Characterizing Hedge Fund Risks with Buy-and-Hold and Option-Based Strategies

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Abstract

Since hedge fund returns exhibit non-linear option-like exposures to standard asset classes (Fung and Hsieh (1997a, 2000a)), traditional linear factor models offer limited help in explaining the returns of hedge funds. We model the returns of two popular hedge fund strategies, Event Driven and Relative Value Arbitrage, by employing a contingent-claim-based approach first suggested by Glosten and Jagannathan (1994). We employ a combination of passive option-based strategies and on buy-and-hold strategies to explain the returns of the two hedge fund strategies. Although, in practice, these hedge funds can follow a myriad of dynamic trading strategies, we find that a few simple option writing/buying strategies are able to explain a significant proportion of variation in their returns over time. Our general approach can be extended to other hedge fund strategies and can be useful in designing an appropriate benchmark for evaluating their risk-adjusted performance.

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Due to the lack of regulatory or voluntary disclosure, the hedge fund industry has been perceived by investors as somewhat of a black box. Researchers have only recently begun to analyse the risk return tradeoffs involved in hedge funds and have noticed that they exhibit non-linear option-like exposures to standard asset classes (Fung and Hsieh (1997a, 2000a)). In this paper, we shed light on the black box called hedge funds by attempting to replicate the payoffs on hedge funds using passive option buying/writing strategies and index buy-and-hold strategies. In particular, we model the returns of two popular hedge fund strategies, Event Driven and Relative Value Arbitrage, employing a contingent-claim-based approach first proposed by Glosten and Jagannathan (1994).

Although, in practice, these two hedge fund strategies may follow a myriad of complex dynamic trading strategies, we find that a few simple option-based strategies capture a large proportion of the variation in their returns over time. Our general approach can be extended to other hedge fund strategies and can be useful in designing appropriate benchmarks for evaluating the performance of hedge funds. This paper makes two important contributions to the existing empirical literature on hedge funds. First, it provides a simple method to capture the linear and non-linear systematic risks involved in investing in hedge funds. Second, it provides useful information about their dominant risk exposures to compare them with their stated objectives and style classification.

Our objective is to examine whether there exist some simple option writing/buying strategies and buy-and-hold strategies that a passive investor could engage in and replicate reasonably well the returns of Event Driven and Relative Value Arbitrage funds. Our work is motivated by the same idea that led Sharpe (1992) to conduct the style analysis of mutual funds. However, the linear factor model suggested by Sharpe is unable to capture the non-linearities of hedge fund returns. In addition, Sharpe's returns-based style analysis is too restrictive in case of hedge funds. Hence, we relax the two constraints in Sharpe's linear factor model. First, we do not impose the constraint on the factor loadings of the passive buy-and-hold and option-based indices to be non-negative. This accounts for the fact that hedge funds take both long and short positions in different asset classes. Second, we do not require the factor loadings to add to one[1]. Relaxing this constraint allows for the use of leverage by hedge funds. Essentially, we augment Sharpe's linear factor model using buy-and-hold returns on standard asset classes with options on these asset classes to model the non-linear component of hedge fund returns.

The lack of public disclosure by hedge funds poses a fundamental challenge in validating our approach to characterize their risks. Although we find that we are able to construct portfolios (consisting of option-based and buy-and-hold strategies) that replicate reasonably well the variation in the returns earned by hedge funds over time, it would be nice to have an independent confirmation that they indeed capture the true risks involved in the different hedge fund strategies. Most hedge funds are very secretive about their trading strategies making the task of validating our approach with portfolio information impossible. Therefore, we chose "Event Driven" and "Relative Value Arbitrage" strategies in order to compare and contrast our findings with those of other researchers who have used replication methodology to examine the risk-return tradeoffs in these strategies. In particular, we conduct our investigation using data on individual funds following these two hedge fund strategies as well as equally weighted indices of these strategies. "Event Driven" strategy has been examined by Mitchell and Pulvino (2000) using 4750 merger and acquisition events and "Relative Value Arbitrage" strategy that incorporates the "pairs trading" strategy has been studied by Gatev, Goetzmann and Rouwenhorst (1999) (henceforth GGR).

To the best of our knowledge, Fung and Hsieh (2000a) is the only other work that employs option strategies to model the returns of commodity trading advisors (CTAs). They

[1] A similar model specification has been used by Brown, Goetzmann and Park (2000a) to study the role of hedge funds in Asian crisis. This specification is standard in the literature on hedge funds with Fung and Hsieh (1997a) and Brown, Goetzmann and Ibbotson (1999) having used it earlier.

explore the nature of trading strategies followed by CTAs and attempt to replicate them. The difference in their and our approach is that they have information about the nature of strategies followed by CTAs while we do not have such information on different hedge fund strategies. In addition, our approach has two main advantages. First, it can be universally applied to all hedge fund strategies. Second, our approach provides a simple and intuitive way of capturing the important risk exposures of hedge funds. In fact, Fung and Hsieh's (2000a) result on the CTA returns being similar to that of a straddle can be considered as one of the various combinations of option-based strategies in our generalized procedure.

Our approach builds on the important insights provided by the pioneering work of Fung and Hsieh (1997a) about the payoff on a hedge fund arising from primarily two factors: Trading Strategy factors (Option-like payoffs) and Location factors (payoffs from Buy-and-Hold policy)[2]. We capture the returns from Trading Strategy factors by returns on passive strategies that involve buying or writing Put or Call options on standard asset classes. In order to ensure that a passive investor can follow these strategies, we keep them easy to understand and straightforward to implement. In particular, we only consider trading in one-month-to-maturity European options on standard asset classes with differing degree of moneyness. The option-based strategy involves buying one-month-to-maturity European option on an index, e.g. Russell 3000 index at the beginning of the month. At the end of the month, depending on the level of Russell 3000 index, the option is either in-the-money or out-of-the-money. If the option is in-the-money, our passive investor exercises the option otherwise the option expires worthless and the investor loses the cost of the option. We test the robustness of our results using the data on the S&P 500 index traded on the Chicago Board Options Exchange (hereafter CBOE) (available from Futures Industry Institute (FII)) in place of the theoretical prices of Russell 3000 options.

[2] In addition, hedge funds can scale up their returns by employing leverage explicitly or implicitly. Explicit leverage implies the use of gearing in the balance sheet of hedge funds while implicit leverage is driven by the use of derivatives, short-selling techniques and repurchase agreements by hedge funds.

We capture the returns from Location factors (Buy-and-Hold strategy) by different equity, bond, currency and commodity index returns, and by returns to Fama-French's (1996) Size (henceforth SMB) and Book-to-Market (henceforth HML) factors and Carhart's (1997) Momentum factor. The Fama-French and Momentum factors are well known for their ability to explain returns earned by different assets over time.

Our empirical investigation is in the spirit of Glosten and Jagannathan (1994). Merton (1981) and Dybvig and Ross (1985) had noted that portfolios managed with superior information would exhibit option-like features. However, Glosten-Jagannathan's (1994) work was the first attempt to develop the necessary theoretical framework and to use the contingent-claim-based approach to evaluate the excess returns of managed portfolios[3]. Although Glosten-Jagannathan's (1994) work and our work share some similar features, we have three additional reasons for including payoffs on option-based trading strategies, reasons that do not arise in case of mutual funds examined by them.

1. Unlike mutual fund managers, hedge fund manager's compensation involves an explicit element of sharing of the profits. This is equivalent to the investor having written a call option[4]. Due to this incentive fee element of manager's compensation, even if the pre-fee returns don't exhibit option-like element, the post-fee returns will.
2. Unlike a large majority of mutual fund managers that do not use derivatives, hedge fund managers frequently trade in derivatives either explicitly or implicitly through dynamic trading[5]. Moreover, these dynamic trading strategies contribute to a very

[3] Also, see Schneeweis and Spurgin (2000) for the use of options on S&P500 to compare the performance of two active mutual fund managers that employ hedged equity strategies.
[4] If the incentive fee is 20% of profits, then the investor is short one-fifth of a call option. This call option is written on the portfolio of assets held by the manager and the exercise price depends on hurdle rate and high watermark provisions with the expiration date being the end of the period used to calculate the fee.
[5] Ackermann, McEnally and Ravenscraft (1999) document that the Investment Company Act of 1940 requires mutual funds to state their likely use of derivatives in their prospectuses. Although most of the mutual funds do explicitly state this fact in their prospectuses, they rarely use derivatives. For example, Koski and Pontiff (1999) find that only 20% of the mutual funds in their sample of 675 equity mutual funds invest in derivatives.

significant part of their returns, as is evident from the failure of traditional linear factor models like Sharpe (1992) in explaining their returns[6].

3. Finally, hedge funds are well known for their "opportunistic" nature of trading and a significant part of their returns is due to their taking state-contingent bets. Returns from option strategies help capture, at least in part, these state-contingent bets.

All these reasons necessitate the inclusion of returns from option-based strategies while replicating the payoffs obtained from investing in hedge funds[7].

We find that, in general, the returns on Event Driven and Relative Value Arbitrage strategies display more significant loading on Trading Strategy factors compared to Location factors. This indicates the importance of including option-based strategies in capturing the non-linear systematic risks of hedge funds. Second, the R-square values from our model are substantially higher than those obtained using Sharpe's (1992) style analysis indicating the importance of including the Trading Strategy factors in addition to the Location factors[8]. Finally, the risk exposures we obtain are similar to those observed by other researchers (Mitchell and Pulvino (2000), and Gatev et al (1999)) using detailed replication of strategies. This suggests that our method is able to accurately characterize the important risk exposures of Event Driven and Relative Value Arbitrage funds.

Rest of the paper is organized as follows. Section 1 provides the sample description. Section 2 describes the passive option-based strategies and buy-and-hold strategies that an investor can employ to replicate the payoffs of hedge funds. Section 3 provides the detailed intertemporal analysis of the important risk exposures of Event Driven and Relative Value

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[6] Fung and Hsieh (1997a) report that Sharpe's (1992) eight-asset-class-factor model provide them with an adjusted R^2 of only 7%. Fung and Hsieh (2000a) find that Sharpe's model performs equally poorly for "trend-following" CTA strategies with the adjusted R-squares ranging from –3.2% to 7.5% (see their Table 2).

[7] Bansal and Viswanathan's (1993) show that the pricing kernel from a linear model is inappropriate for pricing securities whose payoffs are non-linear functions of asset class factors. Bansal, Hsieh and Viswanathan (1993) derive the non-linear pricing kernel using non-parametric methods to price such securities. We try to capture these non-linearities by including option-based strategies as additional factors in explaining the hedge fund returns.

[8] Fung and Hsieh (2000a) also find that the explanatory power goes up from less than 7.5% to about 48% when they include primitive trend following strategies to explain variation of returns over time of Trend following commodity trading advisors. All R-squares reported in this paper are adjusted R-

Arbitrage strategies at the index level and individual hedge fund level and the validation of our model. Finally, section 4 offers concluding remarks and suggestions for future research.

1. Data Description

Although the term 'hedge fund' originated from the equally long and short strategy employed by managers like Alfred Winslow Jones, the new definition of hedge funds covers a multitude of different strategies. Basically, hedge funds are private investment pools where the manager has a significant stake in the fund and is freely allowed to employ derivatives, short selling and leverage to enhance returns and better manage risk.

For our analysis, we employ monthly net-of-fee returns of individual Event Driven and Relative Value Arbitrage funds reported in the Hedge Fund Research (HFR) database over January 1988 to August 1999 period. For robustness, we also employ monthly net-of-fee returns on Event Driven and Relative Value Arbitrage equally weighted index data reported by HFR over January 1990 to December 1999. Our sample period cover both market upturns and downturns, as well as relatively calm and turbulent periods. To capture potentially interesting intertemporal variation in risk exposures, we conduct our analysis over 24-month rolling windows starting from February 1988 and ending in July 1999[9]. In particular, we use data on 54 individual funds following Event Driven strategy and 25 funds following Relative Value Arbitrage strategy[10]. Although our approach considers the style classifications as provided by HFR, the beauty of our approach is that it is not only independent of these classifications but also allows us to investigate if these strategies are accurately classified.

We report the summary statistics for the individual hedge funds following the Event Driven and Relative Value Arbitrage strategies in Table 1. We also report the moments of

squares, for expositional convenience, we refer to them as R-squares.

[9] We drop the first month (January 88) and the last month (August 99) to get an integer number of rolling windows.

[10] See Appendix A for definitions of Event Driven and Relative Value Arbitrage strategies reproduced from Hedge Fund Research Inc. (1997). Each fund is classified by HFR in a single category only identified by the unique code of the fund.

Russell 3000 index[11], MSCI World (excluding USA), MSCI Emerging Markets, Salomon Brothers Government and Corporate Bond index, Salomon Brothers World Government Bond index, Lehman High Yield index, Federal Reserve Bank Competitiveness-Weighted Dollar index[12] and the Goldman Sachs Commodity index[13]. Panel B of Table 1 provides the summary statistics of these eight indices and "Size" (SMB) factor, "Value-Growth" (HML) factor and "Momentum" factor over the same period. We can see that in contrast to the moments of individual hedge funds following Event Driven and Relative Value Arbitrage strategies, all Location factors except Lehman High Yield index exhibit close to normally distributed returns.

Having described the salient features of the data, in the next section, we describe the passive option-based and buy-and-hold strategies that an investor can use to replicate the payoffs from Event Driven and Relative Value Arbitrage funds.

2. Description of Passive Option-based Strategies and Buy-and-Hold Strategies

We now examine the extent to which a passive investor can use option-based strategies (Trading Strategy factors) and traditional buy-and-hold strategies (Location factors) to replicate the payoffs of Event Driven and Relative Value Arbitrage funds. Towards that end, we regress the net-of-fee monthly excess return (in excess of the risk free rate of interest) on a hedge fund on the excess return earned by Trading Strategy factors and that earned by

[11] The popular press generally compares the performance of hedge funds with that of the S&P 500 Composite index. However, considering the fact that most hedge funds invest in a wide range of equities including small cap, medium cap and large cap companies, we believe that Russell 3000 index (that represents over 95% of investable US equity market) captures their investment style better.

[12] Federal Reserve Bank recently replaced its Trade-Weighted Dollar index with a Competitiveness-Weighted Dollar index, as the latter is a better indicator of the exchange rate. The new index is a weighted average of the foreign exchange value of the dollar against currencies of major U.S. trading partners. The index weights, which change over time, are derived from U.S. export shares as well as from U.S. and foreign import shares. This broad index covers 36 countries and 26 currencies.

[13] We chose the Goldman Sachs Commodity index (GSCI) instead of a Gold index used by Fung & Hsieh (1997a) as the former indicates better the exposure of hedge funds in commodities especially considering the fact that hedge funds may not be investing solely in gold among commodities. GSCI is designed to measure investment performance in the commodity futures market. Its components are weighted according to the quantity of production in the world economy giving greater weight to those commodities that have a greater impact.

Location factors. To conserve degrees of freedom and to mitigate potential multi-collinearity problems, we use a stepwise regression approach[14]. In this procedure, the variables are entered or removed from the model depending on the significance of the F-value. We use this procedure to ascertain the factors that, ex-post, explain the returns earned by hedge funds during our sample period. We compute the statistical significance of the factors by using Newey-West (1987) standard errors to adjust for any autocorrelation in the monthly returns[15].

The Trading Strategies we allow for are passive in nature and require the investor to, say for example, buy a one-month-to-maturity European put (or call) option on an index portfolio like the Russell 3000 index. Since we do not know the precise strategy followed by the hedge funds, we consider buying or writing options with three different strike prices[16]. In particular, we consider an at-the-money option trading strategy (where present value of exercise price equals the current index value), an out-of-the-money option trading strategy (where the exercise price is half a standard deviation away from that of the at-the-money option) and a deep-out-of-the-money option trading strategy (where the exercise price is one standard deviation away from that of the at-the-money option)[17]. We denote at-the-money Call (Put) option by C_a (P_a), out-of-the-money Call (Put) option by C_o (P_o) and deep out-of-the-money Call (Put) option by C_d (P_d).

Figure 1 illustrates the payoff at maturity from buying a put or a call option on an index with different degrees of moneyness. The payoff at maturity from writing an option is simply the mirror image of the payoff shown. We use Black and Scholes' (1973) formula to estimate the cost of following such a passive trading strategy. We test the robustness of our results

[14] Multivariate stepwise regression has been used by other researchers including recent work by Liang (1999) and Fung and Hsieh (2000c). Please note that stepwise regression procedure can be used with different selection criteria. We consciously do not use maximizing the in-sample R^2 as our selection criteria.

[15] We also perform the standard robustness checks for outliers and heteroskedasticity in our data.

[16] In reality, hedge funds may be engaging in more exotic derivatives and complex trading strategies. However, we consider a "naïve" passive investor, who can only employ simple option-based trading strategies to capture the investment style of these hedge funds. Further, a combination of our simple option buying/writing strategies may be able to provide payoffs similar to those from more exotic instruments.

[17] We use the historical volatility for determining the exercise price of out-of-the-money options. See Canina and Figlewski (1993) and Dumas, Fleming and Whaley (1998) for the relative advantages of

using the daily data on S&P 500 index options traded on the CBOE in place of the theoretical prices of Russell 3000 index options[18]. If the option expires in the money, we compute the return on initial investment of the cost of buying the one-month-to-maturity European call option. If the option expires out of the money, we assign a return of –100% for that month. We subtract the risk free rate of interest from these raw returns to obtain excess returns on these option-based trading strategies. We allow our investor to use passive option trading strategies on the Russell 3000 index, the MSCI Emerging Markets index, the Salomon Brothers (SB) World Government Bond index, the Lehman High Yield Composite index and the Federal Reserve Bank Competitiveness-Weighted Dollar index.

The Location factors, we use, consist of indices representing equities (Russell 3000 index, MSCI World excluding USA index and MSCI Emerging Markets index), bonds (SB Government and Corporate Bond index, SB World Government Bond index and Lehman High Yield index), Federal Reserve Bank Competitiveness-Weighted Dollar index and the Goldman Sachs Commodity index. We also include three zero investment strategies representing Fama-French's (1996) "Size" factor (Small minus Big - SMB), "Book-to-Market" factor (High minus Low - HML) and Carhart's (1997) "Momentum" factor (Winners minus Losers)[19]. In total, we use a maximum of eleven Location factors. Using these Location and Trading Strategy factors, we estimate the constituents of the replicating portfolio.

In particular, we estimate the following regression[20]

$$R_t^i = \alpha^i + \sum_{k=1}^{K} b_k^i F_{k,t} + u_t^i \qquad \textbf{(1)}$$

where,

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using different volatility measures in option valuation.

[18] Our results remain qualitatively similar with the exchange traded S&P 500 options. Due to non-availability of data on exchange traded options data for other asset indices used in this study, we use Black and Scholes (1973) prices for options on those indices.

[19] Edwards and Liew (1999a) find that hedge funds fail to deliver positively significant alphas when the size, book-to-market and momentum factors are added to the standard capital asset pricing model.

[20] This is essentially similar to Sharpe (1992) linear factor model after including the intercept and relaxing the constraints that style weights need to be non-negative and should add to one. If the R-square from such a regression is 100%, the intercept can be considered as the value added by hedge

R_t^i = net-of-fees excess return (in excess of the risk free rate of interest) on an individual hedge fund i for month t,

α^i = intercept for hedge fund i over the regression period,

b_k^i = average factor loading of an individual hedge fund i on k^{th} factor during the regression period,

F_{kt} = excess return (in excess of the risk free rate of interest) on k^{th} factor for month t, (k=1,.......,K) where the factor could be a Trading Strategy factor (an option-based strategy) or a Location factor (buy-and-hold position in an index), and

u_t^i = error term.

3. Intertemporal Estimation of the Risk Exposures of Event Driven and Relative Value Arbitrage Strategies and Validation of our model

Any regression-based approach involves a classic tradeoff. On one hand, we would prefer more observations to increase statistical confidence, while on the other hand, the risk exposures may not stay constant over a long period. Since theory provides little guidance, we choose the length of the regression window as 24 months[21]. This provides us with sufficient degrees of freedom to estimate the risk exposures and RER of hedge funds based on average risk exposures during the 24-month period. We examine the intertemporal variation in the risk exposures of hedge funds by dividing the entire sample period of 140 months (from January 1988 to August 1999) using 24-month rolling windows[22].

We conduct our analysis for the HFR Event Driven and Relative Value Arbitrage Indices over five equal 24-month non-overlapping sub-periods starting from January 1990 and

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funds.

[21] Brealey and Kaplanis (2000) find that the out-of-sample forecasting accuracy of the hedge fund return generating process is maximized at around 24 months. Ackermann, McEnally and Ravenscraft (1999) also consider 24-month window for their study on hedge funds.

[22] Although we analyze all the hedge funds at the individual and index level using rolling windows, for the purpose of illustrating the intertemporal variation in the risk exposures over distinct sub-periods and

ending in December 1999. Similarly, for the individual hedge funds following these two strategies, we consider five equal 24-month non-overlapping sub-periods starting from September 1989 and ending in August 1999. The reason for the slight difference in the start and end date for the indexes and individual hedge funds is the non-availability of the data for an exactly identical period. We estimate the factor loadings on the asset class factors that best replicate the payoffs on hedge funds. We now examine the risk exposures of all hedge funds following these two strategies over the five sub-periods.

3.1 Results using HFR Event Driven and Relative Value Arbitrage Indices

Since hedge funds do not provide information on their portfolio holdings, we need to rely on validating our model by comparing our results with those of other researchers, who employ alternative specifications. Therefore, we compare our results with those of Mitchell and Pulvino (2000) and GGR, who analyze the risk-return characteristics of the two hedge fund strategies, Event Driven and Relative Value Arbitrage respectively, using detailed replication methodology. For this purpose, we first employ the HFR index level data for these two strategies to determine their important risk exposures and RER. Then, we confirm our results at the index level through our detailed analysis at the individual fund level. We divide our sample period from January 1990 and December 1999 into five equal non-overlapping periods of 24 months each and run the stepwise regressions for the HFR Event Driven and Relative Value Arbitrage indices[23]. We report our results in Table 2.

Mitchell and Pulvino (2000) compile a large sample of merger/acquisition events and find that event or merger arbitrage strategies exhibit a payoff similar to writing an uncovered put option on the market index. The results for the Event Driven strategy[24] in Panel A of

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expositional convenience, we report the results for five non-overlapping periods throughout the paper.

[23] We consider the five non-overlapping periods of 24 months as Jan 90 to Dec 91, Jan 92 to Dec 93, and so on. For robustness of our results, we considered alternative 24-month sub-periods shifted by six months, e.g., Jul 90 to Jun 91, Jul 91 to Jun 92, and so on but the results remain qualitatively similar.

[24] Event Driven strategy seeks to benefit from the opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations and share buybacks. This broad strategy incorporates the risk arbitrage strategy examined by Mitchell and

Table 2 are very similar to those of Mitchell and Pulvino (2000). Like them, we find that a put option on Russell 3000 index is an important factor in explaining the returns of the Event Driven strategy. In particular, our stepwise regression selects writing naked put options on Russell 3000 index (with different degrees of moneyness) as the most important factors in three out of the five 24-month sub-periods. In addition, the order of entry for these put options is one or two indicating that they are the first or second most important factors in the model. In all the three cases, the slope coefficient for these put options are negative suggesting that returns on Event Driven strategy are similar to those obtained by selling uncovered index put options.

These results are remarkably similar to those documented by Mitchell and Pulvino (2000). Like them, we also find significant coefficients on Fama-French SMB factor. This is not surprising as the Event Driven strategy generally entails stock transactions, e.g., in case of takeovers, such a strategy would involve taking a long position in a small-sized target and short position in large-sized acquirer. This results in a natural exposure to the SMB factor. The exposure to uncovered index put options seem to suggest that these strategies suffer during the market downturns but provide limited upside during the market upturns. This result is intuitive as Event Driven strategies involve risk of deal failure, i.e. the risk of the merger and acquisition not being successful. As the acquirer is less likely to pay a higher price for the shares of the target firm in down market compared to the upmarket, the probability of deal failure is higher in market downturns compared to the upturns. Overall, we notice that the R-squares range from 54% to 86% (average being 70%) during the five sub-periods suggesting that the replicating portfolios are able to capture a significant proportion of the variation in the hedge fund returns over time. Equally importantly, we find that the Trading Strategy factors alone provide about 71% of the average total R-square. This result is consistent with Fung and Hsieh's (1997a) argument that a large proportion of the hedge fund returns arise from dynamic trading strategies.

Pulvino (2000).

Panel B of Table 2 shows the results of the Relative Value Arbitrage[25] index. Like GGR, we also find significant exposures to the Size factor along with a long exposure to the market index[26]. The size factor is significant in two of the five sub-periods. Interestingly, at the index level, we do not find a significant exposure to the HML factor. However, our results at the individual hedge fund level in Panel B of Table 4 are more in line with the results of GGR as both SMB and HML are some of the five most important factors in two of the five sub-periods. We find R-squares ranging from 30% to 97% (average being 69%) over the five sub-periods suggesting that we are successful in capturing a large proportion of the dominant risks of Relative Value Arbitrage funds.

Having calibrated our results at the index level, we now conduct similar investigation at individual hedge fund level to examine the robustness of our results.

3.2 Results using individual Event Driven and Relative Value Arbitrage Funds

We now conduct our analysis at the individual hedge fund level for the Event Driven and Relative Value Arbitrage funds. To ensure that our model captures some part of the risk exposure of a hedge fund, we require the fund to have at least one significant factor loading on any factor in our model. This criterion provides us with 54 and 25 hedge funds following Event Driven and Relative Value Arbitrage strategies.

We report our results for the important risk exposures for all the funds following these two strategies during the five equal non-overlapping 24-month sub-periods starting from September 1989 and ending in August 1999 (e.g., September 1989 to August 1991, September 1991 to August 1993, and so on). In order to compare and contrast our results at the index level with those at the individual hedge fund level, we chose these sub-periods as close to the five sub-periods for our analysis at the index level as allowed by the data at the

[25] Relative Value Arbitrage strategy attempts to take advantage of relative pricing discrepancies between instruments including equities, debt, options and futures. This broad strategy includes divided arbitrage, pairs trading, options arbitrage and yield curve trading.

[26] During some periods, the exposure to market index is indirect through writing of put options primarily. For the idiosyncratic risk of relative value strategies, see Richards (1999).

individual hedge fund level. To begin with, we report the distribution of the number of Location and Trading Strategy factors that show significant loadings for these two strategies for the five sub-periods. Then we describe the five most important risk factors explaining the returns on hedge funds following each of these strategies.

Table 3 reports the number of factors that come out significant in regressions conducted for the five sub-periods for all the funds following Event Driven and Relative Value Arbitrage strategies. For all the funds following these two strategies, a large percentage of the funds show significant loading on up to three (up to five) Location factors. Similarly, a large percentage of the funds also show significant loading on up to three (up to five) Trading Strategy factors for each sub-period. When we pool the two types of factors together, we find that a large majority of funds show significant loadings on up to three (up to five) factors. Overall, Table 3 gives us an idea of the number of significant factor risks borne by individual hedge funds. Thus, it seems that the portfolio that best replicates hedge fund payoffs consists of at the most five constituents.

Table 4 reports the results of the composition of the replicating portfolios for the 54 and 25 funds following Event Driven and Relative Value Arbitrage strategies. At the first sight, we can see that the R-square values we obtain using our specification are considerably higher than the ones obtained by Fung and Hsieh (1997a, 2000a) using Sharpe’s (1992) asset class factor model. Interestingly, we find that simple option-based Trading Strategies play a major role in explaining the variation of return on these hedge funds over time. In case of the hedge funds following Event Driven and Relative Value Arbitrage strategies, the proportion of observed R^2 attributable to trading strategies is, on average, 58% and 65% of total R^2 across the five sub-periods, respectively. These high percentages confirm the importance of including trading strategies while determining the replicating portfolio for hedge funds.

For the sake of brevity, we report the five factors that come out significant across a large number of funds following Event Driven and Relative Value Arbitrage strategies. We notice from Table 3 that a large percentage of all the hedge funds show significant exposure to five or less factors, hence the five most significant factors explain most of the variation in hedge fund returns. To describe the results, we provide the details of the risk exposures and composition of the replicating portfolio for funds following these two strategies. These strategies are similar to the Event Arbitrage and Pairs Trading strategies analysed by Mitchell and Pulvino (2000) and GGR using detailed replication methodology and therefore enables us to compare and contrast our findings from regression analysis with theirs.

3.2.1 Characterizing Risk Exposures of Event Driven funds

We start by describing the five important factor exposures (in decreasing order of the number of funds that display significant loading on these factors) for the "Event Driven" strategy. We find that a majority of funds (26 out of 51) show significant loading on the Fama-French's Size (SMB) factor indicating an exposure to equities. This result is consistent with our results at the index level. All 26 of these show a loading of the same sign namely positive and the mean (median) factor loading is 0.44 (0.44). The average (median) order of entry of the Size factor is 2.50 (2.00) suggesting that although this factor affect the largest number of funds following the Event Driven strategy, it only enters like the second or the third factor in the stepwise regression.

The next factor that affects a large number of funds is a Trading Strategy factor, a passive strategy involving an at-the-money put option on Russell 3000 index ($RUSP_a$). Note that the mean (median) factor loading is -0.61 (-0.61). The negative sign indicates that investing in Event Driven funds exposes investors to risks similar to that involved in writing an at-the-money put option on the Russell 3000 index. Interestingly, all the 17 funds show loading of the same sign. The mean (median) order of entry is 1.06 (1.00) indicating that although it comes second in the number of funds showing exposure to it, writing an at-the-money put on the Russell 3000 index is the most important factor in terms of entry in the regression. This can be seen from the fact that in 16 out of the 17 cases (not reported in the table), it was selected as the first factor in the stepwise regression procedure.

The third factor in the decreasing sequence of number of funds showing significant exposure to a factor is again a Trading Strategy factor, deep out-of-the-money put option on Russell 3000 index. 10 out of the 51 funds show significant mean (median) loading of –0.50 (-0.34) on this factor and the mean (median) order of entry is 1.20 (1.00) indicating that it enters as the first factor in a large number of cases. Recall from the results for the last sub-period in Panel A of Table 2 that we had found this result at the HFR Event Driven index level too[27]. Now we also find this at an individual fund level. Furthermore, both these results are consistent with the findings of Mitchell and Pulvino (2000).

The fourth factor is at-the-money put option on MSCI Emerging Markets index with 9 out of the 51 funds showing significant loading on this factor. The mean (median) factor loading is –0.36 (-0.37). The mean (median) order of entry of 2.11 (2.00) indicates that this factor like SMB only enters the regression as the second or the third factor. Finally, the last factor in the five most important factors is an out-of-the-money call option on the SB World Government Bond index, where 6 out of 51 funds show a significant loading on it. It shows a mean (median) order of entry of about 1.67 (2.00) indicating that it enters either as the second or the third factor in the regression. Overall, put options on the Russell 3000 index with different degrees of moneyness come out as the most important factors in significant number of cases. This confirms the results at the index level that investing in Event Driven funds exposes investors to risk that is similar to writing put options on the index.

It is important to note that all funds in a given category need not display loading on a given factor with the same sign. It just happens to be the case with the Trading Strategy factors involving writing at-the-money and deep out-of-the-money put option on Russell 3000 index and the SMB factor. For example, as we will see later, in case of the most recent sub-period for the funds following Relative Value Arbitrage strategy (last column of Panel B of Table 4), we find that 5 out of the 20 funds show significant loading on HML factor,

[27] As the index level data is available from Jan 1990 to Dec 1999 and the individual fund data is available from Jan 1988 to Aug 1999, the five sub-periods for the index and individual fund level analysis are not exactly identical. However, we choose the best available option of a difference of only

where 3 of them show positive loading while the remaining 2 show negative loading. A positive (negative) loading on the HML factor indicates a tilt towards value (growth) stocks.

Finally, the four rows after the fifth most important factor report the mean and median R^2 values. For Event Driven strategy, the mean (median) R^2 (denoted by TR^2 $\mu \mid \iota$) across the 51 funds (N) equals 69% (73%). The corresponding R^2 values due to the first factor (denoted by FR^2 $\mu \mid \iota$) are 49% (49%). Location factors collectively contribute mean (median) R^2 of 21% (16%) while Trading strategy factors collectively contribute mean (median) R^2 of 48% (55%)[28]. The very last row tells us that in case of 36 out of 51 (71%) funds, a Trading Strategy factor gets chosen as the first factor.

This summarizes the salient findings from estimating the important risk exposures of the Event Driven strategy. Panel B of Table 4 reports the results for the funds following Relative Value Arbitrage strategy. For the sake of brevity, we highlight below the results for the most recent sub-period from September 1997 to August 1999 for this strategy as well.

3.2.2 Characterizing Risk Exposures of Relative Value Arbitrage funds

Continuing further, we now describe the five important factor exposures (in decreasing order of the number of funds that display significant loading on these factors) for the "Relative Value Arbitrage" strategy. We find that a majority of funds show significant loading on the Fama-French's Size (SMB) factor (9 out of 20) and Value-Growth (HML) factor (5 out of 20) indicating an exposure to equities. This result of the Fama-French factors being the two most important factors in explaining the returns of Relative Value Arbitrage funds is consistent with the findings of GGR using replication methodology for pairs trading.

The next three factors in the decreasing sequence of number of funds showing significant exposure to a factor are call option on the Lehman High Yield index, deep out-of-the-money call option on Russell 3000 index and at-the-money put option on MSCI Emerging Markets

4 months between the two sub-periods.

[28] The mean contributions are additive. Mean TR^2 of 69% consists of 21% from Location factors and

index respectively. Overall, four out of the five most important factor exposures are based on equities. This is consistent with the fact that this strategy entails primarily investing in stocks, e.g., pairs trading involves investing in stocks that move together. Recall from the results for the last sub-period in Panel B of Table 2 that we had found this result at the HFR Relative Value Arbitrage index level. Now we also find this at an individual fund level. This presents strong evidence that our results are robust and consistent with the findings of GGR.

Finally, the four rows after the fifth most important factor report the mean and median R^2 values. For Relative Value Arbitrage strategy, the mean (median) R^2 (denoted by TR^2 μ | ι) across the 20 funds (N) equals 71% (78%). The corresponding R^2 values due to the first factor (denoted by FR^2 μ | ι) are 50% (47%). Location factors collectively contribute mean (median) R^2 of 27% (20%) while Trading strategy factors together contribute mean (median) R^2 of 44% (50%). The last row shows that in case of 14 out of 20 (70%) funds, a Trading Strategy factor gets chosen as the first factor.

3.3 Additional empirical insights into non-linear hedge fund risk exposures

We have already seen that the inclusion of various Trading Strategy factors significantly improves the explanatory power of our model. We further illustrate the non-linear association of hedge fund returns to the different asset classes by employing a locally weighted polynomial regression technique (LOWESS) originally proposed by Cleveland (1979) and further developed by Cleveland and Devlin (1988). This modelling method combines the simplicity of linear least squares regression with the flexibility of non-linear regression to graphically demonstrate the non-linear association between dependent and independent variables.

To exemplify our point, as an example, we chose two different sub-periods, Jan 90 to Dec 91 for the Event Driven strategy and Jan 98 to Dec 99 for the Relative Value Arbitrage strategy. We show that the ordinary least squares (OLS) regression is unable to capture the

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48% from Trading Strategy factors.

non-linear relationship between the returns for these strategies and the Russell 3000 index. Figure 2 demonstrates the effectiveness of LOWESS fit in capturing the non-linearity and relatively poor fit between hedge fund returns and the index using OLS. We also plot the payoffs from buying/writing Russell 3000 put options using our earlier results from Panels A and B of Table 2 in our Figure 2. We notice a prominent similarity in the LOWESS fit and the exposures predicted by our model. For example, the returns of Event Driven strategy during Jan 90 to Dec 91 resembles writing an at-the-money put option on Russell 3000 index. Similarly, the returns of Relative Value Arbitrage strategy during Jan 98 to Dec 99 bears resemblance to a combination of buying an out-of-the-money put option on Russell 3000 index and writing an at-the-money put option on Russell 3000 index.

When we estimate OLS regressions between Event Driven and Relative Value Arbitrage strategies and the Russell 3000 index during the two different sub-periods, we obtain R-square values of 50% and 39% respectively. However, when we replace the buy-and-hold returns on the Russell 3000 index with the returns on Russell 3000 put options, the R-square values increase to 76% and 69% respectively. The graphical smoothening LOWESS technique provides a fit that is strikingly similar to the payoffs from buying and/or writing put options on Russell 3000 index with different degrees of moneyness. This provides supplementary support to our argument of employing option-based strategies to evaluate the performance of hedge fund strategies.

4. Concluding Remarks

This paper determines the composition of a passive portfolio that best replicates the payoff on hedge funds using a combination of passive buy-and-hold (Location) and option-based (Trading Strategy) strategies. We use our model to examine the important risk exposures of hedge funds following Event Driven and Relative Value Arbitrage strategies. We calibrate our model using index level data for two strategies studied by other researchers using different methodology. Further, we confirm our findings by conducting our analysis at an individual hedge fund level and index level for all the hedge funds following the two hedge fund strategies.

We have three main findings. First, we observe that our model consisting of Trading Strategy factors and Location factors is able to explain a significant proportion of the variation in Event Driven and Relative Value Arbitrage fund returns over time. Second, the R-square values from our model are substantially higher than those obtained using Sharpe's (1992) style analysis with the buy-and-hold returns on standard asset classes. This further emphasizes the importance of including option-based strategies in capturing the non-linear systematic risks of hedge funds. Finally, the risk exposures we obtain are similar to those observed by other researchers (Mitchell and Pulvino (2000), and Gatev et al (1999)) using detailed replication of strategies. This offers independent confirmation that our approach is able to accurately characterize the important risk exposures of Event Driven and Relative Value Arbitrage funds.

Estimation of risk exposures of hedge funds is an important area of research. Investing in hedge fund involves significant costs for the investor and selecting the right manager is crucial in case of hedge funds. Hence, a model that accounts for the linear and non-linear risk exposures of hedge funds is necessary for understanding the nature of risks involved in investing in them. Our study also contributes by providing a simple yet powerful approach that can prove to be useful in designing a benchmark for hedge funds and evaluating their risk-adjusted performance. Further, our approach can be employed to study the convergence in the trading styles and risk exposures of hedge funds that can potentially pose threat to financial stability. These issues are being investigated as a part of our ongoing research.

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Appendix A

Event Driven - A strategy that involves investments in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, bankruptcy reorganizations, recapitalizations and share buybacks. The portfolio of some Event-Driven managers may shift in majority weighting between Merger Arbitrage and Distressed Securities, while others may take a broader scope. Instruments include both long and short common and preferred stocks, as well as debt securities and options. Leverage may be used by some managers. Fund managers may hedge against market risk by purchasing S&P put options or put option spreads.

Relative Value Arbitrage – A strategy that attempts to take advantage of relative pricing discrepancies between instruments including equities, debt, options and futures. Managers may use mathematical, fundamental or technical analysis to determine misvaluations. Securities may be mispriced relative to the underlying security, related securities, groups of securities, or the overall market. Many funds use leverage and seek opportunities globally. Arbitrage strategies included divided arbitrage, pairs trading, options arbitrage and yield curve trading.

Table 1. Summary Statistics

This table shows the mean returns, standard deviations (SD), medians, skewness (Skew), Min-Max skewness (MM Skew), kurtosis, minimum and maximum realizations & Sharpe Ratios (SR) for the individual Hedge Funds following Event Driven and Relative Value Arbitrage Strategies and the eleven Passive investment strategies (Location Factors) during January 1988 to August 1999. In Panel A, N represents the number of funds following a particular strategy. We calculate the Sharpe Ratio considering a risk-free rate of 5% p.a. with the only exception of default spread, where it is not applicable (NA). Min-Max skewness is computed as {(Maximum + Minimum - (2*Mean)) / (Maximum - Minimum)}

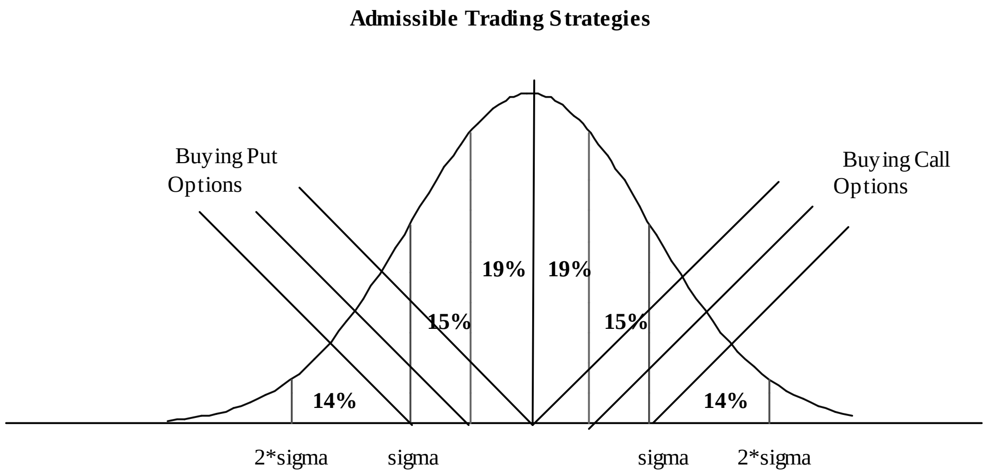
Panel A: **Hedge Fund Strategies**

Hedge fund strategy	N	Mean	SD	Median	Skew	MM Skew	Kurtosis	Min.	Max.	SR
Event Driven	54	1.52	3.63	1.60	-0.67	-0.17	7.43	-11.00	10.97	0.37
Relative Value Arbitrage	25	1.46	2.81	1.43	-0.16	-0.05	5.41	-6.32	8.69	0.57

Panel B: **Passive Strategies**

Passive strategy index	Mean	SD	Median	Skew	MM Skew	Kurtosis	Min.	Max.	SR
Equity									
Russell 3000	1.21	3.60	1.43	-0.23	-0.06	4.20	-11.71	12.68	0.22
MSCI World Excluding US	0.48	4.96	0.63	0.24	0.01	3.48	-13.47	14.67	0.01
MSCI Emerging Markets	0.18	6.76	0.94	1.24	-0.19	5.01	-27.69	19.26	-0.03
Fama-French SMB factor	-0.21	2.68	-0.24	0.25	0.19	3.47	-6.36	8.83	-0.23
Fama-French HML factor	0.19	2.48	-0.04	0.48	0.15	2.88	-4.50	6.55	-0.09
Momentum factor	0.95	3.48	1.22	-0.76	-0.11	5.29	-11.47	10.95	0.15
Bond									
SB Government and Corporate Bond	0.72	1.27	0.85	2.24	0.12	2.92	-2.37	4.65	0.24
SB World Government Bond	0.78	1.78	0.92	3.24	0.09	3.23	-3.63	6.11	0.21
Lehman High Yield	-0.08	3.37	0.13	4.24	-0.43	41.42	-25.47	10.16	-0.15
Currency									
FRB Competitiveness-Weighted Dollar	0.51	1.04	0.50	5.24	0.16	3.08	-1.84	3.77	0.09
Commodity									
Goldman Sachs Commodity	0.28	4.59	0.06	6.24	0.28	4.58	-9.96	18.52	-0.03

Figure 1: Payoffs from buying Call and Put Options on an asset



The figures in percentages have been rounded to whole numbers for illustration purpose.

Table 2. Regression results of HFR Event Driven Index and Relative Value Arbitrage Index Excess Returns on the Excess Returns of the Buy-and-Hold Trading Strategies (Location Factors) and Option-Based Trading Strategies (Trading Strategy Factors)

The following tables show the results of the stepwise regression of the excess returns of the HFR Event Driven Index (Panel A) and the HFR Relative Value Arbitrage Index (Panel B) on the excess returns of the call-option-based trading strategies (C_a, C_o and C_d), put-option-based trading strategies (P_a, P_o and P_d) – the Trading Strategy Factors, and the buy-and-hold trading strategies (Location Factors) during the five 24-month non-overlapping sub-periods between January 1990 and December 1999. For the three call and put option-based trading strategies, subscripts a, o and d refer to at-the-money, out-of-money and deep out-of-money respectively. The table shows the intercept (α), slope coefficients on the various Location and Trading Strategy factors, total R^2 (TR^2), R^2 from the first factor (FR^2), R^2 from the Location factors (LR^2), R^2 from the Trading Strategy factors (TSR^2). The eleven Location Factors are Russell 3000 index (RUS3000), MSCI excluding the US index (MXUS), MSCI Emerging Markets index (MEM), Fama-French Size and Book-to-Market factors (SMB & HML), Momentum factor (MOM), Salomon Brothers Government and Corporate Bond index (SBG), Salomon Brothers World Government Bond index (SBW), Lehman High Yield composite index (LHY), Federal Reserve Bank Competitiveness-Weighted Dollar index (FRB) and the Goldman Sachs Commodity index (GSCI). The Trading Strategy Factors include the at-the-money, out-of-money and deep-out-of-money call and put options on the Russell 3000 index ($RUSC_{a/o/d}$ and $RUSP_{a/o/d}$), MSCI Emerging Markets index ($MEMC_{a/o/d}$ and $MEMP_{a/o/d}$), Salomon Brothers World Government Bond index ($SBWC_{a/o/d}$ and $SBWP_{a/o/d}$), Lehman High Yield composite index ($LHYC_{a/o/d}$ and $LHYP_{a/o/d}$) and Federal Reserve Bank Competitiveness-Weighted Dollar index ($FRBC_{a/o/d}$ and $FRBP_{a/o/d}$). For the slope coefficients, the figures in the brackets indicate their order of entry in the stepwise regression procedure. For the R^2 from the first factor (FR^2), ** indicates that the first factor is a Trading Strategy factor.

Panel A: Results for HFR Event Driven Index

Sig. Factors	Jan 90 – Dec 91	Sig. Factors	Jan 92 – Dec 93	Sig. Factors	Jan 94 – Dec 95	Sig. Factors	Jan 96 – Dec 97	Sig. Factors	Jan 98– Dec 99
α	0.29	α	1.03	α	0.97	α	0.76	α	0.42
$RUSP_a$	-0.81	SMB	0.24	$RUSC_a$	0.74	$RUSP_o$	-0.46	$MEMP_a$	-0.15
$LHYC_o$	0.30	HML	0.21	GSCI	0.12	SMB	0.21	$RUSP_d$	-0.22
		RUS3000	0.24					SMB	0.30
								$SBWC_o$	-0.66
$TR^2 \mid FR^2$	$81.01 \mid 76.68^{**}$	$TR^2 \mid FR^2$	$58.98 \mid 32.30$	$TR^2 \mid FR^2$	$54.33 \mid 42.62^{**}$	$TR^2 \mid FR^2$	$68.11 \mid 42.37^{**}$	$TR^2 \mid FR^2$	$86.26 \mid 63.46^{**}$
$LR^2 \mid TSR^2$	$0.00 \mid 81.01$	$LR^2 \mid TSR^2$	$58.98 \mid 0.00$	$LR^2 \mid TSR^2$	$11.71 \mid 42.62$	$LR^2 \mid TSR^2$	$25.74 \mid 42.37$	$LR^2 \mid TSR^2$	$5.79 \mid 80.47$

Panel B: Results for HFR Relative Value Arbitrage Index

Sig. Factors	Jan 90 – Dec 91	Sig. Factors	Jan 92 – Dec 93	Sig. Factors	Jan 94 – Dec 95	Sig. Factors	Jan 96 – Dec 97	Sig. Factors	Jan 98– Dec 99
α	0.60	α	0.67	α	0.52	α	0.10	α	0.39
MOM	-0.16	$LHYC_a$	8.92	LHY	0.26	$RUSP_o$	-0.21	$RUSP_a$	-0.74
$RUSP_a$	-0.16	$FRBP_a$	1.31			SMB	0.13	MOM	-0.10
		$RUSP_a$	-0.38			$LHYP_a$	-0.30	SMB	0.15
						$FRBP_d$	-0.28	$SBWC_o$	-0.43
								$RUSP_o$	0.40
								$LHYP_a$	-0.19
$TR^2 \mid FR^2$	$64.68 \mid 49.06$	$TR^2 \mid FR^2$	$73.10 \mid 44.85^{**}$	$TR^2 \mid FR^2$	$30.07 \mid 30.07$	$TR^2 \mid FR^2$	$84.64 \mid 40.60^{**}$	$TR^2 \mid FR^2$	$97.62 \mid 68.79^{**}$
$LR^2 \mid TSR^2$	$49.06 \mid 15.62$	$LR^2 \mid TSR^2$	$0.00 \mid 73.10$	$LR^2 \mid TSR^2$	$30.07 \mid 0.00$	$LR^2 \mid TSR^2$	$33.21 \mid 51.43$	$LR^2 \mid TSR^2$	$19.16 \mid 78.46$

Table 3. Summary of Number of Funds and Number of significant Location Factors, Trading Strategy Factors and both in the regressions of Event Driven and Relative Value Arbitrage Fund Excess Returns on the Excess Returns of the Location Factors and Trading Strategy Factors

This table shows the summary of the number of hedge funds following Event Driven and Relative Value Arbitrage strategies showing significant exposures to 1, 2, 3, 4, 5 and more Location Factor, Trading Strategy Factor and both in the stepwise regression of the excess returns of the individual hedge funds on the excess returns of the option-based strategies (Trading Strategy Factors) and the buy-and-hold strategies (Location Factors) during the five equal 24-month sub-periods starting from September 1989 and ending in August 1999. N represents the total number of funds in a particular sub-period for each of the two strategies.

Panel A: Results for the Event Driven Strategy

Period	N	Number of significant Location Factors						Number of significant Trading Strategy Factors						Number of significant Total Factors					
		1	2	3	4	5	More	1	2	3	4	5	More	1	2	3	4	5	More
Sep 89 – Aug 91	10	10	0	0	0	0	0	8	2	0	0	0	0	6	3	1	0	0	0
Sep 91 – Aug 93	17	15	2	0	0	0	0	14	2	1	0	0	0	11	3	2	0	1	0
Sep 93 – Aug 95	24	20	4	0	0	0	0	13	5	6	0	0	0	10	6	3	3	2	0
Sep 95 – Aug 97	34	26	6	2	0	0	0	25	8	1	0	0	0	16	8	7	2	1	0
Sep 97 – Aug 99	51	33	14	4	0	0	0	26	14	7	4	0	0	10	9	18	10	3	1

Panel B: Results for the Relative Value Arbitrage Strategy

Period	N	Number of significant Location Factors						Number of significant Trading Strategy Factors						Number of significant Total Factors					
		1	2	3	4	5	More	1	2	3	4	5	More	1	2	3	4	5	More
Sep 89 – Aug 91	1	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0
Sep 91 – Aug 93	2	2	0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0	0
Sep 93 – Aug 95	8	5	2	1	0	0	0	8	0	0	0	0	0	2	4	2	0	0	0
Sep 95 – Aug 97	8	6	2	0	0	0	0	6	2	0	0	0	0	4	3	1	0	0	0
Sep 97 – Aug 99	20	14	5	1	0	0	0	12	4	1	3	0	0	6	3	5	3	2	1

Table 4. Regression results of Individual Event Driven and Relative Value Arbitrage Hedge Funds for the five sub-periods

The following tables show the results of the stepwise regression of the excess returns of the individual Event Driven and Relative Value Arbitrage hedge funds on the excess returns of the call-option-based trading strategies (C_a, C_o and C_d), put-option-based trading strategies (P_a, P_o and P_d) – the Trading Strategy Factors, and the buy-and-hold trading strategies (Location Factors) during five equal sub-periods of 24 months each starting from September 1989 and ending in August 1999. For the three call and put option-based trading strategies, subscripts a, o and d refer to at-the-money, out-of-money and deep out-of-money respectively. The tables show the five most significant factors in the multi-factor model for the Event Driven (Panel A) and Relative Value Arbitrage (Panel B) strategies. We report the statistics of the intercept (α), slope coefficients, total R^2 (TR^2), R^2 from the first factor (FR^2), R^2 from the Location factors (LR^2), R^2 from the Trading Strategy factors (TSR^2), the number of cases where the first significant factor is a Trading Strategy Factor (#TS) and the percentage of funds in each strategy, where the first significant factor is a Trading Strategy Factor (%TS). We report various statistics of these parameters including the total number of cases (N), total number of positive cases (N^+), mean of total number of cases (μ), mean of the total number of positive cases (μ^+), median of the total number of cases (ι), mean and median order of entry in the stepwise regression procedure (OE ($\mu \mid \iota$)) indicating the importance of the factor in explaining the hedge fund returns, the mean and median of the total R^2 and R^2 from the first factor, $TR^2\ \mu \mid \iota$ and $FR^2\ \mu \mid \iota$, respectively and the mean and median of the R^2 from the Location Factors and R^2 from the Trading Strategy Factors, $LR^2\ \mu \mid \iota$ and $TSR^2\ \mu \mid \iota$, respectively. The eleven Location Factors are Russell 3000 index (RUS3000), MSCI excluding the US index (MXUS), MSCI Emerging Markets index (MEM), Fama-French factors (SMB & HML), Momentum factor (MOM), Salomon Brothers Government and Corporate Bond index (SBG), Salomon Brothers World Government Bond index (SBW), Lehman High Yield composite index (LHY), Federal Reserve Bank Competitiveness-Weighted Dollar index (FRB) and the Goldman Sachs Commodity index (GSCI). The Trading Strategy Factors include the at-the-money, out-of-money and deep-out-of-money call and put options on the Russell 3000 index ($RUSC_{a/o/d}$ and $RUSP_{a/o/d}$), MSCI Emerging Markets index ($MEMC_{a/o/d}$ and $MEMP_{a/o/d}$), Salomon Brothers World Government Bond index ($SBWC_{a/o/d}$ and $SBWP_{a/o/d}$), Lehman High Yield composite index ($LHYC_{a/o/d}$ and $LHYP_{a/o/d}$) and Federal Reserve Bank Competitiveness-Weighted Dollar index ($FRBC_{a/o/d}$ and $FRBP_{a/o/d}$).

Panel A: Results for the Event Driven Strategy

Statistics	Sig. Factors	Sep 89 – Aug 91	Sig. Factors	Sep 91 – Aug 93	Sig. Factors	Sep 93 – Aug 95	Sig. Factors	Sep 95 – Aug 97	Sig. Factors	Sep 97 – Aug 99
N (N^+)		10 (6)		17 (16)		24 (18)		34 (26)		51 (46)
μ (μ^+)	α	0.62 (2.44)	α	1.30 (1.39)	α	0.87 (1.84)	α	1.09 (1.64)	α	0.78 (1.01)
ι		0.45		1.20		0.77		0.48		0.79
N (N^+)		5 (0)		4 (4)		5 (0)		12 (12)		26 (26)
μ (μ^+)	$RUSP_a$	-1.63 (-)	LHY	0.92 (0.92)	$RUSP_d$	-1.09 (-)	SMB	0.53 (0.53)	SMB	0.44 (0.44)
ι		-2.00		0.94		-1.27		0.28		0.33
OE (μ | ι)		1.00 | 1.00		1.00 | 1.00		1.00 | 1.00		1.92 | 2.00		2.50 | 2.00
N (N^+)		2 (0)		4 (0)		4 (2)		9 (9)		17 (0)
μ (μ^+)	SBG	-1.94 (-)	$FRBP_o$	-1.35 (-)	$LHYC_a$	0.19 (2.06)	$RUSC_a$	0.52 (0.52)	$RUSP_a$	-0.61 (-)
ι		-1.94		-1.32		-0.13		0.47		-0.34
OE (μ | ι)		2.00 | 2.00		1.25 | 1.00		2.25 | 2.00		1.44 | 1.00		1.06 | 1.00
N (N^+)		1 (1)		3 (2)		3 (3)		8 (8)		10 (0)
μ (μ^+)	$FRBC_o$	4.46 (4.46)	$LHYC_a$	0.33 (0.92)	$RUSC_o$	1.82 (1.82)	RUS3000	0.87 (0.87)	$RUSP_d$	-0.50 (-)
ι		4.46		0.75		1.79		0.86		-0.34
OE (μ | ι)		1.00 | 1.00		1.33 | 1.50		1.00 | 1.00		1.00 | 1.00		1.20 | 1.00
N (N^+)		1 (0)		3 (3)		3 (2)		6 (4)		9 (0)
μ (μ^+)	$RUSP_o$	-2.05 (-)	HML	0.19 (0.19)	HML	0.94 (1.65)	HML	0.44 (0.78)	$MEMP_a$	-0.36 (-)
ι		-2.05		0.19		1.32		0.26		-0.37
OE (μ | ι)		1.00 | 1.00		1.33 | 1.00		1.00 | 1.00		1.67 | 1.00		2.11 | 2.00
N (N^+)		1 (1)		2 (1)		3 (3)		4 (4)		6 (0)
μ (μ^+)	$MEMC_a$	1.04 (1.04)	RUS3000	0.59 (1.94)	RUS3000	0.82 (0.82)	$MEMC_a$	0.67 (0.67)	$SBWC_o$	-1.87 (-)
ι		1.04		0.59		0.78		0.56		-1.59
OE (μ | ι)		1.00 | 1.00		1.00 | 1.00		1.00 | 1.00		1.25 | 1.00		1.67 | 2.00
	TR^2 μ | ι	65.81 | 72.47	TR^2 μ | ι	43.73 | 41.41	TR^2 μ | ι	56.89 | 57.93	TR^2 μ | ι	55.56 | 54.21	TR^2 μ | ι	69.00 | 72.91
	FR^2 μ | ι	59.46 | 63.97	FR^2 μ | ι	35.00 | 31.05	FR^2 μ | ι	40.38 | 35.29	FR^2 μ | ι	41.95 | 36.17	FR^2 μ | ι	49.06 | 48.73
	LR^2 μ | ι	14.63 | 3.75	LR^2 μ | ι	22.84 | 24.64	LR^2 μ | ι	22.65 | 13.21	LR^2 μ | ι	29.06 | 22.45	LR^2 μ | ι	21.19 | 15.55
	TSR^2 μ | ι	51.18 | 57.99	TSR^2 μ | ι	20.87 | 17.01	TSR^2 μ | ι	34.24 | 35.45	TSR^2 μ | ι	26.50 | 19.83	TSR^2 μ | ι	47.81 | 55.30
	#TS (%TS)	8 (80%)	#TS (%TS)	8 (47%)	#TS (%TS)	12 (50%)	#TS (%TS)	15 (44%)	#TS (%TS)	36 (71%)

Panel B: Results for the Relative Value Arbitrage Strategy

<table>
<tr><th>Statistics</th><th>Sig. Factors</th><th>Sep 89 – Aug 91</th><th>Sig. Factors</th><th>Sep 91 – Aug 93</th><th>Sig. Factors</th><th>Sep 93 – Aug 95</th><th>Sig. Factors</th><th>Sep 95 – Aug 97</th><th>Sig. Factors</th><th>Sep 97 – Aug 99</th></tr>
<tr><td>N (N^+)</td><td></td><td>1(0)</td><td></td><td>2 (2)</td><td></td><td>8 (5)</td><td></td><td>8 (7)</td><td></td><td>20 (17)</td></tr>
<tr><td>μ (μ^+)</td><td>α</td><td>-0.02 (-)</td><td>α</td><td>2.62 (2.62)</td><td>α</td><td>1.60 (2.86)</td><td>α</td><td>1.23 (1.62)</td><td>α</td><td>0.70 (1.02)</td></tr>
<tr><td>ι</td><td></td><td>- 0.02</td><td></td><td>2.62</td><td></td><td>0.59</td><td></td><td>0.75</td><td></td><td>0.65</td></tr>
<tr><td>N (N^+)</td><td></td><td>1 (0)</td><td></td><td>1 (1)</td><td></td><td>2 (1)</td><td></td><td>3 (3)</td><td></td><td>9 (8)</td></tr>
<tr><td>μ (μ^+)</td><td>$RUSP_a$</td><td>-1.15 (-)</td><td>GSCI</td><td>2.44 (2.44)</td><td>HML</td><td>1.64 (3.45)</td><td>SMB</td><td>0.39 (0.39)</td><td>SMB</td><td>0.35 (0.41)</td></tr>
<tr><td>ι</td><td></td><td>-1.15</td><td></td><td>2.44</td><td></td><td>1.64</td><td></td><td>0.21</td><td></td><td>0.30</td></tr>
<tr><td>OE (μ | ι)</td><td></td><td>1.00 | 1.00</td><td></td><td>2.38 | 2.00</td><td></td><td>1.00 | 1.00</td><td></td><td>2.33 | 2.00</td><td></td><td>1.89 | 2.00</td></tr>
<tr><td>N (N^+)</td><td></td><td></td><td></td><td>1 (0)</td><td></td><td>2 (2)</td><td></td><td>2 (2)</td><td></td><td>5 (3)</td></tr>
<tr><td>μ (μ^+)</td><td></td><td></td><td>$MEMP_o$</td><td>-0.22 (-)</td><td>MEM</td><td>0.50 (0.50)</td><td>RUS3000</td><td>0.68 (0.68)</td><td>HML</td><td>-0.03 (0.30)</td></tr>
<tr><td>ι</td><td></td><td></td><td></td><td>-0.22</td><td></td><td>0.50</td><td></td><td>0.68</td><td></td><td>0.16</td></tr>
<tr><td>OE (μ | ι)</td><td></td><td></td><td></td><td>1.00 | 1.00</td><td></td><td>2.00 | 2.00</td><td></td><td>1.00 | 1.00</td><td></td><td>2.60 | 3.00</td></tr>
<tr><td>N (N^+)</td><td></td><td></td><td></td><td></td><td></td><td>2 (0)</td><td></td><td>1 (1)</td><td></td><td>5 (3)</td></tr>
<tr><td>μ (μ^+)</td><td></td><td></td><td></td><td></td><td>MXUS</td><td>-0.18 (-)</td><td>$SBWC_d$</td><td>6.76 (6.76)</td><td>$LHYC_o$</td><td>0.24 (1.40)</td></tr>
<tr><td>ι</td><td></td><td></td><td></td><td></td><td></td><td>-0.18</td><td></td><td>6.76</td><td></td><td>1.04</td></tr>
<tr><td>OE (μ | ι)</td><td></td><td></td><td></td><td></td><td></td><td>2.50 | 2.50</td><td></td><td>1.00 | 1.00</td><td></td><td>3.80 | 4.00</td></tr>
<tr><td>N (N^+)</td><td></td><td></td><td></td><td></td><td></td><td>1 (1)</td><td></td><td>1 (0)</td><td></td><td>4 (0)</td></tr>
<tr><td>μ (μ^+)</td><td></td><td></td><td></td><td></td><td>$LHYP_o$</td><td>4.48 (4.48)</td><td>SBG</td><td>-4.65 (-)</td><td>$RUSC_d$</td><td>-1.22 (-)</td></tr>
<tr><td>ι</td><td></td><td></td><td></td><td></td><td></td><td>4.48</td><td></td><td>-4.65</td><td></td><td>-0.95</td></tr>
<tr><td>OE (μ | ι)</td><td></td><td></td><td></td><td></td><td></td><td>1.00 | 1.00</td><td></td><td>1.00 | 1.00</td><td></td><td>1.00 | 1.00</td></tr>
<tr><td>N (N^+)</td><td></td><td></td><td></td><td></td><td></td><td>1 (0)</td><td></td><td>1 (0)</td><td></td><td>4 (1)</td></tr>
<tr><td>μ (μ^+)</td><td></td><td></td><td></td><td></td><td>$SBWC_d$</td><td>-2.29 (-)</td><td>$FRBP_a$</td><td>-2.99 (-)</td><td>$MEMP_a$</td><td>-0.19 (0.03)</td></tr>
<tr><td>ι</td><td></td><td></td><td></td><td></td><td></td><td>-2.29</td><td></td><td>-2.99</td><td></td><td>-0.14</td></tr>
<tr><td>OE (μ | ι)</td><td></td><td></td><td></td><td></td><td></td><td>1.00 | 1.00</td><td></td><td>1.00 | 1.00</td><td></td><td>1.50 | 1.00</td></tr>
<tr><td></td><td>TR^2 μ | ι</td><td>68.26 | 68.26</td><td>TR^2 μ | ι</td><td>28.47 | 28.47</td><td>TR^2 μ | ι</td><td>54.94 | 57.89</td><td>TR^2 μ | ι</td><td>42.78 | 42.88</td><td>TR^2 μ | ι</td><td>71.18 | 78.22</td></tr>
<tr><td></td><td>FR^2 μ | ι</td><td>68.26 | 68.26</td><td>FR^2 μ | ι</td><td>28.47 | 28.47</td><td>FR^2 μ | ι</td><td>38.62 | 38.55</td><td>FR^2 μ | ι</td><td>31.49 | 27.53</td><td>FR^2 μ | ι</td><td>50.43 | 46.84</td></tr>
<tr><td></td><td>LR^2 μ | ι</td><td>0.00 | 0.00</td><td>LR^2 μ | ι</td><td>18.68 | 18.68</td><td>LR^2 μ | ι</td><td>26.45 | 28.57</td><td>LR^2 μ | ι</td><td>21.94 | 8.42</td><td>LR^2 μ | ι</td><td>27.27 | 19.53</td></tr>
<tr><td></td><td>TSR^2 μ | ι</td><td>68.26 | 68.26</td><td>TSR^2 μ | ι</td><td>9.79 | 9.79</td><td>TSR^2 μ | ι</td><td>28.49 | 28.59</td><td>TSR^2 μ | ι</td><td>20.84 | 18.93</td><td>TSR^2 μ | ι</td><td>43.91 | 49.95</td></tr>
<tr><td></td><td>#TS (%TS)</td><td>1 (100%)</td><td>#TS (%TS)</td><td>1 (50%)</td><td>#TS (%TS)</td><td>5 (63%)</td><td>#TS (%TS)</td><td>5 (63%)</td><td>#TS (%TS)</td><td>14 (70%)</td></tr>
</table>

Figure 2: Non-Linear Exposures of Event Driven and Relative Value Arbitrage Hedge Fund Strategies