Evaluating Hedge Fund Performance: *Traditional Versus Conditional Approaches*

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I. INTRODUCTION

With the growth of hedge funds in the 1990s, considerable research has been conducted on the sources of returns for various hedge fund strategies. Research (Goetzmann, Ingersoll, and Ross [1998], Liang [1999, 2001], Schneeweis, Kazemi, and Martin [2002], Brown, Goetzmann, and Liang [2003]) has concentrated not only on the impact of micro (e.g., firm-based issues such as fees, lockup, high-water marks, etc.) factors on fund performance, but also on market-based (e.g., economic factors) sources of hedge fund returns (Fung and Hsieh [1997], Liang [1999], Agarwal and Naik [2000b], Schneeweis, Kazemi, and Martin [2003]). Results have shown that the returns of some hedge fund strategies (e.g., Equity Hedge and Distressed Securities) are driven by the same market factors (stock and fixed income market returns, credit spreads, market volatility) that drive traditional stock and bond investments. In contrast, other hedge fund strategies (e.g., Equity Market Neutral and Fixed Income Arbitrage) are little affected by market variables that drive traditional stock and bond investments and have sources of return based primarily on short-run market pricing inefficiencies and liquidity requirements.

In this article we review previous research on market-based sources of hedge fund returns and provide empirical results on risk-adjusted performance based on market factors that drive hedge fund returns. The results reported in this article may be used by institutional investors to manage their investment process in numerous ways. First, to the degree that traditional stock and bond investments load on the same return factors as certain hedge fund strategies, those hedge fund strategies may be used as direct substitutes for traditional assets. Second, if a multi-factor model exists which explains hedge fund performance, that model may be used as a basis for creating performance benchmarks. Third, the multi-factor model can also be used to track the time-varying sensitivity of hedge funds to the established factors in order to measure a manager's changing investment philosophy. Lastly, these multi-factor models may also be used in a variety of portfolio optimization techniques and portfolio creation methods based on factor tracking.

In the following section we briefly review previous studies on hedge fund performance and the potential market factors affecting various hedge fund strategies. The methodology used to explore the relationship between hedge fund returns and market factors is then presented. In this article, we evaluate performance and market timing ability using the conditional approaches of Ferson and Schadt [1996]. The key assertion in conditional performance evaluation is that a managed portfolio strategy that can be replicated using commonly available public information should not be judged as having superior performance. For example, a mechanical trading rule that uses lagged credit-spread data is not a value-adding strategy. However, if the manager correctly uses more information than is generally publicly available and achieves superior returns, then she/he is considered to have potentially superior ability. Hence conditional performance evaluation is consistent with the semi-strong form of market efficiency. The greatest advantage of conditional performance evaluation is that it can incorporate any standard of superior information that is deemed to be appropriate by the choice of lagged instruments which are used to represent public information. Chan and Chen [1988], Cochrane [1992], and Jagannathan and Wang [1996] conclude that conditional versions of simple asset pricing models may be better able to explain the cross-section of returns than unconditional models. In this study we use generalized method of moments estimation (see Hansen [1982] and Greene [2000] for a detailed treatment) to study the relationship between hedge fund returns and factor betas. We also test the market-timing ability of hedge fund managers using unconditional and conditional market-timing models. The unconditional market-timing model used was developed by Treynor and Mazuy [1966] and contains a quadratic term in the regression equation. The model's conditional counterpart was developed by Ferson and Schadt [1996]. In section IV, the results are presented. We show that the usage of methodologies that permit beta to be time varying does not affect our estimation of the excess return relative to traditional single-factor non-time-varying models. This points to two scenarios: one, the explanatory variables used in this study may not be able to capture the type of trading strategies followed by hedge fund strategies and, two, the estimated alphas are good estimates of the true alphas and are mostly due to managers' skills and hence cannot be explained by naïve static or dynamic trading strategies. Our results are similar to Kazemi and Schneeweis [2003] who find evidence along the same lines using a set of HFR indices and individual managers. In our evaluation of market-timing ability, unconditional and conditional approaches yield similar results. Hedge fund managers in general lack any market-timing ability and fund level analysis is required to detect the ones that have market-timing ability. The results also suggest that hedge fund returns have option-like properties and future research should include option-based factors in performance evaluation. In section V, we conclude and explore areas of future research.

II. HEDGE FUND PERFORMANCE REVIEW

Hedge funds have been described as skill-based investment strategies, primarily because many hedge fund managers do not explicitly attempt to track a particular index. This gives managers greater flexibility in following a trading style and the execution of that style, and offers a greater probability of obtaining returns due to their unique skill or strategy. As a result, hedge funds have also been described as *absolute return* strategies, as these managers attempt to maximize long-term returns independently of a traditional stock and bond index. In short, they emphasize *absolute return*, and not return relative to a predetermined index.

It is important to realize, however, that the fact that hedge funds do not emphasize benchmark tracking *does not mean* that the return from a hedge fund is based solely on manager skill. Hedge fund managers who manage a particular investment strategy or focus on a particular investment opportunity can be said to track that investment strategy or risk/return opportunity. Studies have shown that the returns to certain hedge fund strategies are driven largely by market factors, such as changes in credit spreads or market volatility (Fung and Hsieh [1997], Liang [1999], Schneeweis and Spurgin [1999], and Agarwal and Naik [2000b]) specific to those strategies. One can therefore think of hedge fund returns as a combination of manager skill in processing information and the underlying return from passive investment in the strategy itself.[1]

With the phenomenal growth of the hedge fund industry in the last decade, hedge fund performance measurement and persistence have become issues of extensive research. Previous studies of hedge fund performance have used a wide range of performance metrics including Jensen's alpha and Sharpe ratios. These approaches, however, have several weaknesses when applied to hedge funds. First, empirical research (Brooks and Kat [2002], Kazemi and Schneeweis [2003], and others) has shown that hedge funds are far from being normally distributed, which weakens the validity of the estimates obtained by traditional approaches. Second, these approaches are also unable to handle the dynamic behavior of returns. Most hedge funds follow dynamic strategies with strongly fluctuating risk exposures through time, which require the use of conditional models that can account for time-varying estimates. One can reasonably assume that inferences on the performance and persistence of an actively managed portfolio could be significantly altered when one uses conditional, instead of unconditional models.

The issue of whether hedge fund managers can deliver returns in excess of a naïve benchmark has been a subject of controversy. Given the fee structure of this industry, strong performance or the lack thereof has important implications. If they can consistently deliver excess returns, then fee structures may be justified. Ackermann, McEnally, and Ravenscraft [1999], Brown, Goetzmann, and Ibbotson [1999], Liang [1999], and Agarwal and Naik [2000a] have all found evidence of positive risk-adjusted returns. Kat and Miffre [2003] find that conditional measures of abnormal performance exceed the static measures by an average return of 0.84%, while the number of funds that exhibit superior skills increase by 10.4%. A tabular, more detailed review of the literature can be found in Exhibit 1.

Even if for particular hedge fund strategies excess returns are indicated over some past period, controversy still exists as to the persistence of that unexplained performance. While Agarwal and Naik [2000a] and Edwards and Caglayan [2001] have found evidence of persistence, Brown, Goetzmann, and Ibbotson [1999], Peskin, Urias, Anjilvel, and Boudreau [2000], and Schneeweis, Kazemi, and Martin [2001] have found little or no evidence of persistence. More recently, Kat and Menexe [2003] study persistence of the fund's overall risk profile and find that while there is little evidence of persistence in mean returns, standard deviation of returns is strongly persistent and skewness and kurtosis are weakly persistent. Bares, Gibson, and Gyger [2003] find that while there is evidence of short-term persistence, it vanishes rapidly as the time horizon is lengthened. The reasons for this controversy lie in data selection. For example, Kat and Miffre [2003] use the CISDM (formerly MAR) database and concentrate on 77 surviving funds. The results of the study might have been dramatically altered had all dead funds been included in the dataset.

The contributions of this article are fourfold. First, the use of generalized method of moments prevents any bias in the estimates arising out of non-normality. Second, the use of conditional models is more accurate than traditional approaches. Third, survivorship bias in the estimates is avoided by the construction of a "dead funds" and an "all funds"[2] portfolio for each strategy. Finally, unconditional and conditional market-timing models suggest that option-based factors may be better able to explain hedge fund performance.

III. METHODOLOGY AND DATA

Investment performance evaluation remains a central part of academic research. It is not the purpose of this article to review the considerable amount of research that has been conducted on alternative means of evaluating traditional or alternative investment strategies. Treynor [1965] proposed the first market-model-based risk-adjusted measure of performance followed by Jensen [1968] who proposed the following similar approach to performance evaluation:

$$r_{it} = \alpha + \beta r_{mt} + \varepsilon_t \qquad (1)$$

where r_{it} is the excess rate of return over the one-month Treasury bill on investment i between the periods $t - 1$ and t and r_{mt} is the excess rate of return on the market over the same period. The performance of the investment is then evaluated by testing the statistical significance of the intercept term in Equation (1) above. To the degree, however, that hedge fund managers routinely pursue dynamic trading strategies, the induction of time variation to the above model is essential for accurate estimation of the parameters. Various approaches have been used to evaluate the impact of dynamic trading strategies on performance evaluation (Treynor and Mazuy [1966], Henriksson and Merton [1981], and Favre and Galeano [2002]). As noted earlier, in this article we will use the conditional approach to performance evaluation of Ferson and Schadt [1996]. The impact of dynamic trading strategies can be best evaluated by conditional approaches since these approaches incorporate time variation.

Methodology: The Performance Evaluation Model

Ferson [2003] notes that virtually all asset-pricing models are special cases of the fundamental equation

$$P_t = E_t(m_{t+1}[P_{t+1} + D_{t+1}])$$

where P_t is the price of the asset at time t, and D_{t+1} is the amount of dividends, interest, or other payments received at time $t + 1$. The market-wide random variable M_{t+1} is the stochastic discount factor (SDF). The current prices are obtained by discounting the payoffs using the stochastic discount factor so that the expected "present value" of the payoffs is equal to the price. The notation $E_t(.)$ denotes

EXHIBIT 1

Previous Research on Hedge Funds

Authors	Subject	Data, Model, and Tested Hypotheses	Results & Supporting Hypothesis
Asness, Krail, Liew [*JPM*, 2001]	Stale Prices	CSFB/Tremont, 1994-2000; regression on lagged S&P returns	Non-synchronous return data can lead to understated estimates of actual market exposure; after adjusting for increased market exposure a broad universe of hedge funds does not add value (most of these are hedge equity funds – hint)
Ackerman, McEnally, and Ravenscraft [*JF*, 1999]	Sources of Hedge Fund Performance (e.g., size, fees, etc.)	MAR and HFR, 1990-1995; restrict funds to at least 24 months of data	Hedge fund size and incentive fees are critical determinants of superior risk-adjusted performance.
Agarwal and Naik [*JAI*, 2000)	Performance Persistence of Hedge Funds	HFR, 1994-1998; style factors and persistence	Reasonable degree of persistence attributable to loser persistence.
Bares, Gibson, and Gyger [*JAI*, 2003]	Performance Persistence	FRM hedge fund database, rankings and APT framework	Evidence of short-term performance vanishes in the long term.
Brooks and Kat [*JAI*, 2002]	Hedge Fund Index Returns	Major hedge fund indices, skewness, kurtosis, and autocorrelation, mean-variance portfolio analysis	Substantial differences between indices that aim to cover the same type of strategy.
Brown, Goetzmann, and Ibbotson [*JOB*, 1999]	Offshore Funds: Survival and Performance	Bernheim Offshore	Differences in survivor bias and return history.
Edwards and Caglayan [*JFM*, 2001]	Performance Persistence	CISDM, 1990-1998; six-factor Jensen alphas	Significant evidence of persistence among both winners and losers.
Fung and Hsieh [*FAJ*, 2002b]	Benchmark Issues	Various indices	Index Universe is “momentum bet” and Individual Index is style bet.

EXHIBIT 1 (continued)
Previous Research on Hedge Funds

Authors	Subject	Data, Model, and Tested Hypotheses	Results & Supporting Hypothesis
Goetzmann, Ingersoll, and Ross [NBER, 1998]	Fee Performance Impacts		Impact of high water marks on performance.
Kat and Menexe [*JAI*, 2003]	Performance Persistence	TASS, June 1994-May 2001; cross-product ratio and cross-sectional regressions	Little evidence of persistence in mean returns, standard deviation, strongly persistent skewness and kurtosis weakly persistent.
Kat and Miffre [2003]	Performance Evaluation	CISDM, May 1990-April 2000; conditional six-factor model	Allowing for conditioning increases measured abnormal performance, both in statistical and economic terms.
Kazemi and Schneeweis [2003]	Performance Evaluation	HFR indices 1990-2001; stochastic discount factor and GMM estimation	Significantly positive risk-adjusted returns for most hedge fund strategies.
Liang [*FAJ*, 1999]	Hedge Fund Historical Performance	HFR, 1990-1997; returns a function of incentive fees, management fee, assets, lockup, and age factors	Each of the listed factors as well as onshore versus offshore affects performance.
Liang [*JFQA*, 2000]	Characteristics of Alternative Hedge Fund Data Bases	TASS and HFR databases	Differences in survivor bias, and return history.
Liang [*FAJ*, 2001]	Return Performance Survivorship Bias Fee Impacts	TASS database, 1,407 live, 609 dead funds, 1990-	Superior risk-adjusted performance for hedge funds. Annual survivor bias – 2.43%. Fund fee changes are performance related.
McCarthy and Spurgin [*JAI*, 1998]	Tracking Error of Various Hedge Fund Indices	MAR, HFR, EACM	Relative tracking error of various styles.
Schneeweis [*JAI*, 1998]	Test the Impact of Absolute and Risk-Adjusted Return Persistence	MAR, 1990-1997	For market neutral and event, little relationship between return persistence relationships and risk-adjusted performance relationships. Non-synchronous return.
Schneeweis and Spurgin [*JAI*, 1998]	Sharpe Style-Based Factors on Hedge Fund Returns	Various databases	Market factors (long volatility and short volatility) explain hedge fund index returns.
Schneeweis and Spurgin [1999]	Sharpe Style-Based Factors on Hedge Fund Returns	Various databases	Market factors (long volatility and short volatility) explain hedge fund index returns.
Schneeweis, Kazemi, and Martin [2001]	Performance Evaluation and Persistence	Various hedge fund indices, various models	Existing indices differ widely in composition and performance, evidence of micro effects, etc.

the conditional expectation, given a market-wide information set, Ω_t. However Ω_t is not observable in practice. Hence an observable subset of instruments, Z_t, is used instead. It is also more convenient to consider expectations conditioned on an observable subset of instruments, Z_t. These conditional expectations are denoted as $E_t(./Z_t)$. When Z_t is the null information set, we have the unconditional expectation, denoted as $E_t(.)$.

We follow the approach of Ferson and Schadt [1996]. Their regression model is as follows:

$$r_{p,t+1} = b_{0p} r_{m,t+1} + B'_p [z_t r_{m,t+1}] + u_{p,t+1}$$

which can be written as

$$r_{p,t+1} = \alpha_p + b_{0p} r_{m,t+1} + B'_p [z_t r_{m,t+1}] + \varepsilon_{p,t+1}$$

where $z_t = Z_t - E(Z)$ is a vector of the deviations of Z_t (the public information variables) from the unconditional means, $r_{p,t+1}$ is the return on the portfolio minus the one-month Treasury bill rate, $r_{m,t+1}$ is the return on the market portfolio minus the one-month Treasury bill, B'_p is a vector of betas, and $\alpha_p = 0$. In our case, we use the total return on the Russell 3000 index as a proxy for the market portfolio (M), a lagged credit spread (CS), a lagged term spread (TS), a lagged dividend yield (DY), a lagged one-month Treasury bill (TB), and a dummy variable for January (J) as information variables. Hence our model can be expressed as:

$$\begin{aligned} r_{p,t+1} = \alpha_p &+ \beta_1 M_{t+1} + \beta_2 M_{t+1} CS_t + \beta_3 M_{t+1} TS_t \\ &+ \beta_4 M_{t+1} DY_t + \beta_5 M_{t+1} TB_t + \beta_6 M_{t+1} J_{t+1} + \varepsilon \end{aligned}$$

Since we estimate parameters using generalized method of moments we can specify certain moment conditions. The moment conditions we use are $E(u_{i,t+1}/Z_t) = 0$ and $E(u_i \otimes z_{t-1}) = 0$.[3]

The Market-Timing Model

Hedge fund strategies can be classified as either directional or non-directional. In terms of the CISDM database classification, directional strategies would include global established, global macro, long only, and short selling. Managers in this category bet on the directions of markets dynamically. In rising markets they hope to profit from the long positions appreciating quicker than their short positions. In falling markets they hope their short positions will appreciate quicker in value than their long positions. Before proceeding further, it is essential to review some of the empirical evidence on market-timing ability. The empirical evidence seems to indicate that significant market-timing ability is rare (Kon [1983], Chang and Lewellen [1984], Henriksson [1984], and Lockwood and Kadiyala [1985]). According to Jagannathan and Korajczyk [1986], the most puzzling aspect is the fact that average timing measures across mutual funds are negative and the funds that do exhibit significant timing performance more often exhibit negative performance than positive performance. Kon [1983] and Henriksson [1984] also find that there is a negative correlation (cross-sectionally) between the measures of security selection and market timing. Henriksson [1984] performs a careful set of diagnostics on market-timing tests to conclude that the specifications used in the parametric tests must be questioned because of the persistence of the negative correlation between security selection and market timing. He suggests a number of potential explanations for this bias including errors-in-variables, bias, misspecification of the market portfolio, and use of a single factor rather than a multi-factor model. Jagannathan and Korajczyk [1986] show that the portfolio strategy (for mutual funds) of buying call options (in this case calls on the market) will exhibit positive timing performance and negative security selection even though no market forecasting or security specific forecasting is being done. This suggests that mutual funds need to sell call options or buy put options in order to explain the negative performance. They note however that their market proxy is the NYSE value-weighted stock index, which consists of stocks that are to a lesser or greater extent options (due to their varying levels of debt). Hence the sign of the "artificial" market-timing performance will depend on whether the "average" stock held by the fund has more or less of an option effect than the "average" stock held by the index. This implies that funds that tend to invest in stocks with little or no risky debt will show negative timing performance and funds that tend to invest in small, highly levered stocks will show positive timing performance. In the case of hedge funds, Fung, Xu, and Yau [2002] have found that although managers show superior security selection ability, they do not show positive market-timing performance. Their study examines 115 global equity-based hedge funds with reference to their target geographical markets over the seven-year period 1994–2001. They also find that incentive fees and leverage both have a significant positive impact on a hedge fund's risk-adjusted return but not on a fund's selectivity index (i.e., its performance after controlling for market-timing effects). They use the model by Henriksson and Merton [1981] where market-timing ability is measured by a dummy variable which equals –1 when the difference between the market index and the return on the risk-free security is negative (declining markets) and zero otherwise. In our case we use conditional methods to measure market-timing ability as well.

The purpose of conditional performance evaluation in the market-timing context is to distinguish timing ability that merely reflects publicly available information as captured by a set of lagged information variables from timing based on better-quality information. This informed timing is referred to by Ferson [2003] as conditional market timing. Treynor and Mazuy [1966] proposed the following market-timing regression with no conditioning information:

$$r_{pt+1} = a_p + b_p r_{mt+1} + \gamma_{tmu}[r_{m,t+1}]^2 + v_{pt+1}$$

where the coefficient γ_{tmu} reflects market-timing ability. The intuition behind this model is based on the approach used by Treynor [1965]. Treynor [1965] used "characteristic lines" to demonstrate market-timing ability of mutual funds. These characteristic lines were constructed as follows: The returns on the market index were plotted on the x-axis whereas the returns to individual funds were plotted on the y-axis. Using least-squares estimation they also plot the line of best fit. The line of best fit is given by the following equation:

$$\hat{r}_{pt+1} = \hat{a}_p + \hat{b}_p r_{mt+1} + v_{pt+1}$$

where $\hat{a}_p$ and $\hat{b}_p$ are the least-squares estimates. We illustrate this in Exhibit 2 using our active portfolios.

Treynor and Mazuy [1966] note that the key to this test for successful anticipation is simple. The only way in which a fund management can translate ability to outguess the market into a benefit to the shareholder is to vary the fund volatility systematically in such a fashion that the resulting characteristic line is concave upward. If a fund manager correctly anticipates the market more often than not, then the characteristic line will no longer be straight. In order to determine whether the characteristic line is smoothly curved or kinked, a least-squares statistical fit of a characteristic line to the performance data for the fund will be improved by inclusion of a quadratic term in the fitting formula. We use both the unconditional and conditional versions of the Treynor-Mazuy model to measure market-timing ability. The fitted curves for the active portfolios are given in Exhibit 3.

The timing coefficients on the fitted curves were negative in most cases with the exception of short sellers. As the graphs in Exhibit 3 show, short sellers tend to perform well in down markets or have some market-timing ability in down markets but perform badly in up markets as historical data over the 1990s has shown. The shapes of the other curves are similar to each other. Hedge fund strategies tend to perform badly in down markets and improve in up markets but flatten out as the market begins to perform really well. This suggests that hedge fund returns exhibit non-linear, option-like characteristics.

We apply the conditional version of the model by Treynor and Mazuy [1966] proposed by Ferson and Schadt [1996] to measure the market-timing ability of managers employing directional and non-directional strategies. The model is given as follows:

$$r_{p,t+1} = a_p + b_p r_{m,t+1} + C'_p(z_t r_{m,t+1}) + \gamma_{tmc}[r_{m,t+1}]^2 + v_{p,t+1}$$

where the coefficient C'_p captures the response of the manager's beta to public information, Z_t.

The sensitivity of the manager's beta to a private market-timing signal is measured by γ_{tmc}. In our case, the model becomes

$$\begin{aligned} r_{p,t+1} = \; & \alpha_p + \beta_1 M_{t+1} + \beta_2 M_{t+1} CS_t + \beta_3 M_{t+1} TS_t + \beta_4 M_{t+1} DY_t + \\ & \beta_5 M_{t+1} TB_t + \beta_6 M_{t+1} J_{t+1} + \gamma_{tmc} M_{t+1}{}^2 + v_{p,t+1} \end{aligned}$$

As Ferson [2003] points out, the part of the correlation of fund betas with the future market return that can be attributed to the public information is not considered to reflect market-timing ability.

Data

The data for this study has been taken from the CISDM database. As of December 2002, the CISDM database contained around 2,200 active hedge funds and CTAs and around 2,800 defunct hedge funds and CTAs. In our study we use both active and defunct hedge funds. We form an equally weighted portfolio of all available hedge funds in their respective strategies to construct the

EXHIBIT 2
Fitted Lines

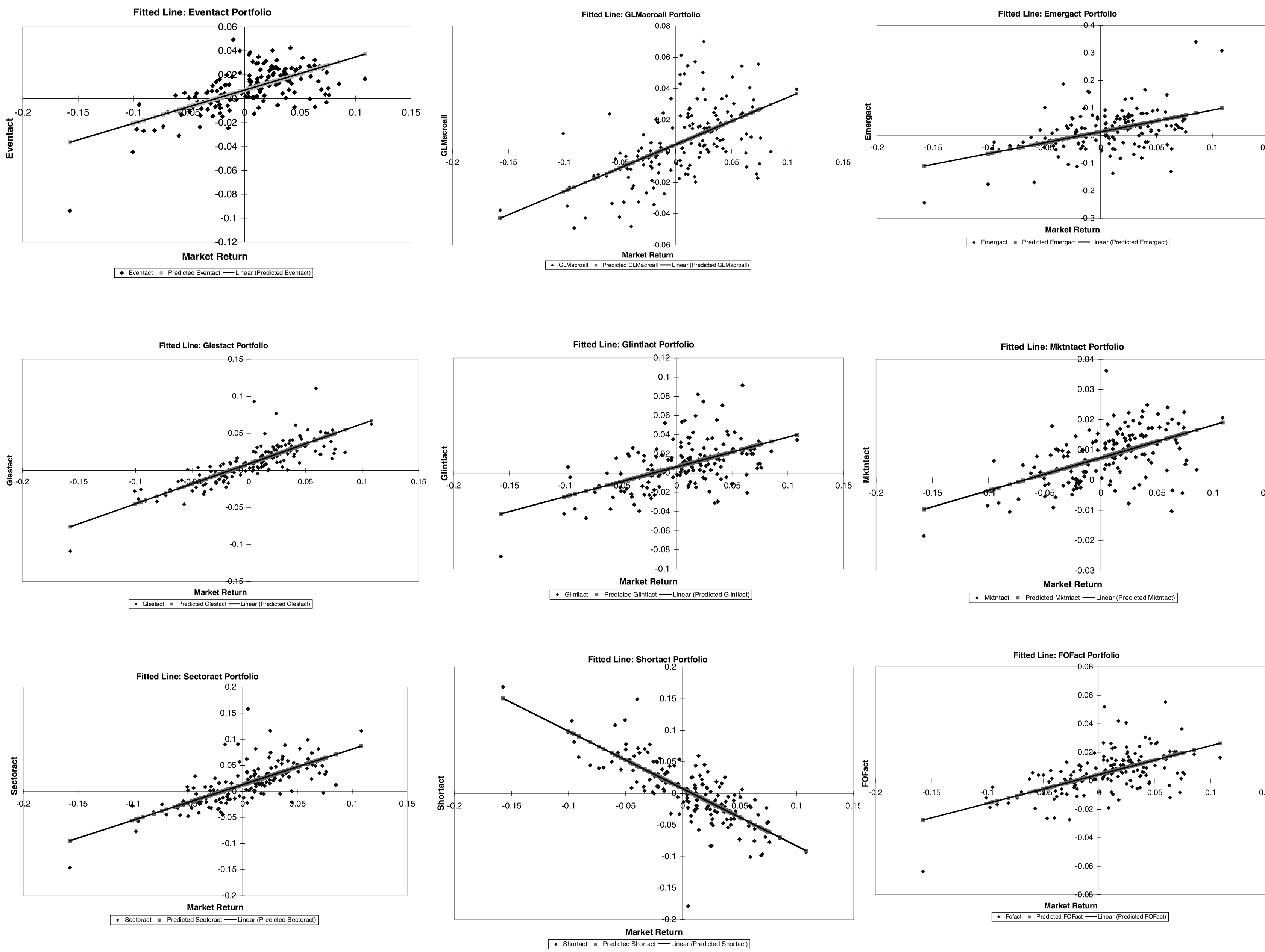
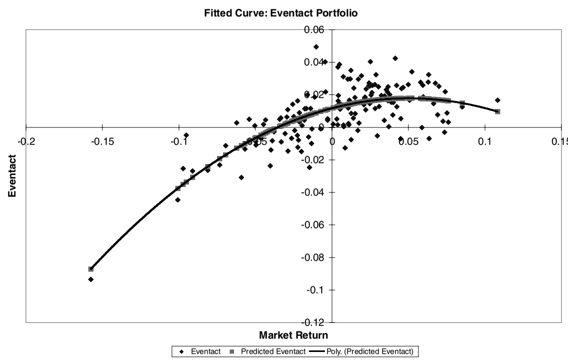
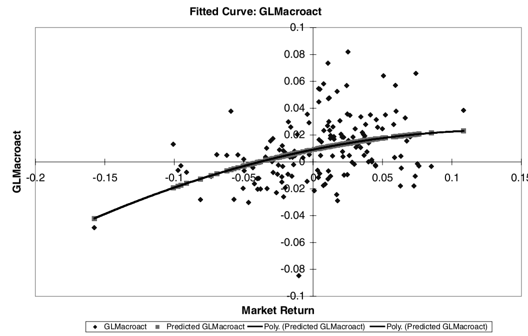
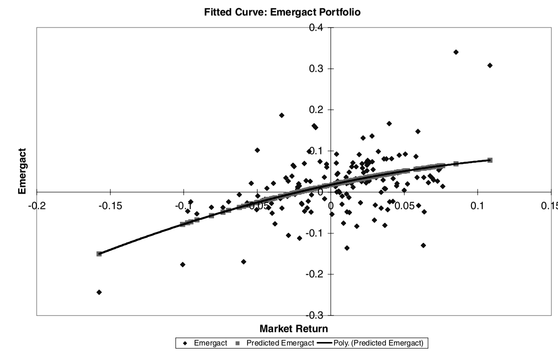
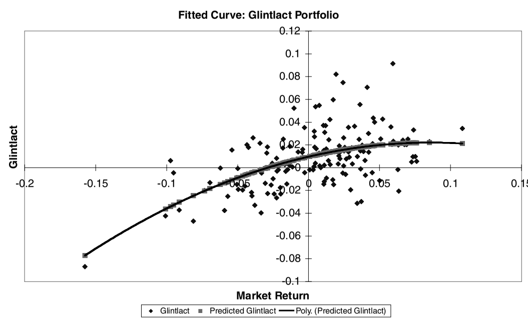


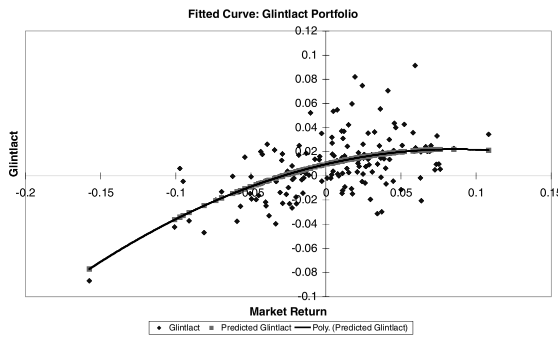
EXHIBIT 3
Fitted Curves

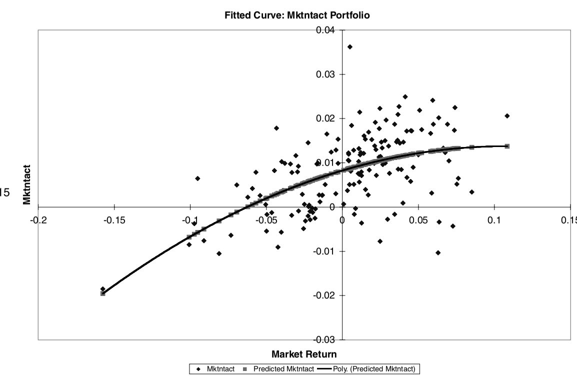


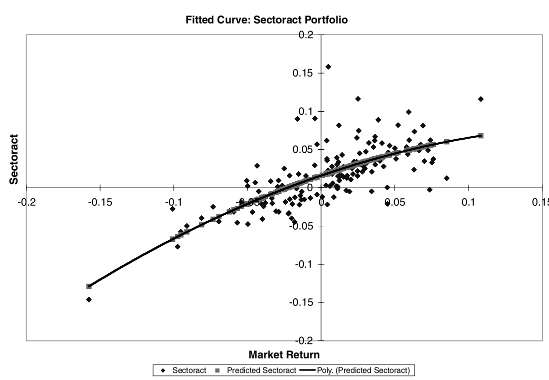


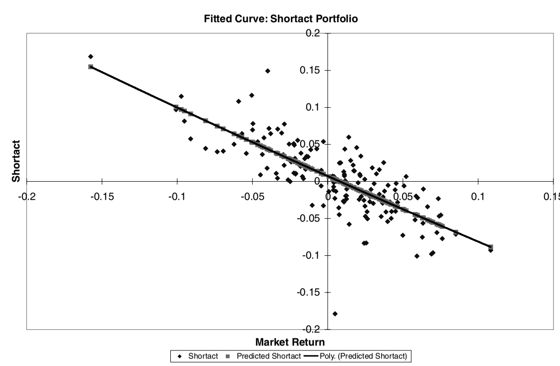


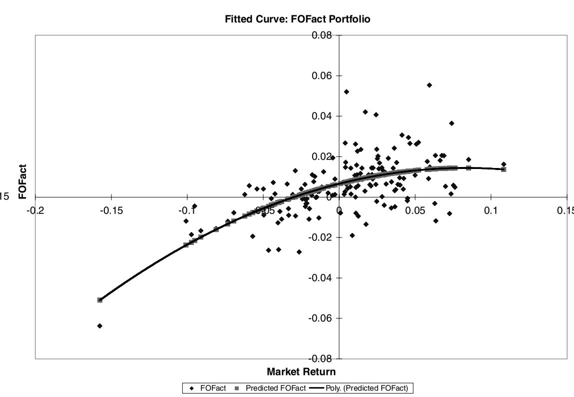












return series. When a fund stopped reporting, we dropped it from the portfolio, and when a fund started reporting we added it to our portfolio. In doing this, we analyze the performance of a portfolio of all hedge funds in the CISDM database. The period of the study is February 1990-August 2002 with the exception of the sector dead funds portfolio which had available data for the period January 1992-August 2002. We have three portfolios for each strategy—an "active funds" portfolio, a "dead funds" portfolio, and an "all funds" portfolio. Exhibit 4 presents the classifications and the number of funds in each strategy. Summary statistics of the excess returns over the one-month Treasury bill are given in Exhibits 5A, 5B, and 5C.

Reported hedge fund returns are subject to several potential biases. Fung and Hsieh [2000] discuss four of the most common following previous literature: survivorship bias,[4] instant history bias,[5] selection bias,[6] and multi-period sampling bias.[7] While this database is subject to selection bias, the tested sample does not suffer from the more significant data base concerns, that is, survivorship bias, instant history, and sampling bias. For the various strategies we use a set of variables that have been shown to be useful in predicting security returns and risks over time. These include 1) the lagged level of the one-month Treasury bill, 2) a lagged dividend yield, 3) a lagged measure of the slope of the yield curve, 4) a lagged measure of the credit risk premium, and 5) a dummy variable for the month of January.[8] The one-month Treasury bill data was obtained from Ibbotson Associates and the other variables were obtained from Datastream. The yield curve is measured by the difference between the yields of the 30-year Treasury bond and the three-month Treasury bill, the dividend is the Datastream calculated total U.S. market dividend yield and the credit risk is measured as the difference between BAA- and AAA-rated yields (published by Moody's).

EXHIBIT 4
Characteristics of the CISDM Hedge Fund Database

Active Funds in the CISDM Database: Jan 1990 - Aug 2002	
Strategy	**Number of Funds**
Emerging Markets	94
Event Driven	164
Fund of Funds	399
Global Established	345
Global International	52
Global Macro	59
Long Only	20
Market Neutral	392
Sector	121
Short Sales	21
Total	**1,667**
Defunct Funds in the CISDM Database: Jan 1990 - Aug 2002	
Strategy	**Number of Funds**
Emerging Markets	81
Event Driven	100
Fund of Funds	258
Global Established	236
Global International	30
Global Macro	124
Long Only	21
Market Neutral	292
Sector	109
Short Sales	23
Total	**1,274**

IV. EMPIRICAL RESULTS

Exhibits 5A, 5B, and 5C present summary statistics of monthly excess returns of equally weighted portfolios of active, dead, and all hedge funds following various strategies. We refer to these portfolios as Active, Dead, and All portfolios. The bottom panels of the above-mentioned exhibits present single-factor estimation results for the portfolios using the Russell 3000 index as the factor. As evident from the exhibits and as one would expect, the mean returns on the Active portfolio are the highest, followed by the means on the All and Dead portfolios. Although the Dead portfolio may contain funds that have stopped reporting for reasons other than going out of business, the results clearly show that on average dead funds do very poorly prior to becoming defunct. However, the standard deviations, skewness, and kurtosis of each of the portfolios are similar and Sharpe ratios are highest for the Active portfolio, followed by the All and Dead portfolios.

As reported in previous literature and Kazemi and Schneeweis [2003], we find negative skewness and positive kurtosis for some strategies for both the Active and the All portfolios. This suggests that monthly returns may not be normally distributed.

The bottom panels of Exhibits 5A, 5B, and 5C report the alphas, betas, t-statistics, and R-squares against the excess returns on the Russell 3000 index. As we should expect, we find positively significant alphas for the Active portfolios. For the Dead portfolios most of the alphas are insignificant and for the All portfolios we find some positively significant alphas as well. Let us now examine the betas from the single-factor regression. For non-directional strategies such as market neutral we find that the betas are significantly lower than directional strategies. For the short-selling strategy betas are negative. However, beta

EXHIBIT 5A
Summary Statistics of Active Portfolios

Summary Statistics of Monthly Excess Returns for Active Portfolios: January 1990-August 2002					
Strategy	**Mean**	**St. Deviation**	**Skewness**	**Kurtosis**	**Sharpe**
Event Driven	9.81%	6.48%	-1.30	5.14	1.45
Global Macro	10.24%	8.40%	0.17	1.30	1.17
Emerging Markets	21.73%	25.36%	0.51	4.25	0.84
Global Established	13.42%	9.64%	-0.14	2.49	1.35
Global Int.	9.33%	8.79%	0.14	1.65	1.02
Market Neutral	9.21%	3.13%	-0.25	0.44	2.82
Sector	19.19%	13.94%	0.02	1.82	1.35
Short Sellers	3.67%	17.28%	0.07	1.32	0.19
Fund of Funds	6.33%	5.19%	-0.17	3.34	1.15
Single Factor Estimation Results					
Portfolio Excess Return = Alpha + Beta * Russell 3000 Excess Return + Error					
Strategy	**Alpha**	**Beta**	**R-Square**	**T-Stat(Alpha)**	**T-Stat(Beta)**
Event Driven	0.70%	27.96%	42.57%	5.88	10.55
Global Macro	0.76%	22.09%	15.81%	4.09	5.29
Emerging Markets	1.49%	74.31%	19.64%	2.70	6.03
Global Established	0.89%	53.00%	69.10%	6.88	18.22
Global Int.	0.64%	30.95%	28.32%	3.66	7.47
Market Neutral	0.72%	11.40%	30.36%	11.57	7.95
Sector	1.31%	66.27%	51.67%	5.62	12.57
Short Sellers	0.69%	-88.17%	59.55%	2.83	-14.96
Fund of Funds	0.44%	20.14%	34.44%	4.33	8.88

EXHIBIT 5B
Summary Statistics of Dead Portfolios

Summary Statistics of Monthly Excess Returns for Dead Portfolios: January 1990-August 2002					
Strategy	**Mean**	**St. Deviation**	**Skewness**	**Kurtosis**	**Sharpe**
Event Driven	6.68%	6.95%	-0.34	1.75	0.90
Global Macro	3.47%	9.38%	-0.52	1.10	0.33
Emerging Markets	3.68%	16.00%	-0.48	1.40	0.21
Global Established	8.34%	13.95%	-0.30	0.85	0.57
Global Int.	4.50%	9.61%	0.58	2.85	0.43
Market Neutral	5.07%	4.45%	-0.47	2.03	1.05
Sector	10.12%	17.87%	0.44	3.11	0.55
Short Sellers	1.17%	28.07%	1.01	8.46	0.03
Fund of Funds	3.76%	6.58%	-0.17	3.29	0.51
Single Factor Estimation Results					
Portfolio Excess Return = Alpha + Beta * Russell 3000 Excess Return + Error					
Strategy	**Alpha**	**Beta**	**R-Square**	**T-Stat(Alpha)**	**T-Stat(Beta)**
Event Driven	0.42%	27.24%	33.79%	3.12	8.75
Global Macro	0.10%	37.35%	34.95%	0.55	8.98
Emerging Markets	0.06%	48.23%	20.01%	0.18	6.13
Global Established	0.29%	79.16%	70.96%	1.63	19.15
Global Int.	0.21%	33.31%	26.47%	1.05	7.35
Market Neutral	0.34%	16.28%	29.47%	3.83	7.92
Sector	0.47%	72.93%	36.70%	1.40	9.33
Short Sellers	0.74%	-126.53%	44.77%	1.51	-11.02
Fund of Funds	0.19%	23.28%	27.57%	1.47	7.58

EXHIBIT 5C
Summary Statistics of All Portfolios

Summary Statistics of Monthly Excess Returns for All Portfolios: January 1990-August 2002					
Strategy	**Mean**	**St. Deviation**	**Skewness**	**Kurtosis**	**Sharpe**
Event Driven	8.19%	6.38%	-0.88	3.23	1.22
Global Macro	6.82%	8.01%	0.21	0.08	0.80
Emerging Markets	12.62%	17.49%	-0.53	2.30	0.70
Global Established	10.73%	11.58%	-0.16	1.21	0.89
Global Int.	6.78%	8.06%	0.47	3.04	0.79
Market Neutral	7.04%	3.46%	-0.28	1.21	1.92
Sector	16.70%	15.72%	0.23	1.92	1.04
Short Sellers	3.00%	20.59%	0.58	2.55	0.13
Fund of Funds	5.02%	5.76%	-0.17	3.54	0.80
Single Factor Estimation Results					
Portfolio Excess Return = Alpha + Beta * Russell 3000 Excess Return + Error					
Strategy	**Alpha**	**Beta**	**R-Square**	**T-Stat(Alpha)**	**T-Stat(Beta)**
Event Driven	0.56%	27.30%	41.91%	4.79	10.43
Global Macro	0.44%	29.10%	30.18%	2.68	8.13
Emerging Markets	0.78%	60.93%	27.76%	2.17	7.56
Global Established	0.61%	65.11%	72.23%	4.06	19.95
Global Int.	0.42%	32.12%	36.31%	2.79	9.02
Market Neutral	0.52%	14.00%	37.51%	8.14	9.2
Sector	1.07%	73.67%	50.20%	3.97	12.27
Short Sellers	0.72%	-106.91%	61.67%	2.59	-15.76
Fund of Funds	0.32%	21.34%	31.34%	2.77	8.35

is measured in terms of CAPM, which assumes that returns are normally distributed and the betas are static over time. As shown by Brooks and Kat [2002] and Kazemi and Schneeweis [2003], hedge funds may not be normally distributed and betas may be time varying, thereby inducing a misspecification in the model. Hence we estimate a multi-factor model, which accounts for time-varying betas and non-normality of returns. The other interesting aspect of our single-factor estimation results is contained in Exhibit 5B. Most of the alphas are insignificant with the exception of event-driven and market-neutral strategies. These portfolios seem to exhibit positively significant alphas. This could results from funds in the defunct database not actually being dead. Some funds may stop reporting to the database because they are closed to new investments. If these funds are large, and had performed well before they stopped reporting, they can have an impact on the results as is suspected in our case.

Exhibits 6 and 7 display the results of the conditional model by the generalized method of moments and ordinary least squares methods, respectively. As before, the estimates are presented for the Active, Dead, and All portfolios, for each of the strategies. Let us first look at the Active portfolio. For the OLS multi-factor lagged model, we can see that all the alphas are positive and statistically significant at the 5% level. The fund of funds portfolio has the lowest alpha, 0.42%, and the sector portfolio has the highest alpha, 1.32%. The adjusted R-squares vary considerably from 18.19% (for global macro) to 69.16% (for global established). Three strategies, global established, sector, and short-selling, have adjusted R-squares greater than 50%. Kazemi and Schneeweis [2003] also report R-squares that vary considerably. Many hedge fund strategies use a combination of asset classes and managers use information on these classes in constructing their strategies. Hence, it is not only appropriate but also necessary to use a multi-factor lagged version of Jensen's model. As reported in the last column and displayed in Exhibit 7, there is very little autocorrelation in the residuals. However, the presence of heteroscedasticity cannot be ruled out. Generalized methods of moments estimation adjusts for heteroscedasticity as well. Using GMM estimation we find that most strategies have significant alphas at the 5% level with the exception of short-selling. Significant alphas range from 0.49% for the fund of funds portfolio to 1.64% for the emerging markets portfolio. The adjusted R-squares vary widely in this case as well, from 11.56% for the emerging markets portfolio to 68.17% for the global-established portfolio. However,

EXHIBIT 6

Results of GMM Estimation

Model: $r_{pt+1} = \alpha_p + \delta_{1p} r_{mt+1} + \delta'_{2p}(z_t r_{mt+1}) + \varepsilon_{pt+1}$

GMM Estimates			
Portfolio	**Alpha**	**t-Value**	**Adjusted R-Square**
Event Driven-Active Portfolio	0.60%	4.44	40.85%
Global Macro-Active Portfolio	0.78%	2.93	18.11%
Emerging Markets-Active Portfolio	1.64%	3.14	11.56%
Global Established-Active Portfolio	0.89%	4.02	68.17%
Global International-Active Portfolio	0.71%	2.45	25.89%
Market Neutral-Active Portfolio	0.72%	6.75	32.20%
Short Selling-Active Portfolio	0.43%	1.20	50.95%
Sector-Active Portfolio	1.33%	3.41	52.47%
FOF-Active Portfolio	0.49%	4.14	36.09%
Portfolio	**Alpha**	**t-Value**	**Adjusted R-Square**
Event Driven-Dead Portfolio	0.33%	1.86	32.58%
Global Macro-Dead Portfolio	-0.04%	-0.21	33.91%
Emerging Markets-Dead Portfolio	0.26%	0.38	-3.77%
Global Established-Dead Portfolio	0.71%	1.78	58.51%
Global International-Dead Portfolio	0.24%	1.35	33.50%
Market Neutral-Dead Portfolio	0.35%	3.62	42.28%
Short Selling-Dead Portfolio	-0.27%	-0.40	19.87%
Sector-Dead Portfolio	0.99%	2.50	48.29%
FOF-Dead Portfolio	0.43%	2.00	15.90%
Portfolio	**Alpha**	**t-Value**	**Adjusted R-Square**
Event Driven-All Portfolio	0.53%	3.84	42.79%
Global Macro-All Portfolio	0.35%	1.55	29.49%
Emerging Markets-All Portfolio	1.06%	2.04	9.81%
Global Established-All Portfolio	0.78%	2.55	66.96%
Global International-All Portfolio	0.32%	1.69	39.14%
Market Neutral-All Portfolio	0.52%	5.68	43.49%
Short Selling-All Portfolio	0.06%	0.14	35.55%
Sector-All Portfolio	1.14%	2.89	51.60%
FOF-All Portfolio	0.46%	2.84	24.57%

EXHIBIT 7

Results of OLS Estimation

Model: $r_{pt+1} = \alpha_p + \delta_{1p} r_{mt+1} + \delta'_{2p}(z_t r_{mt+1}) + \varepsilon_{pt+1}$

OLS Estimates				
			Adjusted	**First Order**
Portfolio	**Alpha**	**t-Value**	**R-Square**	**Autocorrelation**
Event Driven-Active Portfolio	0.60%	4.92	44.58%	0.26
Global Macro-Active Portfolio	0.84%	4.40	18.19%	0.14
Emerging Markets-Active Portfolio	1.19%	2.07	19.62%	0.28
Global Established-Active Portfolio	0.82%	6.14	69.16%	0.13
Global International-Active Portfolio	0.53%	2.82	26.97%	0.24
Market Neutral-Active Portfolio	0.67%	10.67	31.32%	0.27
Short Selling-Active Portfolio	0.76%	2.74	59.67%	0.07
Sector-Active Portfolio	1.32%	5.39	51.50%	0.16
FOF-Active Portfolio	0.42%	4.05	37.27%	0.34
			Adjusted	**First Order**
Portfolio	**Alpha**	**t-Value**	**R-Square**	**Autocorrelation**
Event Driven-Dead Portfolio	0.31%	2.21	37.79%	0.24
Global Macro-Dead Portfolio	0.06%	0.33	36.29%	0.27
Emerging Markets-Dead Portfolio	-0.07%	-0.21	23.60%	0.36
Global Established-Dead Portfolio	0.30%	1.55	70.26%	0.16
Global International-Dead Portfolio	0.22%	1.09	32.46%	0.18
Market Neutral-Dead Portfolio	0.32%	3.65	40.21%	0.16
Short Selling-Dead Portfolio	0.58%	1.09	43.19%	0.10
Sector-Dead Portfolio	0.80%	2.02	47.35%	0.05
FOF-Dead Portfolio	0.20%	1.49	35.67%	0.38
			Adjusted	**First Order**
Portfolio	**Alpha**	**t-Value**	**R-Square**	**Autocorrelation**
Event Driven-All Portfolio	0.45%	3.75	43.08%	0.27
Global Macro-All Portfolio	0.45%	2.68	30.61%	0.20
Emerging Markets-All Portfolio	0.57%	1.50	27.52%	0.41
Global Established-All Portfolio	0.56%	3.64	71.98%	0.16
Global International-All Portfolio	0.38%	2.35	37.72%	0.24
Market Neutral-All Portfolio	0.50%	7.61	42.44%	0.20
Short Selling-All Portfolio	0.69%	2.15	61.49%	0.07
Sector-All Portfolio	1.15%	4.15	51.40%	0.12
FOF-All Portfolio	0.31%	2.67	37.04%	0.38

these alphas are close to a single-factor model as in Exhibit 5 where the Russell 3000 is used as a benchmark. These results are similar to Kazemi and Schneeweis [2003] who find that estimated alphas remain virtually the same regardless of the model used.

Let us now look at the Dead portfolio. We find that most of the alphas (from OLS estimation) with the exception of event driven, market neutral, and sector are insignificant. However, funds sometimes stop reporting even when their performance is healthy. This usually happens with managers who are closed to new investments. This could be the key to the strategies exhibiting significantly positive alphas. The OLS and GMM results in this case are similar with only market-neutral and sector displaying significantly positive alphas when GMM estimation is employed. The adjusted R-squares in the case of Dead portfolios are not very different from the ones in the case of the Active portfolios with the exception of the emerging markets portfolio.

Finally, let us look at the All portfolio. Using OLS estimation most strategies display significantly positive alphas with the exception of emerging markets. However, when the GMM method is used, global macro, global international, and short-selling portfolios also display insignificant alphas. However, in all cases where the alphas were positive and significant, the Active portfolios had the highest alphas, followed by the All portfolios and then Dead portfolios. This is logical since the Dead portfolio contains the largest number of defunct funds. These results help explain some of the previous research on hedge funds. Several studies have found evidence of positive excess return alphas. If we had excluded the CISDM dead funds database from our analysis, we would also have found evidence of positive excess return alphas in all cases. Inclusion of the dead funds database and construction of portfolios of dead funds, however, yield different results. While several strategies showed evidence of positive excess return alphas, even when dead funds were included, some strategies did not (emerging markets in the case of OLS

EXHIBIT 8

Estimation Results of the Conditional Treynor-Mazuy Model

Model: $r_{pt+1} = \alpha_p + b_{1p} r_{mt+1} + C'_p(z_t r_{mt+1}) + \gamma_{tmc}[r_{r,\, t+1}]^2 + v_{pt+1}$

Portfolio	Alpha	t-Value	Timing Coefficient	t-Value	R-Square	First Order Autocorrelation
Event Driven-Active Portfolio	1.08%	8.54	-250.76%	-6.94	58.75%	0.26
Global Macro-Active Portfolio	0.97%	4.26	-69.08%	-1.05	22.07%	0.13
Emerging Markets-Active Portfolio	1.68%	2.45	-256.06%	-1.30	23.73%	0.27
Global Established-Active Portfolio	0.96%	6.04	-73.12%	-1.60	70.91%	0.14
Global International-Active Portfolio	0.85%	3.85	-167.58%	-2.64	33.14%	0.23
Market Neutral-Active Portfolio	0.76%	10.25	-46.96%	-2.20	36.22%	0.27
Short Selling-Active Portfolio	0.75%	2.25	6.34%	0.07	61.28%	0.07
Sector-Active Portfolio	1.60%	5.53	-149.58%	-1.80	54.75%	0.15
FOF-Active Portfolio	0.60%	4.95	-94.18%	-2.72	42.74%	0.34
Portfolio	**Alpha**	**t-Value**	**Timing Coefficient**	**t-Value**	**R-Square**	**First Order Autocorrelation**
Event Driven-Dead Portfolio	0.61%	3.82	-159.16%	-3.47	44.92%	0.18
Global Macro-Dead Portfolio	0.16%	0.72	-52.02%	-0.80	39.11%	0.26
Emerging Markets-Dead Portfolio	0.58%	1.41	-343.19%	-2.90	30.74%	0.34
Global Established-Dead Portfolio	0.49%	2.15	-100.46%	-1.54	71.92%	0.16
Global International-Dead Portfolio	0.12%	0.49	52.96%	0.77	35.43%	0.18
Market Neutral-Dead Portfolio	0.49%	4.83	-89.35%	-3.08	46.17%	0.16
Short Selling-Dead Portfolio	0.02%	0.03	293.68%	1.62	46.44%	0.11
Sector-Dead Portfolio	1.07%	2.31	-150.81%	-1.12	50.35%	0.05
FOF-Dead Portfolio	0.41%	2.60	-110.17%	-2.45	40.72%	0.37
Portfolio	**Alpha**	**t-Value**	**Timing Coefficient**	**t-Value**	**R-Square**	**First Order Autocorrelation**
Event Driven-All Portfolio	0.84%	6.39	-204.96%	-5.41	54.65%	0.22
Global Macro-All Portfolio	0.57%	2.82	-60.55%	-1.05	33.89%	0.19
Emerging Markets-All Portfolio	1.14%	2.57	-300.88%	-2.36	33.03%	0.41
Global Established-All Portfolio	0.72%	3.97	-86.79%	-1.66	73.61%	0.16
Global International-All Portfolio	0.48%	2.53	-57.31%	-1.04	40.67%	0.24
Market Neutral-All Portfolio	0.63%	8.28	-68.15%	-3.14	48.30%	0.20
Short Selling-All Portfolio	0.38%	0.98	166.02%	1.51	63.61%	0.08
Sector-All Portfolio	1.40%	4.25	-133.18%	-1.41	53.98%	0.12
FOF-All Portfolio	0.50%	3.71	-102.17%	-2.63	42.34%	0.37

estimation and global international, global macro, and short-selling in the case of GMM estimation). This underscores the importance of including information and returns on dead funds in any study of performance.

Comparing our single-factor and multi-factor estimates we find, consistent with Kazemi and Schneeweis [2003], that the estimated alphas virtually remain the same. This, as Kazemi and Schneeweis [2003] have suggested, points to two conclusions: one, the explanatory variables used in this study may not be able to capture the type of trading strategies followed by hedge fund strategies and, two, the estimated alphas are good estimates of the true alphas and are mostly due to managers' skills and hence cannot be explained by naïve static or dynamic trading strategies.

Exhibits 8 and 9 present the results of the conditional and unconditional Treynor-Mazuy models respectively. In the unconditional Treynor-Mazuy model (results in Exhibit 9), for the Active portfolios all alphas are positive and significant at the 5% level and most market-timing coefficients are negative and significant at the 5% level with the exception of global macro, emerging markets, and short-selling strategies. For the Dead portfolios, most alphas are positive with the exception of global macro, global international, and short-selling. The market-timing coefficients that are significant and negative for the All portfolios are event driven, emerging markets, global established, market-neutral, and fund of funds. Fung, Xu, and Yau [2002] found in their analysis of 115 hedge funds that 22 or 19% of the funds had significantly negative market-timing coefficients whereas only 2 or 2% had significantly positive market-timing coefficients. In our analysis none of the portfolios had significantly positive market-timing coefficients. Our results, as do the results of Fung, Xu, and Yau, suggest that hedge fund managers lack market-timing ability. The results above do not differ very much from the results that we obtain from the conditional Treynor-Mazuy (Exhibit 8 presents the results) model. We find that among the Active portfolios all alphas are significant and positive whereas

EXHIBIT 9

Estimation Results of the Unconditional Treynor-Mazuy Model

Model: $r_{pt+1} = a_p + b_p r_{mt+1} + \gamma_{tmu}[r_{m,\,t+1}]^2 + \nu_{pt+1}$

Portfolio	Alpha	t-Value	Timing Coefficient	t-Value	R-Square	First Order Autocorrelation
Event Driven-Active Portfolio	1.17%	9.61	-243.14%	-6.87	55.39%	0.28
Global Macro-Active Portfolio	0.91%	4.11	-74.17%	-1.15	15.47%	0.16
Emerging Markets-Active Portfolio	1.74%	2.69	-193.26%	-1.03	21.29%	0.31
Global Established-Active Portfolio	1.04%	6.83	-90.03%	-2.04	69.40%	0.19
Global International-Active Portfolio	0.96%	4.57	-167.13%	-2.74	30.61%	0.25
Market Neutral-Active Portfolio	0.82%	11.40	-47.30%	-2.25	30.24%	0.33
Short Selling-Active Portfolio	0.71%	2.28	20.36%	0.22	59.76%	0.08
Sector-Active Portfolio	1.57%	5.76	-165.27%	-2.07	53.09%	0.16
FOF-Active Portfolio	0.65%	5.60	-112.90%	-3.33	38.06%	0.36
Portfolio	**Alpha**	**t-Value**	**Timing Coefficient**	**t-Value**	**R-Square**	**First Order Autocorrelation**
Event Driven-Dead Portfolio	0.71%	4.53	-157.03%	-3.45	38.68%	0.21
Global Macro-Dead Portfolio	0.21%	1.00	-71.51%	-1.14	35.99%	0.28
Emerging Markets-Dead Portfolio	0.85%	2.16	-418.04%	-3.64	26.24%	0.38
Global Established-Dead Portfolio	0.52%	2.44	-118.38%	-1.90	71.05%	0.18
Global International-Dead Portfolio	0.21%	0.90	-13.82%	-0.20	26.87%	0.19
Market Neutral-Dead Portfolio	0.52%	5.01	-98.31%	-3.26	34.42%	0.23
Short Selling-Dead Portfolio	0.15%	0.25	316.20%	1.83	45.39%	0.12
Sector-Dead Portfolio	0.93%	2.14	-159.85%	-1.20	48.22%	0.07
FOF-Dead Portfolio	0.47%	3.00	-147.00%	-3.25	32.37%	0.38
Portfolio	**Alpha**	**t-Value**	**Timing Coefficient**	**t-Value**	**R-Square**	**First Order Autocorrelation**
Event Driven-All Portfolio	0.94%	7.35	-200.09%	-5.38	50.68%	0.25
Global Macro-All Portfolio	0.56%	2.93	-72.84%	-1.31	30.90%	0.22
Emerging Markets-All Portfolio	1.30%	3.12	-306.77%	-2.52	31.27%	0.42
Global Established-All Portfolio	0.78%	4.54	-104.21%	-2.09	72.91%	0.20
Global International-All Portfolio	0.58%	3.19	-90.47%	-1.69	36.61%	0.24
Market Neutral-All Portfolio	0.67%	8.84	-72.81%	-3.29	39.42%	0.28
Short Selling-All Portfolio	0.45%	1.25	178.69%	1.70	62.68%	0.08
Sector-All Portfolio	1.32%	4.20	-164.48%	-1.80	51.74%	0.12
FOF-All Portfolio	0.56%	4.23	-129.95%	-3.37	36.09%	0.39

market-timing coefficients for the event driven, global international, market neutral and fund of funds are significant and negative. For the Dead portfolios most alphas are insignificant (with the exceptions of event driven, global international, market neutral, sector, and fund of funds) whereas market-timing coefficients for event driven, emerging markets, market neutral, and fund of funds were significant and negative. For the All portfolios most alphas were significant and positive whereas market-timing coefficients for event driven, emerging markets, market neutral, and fund of funds were significant and negative. These results point to three conclusions: one, in general hedge fund managers lack market-timing ability and, two, analysis at the individual fund level is required, as is evident from the results of Fung, Xu, and Yau [2002], to determine the few managers who have market-timing ability or, three, the variables and model used are misspecified and hence cannot measure the market-timing ability of hedge fund managers. Fung, Xu, and Yau [2002] divide their sample into two sets. Set A consisted of funds classified as U.S. Opportunity, European Opportunity, and Global Macro and Set B consisted of funds classified as Emerging Markets and Global International. These two sets are distinctly different in terms of their geographical focus. They found that Set A outperformed Set B in terms of excess return, Sharpe ratio, and selectivity index but underperformed in terms of market-timing ability. They suggest based on this that timing broad market movements is much harder for hedge fund managers in established markets than in emerging markets. Our results cannot confirm this observation since we conduct portfolio level analysis. Fund level analysis is needed to confirm this observation. Jagannathan and Korajczyk [1986] demonstrate that it is possible to create artificial market timing as measured by commonly used parametric models of timing by investing in option-like securities. They note that this artificial timing ability is obtained at the cost of poorer measured security selectivity. They show that when the proxy for the market portfolio contains option-like securities, portfolios with greater (lower) concentration in option-like securities will show positive (negative) timing performance and negative (positive) selectivity. This provides a possible explanation for previous empirical findings that indicate that mutual funds have negative timing ability. This also suggests that the proxy for the hedge fund market portfolio should contain option-like securities since hedge fund returns exhibit option-like behavior. Research in this area is beginning to move in that direction. Fung and Hsieh [2001, 2002a] note that hedge fund strategies typically generate option-like returns and linear-factor models using benchmark asset indices have difficulty explaining them. They use lookback straddles to model trend-following strategies and show that they can explain trend-following funds' returns better than standard market indices. Agarwal and Naik [2003] estimate the risk exposures of hedge funds using a multi-factor model consisting of excess returns on standard assets and options on these assets as risk factors. They examine the ability of risk factors to replicate the out-of-sample performance of hedge funds. Their out-of-sample analysis confirms that the risk factors estimated in the first step are not statistical artifacts of the data, but represent underlying economic risk exposures of hedge funds. Future research should avail of the wide variety of option-based investing strategies to provide a set of transparent rule-based indexes that will enhance our understanding of hedge fund investing.

V. CONCLUSIONS

In this article we use generalized method of moments to study the relationship between hedge fund returns and equity-market-based betas. We show that the usage of models that permit estimates to vary through time does not impact our estimation of the excess return relative to traditional single-factor non-time-varying models. Future research entails using GMM on an enlarged set of explanatory variables. Also, recent work by Ghysels [1998] and Wang [2003] suggests that linear models that relate betas to conditioning variables may lead to functional form misspecification. Hence non-parametric methodologies that avoid functional form misspecification would be interesting to explore as in Wang [2003]. In our analysis of market-timing models, we show that hedge fund managers in general lack market-timing ability and fund level analysis is required to determine the few that do have market-timing ability. Finally we note that hedge fund research is beginning to move in the direction of using option-based factors for performance evaluation. Future research should avail of the wide variety of option-based investing strategies to provide a set of transparent rule-based indexes that will enhance our understanding of hedge fund investing.

ENDNOTES

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[1]See Kazemi, Gupta, and Cerrahoglu [2003] for various approaches to creating passive indices that are optimized to track historical hedge fund returns and strategies.

[2]See Data section.

[3]Note in the latter case since there are five information variables, there are five moment conditions. In total there was one model statement and five moment conditions that were used to estimate parameters.

[4]Most databases exclude the returns of non-surviving hedge funds that creates a survivorship bias. Brown et al. [1999] have estimated this bias to be in the range of 1.5%-3% per year while Edwards and Caglayan [2001] have estimated this to be between 0.36% for market-neutral funds and 3.06% for long-only funds. These are comparable to the findings of Liang [2000] and Fung and Hsieh [2000] as well who use the TASS database for their analyses. It is important to note as Schneeweis, Kazemi, and Martin [2001] point out that most previous studies do not take into consideration the market factors driving fund survival. Hence the levels of survivor bias impact exhibited by the past data may over- or underestimate future bias depending on economic conditions and strategy.

[5]When data vendors add new funds to their database, they may choose to back-fill earlier returns for those funds. It is reasonable to assume that only funds with good performance records choose to report their performance, which may result in upward-biased returns for newly-reporting hedge funds during their early histories. Fung and Hsieh estimate an instant history bias of as much as 1.4% for average annual hedge fund returns while Edwards and Caglayan [2001] estimate that to be 1.17%. It is therefore prudent to exclude the first 12 months of hedge fund returns.

[6]Another form of bias that exists in hedge fund databases is selection bias. This type of bias exists only if managers with good performance choose to report their performance, resulting in the overstatement of true hedge fund performance. However, to the contrary, there is evidence that very successful hedge fund managers may not choose to report their performance since they are closed to new investors. Fung and Hsieh [2000] argue that this bias is very small if it exists at all and Edwards and Caglayan argue that there is no accurate way to estimate this.

[7]The fourth type of bias is called "multi-period sampling" bias—a term coined by Fung and Hsieh. This bias may exist if

some hedge funds have very short return histories. If investors require at least 30 months of history before investing in a hedge fund, then estimates of excess returns based on shorter histories may be misleading to investors. Fung and Hsieh conclude that this bias is very small while Edwards and Caglayan include funds in their study only if 36 months of history are available.

[8]These variables were used in Ferson and Harvey [1993], Ferson and Schadt [1996], Christopherson, Ferson, and Glassman [1998], and others. We estimated our model with several other variables and found no significant impact on the results.

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