types of factor-based models tested to-date are: macro-factor models, micro-factor models and models with non-linear regressors.

The most commonly tested regression-based macro-factors used to explain hedge fund returns include: interest rates, the long vs. short maturity treasury spread, the inflation rate, stock market return, industrial production, and the price of oil. Stepwise regression is often used to select independent variables while avoiding multicollinearity. Agarwaik and Naik (1999) apply typical multifactor models based on macro variables towards four directional hedge fund strategies (macro, long, hedge long bias, and short) and six non-directional strategies (fixed income arbitrage, event driven, equity hedge, restructuring, event arbitrage, and capital structure arbitrage). They find that the alpha is significant for eight strategies at the 5% level of significance and that non-directional strategies are less correlated with the market than directional strategies. The factors considered in their paper include: the S&P Composite Index, the MSCI World Index (excluding the US), the MSCI Emerging Markets Index, the Salomon Brothers Government Bond Index, the Lehman High Yield Composite, the Federal Reserve Trade-Weighted Dollar, and the UK Market Price of Gold.

Micro-factor models are structured in a similar fashion to macro-factor models. However, they require information that is much more difficult to obtain because loosely regulated investment vehicles such as hedge funds are not required to disclose their holdings.

Typical factors examined include: value of assets under management, age of the fund, lockup period, incentive fees, required redemption notice, and partnership participation. Kat and Miffre (2002) show that the past return is the best predictor of the future period return, followed by the default spread, the dividend yield, the term structure, and the interest rate.

The third and final type of explanatory models includes non-linear regressors. This would seem appropriate for hedge funds that exibit non-linear option-like exposures to traditional asset classes. In order to properly replicate such payoffs, first non-linear regressors are included into the model and then a notion of conditional performance is investigated. Two variables are typically used: a portfolio of options and an index. Agarwail and Naik (2000) use an at-the-money option trading strategy, an out-of-the-money option trading strategy and a deep-out-of-the-money option trading strategy on the Russell 3000 Index. Similar studies confirm the added value of including trading factors through options to evaluate and explain hedge fund returns.

Most of the literature on hedge fund portfolio construction suggests that a proper analysis requires more sophisticated techniques than traditional mean-variance optimization. Lo (2001), Brooks and Kat (2002), and Anson (2002) all indicate that certain hedge fund strategies have more downside than upside risk, and thus exhibit negative skewness and excess kurtosis. Krokhmal, Uryasev and Zrazhevsky (2002) and Signer and Favre (2002) confirm that assuming symmetry in hedge funds portfolio construction leads to riskier portfolios, as opposed to the cases in which asymmetry is accounted for. An interesting approach to deal with the problem of asymmetry is proposed by Duarte (1999) who presents portfolio optimization as a general problem with standard optimization methods as special cases. He approaches the problem of portfolio optimization simply as an issue of choosing a proper risk metric. He then presents the following risk measures in his formulation: mean variance, mean semivariance, mean downside risk, mean absolute deviation, mean absolute semideviation, and mean absolute downside risk. For the first three, risk is defined by means of squared deviations and thus large return differences are dealt with more severely. In the case of the latter three, deviations are weighted equally. Lamm (2003) constructs 17 hedge fund portfolios in order to determine which of the risk metrics makes a difference on portfolio characteristics. He tests mean variance, mean semivarince, mean downside risk and mean absolute deviation approaches proposed by Duarte (1999). His results indicate that mean semivariance and mean downside risk approaches improve overall portfolio characteristics by lowering the negative skew and excess kurtosis, while preserving the same level of return. Another alternative specification that is looked at in Lamm's (2003) work is based on the Value-at-Risk (VaR) methodology. When delta-gamma approximations based on Cornish-Fisher (CF) expansions are applied to VaR, Lamm (2003) finds that the resulting portfolio of hedge funds has the lowest skewness and kurtosis among all considered approaches.

Amenc and Martellini (2002) evaluate the out-of-sample performance of an improved estimator of the covariance structure on hedge fund index returns. They focus on the only possible portfolio along the efficient frontier that does not require expected returns forecasting – the minimum variance portfolio. They document that by estimating simple covariances over one period and generating out-of-sample estimates, while remaining on the minimum variance frontier, the ex-post volatility of the resulting portfolio is between

1.5 and 6.0 times lower than that of the value-weighted benchmark, in their case the S&P 500 index. These results suggest that the inclusion of a portfolio of hedge fund indices within a traditional stocks and bonds portfolio provides significant benefits in terms of overall portfolio risk/return characteristics. This comes with no reduction in the expected levels of returns.

Building on the prior literature on the subject, we propose a number of hypotheses for testing:

H1: Minimum variance hedge fund indices portfolios based on <u>Past Volatility</u> provide a better risk-adjusted return than the <u>S&P500 Index</u> - for monthly, weekly and daily data.

H2: If not rejected initially, H1 still holds after accounting for transaction costs - for monthly, weekly and daily data.

H3: Minimum variance hedge fund indices portfolios with the next-period indices volatilities estimated via <u>Univariate GJR-GARCH(1,1)</u> provide a better risk-adjusted return than the minimum variance hedge fund indices portfolio with the next-period indices volatilities estimated via <u>Past Volatility</u> - for monthly, weekly and daily data.

H4: If not rejected initially, H3 still holds after accounting for transaction costs - for monthly data only, but fails to hold for weekly data.

H5: Hedge fund indices portfolios with the next-period indices volatilities and cross-correlations estimated via Multivariate GJR-GARCH(1,1) provide a better risk-adjusted return than the minimum variance hedge fund indices portfolio with the next-period indices volatilities estimated via Univariate GJR-GARCH(1,1) - for daily data.

H6: A Maximum Sharpe Ratio portfolio composed of hedge fund indices provides a better risk-adjusted return than the S&P500 Index - for monthly, weekly and daily data.

H7: If not rejected initially, H6 still holds after accounting for transaction costs - for monthly data only, but fails to hold for weekly data.

H8: A minimum variance portfolio with the next-period indices volatilities estimated via Univariate GJR-GARCH(1,1) provides a better risk-adjusted return than the Maximum Sharpe Ratio portfolio – for monthly, weekly and daily data.

H9: If not rejected initially, H8 still holds after accounting for transaction costs - for monthly data only, but fails to hold for weekly data.

3. Data Description

To represent the style-based investment strategies in an alternative investment universe, two of the most prominent hedge fund index providers are selected. They are: Credit Suisse First Boston/Tremont Hedge Fund Indices (CSFB/T HF Indices) and Standard and Poor's Hedge Fund Indices (S&P HF Indices). Numerous academic studies (Lhabitant (2001), Amenc and Martellini (2002), Agarwal and Naik (2002), and others) have used these indices because of several advantages they present with respect to competitors in terms of both calculation and transparency.

3.1 Credit Suisse First Boston / Tremont Hedge Fund Indices

The CSFB/T Hedge Fund Indices are the industry's only asset-weighted hedge fund indices. Their calculation begins with the TASS+ database, which tracks over 2,600 US and offshore hedge funds, and retain only those that have a minimum of US$50 million under management, have a minimum track record of one-year, and provide current audited financial statements. Until recently, however, minimum requirements for assets under management were US$10 million and a one year track record was not a necessity. About 650 hedge funds pass the criteria and are considered within the CSFB/T Indices. Indices are computed on a monthly basis, using net of fees returns, with the hedge funds re-selected every quarter. In order to minimize the survivorship bias, hedge funds are not excluded from the indices until they liquidate their assets or fail to provide audited financial statements.

The CSFB/T Indices cover nine distinct investment strategies. They are: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed-income arbitrage, global macro, long/short equity and managed futures. Descriptive statistics of these indices, relative to the S&P 500 benchmark, are provided in Table 1 and Appendix 1. Out of nine CSFB/T hedge fund indices, eight outperform the S&P 500 benchmark on a risk-adjusted basis (Sharpe Ratio). The best risk-adjusted return was achieved by an equity market neutral hedge fund index, with an annualized mean return of 10.07% and an annualized standard deviation of 2.93%, for a Sharpe ratio of 3.43. It was followed by event driven and convertible arbitrage indices with respective Sharpe ratios of 2.08 and 1.88. Worst-performing, and the only hedge fund index which underperformed the S&P 500 benchmark, was the dedicated short bias (Sharpe ratio of -0.06). The S&P 500 Index turn generated an annualized return of 9.51%, at the cost of 18.40% in standard deviation, for a Sharpe ratio of 0.52.

The CSFB/T Indices were launched in 1999 with the data going back to 1994. This study uses data from January 1994 to June 2006 for a total of 150 monthly return observations.

In October 2004, CSFB/T Index LLC launched nine CSFB/T Sector Invest indices, with data going back to 1999. CSFB now offers investment products linked to the Sector Invest Indices that allow investors to construct their portfolios and effectively participate in dynamic asset allocation across the alternative investments styles. Inadequate monthly historical performance data is the primary reason these "investable" indices are not considered in this work. Within this study, traditional CSFB/T HF Indices are used as proxies for nine newly-introduced "investable" indices that cover the same investment strategies.

3.2 Standard & Poor's Hedge Fund Indices

The Standard and Poor's Hedge Fund Index was launched in October 2002. The index is equally-weighed across various alternative investment strategies and is re-balanced annually. The distinctive characteristic of this index is the availability of daily returns data and the index construction methodology.

The main S&P Hedge Fund Index consists of three Indices (styles) that broadly represent the hedge fund investing universe. They are: arbitrage, event-driven and directional/tactical. Each strategy in turn consists of three underlying strategy components. The arbitrage index includes equity market neutral, fixed income arbitrage and convertible arbitrage. The event-driven index includes merger arbitrage, distressed situations, and special situations. The directional/tactical index incorporates equity long/short, managed futures, and global macro.

The construction of the S&P Hedge Fund Index uses rigorous quantitative and qualitative methods to determine fund selection. The index construction process involves two complementary procedures. The first procedure determines the number of funds required to construct a representative and "investable" index. Based on stratified sampling and bootstrap simulation techniques, Standard and Poor's suggest that a portfolio of 30 to 40 hedge funds represents the risk/return characteristics of broader portfolios of hedge funds. The second procedure determines a universe of suitable candidates for inclusion in the index. This process begins with an examination of strategy consistency, screening the hedge fund sample for self-reporting bias and inconsistency to create a candidate pool cohesively defined in terms of styles and strategies. The candidate pool is then further screened for length of track record, assets under management, and investment capacity. The remaining funds undergo a rigorous due diligence process to verify management experience, investment philosophy, risk management policy, and operational capabilities.

The main S&P Hedge Fund Index is an index suitable for dynamic asset allocation. Constituent strategies however cannot be invested in on a stand-alone basis. Thus, the results of the analysis conducted on weekly and daily data using three constituent strategies of which the main index is composed are theoretical in nature and may not be replicated at the time of this writing using a tradable investment portfolio. Nevertheless, examination of dynamic/tactical asset allocation strategies with weekly and daily re-balancing horizons serves as an important complementary work to further conclusions reached under the monthly rebalancing strategies with CSFB/T Indices. The results serve as a proxy for the expected characteristics of strategy returns for weekly and daily hedge fund indices soon to enter the marketplace. Analysis of the monthly data based on CSFB/Tremont indices however is presently replicable through the CSFB/T Sector Invest indices, as discussed above.

For descriptive statistics of the three main S&P HF Indices, compared to the S&P 500 benchmark, please refer to Table 2 and Appendix 2. All three hedge fund indices outperformed the S&P 500 Index, on a risk adjusted basis (Sharpe ratio). The event driven, directional/tactical and arbitrage indices generated Sharpe ratios of 4.40, 1.44 and

0.94, respectively. This compares to the S&P 500 index Sharpe ratio of 0.89. It is noteworthy to mention however, that the S&P 500 Index had the highest annualized return of 12.75%, which came at the cost of 14.26% in annualized standard deviation.

3.3 Possible Data Biases

The CSFB/T HF Indices and S&P HF Indices may be subject to certain biases worth mentioning. The most notable hedge fund index data biases are: the survivorship bias, the selection bias, the stale price bias, and the instant history bias (also referred to as the backfill bias).

A survivorship bias occurs when the database contains only information on funds that survive. According to Fung and Hsieh (2000), and Brown, Goetzmann and Ibbotson (1999), the difference in the performance of the "observable" portfolio and the portfolio of surviving funds is about 3% per year. The TASS database accounts for this bias by keeping returns of defunct funds in its database since 1994, the same time CSFB begins its index returns calculations.

A selection bias is caused by inclusion of the funds with good returns in the database, and thus reporting their results. This bias however is limited due to successful managers, who have reached their assets under management objectives, not reporting to the database as well. Most of those managers are assumed to have stopped accepting new capital in their funds in order to protect the success of a given investment strategy. According to Fung and Hsieh (2000), the two effects cancel each other out and thus this bias may be considered negligible.

The stale price bias refers to prices that may not reflect true market conditions. By using the last trade price available in a given security, as is often done in practice, true hedge fund returns may easily be distorted.

The instant history bias (also referred to as backfill bias) occurs as a result of adding a hedge fund whose earlier good returns are backfilled between the inception date of the fund and the date it enters the database, while bad track records are not backfilled. The bias is therefore the difference between the return of an adjusted observable portfolio and the return of a non-adjusted observable portfolio. Fung and Hsieh (2000) estimate the instant history bias to be equal to 1.4% per year for the TASS database using data from 1994 to 1998. Caglayan and Edwards (2001) eliminate this bias by dropping the first twelve months of fund returns. CSFB/T HF Indices have recently added one year track record requirement that effectively accounts for the instant history bias and makes the index returns calculations more objective.

4. Methodology

4.1 Portfolio Construction based on Maximum Sharpe Ratios

The simplest dynamic hedge fund indices portfolios considered in this work are based on standard mean-variance Markowitz optimization. Past returns, volatilities and cross-correlations serve as an input into the software, which calculates the next-period efficient frontier. Maximum Sharpe ratio point along the efficient frontier indicates the weights of each hedge fund index in the portfolio. Maximum Sharpe ratio portfolios are constructed for monthly and weekly hedge fund indices data.

4.2 Portfolio Construction based on Past Volatility

In order to construct portfolios based on historical volatility, the weights of each hedge fund index within the next period portfolios need to be computed. A Global Minimum Variance (GMV) asset allocation approach is used in this work. Thus the optimal weights ω_i depend on the predicted variance matrix H_{t+1}.

Assuming a diagonal variance matrix for nine univariate CSFB/T Hedge Fund Indices, the weights of the univariate diagonal portfolio are given by:

$$\omega_{t,i} = \frac{\hat{\sigma}^{-2}_{t+1,i}}{\sum_{j=1}^{9} \hat{\sigma}^{-2}_{t+1,j}} \qquad (1)$$

where for CSFB/T indices $i = 1,2,3,...,9$ and for S&P indices $i = 1,2,3$. $\hat{\sigma}^{2}_{t+1,i}$ is the past variance of the monthly returns of the ith CSFB/T Hedge Fund index or is the past variance of weekly or daily returns of the ith S&P Hedge Fund Index. The variance is either forecasted by the univariate GJR-GARCH(1,1) model or estimated based on past volatility. The same approach is used for finding the optimal weights of Standard and Poor's Hedge Fund Indices for weekly and daily rebalanced portfolios.

In addition to the univariate GJR-GARCH(1,1) estimations and Past Volatility, multivariate GJR-GARCH(1,1) estimations are used for the weights calculation for daily-rebalanced portfolios. The multivariate GJR-GARCH(1,1) portfolio, based on the three S&P HF indices uses Markowitz's (1952) mean variance optimization to find optimal next-period index weights. Portfolio optimization based on Markowitz requires inputs of expected returns, variances and cross-correlations to generate an efficient investment frontier for optimal portfolio selection. The performance of such a portfolio critically depends on the quality of forecasts of the first two moments: the returns and the variance matrix. In this paper, next-day variances and cross-correlations are forecasted by the Multivariate GJR-GARCH(1,1) model, whereas the expected returns are equal to the average returns over the in-sample period.

4.3 Testing for Presence of ARCH

For portfolio construction that includes forecasted volatilities, residuals from a preliminary OLS estimation are tested for ARCH (autoregressive conditional heteroscedasticity) behavior. The presence of ARCH would show non-normal unconditional error distribution: the residuals would be uncorrelated, but the squared residuals would show autocorrelation. As per Engle (1984), the Lagrange Multiplier (LM) test is conducted. The null hypothesis of no ARCH errors is tested against the alternative hypothesis that the conditional error variance has an ARCH(q) process for all time frames and indices under consideration. Squared residuals are therefore regressed on a constant and q lagged values of the squared residuals. To test the null hypothesis that there is no ARCH up to order q in the residuals, the following regression needs to be estimated:

$$e_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s e_{t-s}^2 \right) + \upsilon_t \tag{2}$$

where e is the error term.

In this project the presence of ARCH up to order 1 is tested by estimating the following equation:

$$e_t^2 = \beta_0 + \beta_1 e_{t-1}^2 + \upsilon_t \tag{3}$$

the LM test indicates a significant presence of ARCH (at the 5% level) in two out of three daily hedge fund index returns data: the event index and the arbitrage index. When estimating in-sample equations, two out of three indices confirmed significant GARCH coefficients at the 5% level (refer to Table 3). Weekly data indicated presence of ARCH in three indices (for GARCH coefficients when estimating in-sample equations refer to Table 4). Monthly index data shows significant ARCH, at the 5% level, for the market neutral and fixed income indices only (for in-sample GARCH equations refer to Table 5).

4.4 Portfolio Construction based on Conditional Volatility

To predict the volatilities of next-period returns, an Asymmetric GARCH model (GJR-GARCH) with t-distributed errors is used.

While a standard ARMA-GARCH model with normality assumptions adequately captures time-varying volatility, it is not the most effective in capturing the excess kurtosis or fat tails that is present in hedge fund indices returns. A student-t distribution (Bollerslev 1986) is therefore used in place of a normal distribution.

The density function of a student-t distribution with ν degrees of freedom is given by

$$f(\varepsilon_t|\Omega_{t-1}) = \frac{\Gamma\{(\nu+1)/2\}}{\sqrt{\pi(\nu-2)}\Gamma(\nu/2)}\left[1+\frac{\varepsilon_t^2}{(\nu-2)}\right]^{-(\nu+1)/2} \qquad (4)$$

where $\Gamma(.)$ is the gamma function.

Asymmetric return distribution patterns are apparent in almost all of hedge fund indices data, as shown in Tables 1, 6 and 7. Asymmetric GARCH is often referred to in the literature as GJR-GARCH after the originators Glosten et al. (1993). The same notation is used throughout this paper.

The rationale for using a GJR-GARCH specification is to account for the negative shocks that provide additional sources of risk. This arises from the asymmetric return patterns, characterized by negative skewness and excess kurtosis, present in most hedge fund strategies. Krokhmal, Uryasev, and Zrazhevky (2002) and Favre and Signer (2002) state that assuming normality in hedge fund returns leads to portfolios that are more risky than in the case when asymmetry is accounted for. Conditional variances are parameterized by a GJR-GARCH model of orders p and q.

The GJR-GARCH(p,q) model is thus of the following form:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} (\alpha_i + \gamma_i S_{t-i}) \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \qquad (5)$$

where S_t is a dummy variable for negative residuals, defined as:

$$S_t = \begin{cases} 1, \varepsilon_t < 0 \\ 0, \varepsilon_t > 0 \end{cases} \qquad (6)$$

Using the GJR-GARCH model, the next-day conditional volatility for monthly, weekly and daily-rebalanced hedge fund indices is then forecasted by:

$$\hat{\sigma}_{t+1}^2 = \hat{\alpha}_0 + (\hat{\alpha}_1 + \hat{\gamma}_1 S_t) \varepsilon_t^2 + \hat{\beta}_1 \sigma_t^2 \qquad (7)$$

with, once again, S_t being the dummy variable for negative residuals, as defined in Equation (6).

A univariate GJR-GARCH(1,1) model with a BHHH (Berndt et al. (1974)) algorithm is estimated on CSFB/T Hedge Fund indices, some of which have been found to contain significant ARCH effects, using 100 in-sample return observations.

This procedure is repeated 50 times using rolling a window of 100 monthly observations. January 1994 through March 2002 serves as an initial calibration period for subsequent volatility forecasts from April 2002 until June 2006. For models estimated based on the first in-sample calibration period refer to Table 5.

The usage of GARCH specification does not arise directly from economic theory, but it provides a close and parsimonious approximation to the form of heteroscedasticity encountered with hedge fund time-series data. For its applicability to other economic time-series data refer to Bollerslev (1986) and Engle and Bollerslev (1986).

Similar methodology is employed to forecast the next-day conditional volatility for Standard & Poor's event driven, directional and arbitrage hedge fund indices. For weekly returns data 157 in-sample weekly observations are used to forecast volatilities for 31 out-of-sample weeks, from the beginning of December 2005 until the end of June 2006. Models estimated based on first in-sample calibration period are shown in Table 4. For daily returns, 800 in-sample observations are used to forecast volatilities for 143 out-of-sample days, also from December 2005 until the end of June 2006. First in-sample models are shown in Table 3.

In addition to the univariate GJR-GARCH(1,1) specification, a multivariate GJR-GARCH(1,1) model is applied for daily S&P Hedge Fund Indices data. Output from the initial calibration 800-day period is presented in Table 8.

By eliminating the performance of the Multivariate GJR-GARCH(1,1) portfolio with the weights directed by the minimum variance portfolio along the efficient frontier of mean-variance Markowitz optimization, versus the Univariate GJR-GARCH(1,1) portfolio with the weights coming from the global minimum variance formula, the added benefits of univariate versus multivariate specifications, when it comes to dynamic hedge fund indices asset allocation, are thus explicitly examined.

4.5 Benchmark Portfolio

Four main investment portfolios are considered in this work; maximum Sharpe portfolios, Past Volatility portfolios and GJR-GARCH(1,1) portfolios are compared against the performance of the S&P 500 Index. In the case of daily rebalancing, Multivariate GJR-GARCH(1,1) portfolio results are used in place of the maximum Sharpe portfolio and are matched against the three above-mentioned portfolios.

The Standard & Poor's 500 Index is used as the primary benchmark against which portfolios composed of hedge fund indices are judged. The S&P 500 Index is treated as just another portfolio (making the total number of portfolios equal to four) with 100% of capital allocated to it at the beginning of the in-sample period (May 2003 for monthly data; December 1, 2005, for weekly and daily data) and held for a whole period under consideration (until the end of June 2006 for all data series).

5. Transaction Costs

To evaluate the added benefits of a given investment strategy in the real world, transaction costs need to be considered. In this work, roundtrip transaction costs of 50 basis points are assumed. Comparative and lower levels have been used in prior academic works that looked into investment strategies for traditional asset classes and are believed to be appropriate for an alternative investment universe composed of "investable" hedge fund indices.

Transaction costs are considered for monthly rebalanced portfolio that consist of CSFB/T Indices as well as for weekly-rebalanced portfolios made from S&P hedge fund indices. For daily-rebalanced portfolios, transaction costs are incorporated for the past-volatility strategy and S&P 500 Index returns. Daily-rebalanced portfolios constructed based on Maximum Sharpe, univariate GJR-GARCH and multivariate GJR-GARCH are excluded from this analysis, as significant benefits of those strategies versus the S&P 500 (refer to the results section) would be mitigated by high transaction costs. The examination of those dynamics for daily returns is therefore not feasible in practice, unless transaction costs decrease significantly.

For the first period under consideration, as well as for the S&P 500 Index, 25 basis points are added as an initial cost of investing, in addition to the costs associated with any switching/re-balancing necessary at the end of each investment period.

The effects of transaction costs and wealth effects on various portfolios under consideration are shown in Table 9 and Figure 1 for monthly-rebalanced portfolios, in

Table 10 and Figure 2 for weekly-rebalanced portfolios and in Table 11 and Figure 3 for daily-rebalanced portfolios.

6. Results

6.1 CSFB/Tremont Monthly Rebalanced Portfolios

The performance of the CSFB/Tremont monthly rebalanced dynamic portfolio based on conditional volatility forecasting from GJR-GARCH(1,1) is compared to the Past Volatility portfolio and the S&P 500 Index.

The risk-adjusted performance of the portfolios under consideration (Maximum Sharpe, Past Volatility, Univariate GARCH and S&P500) are compared based on Sharpe Ratio, as per Sharpe (1966), which is equal to annualized mean portfolio return divided by annualized portfolio standard deviation:

$$SR_P = \mu_P / \sigma_P \qquad (8)$$

The out-of-sample testing period for monthly returns data extends from May 2002 until June 2006, for a total of 50 monthly return observations. Results show that the dynamic global minimum variance portfolio based on GJR-GARCH(1,1) volatility forecasting (SR_P=3.79) outperforms – on a risk-adjusted basis – the S&P 500 Index (SR_P=0.37), the Past Volatility portfolio (SR_P=3.48), and the Maximum Sharpe Ratio portfolio (SR_P=3.57). The Maximum Sharpe portfolio in turn outperforms the S&P 500 Index, as does the Past Volatility Portfolio.

Based on the above results we fail to reject hypotheses H1, H3, H6 and H7 for monthly returns data. Out-of-sample testing supports our initial beliefs with regard to the risk-adjusted returns ranking, which were guided by the prior literature on this subject.

Since most CSFB/T hedge fund indices do not exhibit volatility clustering (as expected), GJR-GARCH (1,1) model results are only used for market neutral and fixed income indices volatility forecasting (refer to Table 5). Other indices next-period volatility is estimated based on past in-sample volatility. This explains little deviation in returns between the Past Volatility portfolio and the GJR-GARCH(1,1) portfolio. Nevertheless, the ability to forecast next-period volatility for only two out of nine hedge fund indices provides a significant added benefit in enhancing the risk/return profile of the portfolio as a whole (the annualized standard deviation decreases from 2.67% to 2.00%; see Table 12).

After accounting for transaction costs, Sharpe Ratio rankings of the portfolios change, so that the Past Volatility portfolio (SR_p=3.46) performs as well as the Maximum Sharpe Ratio portfolio (SR_p=3.44) and better than the GJR-GARCH(1,1) portfolio (SR_p=3.33) and the S&P 500 Index (SR_p=0.37). We therefore fail to reject H2 and H7, but reject H4 and H9, for monthly data. The extent of the transaction costs on the GJR-GARCH(1,1) is large enough to bring it from the top spot down to third place. The benefits of the conditional volatility forecasting model, clearly demonstrated in Table 12, have been eliminated by transaction costs. All three portfolios still largely outperform their benchmark S&P 500 Index. For full results refer to Table 9.

For wealth effects on the out-of-sample data for all portfolios considered, before and after transaction costs, refer to Figures 4 and 1, respectively.

6.2 Standard and Poor's Weekly Rebalanced Portfolios

For weekly data, results indicate that the GJR-GARCH(1,1) portfolio outperforms other hedge fund indices portfolios and the benchmark S&P 500 Index, on a risk adjusted basis (Sharpe Ratio). With SR_P=5.65 (for GJR-GARCH(1,1)), SR_P=5.51 (for Past Volatility), SR_P=4.98 (for Maximum Sharpe Ratio) and SR_P=0.07 (for the S&P 500 Index). Surprisingly, however, the benefits of conditional volatility forecasting (GARCH) versus historical volatility (Past Volatility) do not result in a reduction in volatility (annualized standard deviation of 2.09% versus 2.02%), which leads to believe that the marginal benefits in terms of risk/return between the GARCH(1,1) and Past Volatility are misleading and that H3 should to rejected. Overall, results fail to reject hypotheses H1, H6 and H8, but reject H3.

After accounting for transaction costs, Past Volatility comes out on top (SR_P=5.06), followed by the Maximum Sharpe Ratio (SR_P=4.47), GARCH (1,1) (SR_P=3.86) and the S&P 500 Index (SR_P=0.03). The relative effect of transaction costs on GARCH(1,1) versus other portfolios is once again larger than what it was initially believed to be. Thus, we fail to reject H2 and H7, but reject H9. H4 does not apply, as H3 was rejected before transaction costs were incorporated.

For wealth effects associated with weekly-rebalanced hedge fund indices portfolios versus S&P 500 Index refer to Figure 5 (without transaction costs) and Figure 2 (with transaction costs).

6.3 Standard and Poor's Daily Rebalanced Portfolios

For daily data, risk-adjusted returns are significantly better for the Multivariate GARCH(1,1) (SR_P=7.45) and the Univariate GARCH(1,1) model (SR_P=7.30), as opposed to the Past Volatility model (SR_P=6.20) and the distant S&P 500 Index benchmark (SR_P=0.32). Surprisingly however, portfolios constructed based on conditional volatility models outperform on a risk-adjusted basis because of the larger returns, as opposed to a reduction in volatility, versus a portfolio structured based on the Past Volatility model. Whether this can be attributed to specific characteristics of returns or is a phenomenon remains unclear at this time and is left for other studies to examine. At this time, however, the benefits of conditional volatility forecasting versus past volatility, and the multivariate GARCH versus univariate GARCH volatility modeling, for daily hedge fund indices return data, remain inconclusive. Based on the above results we fail to reject H1 (Past Volatility vs. S&P 500) and H6 (Maximum Sharpe vs. S&P 500), for daily returns data. H3 (univariate GARCH(1,1) vs. Past Volatility), H5 (multivariate GARCH(1,1) vs. univariate GARCH(1,1)) and H8 (univariate GARCH(1,1) vs. Maximum Sharpe) remain inconclusive and warrant further investigation. For complete results refer to Table 11.

After including transaction costs, the Past Volatility SR_P drops to 5.98 and the S&P 500 SR_P drops to 0.28. Therefore, I fail to reject hypothesis H2. For results see Table 13.

Wealth effects, before and after transaction costs, are demonstrated in Figures 6 and 3, respectively.

7. Conclusion and Implications for Future Research

The results of this research clearly demonstrate large benefits of considering hedge fund indices as a stand-alone investment vehicle with a much better risk-return profile than the benchmark S&P 500 Index. Several hedge fund indices portfolios considered in this work were compared with each other, with the objective of determining what kind of portfolios have the best out-of-sample risk-return characteristics. The answer to the second question proved to be less straight-forward, as portfolios constructed based on conditional volatility forecasting rarely demonstrated a reduction in volatility when compared with the Maximum Sharpe portfolio and the Past Volatility portfolio. They did nevertheless generate the largest out-of-sample Sharpe ratios for all periods under consideration.

The results of this research are therefore inconclusive with respect to the hypotheses that conditional volatility forecasting provides added value when it comes to optimal dynamic portfolio asset allocation, composed of hedge fund indices.

After transaction costs are incorporated into the analysis, all hedge fund indices portfolios still largely outperform their benchmark – the S&P 500 Index. The proportionate benefits are somewhat lower, as the S&P 500 Index does not require any intra-period rebalancing. The largest transaction costs are incurred by the portfolios structured based on minimum variance conditional volatility forecasting, which explains the large reduction in benefits attributable to this investment strategy versus the Past Volatility and Maximum Sharpe Ratio strategies.

Potential topics for future work include: changes in volatility patterns of hedge fund styles through time, sources of the macro-economic and other shocks that have in the past led to unusually-high conditional volatility for a given hedge fund strategy, and common factors that have led to spikes in cross-correlations across hedge fund styles. All those inherent risks also need to be accounted for when designing an ultimate hedge fund indices investment strategy.

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Appendix 1: Credit Suisse First Boston / Tremont Hedge Fund Strategies Description

Convertible Arbitrage	This strategy is identified by hedge investing in the convertible securities of a company. A typical investment is to be long the convertible bond and short the common stock of the same company. Positions are designed to generate profits from the fixed income security as well as the short sale of stock, while protecting principal from market moves.
Dedicated Short Bias	Dedicated short sellers were once a robust category of hedge funds before the long bull market rendered the strategy difficult to implement. A new category, short biased, has emerged. The strategy is to maintain net short as opposed to pure short exposure. Short biased managers take short positions in mostly equities and derivatives. The short bias of a manager's portfolio must be constantly greater than zero to be classified in this category.
Emerging Markets	This strategy involves equity or fixed income investing in emerging markets around the world. Because many emerging markets do not allow short selling, nor offer viable futures or other derivative products with which to hedge, emerging market investing often employs a long-only strategy.
Equity Market Neutral	This investment strategy is designed to exploit equity market inefficiencies and usually involves being simultaneously long and short matched equity portfolios of the same size within a country. Market neutral portfolios are designed to be either beta or currency neutral, or both. Well-designed portfolios typically control for industry, sector, market capitalization, and other exposures. Leverage is often applied to enhance returns.
Event Driven	This strategy is defined as "special situations" investing designed to capture price movement generated by a significant pending corporate event such as a merger, corporate restructuring, liquidation, bankruptcy or reorganization. There are three popular sub-categories in event-driven strategies: risk (merger) arbitrage, distressed/high yield securities, and Regulation D.

Fixed Income Arbitrage The fixed income arbitrageur aims to profit from price anomalies between related interest rate securities. Most managers trade globally with a goal of generating steady returns with low volatility. This category includes interest rate swap arbitrage, US and non-US government bond arbitrage, forward yield curve arbitrage, and mortgage-backed securities arbitrage. The mortgage-backed market is primarily US-based, over-the-counter and particularly complex.

Global Macro Global macro managers carry long and short positions in any of the world's major capital or derivative markets. These positions reflect their views on overall market direction as influenced by major economic trends and or events. The portfolios of these funds can include stocks, bonds, currencies, and commodities in the form of cash or derivatives instruments. Most funds invest globally in both developed and emerging markets.

Long/Short Equity This directional strategy involves equity-oriented investing on both the long and short sides of the market. The objective is not to be market neutral. Managers have the ability to shift from value to growth, from small to medium to large capitalization stocks, and from a net long position to a net short position. Managers may use futures and options to hedge. The focus may be regional, such as long/short US or European equity, or sector specific, such as long and short technology or healthcare stocks. Long/short equity funds tend to build and hold portfolios that are substantially more concentrated than those of traditional stock funds.

Managed Futures This strategy invests in listed financial and commodity futures markets and currency markets around the world. The managers are usually referred to as Commodity Trading Advisors, or CTAs. Trading disciplines are generally systematic or discretionary. Systematic traders tend to use price and market specific information (often technical) to make trading decisions, while discretionary managers use a judgmental approach.

Appendix 2: Standard & Poor's Hedge Fund Sub-Indexes Strategy Descriptions

S&P Arbitrage Index	The S&P Arbitrage Index (a sub-index of the S&P Hedge Fund Index) is composed of funds attempting to exploit pricing differences among securities with similar risk characteristics, generally by taking long positions in the under-priced security and short positions in the relatively over-priced security. Typically, these strategies employ leverage to accentuate relatively small differences in price movements. These funds tend to have low systematic market exposure. The S&P Arbitrage Index has three component strategies: Equity Market Neutral, Fixed Income Arbitrage (including Mortgage Arbitrage), and Convertible Arbitrage.
S&P Event-Driven Index	The S&P Event-Driven Index (a sub-index of the S&P Hedge Fund Index) is composed of funds attempting to exploit mispricings of securities as it pertains to specific events, which are typically security specific (as opposed to macro-economic trends). Generally, funds in this category are looking for significant changes in outlook for firms that are in financial distress, are merger candidates, or have mispriced securities. The S&P Event-Driven Index has three component strategies: Merger Arbitrage, Distressed, and Special Situations.
S&P Directional/Tactical Index	The S&P Directional/Tactical Index (a sub-index of the S&P Hedge Fund Index) is composed of funds attempting to exploit general market trends or specific tactical situations. These funds are not market neutral, but rather are looking for anomalous prices using systematic or fundamental processes. They tend to have higher systematic market exposure. This S&P Directional/Tactical Index has three component strategies: Equity Long/Short, Managed Futures, and Macro.

Table 1: CSFB/Tremont Hedge Fund Indices Descriptive Statistics vs. S&P 500 Benchmark

	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity	Managed Futures	S&P 500 Index
2006 (until June)	7.48%	3.58%	7.23%	6.80%	7.35%	5.65%	8.60%	5.20%	2.13%	1.76%
2005	-2.55%	17.00%	17.39%	6.14%	8.95%	0.63%	9.25%	9.68%	-0.11%	3.00%
2004	1.98%	-7.72%	12.49%	6.48%	14.47%	6.86%	8.49%	11.56%	5.97%	8.99%
2003	12.90%	-32.59%	28.75%	7.07%	20.02%	7.97%	17.99%	17.27%	14.13%	26.38%
2002	4.05%	18.14%	7.36%	7.42%	0.16%	5.75%	14.66%	-1.60%	18.33%	-23.37%
2001	14.58%	-3.58%	5.84%	9.31%	11.50%	8.04%	18.38%	-3.65%	1.90%	-13.04%
2000	25.64%	15.76%	-5.52%	14.99%	7.26%	6.29%	11.67%	2.08%	4.24%	-10.14%
1999	16.04%	-14.22%	44.82%	15.33%	22.26%	12.11%	5.81%	47.23%	-4.69%	19.53%
1998	-4.41%	-6.00%	-37.66%	13.31%	-4.87%	-8.16%	-3.64%	17.18%	20.64%	26.67%
1997	14.48%	0.42%	26.59%	14.83%	19.96%	9.34%	37.11%	21.46%	3.12%	31.01%
1996	17.87%	-5.48%	34.50%	16.60%	23.06%	15.93%	25.58%	17.12%	11.97%	20.26%
1995	16.57%	-7.35%	-16.91%	11.04%	18.34%	12.50%	30.67%	23.03%	-7.10%	34.11%
1994	-8.07%	14.91%	12.51%	-2.00%	0.75%	0.31%	-5.72%	-8.10%	11.95%	-1.54%
Annualized Mean	8.97%	-1.05%	10.41%	10.07%	11.80%	6.40%	14.44%	12.83%	7.34%	9.51%
Annualized St.Dev	4.77%	17.20%	16.33%	2.93%	5.67%	3.73%	11.04%	10.24%	12.02%	18.40%
Sharpe Ratio	1.88	-0.06	0.64	3.43	2.08	1.72	1.31	1.25	0.61	0.52
Skewness	-1.2959	0.8508	-0.6711	0.3157	-3.3827	-3.0746	0.0175	0.2082	0.0268	-0.2749
Kurtosis	5.8260	5.0472	7.5070	3.3178	26.3733	19.0043	5.7335	6.7270	3.3272	1.8644
Jarque-Bera	90.0571	43.4069	135.4489	3.0604	3626.4930	1800.4450	45.7724	86.1438	0.6733	0.8623
Probability	0.0000	0.0000	0.0000	0.2165	0.0000	0.0000	0.0000	0.0000	0.7142	0.6498
Positive Months	77.87%	45.58%	63.27%	84.35%	81.63%	80.27%	73.47%	68.03%	55.78%	62.67%

This table presents summary statistics for Credit Suisse First Boston / Tremont Hedge Fund Indices monthly returns data extending from January 1994 until the end of June 2006 (for a total of 150 monthly returns), as well as their benchmark – the S&P 500 Index. CSFB/T Hedge Fund Indices consist of nine distinct strategies: Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long Short Equity, and Managed Futures.

Table 2: Annualized Standard and Poor's Hedge Fund Indices Descriptive Statistics vs. S&P 500 Benchmark (October 2002 – June 2006)

	Event Driven	Directional / Tactical	Arbitrage	S&P 500 Index
2006 (until June)	7.70%	5.67%	6.59%	1.76%
2005	4.61%	2.54%	-0.32%	3.00%
2004	5.66%	3.62%	2.36%	8.99%
2003	16.40%	15.29%	1.60%	26.38%
2002 (starting October)	2.85%	0.53%	1.46%	7.92%
Annualized Mean	9.38%	7.08%	3.07%	12.75%
Annualized St.Dev	2.13%	4.92%	3.28%	14.26%
Sharpe Ratio	4.40	1.44	0.94	0.89
Skewness	0.1751	-0.2588	0.1325	0.3856
Kurtosis	5.6171	4.1309	3.8129	5.2839
Jarque-Bera	275.1025	61.0353	28.8470	228.8040
Probability	0.0000	0.0000	0.0000	0.0000
Positive Days	64.52%	55.86%	50.69%	54.39%
Positive Weeks	76.06%	64.36%	55.32%	58.16%
Positive Months	82.22%	68.89%	62.22%	66.67%

This table presents summary statistics for the three main Standard & Poor's Hedge Fund Indices (Event Driven, Directional/Tactical, and Arbitrage) returns, as compared to the S&P 500 Index benchmark. Annualized mean return is calculated by multiplying average daily returns (from October 2002 until June 2006) by 250. Standard deviations are calculated by multiplying average daily standard deviations by $\sqrt{250}$. Sharpe Ratio is equal to resulting annualized returns divided by resulting annualized standard deviations.

Table 3: In-Sample (October 1, 2002 – November 30, 2005) Univariate Asymmetric GARCH(1,1) Model Estimates - Standard and Poor's Hedge Fund Indices, Daily Returns Data

Mean equation: $r_t = \mu + \varepsilon_t$, where $\varepsilon_t | \Omega_{t-1} \sim td(0, \sigma_t^2, v)$

Volatility equation: $\hat{\sigma}_{t+1}^2 = \hat{\alpha}_0 + (\hat{\alpha}_1 + \hat{\gamma}_1 S_t)\varepsilon_t^2 + \hat{\beta}_1 \sigma_t^2$, where $S_t = \begin{cases} 1, \varepsilon_t < 0 \\ 0, \varepsilon_t > 0 \end{cases}$

	Event	T-stat	Signif.	Directional	T-stat	Signif.	Arbitrage	T-stat	Signif.
μ	0.036816** [0.003970]	9.2740	0.0000	0.033827** [0.009936]	3.4045	0.0007	0.001567 [0.006539]	0.2397	0.8106
$\hat{\alpha}_0$	0.001669* [0.000856]	1.9484	0.0514	0.070801** [0.020616]	3.4342	0.0006	0.001197* [0.000638]	1.8780	0.0604
$\hat{\alpha}_1$	0.123671** [0.049059]	2.5209	0.0117	0.220625** [0.092039]	2.3971	0.0165	0.116918** [0.037950]	3.0808	0.0021
$\hat{\beta}_1$	0.830254** [0.068249]	12.1651	**0.0000**	0.118215 [0.212748]	0.5557	0.5784	0.888166** [0.031091]	28.5671	**0.0000**
$\hat{\gamma}_1$	-0.090359* [0.047657]	-1.8960	0.0580	-0.227772** [0.096212]	-2.3674	0.0179	-0.061791 [0.048166]	-1.2829	0.1995

This table shows the in-sample, Univariate Asymmetric GARCH(1,1) calibration statistics for the three main S&P Hedge Fund Indices, based on the daily returns data. Standard errors are reported in parentheses. ** refers to significance at a 5% level and * refers to significance at a 10% level. Event Driven and Arbitrage Hedge Fund Indices show significant $\hat{\beta}_1$ coefficients indicating that next period volatility is conditional upon the prior experienced volatility.

Table 4: In-Sample (October 1, 2002 – November 30, 2005) Univariate Asymmetric GARCH(1,1) Model Estimates - Standard and Poor's Hedge Fund Indices, Weekly Returns Data

Mean equation: $r_t = \mu + \varepsilon_t$, where $\varepsilon_t | \Omega_{t-1} \sim td(0, \sigma_t^2, v)$

Volatility equation: $\hat{\sigma}_{t+1}^2 = \hat{\alpha}_0 + (\hat{\alpha}_1 + \hat{\gamma}_1 S_t)\varepsilon_t^2 + \hat{\beta}_1 \sigma_t^2$, where $S_t = \begin{cases} 1, \varepsilon_t < 0 \\ 0, \varepsilon_t > 0 \end{cases}$

	Event	T-stat	Signif.	Directional	T-stat	Signif.	Arbitrage	T-stat	Signif.
μ	0.194679** [0.022870]	8.5124	0.0000	0.212045** [0.055757]	3.8030	0.0001	0.036869 [0.027286]	1.3512	0.1766
$\hat{\alpha}_0$	0.216692** [0.049637]	4.3655	0.0000	0.076762** [0.035605]	2.1560	0.0311	0.231606** [0.026965]	8.5892	0.0000
$\hat{\alpha}_1$	-0.052612 [0.082278]	-0.6394	0.5225	-0.100240** [0.015416]	-6.5021	0.0000	-0.050612 [0.036666]	-1.3804	0.1675
$\hat{\beta}_1$	-0.852881** [0.272252]	-3.1327	**0.0017**	0.886674** [0.085063]	10.4237	**0.0000**	-0.962064** [0.048855]	-19.6921	**0.0000**
$\hat{\gamma}_1$	0.103047 [0.150526]	0.6846	0.4936	0.255427 [0.167270]	1.5270	0.1268	0.055443 [0.048859]	1.1348	0.2565

This table shows the in-sample Univariate Asymmetric GARCH(1,1) calibration statistics for the three main S&P Hedge Fund Indices, based on the weekly returns data. Standard errors are reported in parentheses. ** refers to significance at a 5% level and * refers to significance at a 10% level. All three Hedge Fund Indices show significant $\hat{\beta}_1$ coefficients indicating that next period volatility is conditional upon the prior experienced volatility.

Table 5: In-Sample (January 1994 – April 2002) Univariate Asymmetric GARCH(1,1) Model Estimates – Credit Suisse First Boston Hedge Fund Indices, Monthly Returns Data

Mean equation: $r_t = \mu + \varepsilon_t$, where $\varepsilon_t | \Omega_{t-1} \sim td(0, \sigma_t^2, v)$

Volatility equation: $\hat{\sigma}_{t+1}^2 = \hat{\alpha}_0 + (\hat{\alpha}_1 + \hat{\gamma}_1 S_t)\varepsilon_t^2 + \hat{\beta}_1 \sigma_t^2$, where $S_t = \begin{cases} 1, \varepsilon_t < 0 \\ 0, \varepsilon_t > 0 \end{cases}$

	Convertible Arbitrage	T-stat	Signif.	Short Bias	T-stat	Signif.	Emerging Markets	T-stat	Signif.
μ	1.260775** [0.072148]	17.4747	0.0000	-0.279452 [0.541769]	-0.5158	0.6060	1.438008** [0.427369]	3.3648	0.0008
$\hat{\alpha}_0$	0.514379 [0.345636]	1.4882	0.1367	45.175571* [25.419934]	1.7772	0.0755	28.624594** [11.211867]	2.5531	0.0107
$\hat{\alpha}_1$	2.268389 [1.655709]	1.3700	0.1707	0.112295 [0.322947]	0.3477	0.7281	0.198297 [0.289209]	0.6857	0.4929
$\hat{\beta}_1$	0.016008 [0.116408]	0.1375	0.8906	-0.724594 [0.885808]	-0.8180	0.4134	-0.259281 [0.477472]	-0.5430	0.5871
$\hat{\gamma}_1$	-1.561378 [1.429861]	-1.0920	0.2748	-0.112997 [0.325568]	-0.3471	0.7285	-0.085176 [0.371171]	-0.2295	0.8185

Note – Standard Errors are reported in parentheses; ** Refers to significance at a 5% level; * Refers to significance at a 10% level. More detailed description of the table 5 is provided on page 47.

Table 5 cont: In-Sample (January 1994 – April 2002) Univariate Asymmetric GARCH(1,1) Model Estimates – Credit Suisse First Boston Hedge Fund Indices, Monthly Returns Data

Mean equation: $r_t = \mu + \varepsilon_t$, where $\varepsilon_t | \Omega_{t-1} \sim td(0, \sigma_t^2, v)$

Volatility equation: $\hat{\sigma}_{t+1}^2 = \hat{\alpha}_0 + (\hat{\alpha}_1 + \hat{\gamma}_1 S_t)\varepsilon_t^2 + \hat{\beta}_1 \sigma_t^2$, where $S_t = \begin{cases} 1, \varepsilon_t < 0 \\ 0, \varepsilon_t > 0 \end{cases}$

	Market Neutral	T-stat	Signif.	Event Driven	T-stat	Signif.	Fixed Income	T-stat	Signif.
μ	0.937856** [0.080982]	11.0093	0.0000	1.120357** [0.117580]	9.5285	0.0000	0.841088** [0.061180]	13.7478	0.0000
$\hat{\alpha}_0$	0.096434 [0.077273]	0.7881	0.4306	1.931446** [0.888482]	2.1739	0.0297	0.210009** [0.105577]	1.9892	0.0467
$\hat{\alpha}_1$	0.136829 [0.087850]	1.0165	0.3094	0.463186 [0.570523]	0.8119	0.4169	0.845864 [0.5401]	1.5661	0.1173
$\hat{\beta}_1$	0.759854** [0.130119]	3.5456	**0.0004**	-0.107471 [0.334867]	-0.3209	0.7483	0.308894** [0.152617]	2.0240	**0.0430**
$\hat{\gamma}_1$	-0.032632 [0.087863]	-0.2510	0.8018	-0.533764 [0.568413]	-0.9390	0.3477	-0.846757 [0.603510]	-1.4031	0.1606

Note – Standard Errors are reported in parentheses; ** Refers to significance at a 5% level; * Refers to significance at a 10% level. More detailed description of the table 5 is provided on page 47.

Table 5 cont: In-Sample (January 1994 – April 2002) Univariate Asymmetric GARCH(1,1) Model Estimates – Credit Suisse First Boston Hedge Fund Indices, Monthly Returns Data

Mean equation: $r_t = \mu + \varepsilon_t$, where $\varepsilon_t | \Omega_{t-1} \sim td(0, \sigma_t^2, v)$

Volatility equation: $\hat{\sigma}_{t+1}^2 = \hat{\alpha}_0 + (\hat{\alpha}_1 + \hat{\gamma}_1 S_t)\varepsilon_t^2 + \hat{\beta}_1 \sigma_t^2$, where $S_t = \begin{cases} 1, \varepsilon_t < 0 \\ 0, \varepsilon_t > 0 \end{cases}$

	Global Macro	T-stat	Signif.	Long-Short	T-stat	Signif.	Managed Futures	T-stat	Signif.
μ	1.426439** [0.329641]	4.3273	0.0000	0.821498** [0.259316]	3.2402	0.0012	0.324616 [0.285542]	1.1368	0.2556
$\hat{\alpha}_0$	18.933762* [11.367276]	1.6656	0.0958	0.720836 [0.715040]	0.8394	0.4012	5.596718 [3.935533]	1.4221	0.1550
$\hat{\alpha}_1$	0.162303 [0.191224]	0.8488	0.3960	-0.011850 [0.077743]	0.4243	0.6713	-0.063144 [0.158677]	-0.3979	0.6907
$\hat{\beta}_1$	-0.449809 [0.568971]	-0.7906	0.4292	0.735191 [0.131971]	0.0169	0.9865	0.358140 [0.379422]	0.9439	0.3452
$\hat{\gamma}_1$	0.068028 [0.303707]	0.2240	0.8228	0.418529 [0.210832]	0.0000	1.0000	0.535057 [0.479897]	1.1149	0.2649

This table shows the in-sample Univariate Asymmetric GARCH(1,1) calibration statistics for the nine CSFB/Tremont Hedge Fund Indices, based on the monthly returns data. Standard errors are reported in parentheses. ** refers to significance at a 5% level and * refers to significance at a 10% level. Two (Market Neutral and Fixed Income) out of nine indices show significant $\hat{\beta}_1$ coefficients indicating that the next period volatility is conditional upon the prior recorded volatility.

Table 6: Standard & Poor's Hedge Fund Indices Weekly Returns Descriptive Statistics (October 2002 – June 2006)

	Arbitrage	Directional	Event Driven
Mean	0.0624%	0.1470%	0.1843%
St.Dev	0.3421%	0.7483%	0.3363%
Skewness	0.1071	-0.6313	-0.5207
Kurtosis	3.1277	3.8115	4.4422
Jarque-Bera	0.4874	17.6455	24.7899
Probability	0.7837	0.0001	0.0000
Positive Weeks	55.32%	64.36%	76.06%

Table 7: Standard & Poor's Hedge Fund Indices Daily Returns Descriptive Statistics (October 2002 – June 2006)

	Arbitrage	Directional	Event Driven
Mean	0.0125%	0.0291%	0.0365%
St.Dev	0.2077%	0.3118%	0.1383%
Skewness	0.1305	-0.2588	0.1751
Kurtosis	3.8116	4.1309	5.6171
Jarque-Bera	28.7106	61.0353	275.1025
Probability	0.0000	0.0000	0.0000
Positive Days	50.69%	55.86%	64.52%

Table 8: In-Sample (October 1, 2002 – November 30, 2005) Multivariate GJR-GARCH(1,1) Model Estimates - Standard and Poor's Hedge Fund Indices, Daily Returns Data

Variable	Coefficients	Standard Error	T-Stat	Significance
μ_1	0.038395207**	0.004133434	9.28894	0.00000000
μ_2	0.041938612**	0.010109295	4.14852	0.00003346
μ_3	0.001533973	0.006426283	0.23870	0.81133589
C(1,1)	0.001461460**	0.000598560	2.44162	0.01462134
C(2,1)	0.000097808	0.000112902	0.86630	0.38632338
C(2,2)	0.072116913**	0.031295378	2.30439	0.02120048
C(3,1)	-0.000241504	0.000254535	-0.94880	0.34272043
C(3,2)	-0.000289726	0.000504747	-0.57400	0.56596640
C(3,3)	0.001328351*	0.000699867	1.89800	0.05769561
A(1,1)	0.110604145**	0.033139164	3.33757	0.00084516
A(2,1)	0.024714130**	0.011165119	2.21351	0.02686233
A(2,2)	0.115200506*	0.062952250	1.82997	0.06725496
A(3,1)	0.032090772	0.022035276	1.45634	0.14529968
A(3,2)	0.016639822	0.017921318	0.92849	0.35315180
A(3,3)	0.148535525**	0.043299171	3.43045	0.00060259
B(1,1)	0.836867726**	0.052041417	16.08080	0.00000000
B(2,1)	0.965492945**	0.018188173	53.08356	0.00000000
B(2,2)	0.160989371	0.340082513	0.47338	0.63593977
B(3,1)	0.909155345**	0.073812889	12.31703	0.00000000
B(3,2)	0.935552706**	0.095217424	9.82544	0.00000000
B(3,3)	0.876087488**	0.031761246	27.58354	0.00000000
D(1)	-0.076309683**	0.032556134	-2.34394	0.01908115
D(2)	-0.140341832**	0.067602937	-2.07597	0.03789650
D(3)	-0.090101684*	0.052597150	-1.71305	0.08670287
Shape	7.831669522**	1.257613937	6.22740	0.00000000

This table shows the in-sample Multivariate Asymmetric GARCH(1,1) calibration statistics jointly estimated based on the three (Event Driven, Directional/Tactical, and Arbitrage) Standard & Poor's Hedge Fund Indices daily returns data. ** refers to significance at a 5% level and * refers to significance at a 10% level.

Table 9: Out-of-Sample (May 2002 – June 2006) Monthly-Rebalanced Portfolios Composed of Nine Credit Suisse First Boston / Tremont Hedge Fund Indices, After Accounting for Transaction Costs

	Max Sharpe Portfolio	**Past Volatility Portfolio**	**Univariate GJR-GARCH Portfolio**	**S&P 500 Index**
Average Monthly Return	0.54%	0.65%	0.56%	0.39%
Average Monthly St.Dev	0.55%	0.65%	0.59%	3.70%
Annualized Mean Return	6.52%	7.82%	6.76%	4.72%
Annualized St. Dev	1.89%	2.26%	2.03%	12.83%
Sharpe Ratio	**3.44**	**3.46**	**3.33**	**0.37**
Out-of-sample Months	50	50	50	50
Positive Months	82.69%	86.00%	80.77%	62.00%
Average Decline	-0.19%	-0.36%	-0.26%	-3.07%
Worst Month	-0.75%	-0.82%	-0.71%	-11.00%
Largest Drawdown	-0.88%	-1.26%	-1.09%	-16.05%

This table shows the Maximum Sharpe, Past Volatility, and the Univariate GJR-GARCH investment portfolios characteristics and how they compare against each other and to the S&P 500 Index benchmark, after the round-trip transaction costs of 50bp are incorporated into the performance calculations. Monthly returns data from nine Credit Suisse First Boston / Tremont Hedge Fund Indices is used for portfolios construction.

Table 10: Out-of-Sample (December 1, 2005 – June 30, 2006) Weekly-Rebalanced Portfolios Composed of Three Standard and Poor's Hedge Fund Indices, After Accounting for Transaction Costs

	Max Sharpe Portfolio	**Past Volatility Portfolio**	**Univariate GJR-GARCH Portfolio**	**S&P 500 Index**
Average Weekly Return	0.20%	0.20%	0.16%	0.01%
Average Weekly St. Dev.	0.33%	0.29%	0.30%	1.39%
Annualized Mean Return	10.54%	10.61%	8.40%	0.32%
Annualized St. Dev.	2.36%	2.10%	2.18%	10.03%
Sharpe Ratio	**4.47**	**5.06**	**3.86**	**0.03**
Out-of-sample Weeks	31	31	31	31
Positive Weeks	74.19%	77.42%	74.19%	48.39%
Average Weekly Decline	-0.19%	-0.18%	-0.22%	-1.01%
Worst Week	-0.41%	-0.27%	-0.57%	-2.79%
Largest Drawdown	-0.41%	-0.27%	-0.59%	-4.48%

This table shows the Maximum Sharpe, Past Volatility, and the Univariate GJR-GARCH investment portfolios characteristics and how they compare against each other and to the S&P 500 Index benchmark, after the round-trip transaction costs of 50bp are incorporated into the performance calculations. Weekly returns data from three Standard & Poor's Hedge Fund Indices is used for portfolios construction.

Table 11: Out-of-Sample (December 1, 2005 – June 30, 2006) Daily Rebalanced Portfolios Composed of Standard and Poor's Hedge Fund Indices, Before Transactions Costs are Included

	Past Volatility Portfolio	**Univariate GJR-GARCH Portfolio**	**Multivariate GJR-GARCH Portfolio**	**S&P 500 Index**
Average Daily Return	0.0485%	0.0563%	0.0592%	0.0135%
Average Daily St. Dev.	0.1314%	0.1308%	0.1354%	0.6767%
Annualized Mean Return	12.87%	15.11%	15.95%	3.38%
Annualized St. Dev.	2.08%	2.069%	2.141%	10.70%
Sharpe Ratio	**6.20**	**7.30**	**7.45**	**0.32**
Out-of-sample Days	146	146	146	146
Positive Days	69.86%	69.86%	70.55%	52.05%
Average Daily Decline	-0.1041%	-0.0966%	-0.0943%	-0.5125%
Worst Day	-0.2742%	-0.2623%	-0.2819%	-1.8326%
Largest Drawdown	-0.4244%	-0.4545%	-0.4016%	-2.7453%

This table shows the Past Volatility, Univariate GJR-GARCH, and the Multivariate GJR-GARCH investment portfolios characteristics and how they compare against each other and to the S&P 500 Index benchmark. Daily returns data from three Standard & Poor's Hedge Fund Indices is used for portfolios construction.

Table 12: Out-of-Sample (May 2002 – June 2006) Monthly-Rebalanced Portfolios Composed of Nine Credit Suisse First Boston / Tremont Hedge Fund Indices, Before Transactions Costs are Included

	Max Sharpe Portfolio	**Past Volatility Portfolio**	**Univariate GJR-GARCH Portfolio**	**S&P 500 Index**
Average Monthly Return	0.56%	0.66%	0.63%	0.40%
Average Monthly St.Dev	0.54%	0.65%	0.58%	3.70%
Annualized Mean Return	6.73%	7.90%	7.60%	4.78%
Annualized St. Dev	1.88%	2.67%	2.00%	12.82%
Sharpe Ratio	**3.57**	**3.48**	**3.79**	**0.37**
Out-of-sample Months	50	50	50	50
Positive Months	84.62%	86.00%	86.54%	62.00%
Average Decline	-0.20%	-0.36%	-0.27%	-3.05%
Worst Month	-0.72%	-0.82%	-0.64%	-11.00%
Largest Drawdown	-0.84%	-1.25%	-0.99%	-16.05%

This table shows the Maximum Sharpe, Past Volatility, and the Univariate GJR-GARCH investment portfolios characteristics and how they compare against each other and to the S&P 500 Index benchmark, before the round-trip transaction costs of 50bp are incorporated into the performance calculations. Monthly returns data from nine Credit Suisse First Boston / Tremont Hedge Fund Indices is used for portfolios construction.

Table 13: Out-of-Sample (December 1, 2005 – June 30, 2006) Daily Rebalanced Portfolios Composed of Standard and Poor's Hedge Fund Indices, After Accounting for Transaction Costs

	Past Volatility Portfolio	**S&P 500 Index**
Average Daily Return	0.0465%	0.0118%
Average Daily St. Dev.	0.1303%	0.6740%
Annualized Mean Return	12.31%	2.96%
Annualized St. Dev.	2.06%	10.66%
Sharpe Ratio	**5.98**	**0.28**
Out-of-sample Days	146	146
Positive Days	69.86%	52.05%
Average Daily Decline	-0.1044%	-0.5125%
Worst Day	-0.2743%	-1.8326%
Largest Drawdown	-0.4248%	-2.7453%

This table shows the Past Volatility investment portfolios characteristics and how it compares to the S&P 500 Index benchmark, after 50bp round-trip transaction costs are incorporated into the performance calculations. Daily returns data from three Standard & Poor's Hedge Fund Indices is used to construct Past Volatility portfolio.

Table 14: Out-of-Sample (December 1, 2005 – June 30, 2006) Weekly-Rebalanced Portfolios Composed of Three Standard and Poor's Hedge Fund Indices, Before Transactions Costs are Included

	Max Sharpe Portfolio	Past Volatility Portfolio	Univariate GJR-GARCH Portfolio	S&P 500 Index
Average Weekly Return	0.22%	0.21%	0.23%	0.01%
Average Weekly St. Dev.	0.32%	0.28%	0.29%	1.39%
Annualized Mean Return	11.48%	11.12%	11.78%	0.74%
Annualized St. Dev.	2.30%	2.02%	2.09%	10.01%
Sharpe Ratio	**4.98**	**5.51**	**5.65**	**0.07**
Out-of-sample Weeks	31	31	31	31
Positive Weeks	77.42%	77.42%	80.65%	48.39%
Average Weekly Decline	-0.18%	-0.14%	-0.17%	-0.99%
Worst Week	-0.40%	-0.27%	-0.21%	-2.79%
Largest Drawdown	-0.40%	-0.27%	-0.37%	-4.48%

This table shows the Maximum Sharpe, Past Volatility, and the Univariate GJR-GARCH investment portfolios characteristics and how they compare against each other and to the S&P 500 Index benchmark, before transaction costs are incorporated into the performance calculations. Weekly returns data from three Standard & Poor's Hedge Fund Indices is used for portfolios construction.

Table 15: CSFB/Tremont Hedge Fund Indices Monthly Returns Cross-Correlations (January 1994 – June 2006)

	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity	Managed Futures
Convertible Arbitrage	1	0.3084	0.5746	0.5339	0.2965	0.2870	-0.1310	0.3419	-0.2493
Dedicated Short Bias	0.3084	1	0.6770	0.2795	0.4167	0.5982	-0.0749	0.2220	-0.5550
Emerging Markets	0.5746	0.6770	1	0.3929	0.3825	0.6673	-0.1408	0.3627	-0.6323
Equity Market Neutral	0.5339	0.2795	0.3929	1	0.4500	0.2093	-0.0617	0.1219	-0.0756
Event Driven	0.2965	0.4167	0.3825	0.4500	1	0.4322	0.2504	0.2167	-0.1375
Fixed Income Arbitrage	0.2870	0.5982	0.6673	0.2093	0.4322	1	0.0142	0.3496	-0.7210
Global Macro	-0.1310	-0.0749	-0.1408	-0.0617	0.2504	0.0142	1	0.1297	0.1177
Long Short Equity	0.3419	0.2220	0.3627	0.1219	0.2167	0.3496	0.1297	1	-0.3273
Managed Futures	-0.2493	-0.5550	-0.6323	-0.0756	-0.1375	-0.7210	0.1177	-0.3273	1

Table 16: Standard & Poor's Hedge Fund Indices Weekly Returns Cross-Correlations (October 2002 – June 2006)

	Arbitrage	Directional	Event Driven
Arbitrage	1	0.0250	-0.0047
Directional	0.0250	1	0.3139
Event Driven	-0.0047	0.3139	1

Table 17: Standard & Poor's Hedge Fund Indices Daily Returns Cross-Correlations (October 2002 – June 2006)

	Arbitrage	Directional	Event Driven
Arbitrage	1	-0.0499	-0.1572
Directional	-0.0499	1	0.2397
Event Driven	-0.1572	0.2397	1

Table 18: Credit Suisse First Boston / Tremont Maximum Sharpe Portfolio Monthly Allocations as of the 1st trading day of January (2003-2006)

	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity	Managed Futures
January 2006	0.00%	5.96%	0.00%	74.45%	12.22%	0.12%	3.19%	0.83%	3.23%
January 2005	8.64%	7.40%	0.00%	66.12%	8.13%	4.92%	0.00%	3.67%	1.12%
January 2004	18.56%	6.80%	0.00%	67.71%	0.00%	1.33%	0.00%	4.60%	1.00%
January 2003	17.92%	8.00%	0.00%	65.63%	0.00%	2.68%	0.00%	5.76%	0.00%

This table shows the optimal asset allocation weights to each of the nine CSFB/Tremont Hedge Fund Indices under consideration, as directed by the Maximum Sharpe portfolio investment strategy. Optimal weights are shown for the months of January and the out-of-sample years are 2003, 2004, 2005 and 2006.

Table 19: Credit Suisse First Boston / Tremont Past Volatility Portfolio Monthly Allocations as of the 1st trading day of January (2003-2006)

	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity	Managed Futures
January 2006	13.73%	3.78%	4.52%	29.68%	11.36%	17.33%	7.54%	6.31%	5.75%
January 2005	15.63%	3.99%	4.60%	25.99%	11.91%	18.45%	6.88%	6.55%	6.00%
January 2004	16.10%	3.95%	4.49%	26.18%	11.92%	18.61%	6.20%	6.52%	6.04%
January 2003	16.12%	4.14%	4.37%	25.15%	12.16%	19.11%	6.08%	6.62%	6.25%

This table shows the optimal asset allocation weights to each of the nine CSFB/Tremont Hedge Fund Indices under consideration, as directed by the Past Volatility portfolio investment strategy. Optimal weights are shown for the months of January and the out-of-sample years are 2003, 2004, 2005 and 2006.

Table 20: Credit Suisse First Boston / Tremont Univariate GJR-GARCH Portfolio Monthly Allocations as of the 1st trading day of January (2003-2006)

	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Global Macro	Long Short Equity	Managed Futures
January 2006	8.94%	2.46%	2.94%	30.52%	7.39%	34.98%	4.91%	4.11%	3.75%
January 2005	11.72%	2.99%	3.45%	26.71%	8.93%	31.63%	5.16%	4.91%	4.50%
January 2004	7.82%	1.92%	2.18%	50.37%	5.79%	22.81%	3.01%	3.17%	2.94%
January 2003	14.22%	3.65%	3.86%	44.38%	10.73%	6.46%	5.36%	5.84%	5.52%

This table shows the optimal asset allocation weights to each of the nine CSFB/Tremont Hedge Fund Indices under consideration, as directed by the Univariate GJR-GARCH portfolio investment strategy. Optimal weights are shown for the months of January and the out-of-sample years are 2003, 2004, 2005 and 2006.

Table 21: Standard & Poor's Hedge Fund Indices Maximum Sharpe Portfolio Weekly Allocations as of the 1st trading day of each month (December 2005-June 2006)

	Event Driven	Directional/Tactical	Arbitrage
June 2006	70.95%	9.51%	19.54%
May 2006	74.06%	9.60%	16.35%
April 2006	73.86%	9.96%	16.18%
March 2006	74.43%	10.92%	14.65%
February 2006	72.17%	10.52%	17.31%
January 2006	73.39%	10.65%	15.96%
December 2005	73.62%	12.04%	14.34%

This table shows the optimal asset allocation weights to each of the three Standard & Poor's Hedge Fund Indices under consideration, as directed by the Maximum Sharpe portfolio investment strategy. Optimal weights are shown for the first week of the seven months between December 2005 and June 2006.

Table 22: Standard & Poor's Hedge Fund Indices Past Volatility Portfolio Weekly Allocations as of the 1st trading day of each month (December 2005-June 2006)

	Event Driven	Directional/Tactical	Arbitrage
June 2006	41.37%	17.07%	41.56%
May 2006	41.98%	17.31%	40.70%
April 2006	42.21%	17.62%	40.17%
March 2006	42.04%	17.80%	40.16%
February 2006	42.28%	17.70%	40.02%
January 2006	41.93%	17.50%	40.57%
December 2005	41.16%	18.28%	40.55%

This table shows the optimal asset allocation weights to each of the three Standard & Poor's Hedge Fund Indices under consideration, as directed by the Past Volatility portfolio investment strategy. Optimal weights are shown for the first week of the seven months between December 2005 and June 2006.

Table 23: Standard & Poor's Hedge Fund Indices Univariate GJR-GARCH Portfolio Weekly Allocations as of the 1st trading day of each month (December 2005-June 2006)

	Event Driven	Directional/Tactical	Arbitrage
June 2006	29.84%	4.66%	65.50%
May 2006	47.56%	8.58%	43.86%
April 2006	49.96%	6.93%	43.11%
March 2006	44.71%	7.83%	47.46%
February 2006	29.97%	4.59%	65.44%
January 2006	58.59%	6.91%	34.50%
December 2005	30.28%	5.85%	63.87%

This table shows the optimal asset allocation weights to each of the three Standard & Poor's Hedge Fund Indices under consideration, as directed by the Univariate GJR-GARCH portfolio investment strategy. Optimal weights are shown for the first week of the seven months between December 2005 and June 2006.

Table 24: Standard & Poor's Hedge Fund Indices Past Volatility Portfolio Daily Allocations as of the 1st trading day of each month (December 2005-June 2006)

	Event Driven	Directional/Tactical	Arbitrage
June 2006	48.02%	19.50%	32.47%
May 2006	48.40%	19.96%	31.64%
April 2006	47.89%	20.29%	31.82%
March 2006	48.30%	20.29%	31.40%
February 2006	48.37%	20.47%	31.16%
January 2006	47.78%	20.61%	31.61%
December 2005	48.23%	20.99%	30.78%

This table shows the optimal asset allocation weights to each of the three Standard & Poor's Hedge Fund Indices under consideration, as directed by the Past Volatility portfolio investment strategy. Optimal weights are shown for the first day of the seven months between December 2005 and June 2006.

Table 25: Standard & Poor's Hedge Fund Indices Univariate GJR-GARCH Portfolio Daily Allocations as of the 1st trading day of each month (December 2005-June 2006)

	Event Driven	Directional/Tactical	Arbitrage
June 2006	83.03%	1.40%	15.57%
May 2006	60.23%	11.13%	28.64%
April 2006	49.30%	45.10%	5.60%
March 2006	59.39%	6.72%	33.89%
February 2006	19.43%	47.74%	32.84%
January 2006	84.89%	8.90%	6.21%
December 2005	47.96%	4.57%	47.47%

This table shows the optimal asset allocation weights to each of the three Standard & Poor's Hedge Fund Indices under consideration, as directed by the Univariate GJR-GARCH portfolio investment strategy. Optimal weights are shown for the first day of the seven months between December 2005 and June 2006.

Table 26: Standard & Poor's Hedge Fund Indices Multivariate GJR-GARCH Portfolio Daily Allocations as of the 1st trading day of each month (December 2005-June 2006)

	Event Driven	Directional/Tactical	Arbitrage
June 2006	95.18%	0.00%	4.82%
May 2006	78.90%	0.63%	20.47%
April 2006	54.45%	44.44%	1.13%
March 2006	79.81%	0.00%	20.19%
February 2006	25.78%	55.25%	18.97%
January 2006	98.74%	0.00%	1.19%
December 2005	45.37%	0.00%	54.61%

This table shows the optimal asset allocation weights to each of the three Standard & Poor's Hedge Fund Indices under consideration, as directed by the Multivariate GJR-GARCH portfolio investment strategy. Optimal weights are shown for the first day of the seven months between December 2005 and June 2006.

Figure 1: Out-of-Sample Wealth Effects of Monthly-Rebalanced Credit Suisse First Boston Hedge Fund Indices Portfolios, After Transaction Costs are Included

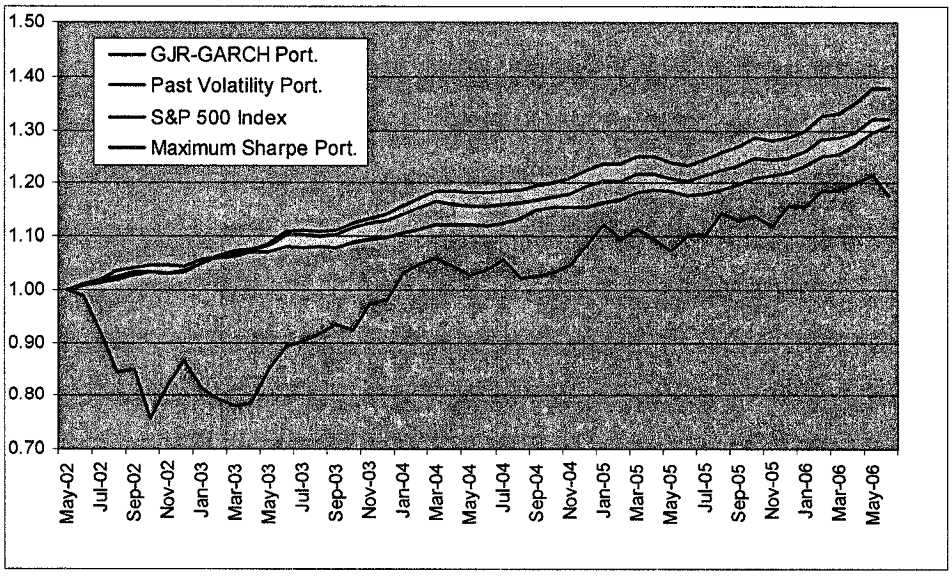

Figure 2: Out-of-Sample Wealth Effects of Weekly-Rebalanced Standard & Poor's Hedge Fund Indices Portfolios, After Transaction Costs are Included

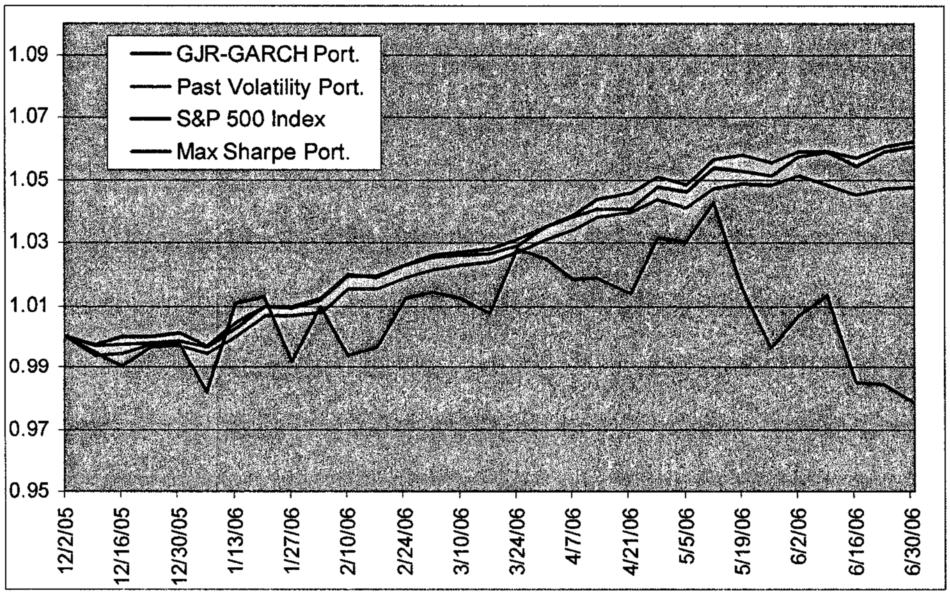

Figure 3: Out-of-Sample Wealth Effects of Daily-Rebalanced Standard & Poor's Hedge Fund Indices Portfolios, After Transaction Costs are Included

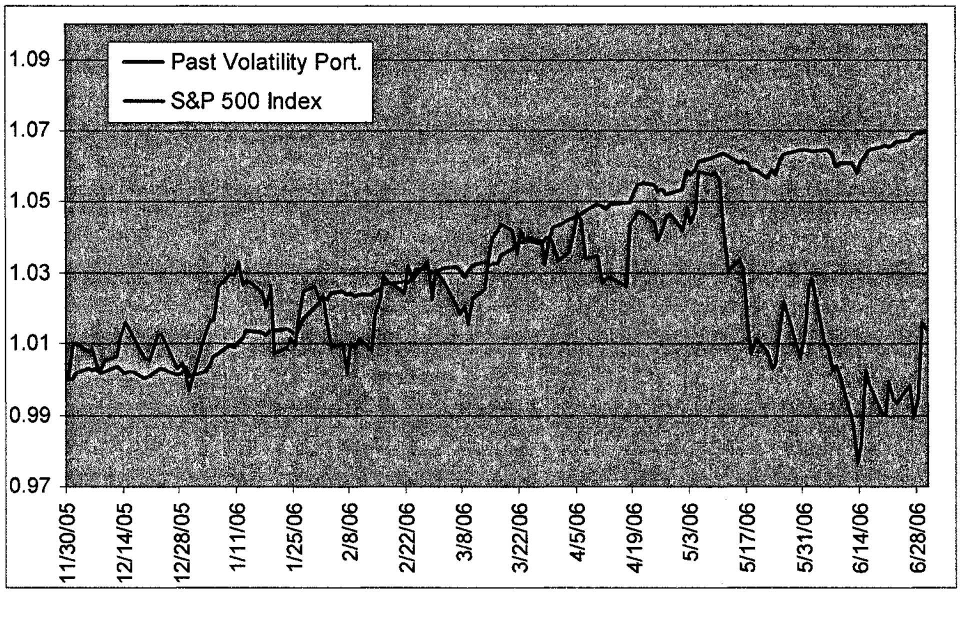

Figure 4: Out-of-Sample Wealth Effects of Monthly-Rebalanced Credit Suisse First Boston Hedge Fund Indices Portfolios, Before Transaction Costs are Included

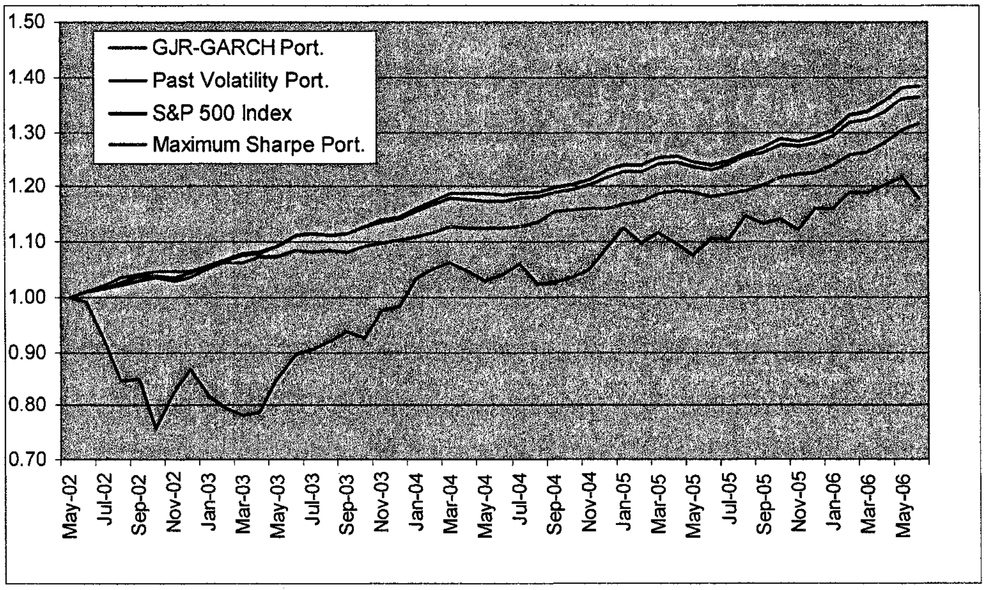

Figure 5: Out-of-Sample Wealth Effects of Weekly-Rebalanced Standard & Poor's Hedge Fund Indices Portfolios, Before Transaction Costs are Included

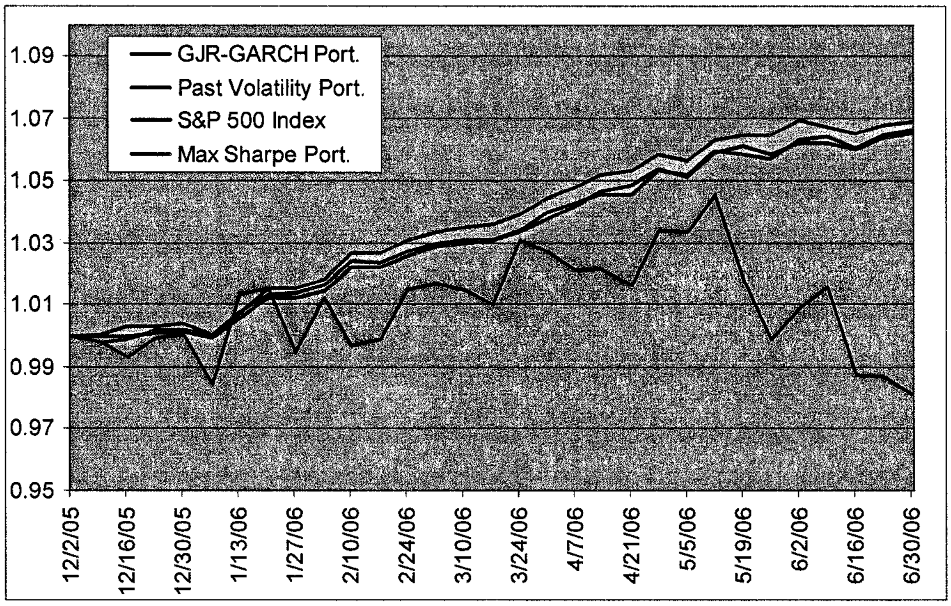

Figure 6: Out-of-Sample Wealth Effects of Daily-Rebalanced Standard & Poor's Hedge Fund Indices Portfolios, Before Transaction Costs are Included