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Hedge Fund Strategy Performance: Using Conditional Approaches

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Prepared by:

Bhaswar Gupta, *Research Director*

Burak Cerrahoglu, *Research Associate*

Alper Daglioglu, *Research Associate*

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Isenberg School of Management, University of Massachusetts, Amherst, Massachusetts, 01003
Tel: 413-253-4601 & 413-545-5641; Fax: 413-253-4613 & 413-545-3858
Email: cisdm@som.umass.edu WEB: www.cisdm.org

Abstract

The search for methodologies that accurately measure performance and performance persistence continues to evolve. This is especially true for investment strategies such as hedge funds, which have been shown, in several instances, to not be normally distributed. In this article, we evaluate performance of hedge funds using conditional approaches and GMM. Unlike the Sharpe ratio or Jensen's alpha, our results would still be valid even if hedge funds were not normally distributed. We use the CISDM hedge fund database for this study. We create three portfolios to measure performance: an Active portfolio (which consists of funds in the active database), a Dead portfolio (which consists of funds in the defunct database) and an All portfolio (which consists of funds in both the active and defunct databases). We find that while the Active portfolios show evidence of positive risk-adjusted returns in most cases, the Dead portfolios do not and only some of the All portfolios show evidence of positive risk-adjusted returns. The results are similar irrespective of whether we use Jensen's alpha or conditional approaches. Our results point to two conclusions: one the explanatory variables used in this paper 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 which are mostly due to managers' skills and hence cannot be explained by naïve static or dynamic trading strategies. 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. The results also suggest that hedge fund returns have option-like properties and future research should include option-based factors in performance evaluation.

Hedge Fund Strategy Performance: Using Conditional Approaches

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 (Schneeweis, Kazemi and Martin [2002], Brown, Goetzmann and Liang [2003], Goetzmann, Ingersoll and Ross [1998], Liang [1999, 2001]) 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 the market-based (e.g., exposure to economic factors) sources of hedge fund returns (Schneeweis, Kazemi and Martin [2003], Fung and Hsieh [1997], Fung and Hsieh [2002], Agarwal and Naik [2000b] and Liang [1999]). In this paper 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 funds returns. Results show, 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.

The results reported in this paper 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 funds 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 using the conditional approach 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 it is consistent with the semi-strong form of market efficiency. The biggest 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 that are used to represent public information. Chan and Chen [1988], Cochran [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 paper we use various GMM based means of regression analysis, which is also discussed in the methodology section to study the relationship between hedge fund returns and factor betas. 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 paper 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 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. Hedge fund returns within a particular investment strategy have been shown to be driven largely by market factors, such as changes in credit spreads or market volatility (Fung and Hsieh [1997], Schneeweis and Spurgin [1999], Fung and Hsieh [2002], Agarwal and Naik [2000b] and Liang [1999]) specific to that strategy. 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 specific versions of the Jensen's alpha and Sharpe ratios. These approaches, however have several weaknesses when applied to hedge funds. First, empirical research (Brooks and Kat [2002]) 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. Inferences on the performance and persistence of an actively managed portfolio can be significantly altered when one allows for conditional, instead of unconditional moments.

[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.*

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 its lack thereof has important implications. If they can consistently deliver excess returns then fee structures may be justified. Brown, Goetzmann and Ibbotson [1999], Ackermann, McEnally and Ravenscraft [1999], Liang [1999] and Agarwal and Naik [2000a] have all found evidence of positive risk-adjusted returns. Kat and Miffre[2002] 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.

Insert Exhibit 1 About Here

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, Peskin, Urias, Anjilvel and Boudreau [2000], Brown, Goetzmann and Ibbotson [1999] and Schneeweis, Kazemi and Martin [2001] have found little or no evidence of persistence. More recently, Kat and Menexe [2002] 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 [2002] 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, Edwards and Caglayan[2001], use the CISDM (formerly MAR) database. The dataset used in that study included 1665 hedge funds and less than 500 dead funds. However the CISDM (formerly MAR) dead funds database, at the present time contains about 2800-2900 funds. The results of the study might have been dramatically altered had all dead funds been included in the dataset.

III. Methodology and Data

Investment performance evaluation remains a central part of academic research. It is not the purpose of this paper to review 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:

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

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 α 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]; Merton and Hendrikson [1981]; and Favre and Galeano [2002]). Time variation can be induced into the model by assuming a linear relationship between β and a set of L mean zero information variables available at time *t-1*, z_{t-1} (see Ferson and Schadt [1996]). This approach has come to be known as conditional performance evaluation in the literature.

IIIA. Methodology: Generalized Method of Moments

We use stochastic discount factors in our study of hedge fund performance. 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 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 $E(.)$. Empirical work on asset pricing models like the one above typically relies on *rational expectations*, interpreted as the assumption that the expectation terms in the model are mathematical conditional expectations. Taking the expected values of equation above, rational expectations implies that versions of it must hold for the expectations $E_t(./Z_t)$ and $E(.)$. Assuming non-zero prices, the equation above is equivalent to

$$E(m_{t+1}R_{t+1} - \mathbf{1}/\Omega_t) = 0$$

$$E(m_{t+1}R_{t+1}/\Omega_t) = 1$$

where R_{t+1} is a *N*-vector of primitive asset gross returns, **1** is a *N*-vector of 1s. The gross return is $R_{i,t+1}$ defined as

$$R_{i,t+1} = \frac{P_{i,t+1} + D_{i,t+1}}{P_{i,t}}$$

We say that a stochastic discount factor "prices" the assets if the equations above are satisfied. Most empirical tests of asset pricing models work directly with the equation $E(m_{t+1}R_{t+1} - \mathbf{1}/\Omega_t) = 0$ and the relevant definition of m_{t+1}. Farnsworth, Ferson, Jackson and Todd [2002] define a fund's conditional alpha for a given stochastic discount factor as:

$$\alpha_{pt} = E(m_{t+1}R_{p,t+1} - \mathbf{1}/\Omega_t) = 0$$

where one dollar invested with the fund at time *t,* yields $R_{p,t+1}$ dollars at time *t+1,* $R_{p,t+1}$ is the vector of primitive-asset gross returns at time *t+1*, **1** is a vector of ones and Ω_t is the information set at time *t*. Ferson [2003] note that if the SDF prices a set of "primitive" assets, R_{t+1}, then α_{pt} will be zero when the fund costlessly forms a portfolio of primitive assets, if the portfolio strategy uses only the public information at time *t*. In that case,

$$R_{p,t+1} = x(Z_t)'R_{t+1},$$

which is equivalent to

$$R_{p,t+1} = x_1(Z_t)R_{1,t+1} + x_2(Z_t)R_{2,t+1}$$

for the case of two primitive assets. $x_1(Z_t)$ and $x_2(Z_t)$ are the portfolio weight vectors.

The expression $\alpha_{pt} = E(m_{t+1}R_{p,t+1} / \Omega_t) - \mathbf{1} = 0$, this can be written as

$$\alpha_{pt} = E(m_{t+1}x(Z_t)'R_{t+1} / \Omega_t) - \mathbf{1} = 0$$

$$\alpha_{pt} = x(Z_t)'E(m_{t+1}R_{t+1} / \Omega_t) - \mathbf{1} = 0$$

$$\alpha_{pt} = x(Z_t)'\mathbf{1} - \mathbf{1} = 0$$

We follow the approach of Ferson and Schadt [1996] and hence in our case the stochastic discount factor is a linear function of the market excess return where the coefficients may depend linearly on Z_t. Models in which m_{t+1} is linear in predefined factors are called linear factor models. Ferson and Schadt [1996] start with the conditional CAPM, which implies that the following equations are satisfied for the assets of portfolio managers.

$$r_{it+1} = \beta_{im}(Z_t)r_{mt+1} + u_{i,t+1}, \forall i = 0,\ldots,N; t = 0,\ldots,T-1 \qquad \text{(1a)}$$

$$E(u_{i,t+1} / Z_t) = 0 \qquad \text{(1b)}$$

$$E(u_{i,t+1}r_{m,t+1} / Z_t) = 0 \qquad \text{(1c)}$$

where R_{it+1} is the rate of return on asset *i,* between times *t* and *t+1,* $r_{it} = R_{it} - R_{ft}$, is the excess return, R_{ft} is the return on a one-month treasury bill, Z_t, is a vector of instruments for the information available at time *t*, and r_{mt+1} is the excess return of the market factor. The $\beta_{im}(Z_t)$ are the time *t,* conditional market betas of the excess return of asset *i*. Equation (1b) follows from the market efficiency assumption and equation (1c) says that the $\beta_{im}(Z_t)$ are conditional regression coefficients. The above equation implies that the difference between the excess return on a security and the product of its beta and the excess return on the market, which differs, from zero must be based on an information set that is more informative than Z_t. The forecast of this difference is zero if we use only the information Z_t. A similar regression will be satisfied by the portfolio strategy. The intercept should be zero and the error term should not be related to the public information variables.

Since we hypothesize that the manager uses no more information than Z_t, the portfolio beta $\beta_{pm}(Z_t)$, is only a function of Z_t. This function can be approximated linearly using a Taylor series, following Shanken [1990] and others:

$$\beta_{pm}(Z_t) = b_{0p} + B'_p z_t \qquad (2)$$

where $z_t = Z_t - E(Z)$ is a vector of the deviations of Z_t from the unconditional means and B_p is a vector with dimension equal to the dimension of Z_t. The coefficient b_{0p} may be interpreted as an **average beta**, i.e. the unconditional mean of the conditional beta: $E(\beta_{pm}(Z_t))$.

Equation (1a) implies that a portfolio strategy that depends only on public information Z_t will satisfy a similar regression. Hence for the portfolio, the regression can be expressed as

$$r_{p,t+1} = \beta_{pm}(Z_t) r_{mt+1} + u_{i,t+1} \qquad (3)$$

Substituting the expression for $\beta_{pm}(Z_t)$ from (2) into (3), we get

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

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

Since $\alpha_p = 0$, for our estimation purposes, we will use the regression equation

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

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 and B'_p is a vector of betas. 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:

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

Since the error term must be uncorrelated with the information variables we use the conditions $E(u_{i,t+1} / Z_t) = 0$ and $E(u_t \otimes z_{t-1}) = 0$ [2] as moment conditions. 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 betas.

IIIB. Market Timing Models

Hedge fund strategies can be classified as either directional or non-directional. In terms of the CISDM database classification directional strategies would include long/short equity, global macro, global, long only and short selling. Managers in this category bet on the directions of

[2] Ferson and Schadt [1996] show that these are the moment conditions in GMM estimation.

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 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 measures 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.

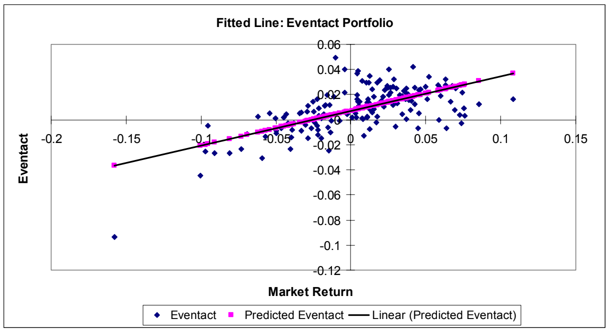
The purpose of conditional performance evaluation in the market-timing context is to distinguish timing ability that merely reflects publicly available information as captured by a set of lagged information variables from timing based on better quality information. This informed timing, is referred to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

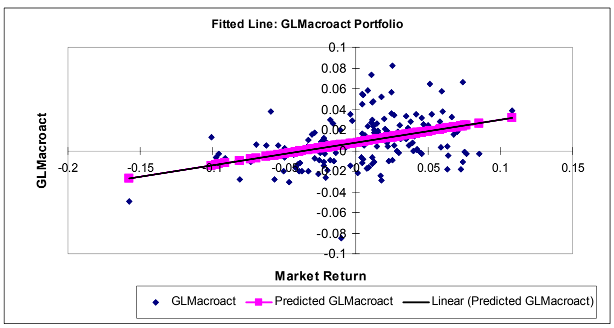
$$r_{pt+1} = a_p + b_p r_{mt+1} + \gamma_{tmu}[r_{m,t+1}]^2 + v_{pt+1}$$

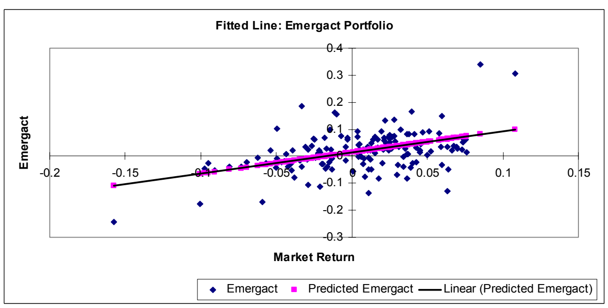
where the coefficient γ_{tmu} reflects market timing ability. The intuition behind this model is based on the approach used by Treynor [1965]. Treynor [1965] used "characteristic lines" to demonstrate market timing ability of mutual funds. These characteristic lines were constructed as follows: The returns 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:

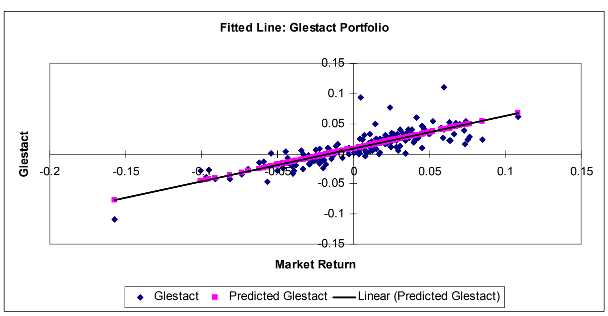
$$\hat{r}_{pt+1} = \hat{a}_p + \hat{b}_p r_{mt+1} + v_{pt+1}$$

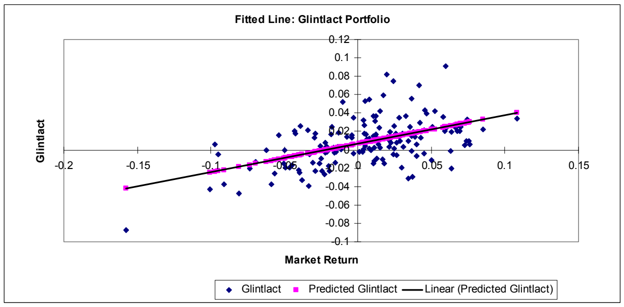
where $\hat{a}_p$ and $\hat{b}_p$ are the least squares estimates. We illustrate this using our active portfolios.







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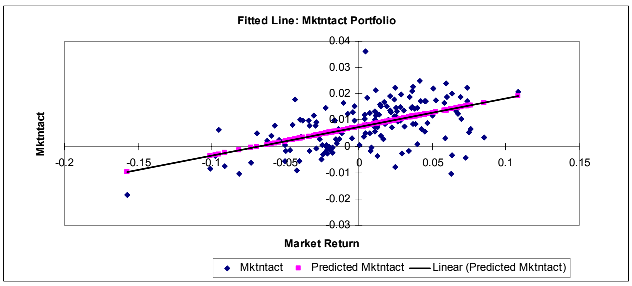
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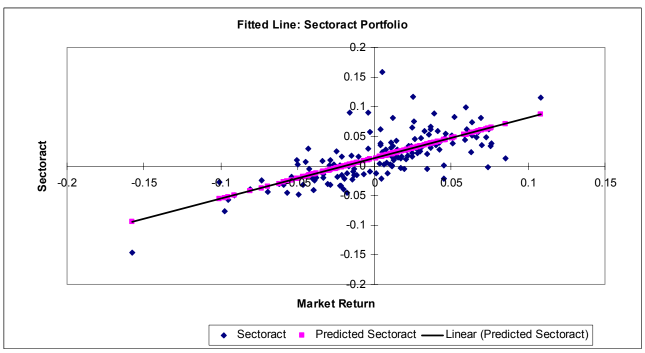
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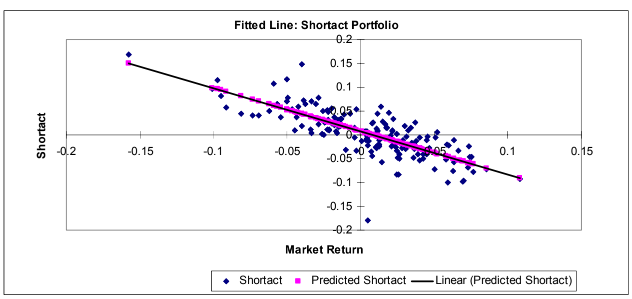
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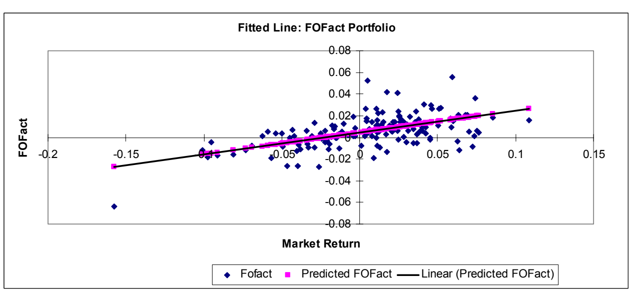
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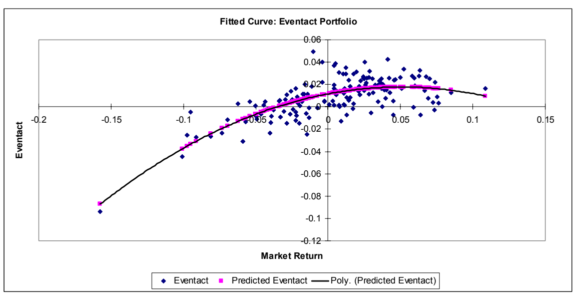
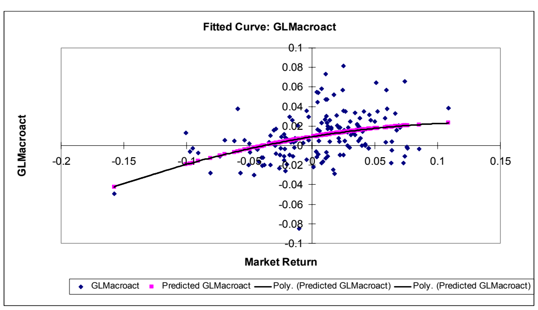
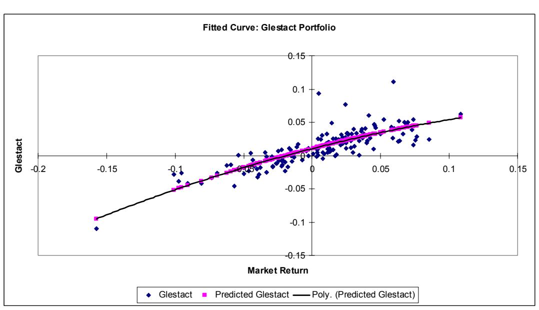
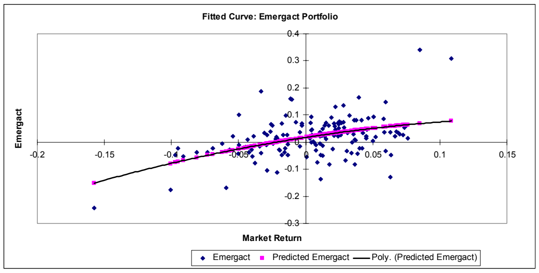
Treynor and Mazuy [1966] note that the key to this test for successful anticipation is simple. The only way in which a fund management can translate ability to outguess the market into a benefit to the shareholder is to vary the fund volatility systematically in such a fashion that the resulting characteristic line is concave upward. If a fund manager correctly anticipates the market more often that 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 version of the Treynor-Mazuy model to measure market timing ability. The fitted curves for the active portfolios are given below.








Fitted Curve: Emergact Portfolio
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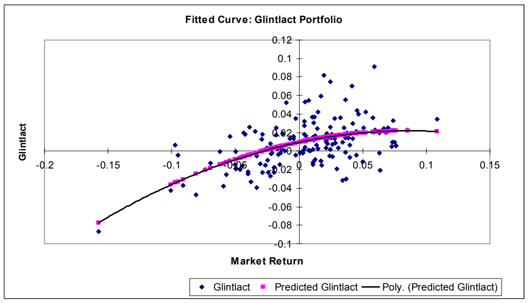
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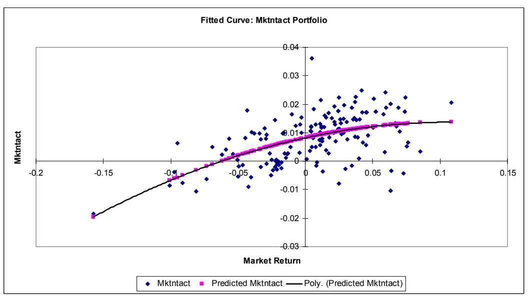
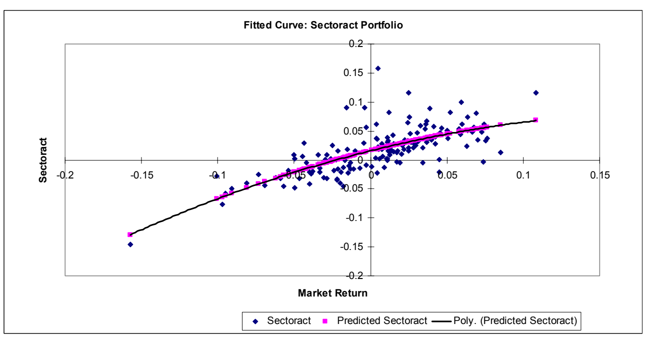
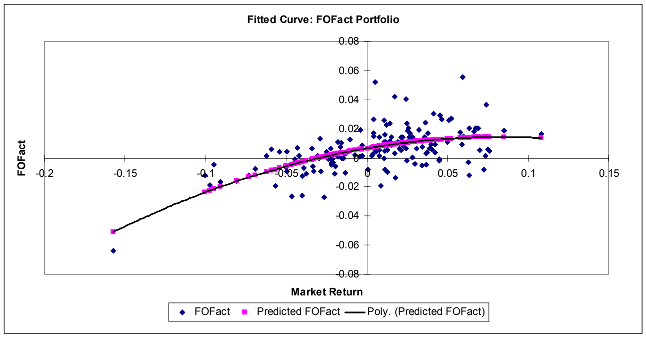
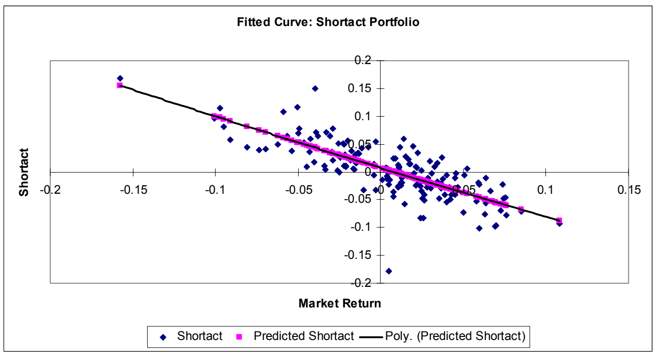

Fitted Curve: Mktntact Portfolio
Mktntact
Market Return
Mktntact
Predicted Mktntact
Poly. (Predicted Mktntact)


Fitted Curve: Sectoract Portfolio
Sectoract
Market Return
Sectoract
Predicted Sectoract
Poly. (Predicted Sectoract)





The timing coefficients on the fitted curves were negative in most cases with the exception of Short-sellers. As the graphs above 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 other curves have similar shapes. 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

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

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.

IIIC. Data

The data for this study has been taken from the CISDM database. As of December 2002, the CISDM database contained around 2200 active hedge funds and CTAs and around 2800 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 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 January 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 2 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 Exhibit 3.

Insert Exhibit 2 About Here

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[3], instant history bias[4], selection bias[5] and multi-period sampling bias[6]. 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

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[3] 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.

[4] 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 an 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] that to be 1.17%. It is therefore prudent to exclude the first twelve months of hedge fund returns.

[5] 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 argue that this bias is very small if at all it exists and Edwards and Caglayan argue that there is no accurate way to estimate this.

[6] 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 atleast 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 Edward and Caglayan include funds in their study only if there is 36 months of history available.

and (5) a dummy variable for the month of January.[7] 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 3 month Treasury bill, the dividend is the DataStream calculated total US market dividend yield and the credit risk is measured as the difference between BAA and AAA rated yields (published by Moody's).

IV. Empirical Results

Exhibits 3A, 3B and 3C 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 panel 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.

Insert Exhibit 3 About Here

[7] 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.

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 3A, 3B and 3C 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 event-driven and market neutral we find that the betas are significantly lower than directional strategies. For the short-selling strategy betas are negative. However, beta 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 multifactor 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 3B. 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.

Insert Exhibits 4, 5 and 6 around here.

Exhibits 4, 5 and 6 present the conditional market betas of the excess return of the Active, Dead and All portfolios respectively. Exhibits 7 and 8 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 multifactor 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 R-squares vary considerably from 21.47% (for global macro) to 70.39% (for global established). Three strategies, global established, sector and short-selling have 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 8 there is very little autocorrelation in the residuals. However, the presence of heteroskedasticity cannot be ruled out. In order to account for heteroskedasticity, we perform Generalized Methods of Moments 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 R-squares vary widely in this case as well from 11.65% for the emerging markets portfolio to 68.21% percent for the global-established portfolio. However, these alphas are close to a single factor model as in exhibit 3 where the Russell 3000 is used as a benchmark. These results are similar to Kazemi and

Schneeweis (2003) who find that estimated alphas virtually remain the same regardless of the model used.

Insert exhibits 7 and 8 around here.

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 R-squares in the case of Dead Portfolio are not very different from the ones in the case of the Active 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 most 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 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 paper 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.

Insert exhibits 9 and 10 around here.

Exhibits 9 and 10 present the results of the conditional and unconditional Treynor-Mazuy models respectively. In the unconditional Treynor-Mazuy model (Results in Exhibit 10), 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 9 presents the results) model. We find that among the Active portfolios all alphas are significant and positive whereas 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 [1984] 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, 2002] 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 fund's 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 paper we use various GMM based means of regression analysis to study the relationship between hedge fund returns and equity market based betas. In this paper we show that including variables which permit beta to be time varying 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) suggest 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.

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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, Mcnally, 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 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 [2002]	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 and Goetzmann [JOB, 1999]	Offshore Funds: Survival and Performance.	Bernheim Offshore	Differences in survivor bias, and return history
Edwards and Caglayan [2001]	Performance Persistence	CISDM [1990-1998], Six factor Jensen Alphas	Significant evidence of persistence among both winners and losers.
Fung and Hsieh (FAJ, 2000d)	Benchmark Issues	Various Indices	Index Universe is 'momentum bet" and Individual Index is style bet

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 [2002]	Performance Persistence	TASS, June 1994 – May 2001, Cross-Product Ration and Cross-Sectional Regressions	Little evidence of persistence in mean returns, standard deviation strongly persistent skewness & kurtosis weakly persistent.
Kat and Miffre [2002]	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 [2002]	Performance Evaluation	HFR indices 1990-2001, Stochastic Discount Factor and GMM Estimation	Significantly positive risk-adjusted returns for most hedge fund strategies.
Liang (JFQA,2000)	Characteristics of Alternative Hedge Fund Data Bases.	TASS and HFR Data Bases	Differences in survivor bias, and return history
Liang (FAJ, 2000)	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 (FAJ,2001)	Return Performance Survivorship Bias Fee Impacts.	TASS Data base, 1407 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 Data bases, 1990-2001	Market factors (Long volatility and short volatility) explain hedge fund index returns
Schneeweis and Spurgin [Lake etc., 1999]	Sharpe style based factors on hedge fund returns	Various Data bases, 1990-2001	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.

Exhibit 2: Characteristics of the CISDM Hedge Fund Database

Exhibit 2A	
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	**1667**
Exhibit 2B	
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	**1274**

Exhibit 3: Summary Statistics of Monthly Returns: January 1990-August 2002

Exhibit 3A: Summary Statistics of Monthly Excess Returns for Active Funds: 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 3B: Summary Statistics of Monthly Excess Returns for Dead Funds: 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 3C: Summary Statistics of Monthly Excess Returns for All Funds: 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

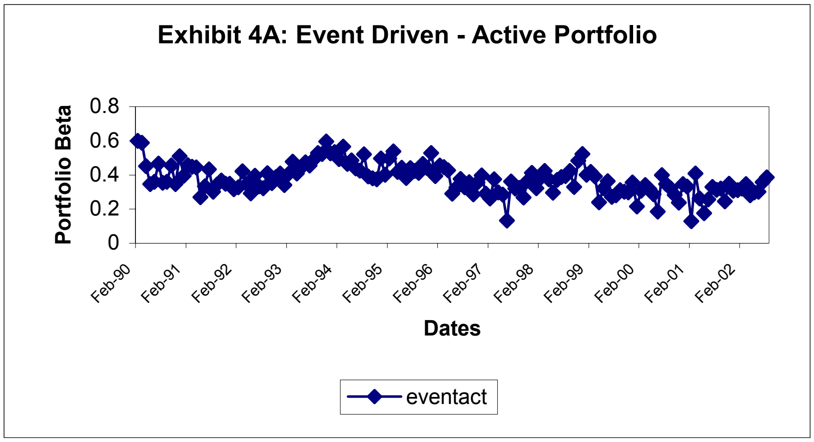
Exhibit 4A: Event Driven - Active Portfolio
Portfolio Beta
0.8
0.6
0.4
0.2
0
Feb-90
Feb-91
Feb-92
Feb-93
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Feb-96
Feb-97
Feb-98
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Feb-00
Feb-01
Feb-02
Dates
eventact

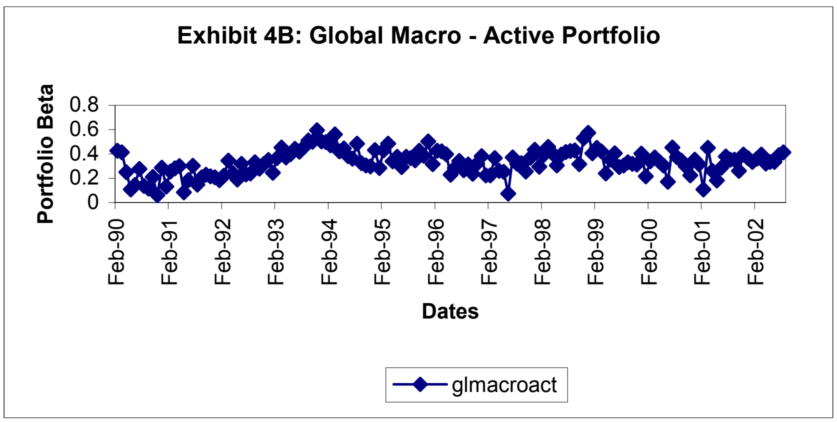
Exhibit 4B: Global Macro - Active Portfolio
Portfolio Beta
0.8
0.6
0.4
0.2
0
Feb-90
Feb-91
Feb-92
Feb-93
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Feb-95
Feb-96
Feb-97
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Feb-01
Feb-02
Dates
glmacroact

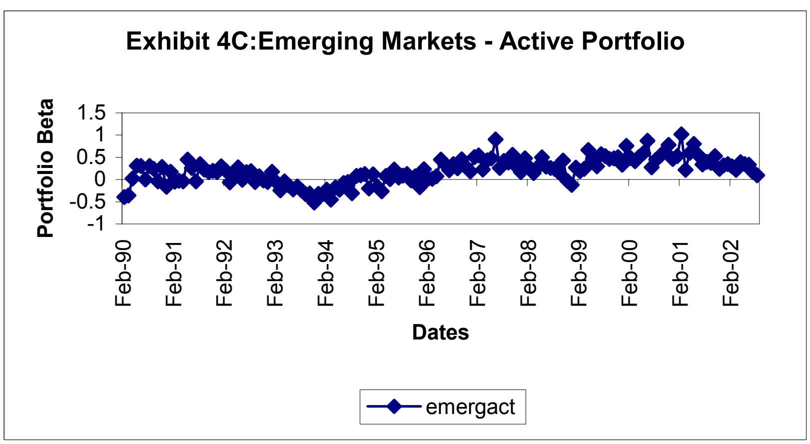
Exhibit 4C:Emerging Markets - Active Portfolio
Portfolio Beta
1.5
1
0.5
0
-0.5
-1
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
emergact

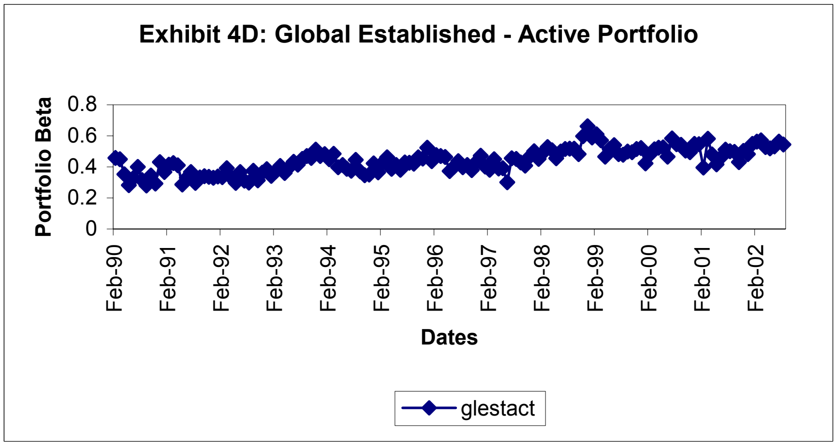
Exhibit 4D: Global Established - Active Portfolio
Portfolio Beta
0.8
0.6
0.4
0.2
0
Feb-90
Feb-91
Feb-92
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Feb-02
Dates
glestact

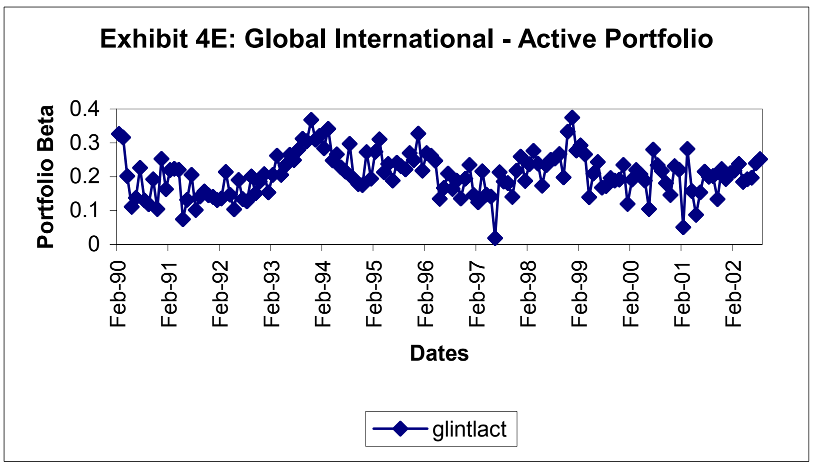
Exhibit 4E: Global International - Active Portfolio
Portfolio Beta
0.4
0.3
0.2
0.1
0
Feb-90
Feb-91
Feb-92
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Feb-96
Feb-97
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Feb-00
Feb-01
Feb-02
Dates
glintlact

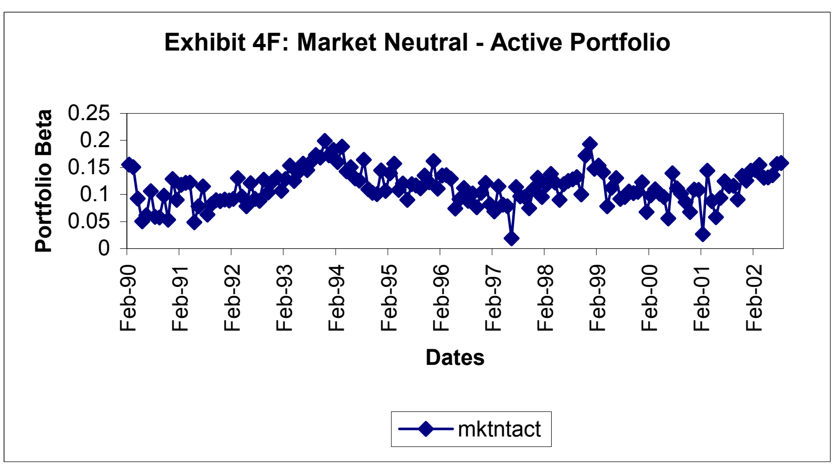
Exhibit 4F: Market Neutral - Active Portfolio
Portfolio Beta
0.25
0.2
0.15
0.1
0.05
0
Feb-90
Feb-91
Feb-92
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Feb-96
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Feb-02
Dates
mktntact

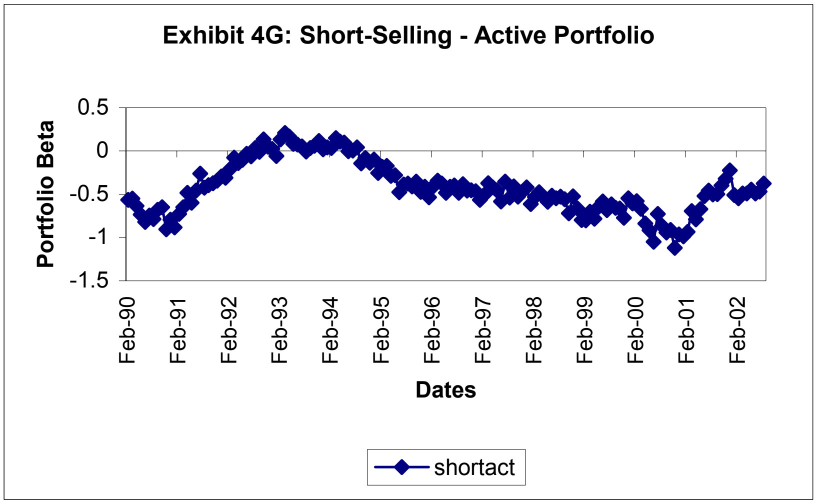
Exhibit 4G: Short-Selling - Active Portfolio
Portfolio Beta
0.5
0
-0.5
-1
-1.5
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
shortact

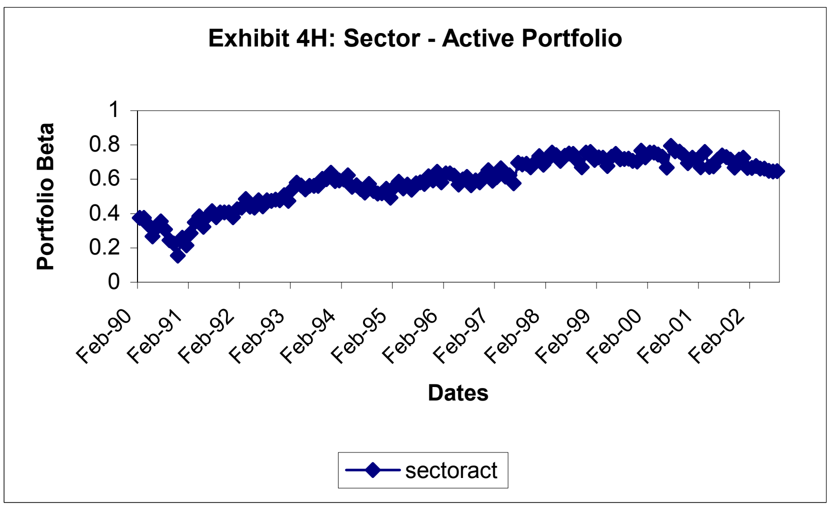
Exhibit 4H: Sector - Active Portfolio
Portfolio Beta
1
0.8
0.6
0.4
0.2
0
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
sectoract

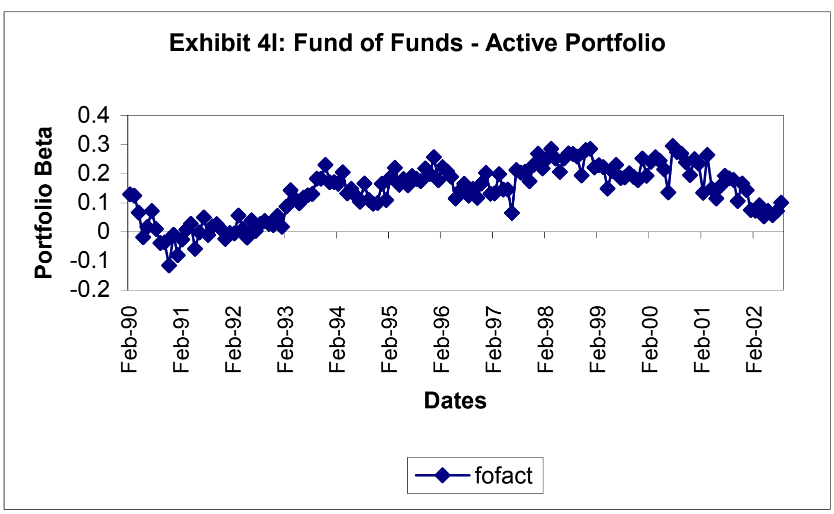
Exhibit 4I: Fund of Funds - Active Portfolio
Portfolio Beta
0.4
0.3
0.2
0.1
0
-0.1
-0.2
Feb-90
Feb-91
Feb-92
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Feb-02
Dates
fofact

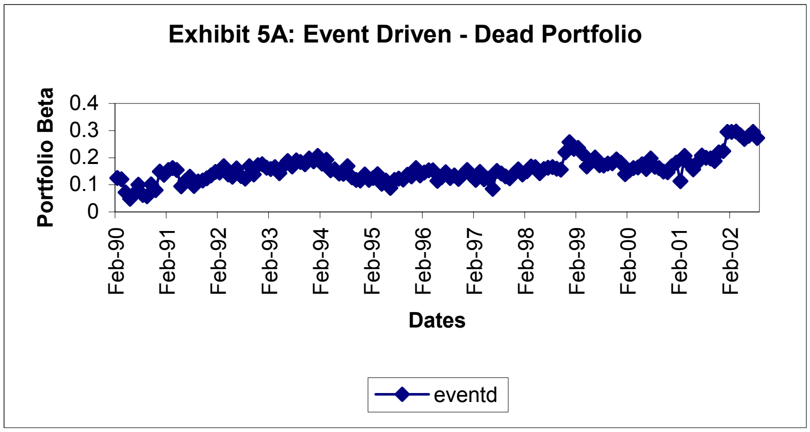
Exhibit 5A: Event Driven - Dead Portfolio
Portfolio Beta
0.4
0.3
0.2
0.1
0
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
eventd

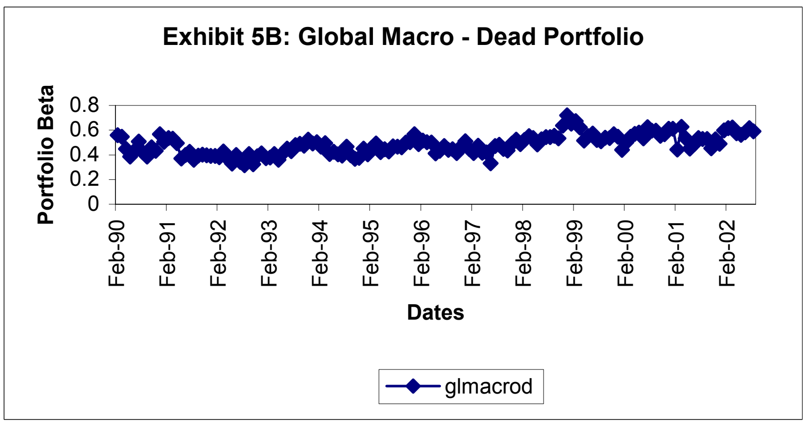
Exhibit 5B: Global Macro - Dead Portfolio
Portfolio Beta
0.8
0.6
0.4
0.2
0
Feb-90
Feb-91
Feb-92
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Feb-02
Dates
glmacrod

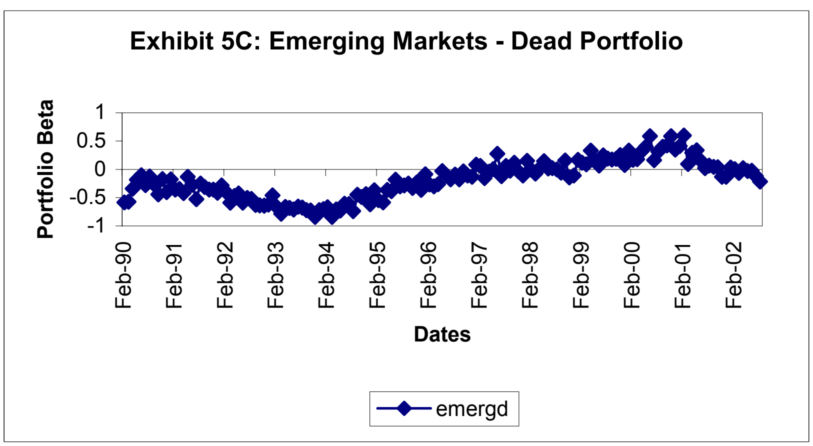
Exhibit 5C: Emerging Markets - Dead Portfolio
Portfolio Beta
1
0.5
0
-0.5
-1
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
emergd

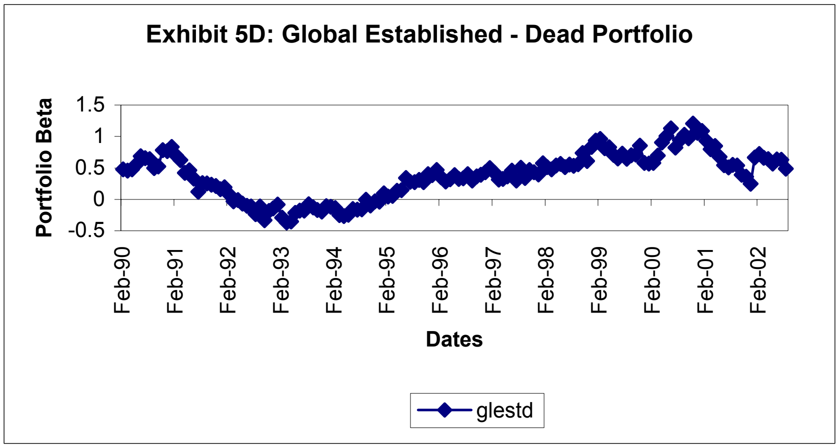
Exhibit 5D: Global Established - Dead Portfolio
Portfolio Beta
1.5
1
0.5
0
-0.5
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
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Feb-00
Feb-01
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Dates
glestd

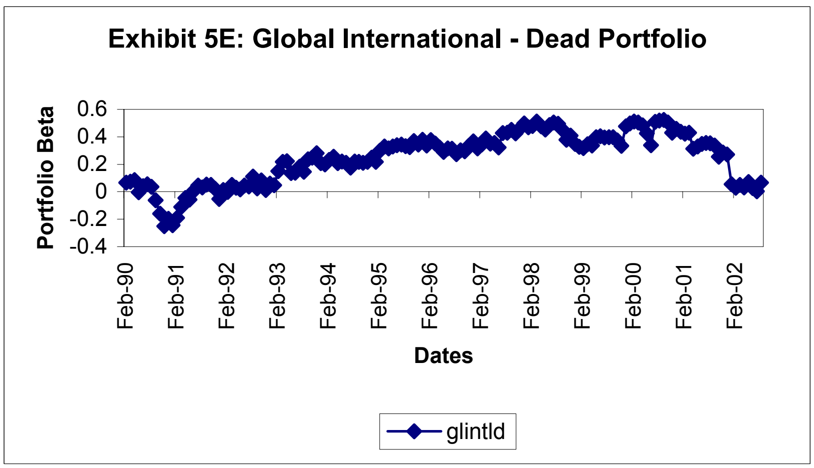
Exhibit 5E: Global International - Dead Portfolio
Portfolio Beta
0.6
0.4
0.2
0
-0.2
-0.4
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
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Feb-00
Feb-01
Feb-02
Dates
glintld

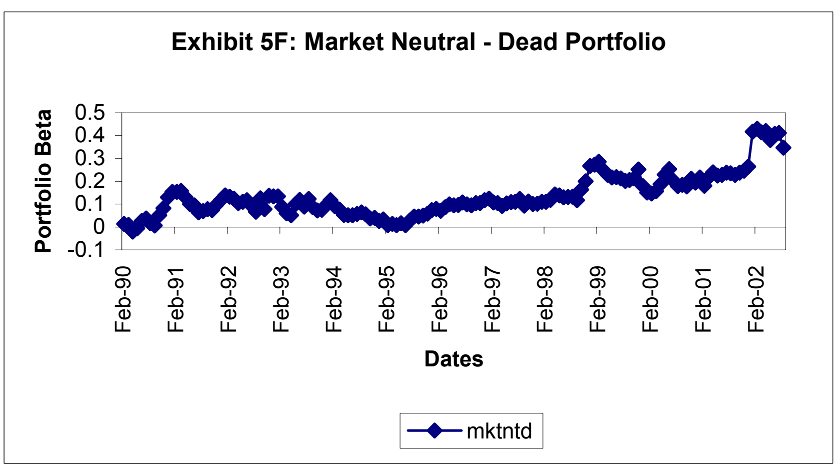
Exhibit 5F: Market Neutral - Dead Portfolio
Portfolio Beta
0.5
0.4
0.3
0.2
0.1
0
-0.1
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
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Feb-99
Feb-00
Feb-01
Feb-02
Dates
mktntd

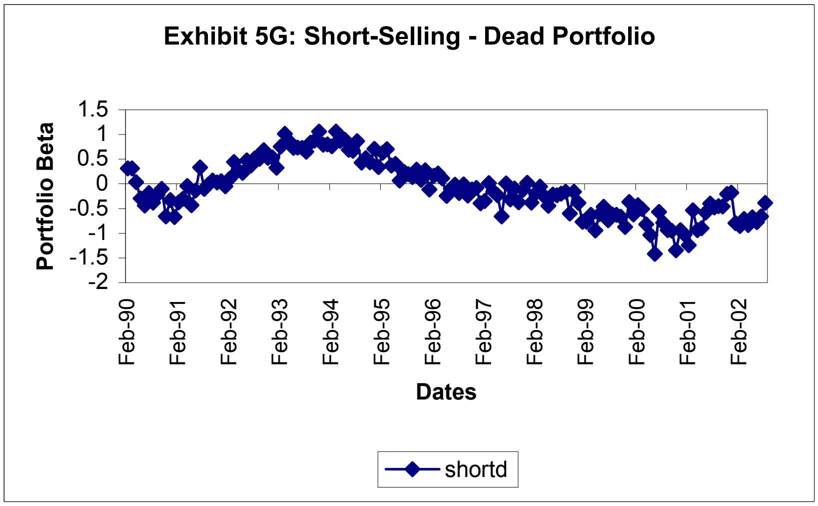
Exhibit 5G: Short-Selling - Dead Portfolio
Portfolio Beta
1.5
1
0.5
0
-0.5
-1
-1.5
-2
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
shortd

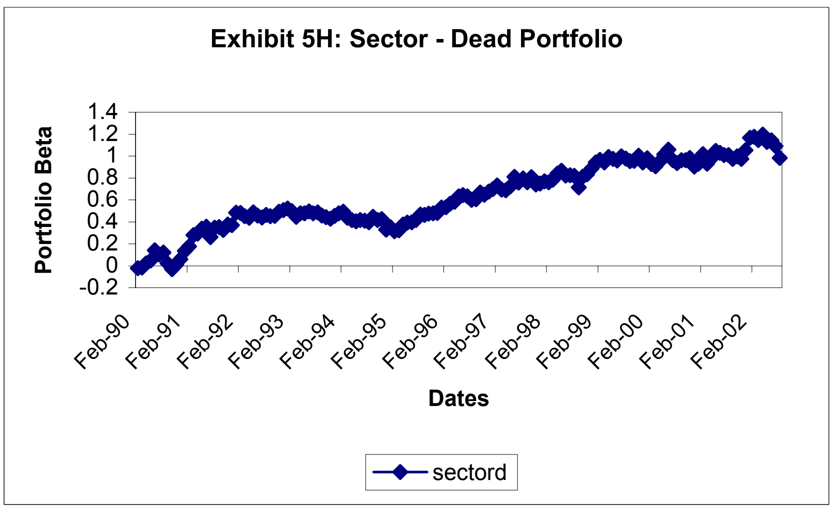
Exhibit 5H: Sector - Dead Portfolio
Portfolio Beta
1.4
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
sectord

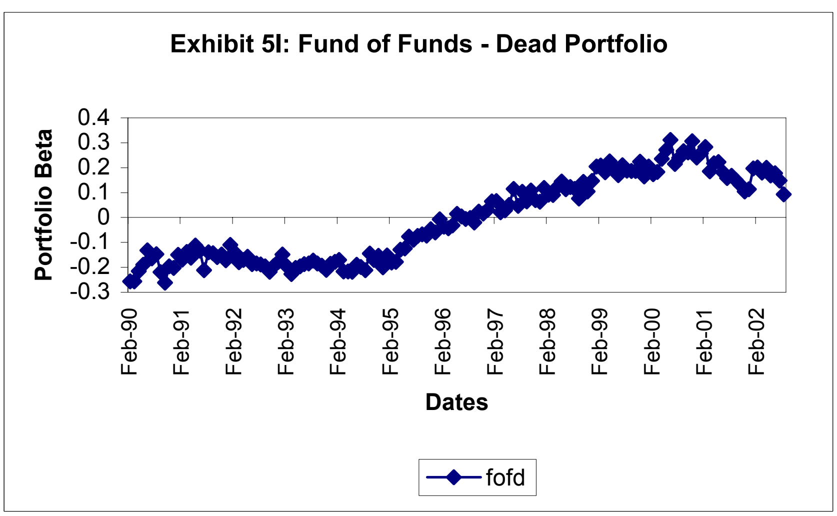
Exhibit 5I: Fund of Funds - Dead Portfolio
Portfolio Beta
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
fofd

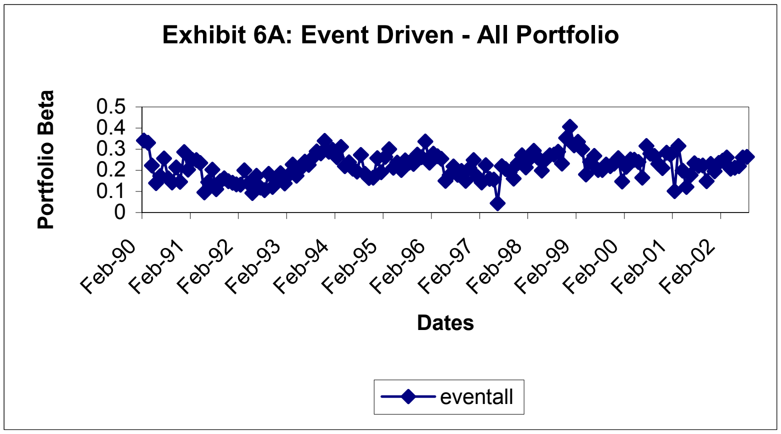
Exhibit 6A: Event Driven - All Portfolio
Portfolio Beta
0.5
0.4
0.3
0.2
0.1
0
Feb-90
Feb-91
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Feb-02
Dates
eventall

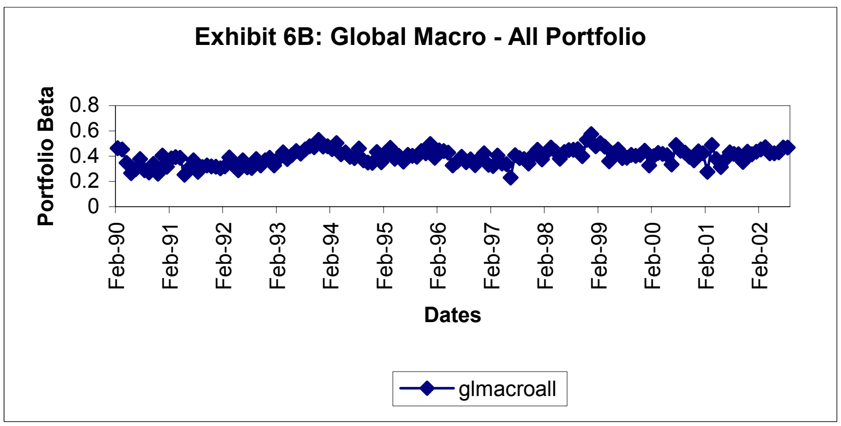
Exhibit 6B: Global Macro - All Portfolio
Portfolio Beta
0.8
0.6
0.4
0.2
0
Feb-90
Feb-91
Feb-92
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Feb-02
Dates
glmacroall

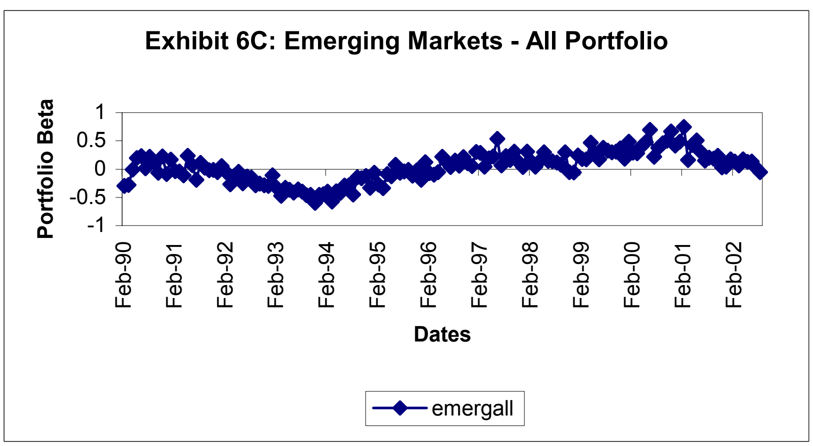
Exhibit 6C: Emerging Markets - All Portfolio
Portfolio Beta
1
0.5
0
-0.5
-1
Feb-90
Feb-91
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Dates
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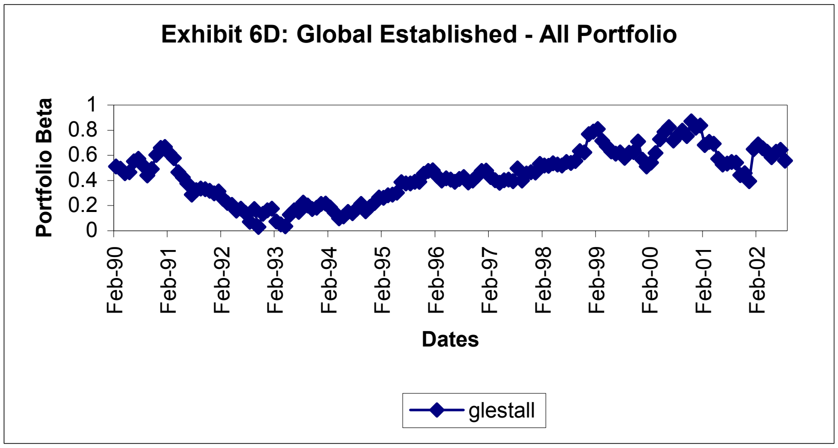
Exhibit 6D: Global Established - All Portfolio
Portfolio Beta
1
0.8
0.6
0.4
0.2
0
Feb-90
Feb-91
Feb-92
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Feb-02
Dates
glestall

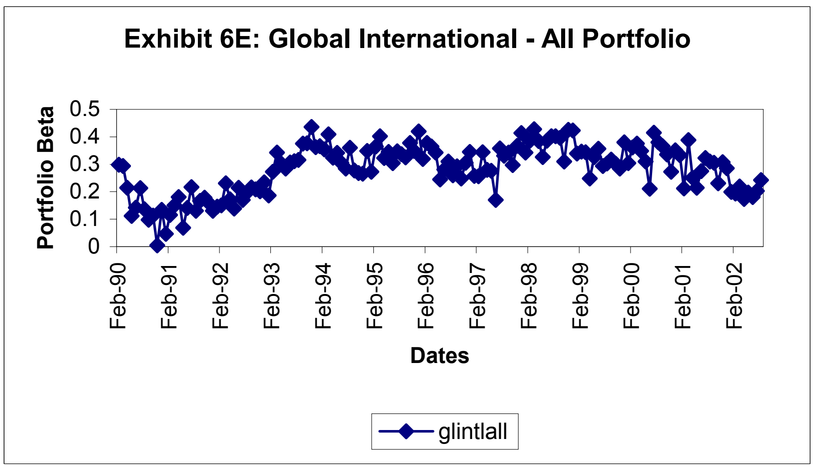
Exhibit 6E: Global International - All Portfolio
Portfolio Beta
0.5
0.4
0.3
0.2
0.1
0
Feb-90
Feb-91
Feb-92
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Feb-96
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Feb-01
Feb-02
Dates
glintlall

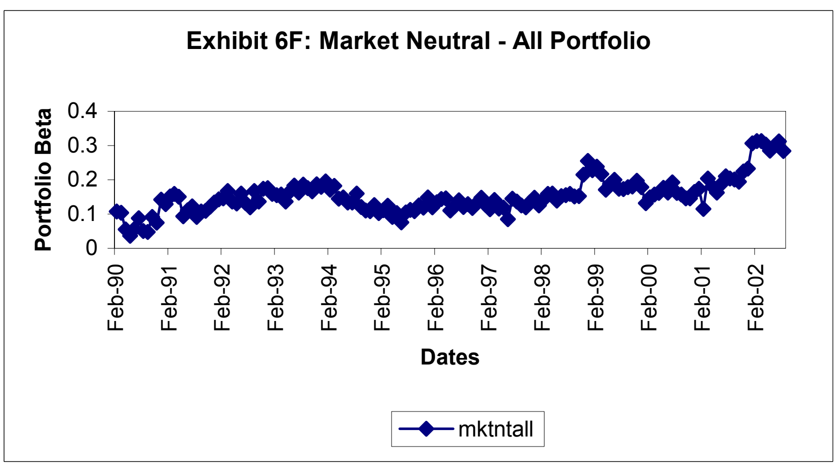
Exhibit 6F: Market Neutral - All Portfolio
Portfolio Beta
0.4
0.3
0.2
0.1
0
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
mktntall

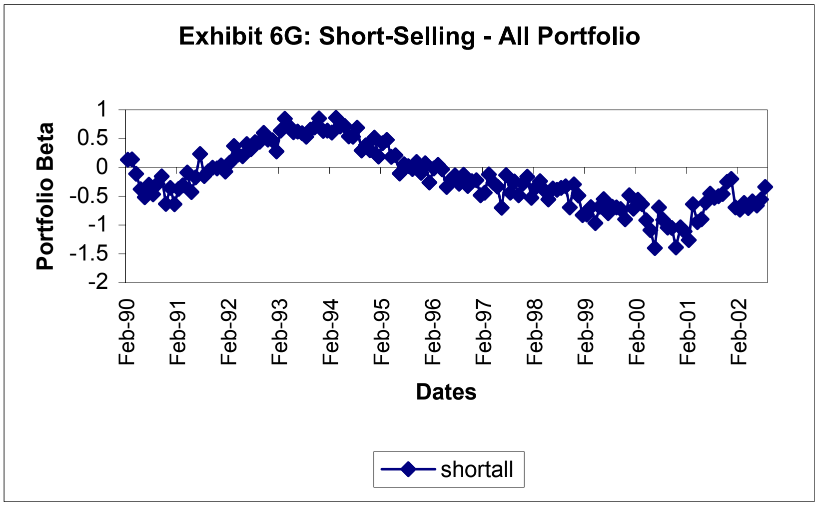
Exhibit 6G: Short-Selling - All Portfolio
Portfolio Beta
1
0.5
0
-0.5
-1
-1.5
-2
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
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Feb-02
Dates
shortall

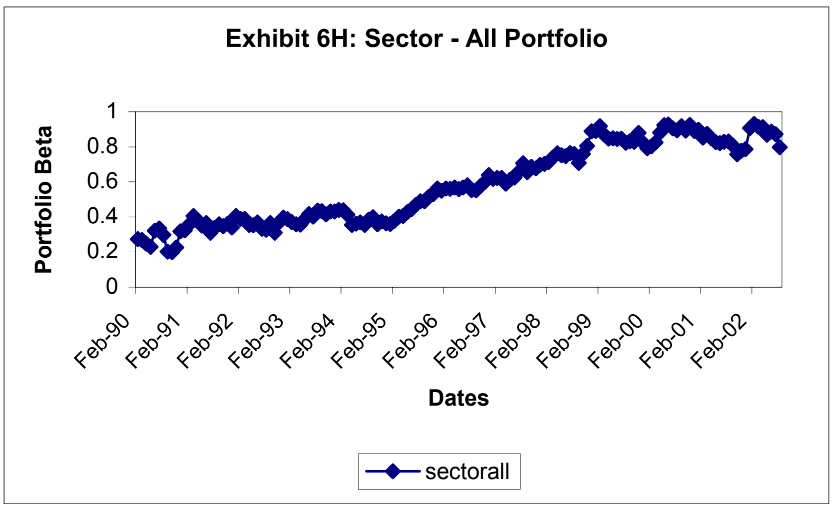
Exhibit 6H: Sector - All Portfolio
Portfolio Beta
1
0.8
0.6
0.4
0.2
0
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
sectorall

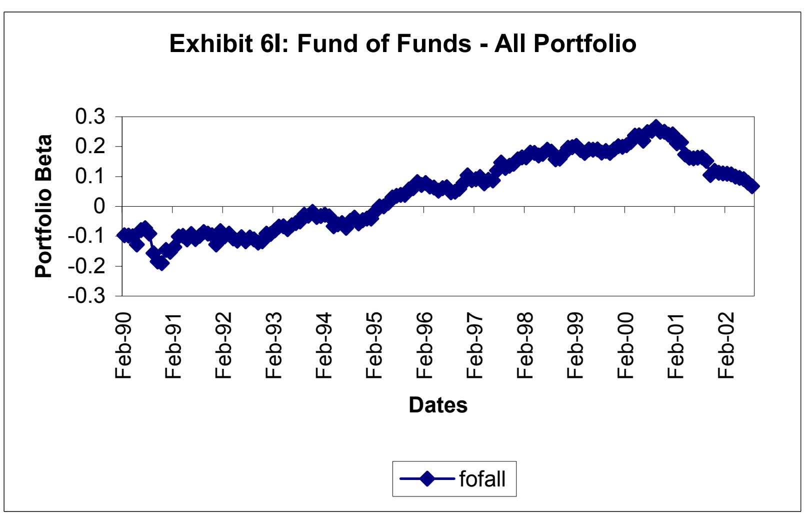
Exhibit 6I: Fund of Funds - All Portfolio
Portfolio Beta
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
Feb-90
Feb-91
Feb-92
Feb-93
Feb-94
Feb-95
Feb-96
Feb-97
Feb-98
Feb-99
Feb-00
Feb-01
Feb-02
Dates
fofall

Exhibit 7: 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**	**R-Square**
Event Driven-Active Portfolio	0.60%	4.44	40.91%
Global Macro-Active Portfolio	0.78%	2.93	18.20%
Emerging Markets-Active Portfolio	1.64%	3.14	11.65%
Global Established-Active Portfolio	0.89%	4.02	68.21%
Global International-Active Portfolio	0.71%	2.45	25.97%
Market Neutral-Active Portfolio	0.72%	6.75	32.28%
Short Selling-Active Portfolio	0.43%	1.20	51.00%
Sector-Active Portfolio	1.33%	3.41	52.52%
FOF-Active Portfolio	0.49%	4.14	36.16%
Portfolio	**Alpha**	**t-Value**	**R-Square**
Event Driven-Dead Portfolio	0.33%	1.86	32.65%
Global Macro-Dead Portfolio	-0.04%	-0.21	33.98%
Emerging Markets-Dead Portfolio	0.26%	0.38	-3.65%
Global Established-Dead Portfolio	0.71%	1.78	58.55%
Global International-Dead Portfolio	0.24%	1.35	33.57%
Market Neutral-Dead Portfolio	0.35%	3.62	42.34%
Short Selling-Dead Portfolio	-0.27%	-0.40	19.96%
Sector-Dead Portfolio	0.99%	2.50	48.36%
FOF-Dead Portfolio	0.43%	2.00	15.99%
Portfolio	**Alpha**	**t-Value**	**R-Square**
Event Driven-All Portfolio	0.53%	3.84	42.86%
Global Macro-All Portfolio	0.35%	1.55	29.57%
Emerging Markets-All Portfolio	1.06%	2.04	9.91%
Global Established-All Portfolio	0.78%	2.55	67.00%
Global International-All Portfolio	0.32%	1.69	39.21%
Market Neutral-All Portfolio	0.52%	5.68	43.55%
Short Selling-All Portfolio	0.06%	0.14	35.62%
Sector-All Portfolio	1.14%	2.89	51.65%
FOF-All Portfolio	0.46%	2.84	24.66%

Exhibit 8: Results from the 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				
Portfolio	**Alpha**	**t-Value**	**R-Square**	**First Order Autocorrelation**
Event Driven-Active Portfolio	0.60%	4.92	44.87%	0.26
Global Macro-Active Portfolio	0.84%	4.40	21.47%	0.14
Emerging Markets-Active Portfolio	1.19%	2.07	22.83%	0.28
Global Established-Active Portfolio	0.82%	6.14	70.39%	0.13
Global International-Active Portfolio	0.53%	2.82	29.89%	0.24
Market Neutral-Active Portfolio	0.67%	10.67	34.07%	0.27
Short Selling-Active Portfolio	0.76%	2.74	61.28%	0.07
Sector-Active Portfolio	1.32%	5.39	53.73%	0.16
FOF-Active Portfolio	0.42%	4.05	39.78%	0.34
Portfolio	**Alpha**	**t-Value**	**R-Square**	**First Order Autocorrelation**
Event Driven-Dead Portfolio	0.31%	2.21	40.28%	0.24
Global Macro-Dead Portfolio	0.06%	0.33	38.83%	0.27
Emerging Markets-Dead Portfolio	-0.07%	-0.21	26.66%	0.36
Global Established-Dead Portfolio	0.30%	1.55	71.45%	0.16
Global International-Dead Portfolio	0.22%	1.09	35.17%	0.18
Market Neutral-Dead Portfolio	0.32%	3.65	42.60%	0.16
Short Selling-Dead Portfolio	0.58%	1.09	45.46%	0.10
Sector-Dead Portfolio	0.80%	2.02	49.83%	0.05
FOF-Dead Portfolio	0.20%	1.49	38.24%	0.38
Portfolio	**Alpha**	**t-Value**	**R-Square**	**First Order Autocorrelation**
Event Driven-All Portfolio	0.45%	3.75	45.35%	0.27
Global Macro-All Portfolio	0.45%	2.68	33.38%	0.20
Emerging Markets-All Portfolio	0.57%	1.50	30.42%	0.41
Global Established-All Portfolio	0.56%	3.64	73.10%	0.16
Global International-All Portfolio	0.38%	2.35	40.21%	0.24
Market Neutral-All Portfolio	0.50%	7.61	44.74%	0.20
Short Selling-All Portfolio	0.69%	2.15	63.03%	0.07
Sector-All Portfolio	1.15%	4.15	53.34%	0.12
FOF-All Portfolio	0.31%	2.67	39.56%	0.38

Exhibit 9: Estimation Results of the Conditional Treynor-Mazuy Model

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

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

Exhibit 10: Estimation Results from the Unconditional Treynor-Mazuy Model

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

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