Hedge fund performance: The role of non-normality risks and conditional asset allocation

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Abstract

Previous research on hedge fund performance failed to recognize the dynamics in the asset allocation of the managers. Simultaneously, no allowance for systematic non-normality risks was explicitly made. This article highlights the shortcomings of the previous studies by showing first, that systematic kurtosis and skewness risks are the two main drivers of hedge fund performance and second, that the opportunistic asset allocation of hedge funds can be modeled with conditioning information. A failure to account for these features leads to wrong statistical inference on performance for 30.19% of hedge funds and to a 1% overstatement of their annualized abnormal performance.

Keywords: Hedge fund performance, Systematic skewness, Systematic kurtosis, Conditional asset allocation.

I. Introduction

Most hedge fund managers have substantial experience in global capital markets, either as investment manager, investment analyst or proprietary trader. Their expertise is often presented to investors as a virtual guarantee for superior performance. To verify the above claim, several authors have studied the risks and performance of hedge funds (Fung and Hsieh (1997), (2001), Ackermann, McEnally and Ravenscraft (1999), Brown, Goetzmann and Ibbotson (1999), Agarwal and Naik (2000a), (2000b), (2004), Liang (1999), Edwards and Caglayan (2001), Mitchell and Pulvino (2001), Capocci and Hübner (2004)). In these papers, no allowance for systematic non-normality risks was explicitly made while assessing hedge fund risks. As they used static asset pricing models, these authors also failed to recognize the highly opportunistic strategies hedge fund managers typically follow. The purpose of our research is to highlight these shortcomings and to show that a failure to capture the dynamic asset allocation of hedge funds and the non-normality in their return distribution has important bearing on performance.

The early performance studies commonly ignored the departure from normality of the distribution of hedge fund returns (Ackermann, McEnally and Ravenscraft (1999), Brown, Goetzmann and Ibbotson (1999), Liang (1999), Agarwal and Naik (2000b), Edwards and Caglayan (2001), Capocci and Hübner (2004)). Recent research however has made it clear that, due to the use of options and dynamic trading strategies, hedge funds exhibit option-like features in their returns and have significant left-tail risk (Fung and Hsieh (1997), (2001), Mitchell and Pulvino (2001), Agarwal and Naik (2004)). To capture the convexity in their return and the departure of their distribution from normality, a new literature recently related hedge fund performance to the payoffs on lookback straddles (Fung and Hsieh (2001)), to short puts on stock indices (Mitchell and Pulvino (2001), Agarwal and Naik (2004)), to short puts on high-yield debt (Okunev and White (2003)), or to quadratic and cubic market returns (Ranaldo and Favre (2003)). Unlike previous authors, this paper models departure from normality with systematic skewness and kurtosis risk factors and analyzes, for the first time, the impact of systematic non-normality risks on the abnormal performance of hedge funds.

We believe that our systematic skewness and kurtosis mimicking portfolios are better suited than the non-normality risk proxies previously proposed for two reasons. First, our non-normality risk factors have lower correlations with stock indices than the payoffs on stock index options of Fung and Hsieh (2001) and Agarwal and Naik (2004). They also have lower correlations with bond indices than the puts on high-yield debt of Okunev and White (2003). As such, they are better candidates for inclusion as risk factors in multifactor pricing models. Second, Ranaldo and Favre (2003) use the square of the market excess returns as a proxy for skewness. This factor is, by construction, always positive, an unlikely outcome as the risk premium for exposure to systematic skewness should be negative in periods of high positive skewness. It also resembles more Treynor and Mazuy (1966) measure of market timing than Kraus and Litzenberger (1976) systematic skewness.

The rationale for including systematic non-normality risks in the pricing of assets is grounded in both theory and practice. It is acknowledged, for example, that the distribution of asset returns often departs from normality.[1] It has also been shown that investors, because of their aversion for negative skewness and positive excess kurtosis, request a premium for exposure to higher levels of systematic non-normality risks (Kraus and Litzenberger (1976), Harvey and Siddique (2000), Chung, Johnson and Schill (2005)). This validates the view taken in this paper that hedge fund abnormal performance could, at least in part, be a compensation for a systematic exposure to an undesirable distribution.

The second assumption that is typically made while assessing the risk-return relationship of hedge funds is that of constant risks and constant abnormal performance (Brown, Goetzmann and Ibbotson (1999), Agarwal and Naik (2000a), Edwards and Caglayan

[1] Departure from normality has been evidenced in emerging market indices (Harvey (1995)), momentum strategies (Harvey and Siddique (2000)), hedge funds and hedge fund indices (Brooks and Kat (2002), Ranaldo and Favre (2003), Agarwal and Naik (2004)).

(2001)). Due to their private nature, hedge funds have few restrictions on asset classes, derivatives, leverage and short-selling compared to more regulated investment vehicles such as mutual funds. This allows for investment strategies that are typically highly opportunistic and thus have risk exposures and performance measures that strongly fluctuate. On this ground, it is sound to drop the assumption of constant expected return embedded in the traditional Jensen's (1968) alpha and to evaluate performance within a conditional pricing model instead (Ferson and Schadt (1996), Christopherson, Ferson and Glassman (1998)).[2] By allowing the measures of risk and abnormal performance to vary with a set of predetermined information variables, we wish to capture parts of the dynamics in the trading strategies that hedge fund managers typically follow.[3]

The paper underlines the inaccuracies of previous papers that assume normality in the distribution of hedge fund returns and constant factor loadings and highlights the role of systematic non-normality risks and conditional information in assessing hedge fund performance. The results are threefold. First, systematic kurtosis and skewness risks are the two most important drivers of hedge fund performance. They explain the returns of 69% and 66% of hedge funds, respectively. Second, information variables available at time $t-1$ model the dynamics in the risks and abnormal performance of hedge funds. Third, a failure to account for systematic non-normality risks and conditioning asset allocation leads to wrong statistical inference on performance for 30.19% of hedge funds and to a 1% overstatement of their annualized abnormal performance. On average, non-normality risks

[2] Ferson and Schadt (1996) and Christopherson, Ferson and Glassman (1998) show that inferences on performance and persistence of actively managed portfolios are highly sensitive to whether one estimates a conditional or an unconditional model. A change in a portfolio's risk profile over the estimation period can have a dramatic impact on its abnormal performance. This point was also made earlier on by Chan (1988), who argues that most of contrarian profits of De Bondt and Thaler (1985) disappear when the risks of the winner and loser portfolios are allowed to be time-dependent.

[3] This paper takes the view that hedge fund managers trade on information that was recently made public. We appreciate that our approach fails to capture the dynamics in asset allocation based on private information. However, as hedge fund managers do not disclose their investment rules, modeling the impact of private information on their trading strategy is an impossible task.

and conditional asset allocation explain 15% of the abnormal performance that was previously identified. In other words, the average abnormal performance of hedge funds is not as good as once thought.

The remainder of the paper is organized as follows. Section II introduces the methodology. Section III presents the dataset, shows that the distribution of hedge fund returns departs from normality and explains the methodology employed to form mimicking portfolios for systematic skewness and kurtosis. Section IV shows that systematic non-normality risks and conditioning information have important bearing on hedge fund performance. Finally section V concludes the paper.

II. Methodology

The traditional approach to performance evaluation is to regress the fund's excess return r_t on a set of K return-generating factors f_t, implicitly assuming that the regression parameters are constant.

(1) $$r_t = \alpha + \beta f_t + \varepsilon_t$$

The performance of the fund is then evaluated by testing the statistical significance of α in (1). f_t are risk factors that capture the fund style. The vector of risk factors typically used for mutual funds and pension funds needs to be augmented for hedge funds with mimicking portfolios for systematic skewness and kurtosis. We take the view that, in a well-diversified portfolio, idiosyncratic skewness and kurtosis are eliminated and thus that investors only earn compensation for exposure to systematic skewness and kurtosis. As a result, we define an hedge fund's systematic skewness as its co-skewness; namely, as the amount by which it contributes to the skewness of a well-diversified portfolio. A similar definition is used for systematic kurtosis.

The assumption of constant parameters implies that asset managers do not alter their asset allocation as new information arises to the market. When it comes to hedge funds, this assumption is, at best, misleading. A change in asset allocation will, in turn, induce a change in the risk profile and abnormal performance of the fund. To model the latter, we assume that there is a linear relation between the parameters in (1) and z_{t-1}, a set of L mean-zero information variables available at time $t-1$.[4] α and β then equal

(2) $$(\alpha_t|z_{t-1}) = \alpha_0 + \alpha_1 z_{t-1}$$

(3) $$(\beta_t|z_{t-1}) = \beta_0 + \beta_1 z_{t-1}$$

where $(.|z_{t-1})$ denotes a parameter that is conditional on z_{t-1}, α_0 is the average abnormal performance of the fund, β_0 is a K-vector of average measures of risk, α_1 and β_1 are L and LK-vectors of parameter estimates and $z_{t-1} = Z_{t-1} - E(Z)$ is a L-vector of mean-zero deviations from Z_{t-1}. $\alpha_1 z_{t-1}$ captures the variation through time in the fund's abnormal performance and measures the departure from α_0, the average abnormal performance of the fund. Similarly, $\beta_1 z_{t-1}$ captures the variation though time in the measures of risk and measures the departure from β_0, the average risk profile of the fund.

Replacing α and β in (1) by $(\alpha_t|z_{t-1})$ and $(\beta_t|z_{t-1})$ in (2) and (3) yields the conditional model of performance first proposed by Ferson and Schadt (1996) and Christopherson, Ferson and Glassman (1998)

(4) $$r_t = \alpha_0 + \alpha_1 z_{t-1} + \beta_0 f_t + \beta_1 f_t z_{t-1} + \varepsilon_t$$

where α_0 is the conditional counterpart of Jensen's (1968) α. Model (4) differs from traditional performance evaluation models in two ways. First, it treats systematic skewness

[4] The assumption of a linear relation between the regression parameters and a set of publicly available instruments was first introduced by Harvey (1989) and has been used extensively ever since (see, for example, Ferson and Harvey (1993)). It is noted that time-variation in risk and abnormal performance could also be introduced by rolling-over equation (1). This route was not taken as such an approach restricts our cross-section to funds with very long return history and thus exacerbates the selection bias mentioned in section III.

and kurtosis as sources of pervasive risk for hedge funds. Second, it adds a L-vector z_{t-1} and a LK-vector $f_t z_{t-1}$ to the regression traditionally used to measure performance. These regressors pick up the variations through time in the performance and risk measures of hedge funds that are related to changing economic conditions and dynamic asset allocation.

Because the omission of some information variables or risk factors could result in the model being misspecified, the standard errors in (1) and (4) are corrected for possible heteroscedasticity and serial correlation using Newey and West (1987). Note also that the static model (1) is nested in the conditional model (4). In particular, the conditional model can be assessed against the static model by testing the restrictions $\alpha_1 = 0$, $\beta_1 = 0$ and $\alpha_1 = \beta_1 = 0$ in (4). These tests are distributed as χ^2 with L, LK and $L(K+1)$ degrees of freedom, respectively.

III. Data and Preliminary Analysis

A. Hedge Funds

The data on hedge funds comes from the TASS database. As of August 2004, the database contains return data on 4,270 US dead and surviving hedge funds over the period 31 January 1985 – 31 August 2004. This period includes 1997 and 1998, which, with crises in Asia and Russia and the subsequent near-collapse of LTCM, were particularly difficult years for hedge funds. In this study, however, we concentrate on the 2,239 (dead and surviving) funds for which at least 45 months of consecutive return data net of fees are available. Our dataset suffers from selection bias as we need to meet the requirement of having at least 45 observations in the regression analysis to draw meaningful inference on the coefficient estimates. It is noted that as a result the performance measures will be biased upward.

Hedge fund investment strategies tend to be quite different from the strategies followed by traditional money managers, making extensive use of derivatives and leverage. In principle, every fund follows its own proprietary strategy, which makes hedge funds a very heterogeneous group. There are, however, a number of ‘ideal types’ to be distinguished. TASS uses the following 11 main categories: Convertible arbitrage, Dedicated short bias, Emerging markets, Equity market neutral, Event driven, Fixed income arbitrage, Fund of funds, Global macro, Long/short equity hedge, Managed futures and Other.

Table 1 reports summary statistics of returns per category of hedge funds (columns 1 to 11). The last column presents the results for the entire cross section. It indicates that hedge funds offered an annualized average return of 11.84% with 61% of the funds having a positive mean at the 5% level. This result however conceals wide differences across styles. Average returns range from a low of 4.04% for dedicated short bias to a high of 14.98% for long/short equity hedge. Similarly, while 92% of convertible arbitrage have mean returns that exceed zero at the 5% level, the mean of only 19% of dedicated short bias significantly exceeds zero.

<< Insert table 1 around here >>

In line with portfolio theory, higher average returns are associated with higher annualized standard deviations. There is one exception however: Dedicated short bias exhibits the second highest volatility and the lowest mean return, suggesting poor performance relative to its peers. As a result, the reward-to-risk ratio of this category, at 0.1689, is the lowest across categories. Based on this performance measure, convertible arbitrage offers the best risk-adjusted return as a group.

Unlike mutual funds, hedge funds frequently use derivatives and follow highly dynamic trading strategies. As a result, the distribution of their returns frequently departs from normality.[5] On average, the skewness coefficient equals 0.0539, suggesting that the distributions tend to be more positively skewed than negatively skewed. Across the entire cross section, the skewness of 44% of the funds is the same as that of the normal, 22% of

[5] The percentages reported in table 1 build on the fact that, for large samples, the skewness and excess kurtosis estimators are distributed as $N(0, 6/T)$ and $N(0, 24/T)$, respectively, under the null hypothesis of normality.

the funds exhibit negative skewness at the 5% level, while 33% of the funds exhibit positive skewness. These averages however mask sharp differences across categories. The return distributions of convertible arbitrage, emerging markets, event driven and fixed income arbitrage tend to be more negatively skewed, while the distributions of global macro, long/short equity hedge, managed futures and other tend to be positively skewed. As investors show aversion for negative skewness and preference for positive skewness, the negatively skewed funds should, other things being equal, offer a higher return than the positively skewed ones.

The average excess kurtosis is positive at 4.7201. This suggests that the typical hedge fund has a return distribution that has more mass in the tails than would be predicted by the normal. With 69% of the funds having a kurtosis that exceeds 3 at the 5% level, it seems that a lot of information regarding the distributions of returns is contained in the tails and thus that the probability of huge losses cannot be overlooked. This corroborates the evidence in Agarwal and Naik (2004). As with skewness, there are wide differences across categories. The distributions of fixed income arbitrage, emerging markets, event driven and other stand out as being more leptokurtic than those of dedicated short bias, equity market neutral or managed futures.

Accordingly, the Jarque-Bera test statistics indicate that the distributions of hedge fund returns frequently depart from normality (in 73% of the cases). Consistent with the analysis that preceded, departures from normality are more frequent for fixed income arbitrage, emerging markets and event driven than for dedicated short bias or managed futures.

Altogether, the evidence in table 1 legitimate our claim that a failure to account for systematic skewness and kurtosis risks might lead to incorrect inference on hedge fund performance. Rational investors should, in efficient markets, accept a lower average return on funds that exhibit desirable features such as positive skewness and negative excess kurtosis. Similarly, one would expect the funds that exhibit undesirable distributions (in terms of negative skewness and positive excess kurtosis) to offer higher returns. Part of the performance that was previously identified (Brown, Goetzmann and Ibbotson (1999), Liang (1999), Agarwal and Naik (2000b), Edwards and Caglayan (2001)) could therefore be a compensation for exposure to systematic skewness and kurtosis risks.

B. Risk Factors

Because hedge funds do not limit themselves to investing into stocks and bonds, we include as risk proxies factors that might reflect their alternative investment style (Edwards and Caglayan (2001), Agarwal and Naik (2004), Capocci and Hübner (2004), Agarwal and Naik (2004)). The factors we consider are the returns in excess of the US Treasury-bill on (1) the MSCI world equity index, (2) the return on an US Treasury-bond index, (3) the return on Reuters spot commodity index and (4) the return on the US dollar against major currency index. We also treat as risk factors the momentum factor of Carhart (1997) and the returns of size (small-minus-big or SMB) and book-to-market value (high-minus-low or HML) sorted portfolios (Fama and French (1993)).

The methodology we employ to construct mimicking portfolios for systematic skewness and kurtosis is a direct extension of that proposed in Fama and French (1993) to form size and book-to-market value sorted portfolios. First, monthly returns over the period 31 January 1980 to 31 August 2004 are obtained from Datastream for all the stocks listed on the Amex, NYSE and NASDAQ exchanges. Delisted stocks are also included. Second, we calculate the systematic skewness (or coskewness with the market portfolio) of each stock using the definition of Kraus and Litzenberger (1976)

$$coSK_i = \frac{E[(r_{it} - \bar{r}_i)(r_{Mt} - \bar{r}_M)^2]}{E[(r_{Mt} - \bar{r}_M)^3]} \quad (5)$$

r_{it} is the return on stock i at month t, r_{Mt} is the return on the S&P500 Composite index, $\bar{r}_i$ and $\bar{r}_M$ are the corresponding unconditional means (where a 60-month window is used to form expectations). Third, we sort the stocks according to $coSK_i$ and form two portfolios that contain the 30% of stocks with the lowest and highest $coSK_i$, respectively. The return on the skewness-mimicking portfolio in each of the subsequent 12 months is calculated as the difference in the average returns on these low and high coskewness portfolios. Finally, the 60-month window to calculate (5) is rolled forward 12 months to form new portfolios. This recursive approach yields a monthly time series of 236 skewness-mimicking portfolio returns.

A similar approach is used to construct the kurtosis-mimicking portfolio. There are however two differences. First, the relevant attribute on which to sort stocks into portfolios is now $coKU_i$, the systematic kurtosis or cokurtosis of each stock

$$coKU_i = \frac{E[(r_{it} - \bar{r}_i)(r_{Mt} - \bar{r}_M)^3]}{E[(r_{Mt} - \bar{r}_M)^4]}$$

which is the equivalent of (5) for the fourth moment. Second, the kurtosis-mimicking portfolio return is the difference in the returns on the high- and low-kurtosis portfolios.

Summary statistics of the factor risk premia are presented in panel A of table 2. The annualized market risk premium equals 7.60%. The risk premia on the bond, FX and commodity indices are negative over the period at -3.47%, -2.93% and -2.16%, respectively. The small size portfolio outperforms the large size portfolio by an average annualized return of 1.06%, while the value portfolio beats the growth portfolio by 2.31%. The momentum strategy pays a sizable return at 9.91%. As expected, the price of risk associated with systematic kurtosis is positive (at 4.49%), suggesting that investors require a premium of 4.49% for exposure to high (as opposed to low) levels of systematic kurtosis. The mimicking portfolio for systematic skewness has a negative mean (-3%). This is not in line with expectations as investors should request compensation (in the form of a positive risk premium) for exposure to assets with lower systematic skewness. Given our short time series, this negative average return could, however, be sample specific and is, in any case, statistically insignificant.

<< Insert table 2 around here >>

Panel B of table 2 reports pairwise correlations across the risk factors. Some of the correlations are very high in absolute terms. Of particular concern is the -0.92 correlation between the returns on the systematic skewness and kurtosis portfolios. As multicollinearity is a problem, the risk analysis is performed with one risk factor at a time. Similarly, while analyzing hedge fund performance, we systematically exclude from the regressions the mimicking portfolio for systematic skewness or kurtosis that is the least significant.

C. The Set of Information Variables

To address concerns of multicollinearity, we restrict the set of information variables to series that have low pairwise correlations. We consider the first lag in two business cycle variables: default spread and the term structure of US interest rates.[6] Two additional information variables are considered. In case of persistence in performance, we condition the measure of abnormal performance on the lagged return on the hedge fund under review. Similarly, we allow the measures of risk to change as a function of the previous month's realization of the systematic risk factor.

IV. Empirical Results

Valid inference on performance can only be drawn from well-specified asset pricing models. With this in mind, section A highlights that systematic skewness and kurtosis risks explain hedge fund returns, while section B shows that previous realizations of the information variables help capture the dynamics in the asset allocation of hedge fund managers. Finally,

[6] Default spread is measured as the difference in yields between Moody's BAA and AAA rated bonds. The term structure is defined as the difference between the redemption yield on the US government bond index with 30-year maturity and the three-month Treasury-bill rate. Dividend yield and the Treasury-bill rate are two variables that are typically treated as proxies for the business cycle. They are excluded here from the information set. This is because of their high correlation with both default and term spreads and to conserve degrees of freedom. Note also that including them does not alter the conclusions of the paper.

section C demonstrates that a failure to account for systematic non-normality risks and conditional information has important bearing on performance.

A. Statistical Significance of the Risk Factors

To address concerns of multicollinearity, we run univariate regressions of hedge fund returns on each of the risk factors separately. Table 3 reports the percentage of funds per category (rows 1 to 11) and across categories (row 12) that have significant factor loadings at the 5% level. For example, 46% of the convertible arbitrage funds have a significant market beta.

<< Insert table 3 around here >>

The univariate regressions highlight the importance of kurtosis and skewness risks in explaining hedge fund returns. In terms of statistical significance, systematic kurtosis ranks first (out of nine factors) and explains the returns of 68.65% of the funds at the 5% level. It is the main driver of performance for 7 of the 11 styles (Convertible arbitrage, Dedicated short bias, Emerging markets, Event driven, Fund of funds, Global macro and Other) and the second most important risk factor for long/short equity hedge. Across styles, the percentage of funds that is sensitive to the kurtosis risk factor ranges from a low of 22% for fixed income arbitrage to a high of 96% for dedicated short bias.

Systematic skewness is the second most important risk factors. It explains the returns of 65.65% of the funds at the 5% level. It is the main driver of performance for fixed-income arbitrage. It is the second most important risk factor for convertible arbitrage, event driven, fund of funds and managed futures. It ranks third in order of statistical significance for dedicated short bias, emerging markets, global macro, long/short equity hedge and other. Like for systematic kurtosis, there are wide differences across styles: skewness risk matters for merely 25% of fixed income arbitrage and for a staggering 92% of dedicated short bias.

Market risk ranks third out of the nine factors in terms of statistical significance. It enters the risk-return relationship of 65.39% of the funds. It is the main driver of the performance of long/short equity hedge and is as important as kurtosis for dedicated short bias and other. It is also the second most important risk factor for emerging markets. The importance of market risk in explaining the returns of hedge funds varies substantially across categories: 18% of the returns of fixed income arbitrage are sensitive to market risk, while 96% of the returns of dedicated short bias have significant market loadings.

In order of statistical significance, the remaining risk factors are SMB, HML, bond, momentum, commodity and FX. They enter the risk-return relationship of 57.4%, 46.9%, 28.4%, 28.2%, 17% and 15.9% of hedge funds, respectively. Note also that there are wide differences across categories. Equity market neutral and managed futures, for example, are much less sensitive to the risk factors than dedicated short bias and long/short equity hedge. Our results pertaining to the importance of SMB in explaining the returns of convertible arbitrage, dedicated short bias, event driven and long/short equity hedge corroborate those of Mitchell and Pulvino (2001) and Agarwal and Naik (2004). Table 3 also confirms the role of HML in explaining the returns of dedicated short bias and long/short equity hedge that was first highlighted in Agarwal and Naik (2004).

The results thus far suggest that (1) the distributions of hedge fund returns depart from normality (table 1) and (2) systematic skewness and kurtosis risks capture some of the variations in hedge fund returns (table 3). Hence a failure to account for the skew and fat tails in the distribution of hedge fund returns might have important bearing on performance.

To address the problem of multicollinearity (highlighted in panel B of table 2), we estimate in the remainder of the paper models that include either systematic skewness or systematic kurtosis as risk factors. The decision to include either one of the non-normality risk factors is based on statistical significance. For each hedge fund, a regression that includes all nine risk factors is first estimated. The non-normality risk factor that is the most significant is included in the pricing equation, while the other one is omitted.

B. Statistical Significance of Conditioning Information

The second contribution of the paper is to model the dynamics in the asset allocation of hedge fund managers with a set of realized information variables. Table 4 reports the percentage of funds that show evidence of time-variation in abnormal performance (panel A), risks (panel B) or both (panel C). The percentage of funds whose abnormal performance changes with, say, default spread is also reported in panel A. Similar information is available for the risk measures in panel B. For example, default spread predicts the abnormal performance of 14% of convertible arbitrage at the 5% level and 88% of the convertible arbitrage funds reject the null hypothesis of constant abnormal performance $(\alpha_1 = 0)$ at the 5% level.

<< Insert table 4 around here >>

The results in panel A of table 4 highlight the importance of modeling the dynamics in the abnormal performance of hedge funds. Across the whole cross section, 69% of the funds reject the null of no time-variation in abnormal performance. The rejection is particularly strong for convertible arbitrage and event driven and weaker for global macro and managed futures. Altogether, the past return on the hedge fund under study describes the change in the abnormal performance of 27% of the funds. As such, it is the best predictor of future abnormal performance. Default spread captures the stochastic movements in the abnormal performance of 17% of the funds, while the term structure predicts the abnormal performance of 19% of the funds.

Similarly panel B of table 4 documents strong evidence of time-variation in the measures of risk. The hypothesis that the measures of risk are constant $(\beta_1 = 0)$ is consistently rejected by the data. Across all hedge funds, each of the information variables has predictive power over roughly 18% of the measures of risks. Altogether, none of the information variables is redundant at the 5% level. Each has a role to play either as a predictor of the measures of risk or as an indicator of future abnormal performance.

When the joint significance of α_1 and β_1 is tested, the evidence in panel C of table 4 overwhelmingly suggests that both the measures of abnormal performance and risk are time-dependent. The hypothesis of constant regression parameters is rejected for all 2,239 funds. Clearly, according to table 4, it is important to allow the measures of abnormal performance and risk to be time-dependent instead of restricting them to be constant. This strongly suggests that the static models traditionally employed to measure performance are misspecified. As a result, restricting the measures of risk and abnormal performance to be constant, instead of conditioning them onto past information, might lead to misleading conclusions on performance.

Altogether, the results in table 4 indicate that hedge fund managers trade on information that was recently made public by changing their asset allocation towards the asset classes that are deemed to outperform. As a result, the fund risks and abnormal performance change in a predictable way that is easily modeled with our proxies for the business cycle.

C. Performance Evaluation

Within our well-specified models, we can now evaluate hedge fund performance and demonstrate that wrong inference on performance will be drawn from the use of misspecified models. Table 5 reports the annualized abnormal performance of hedge funds, averaged within categories (columns 1 to 11) and across categories (column 12). It also presents the associated average t-statistics and the average adjusted-R^2 of three models. The first model in panel A is a static model that excludes non-normality risk factors. It is used as a benchmark to assess the impact that the omission of non-normality risks and conditional asset allocation has on performance. The second model in panel B is a static model that treats the non-normality mimicking portfolios as potential risk factors (as in equation (1)). The third model in panel C accounts for both non-normality risks and conditional asset allocation (as in equation (4)).

<< Insert table 5 around here >>

The main result of table 5 is that the average abnormal performance of hedge funds decreases when (1) a non-normality risk factor is included in the pricing model and (2) the dynamic asset allocation of hedge fund managers is explicitly modeled. While the average abnormal performance across funds stands at 6.47% a year within the static model of panel A, it falls to 5.76% when a non-normality risk factor is included in the risk-return relation of panel B. The difference, 0.71%, is a return that was previously attributed to stock picking, while it is, in effect, a compensation for exposure to an undesirable distribution. It is statistically significant at the 1% level (panel B). Similarly, the average abnormal performance reported in panel C, at 5.54%, is less than that of panel A, at 6.47%. The difference of 0.93% is significant at the 1% level. This suggests that an abnormal return of roughly 1% can be attributed to non-normality risks and time-varying parameters. Therefore, non-normality risk and conditional asset allocation explain, on average, 15% of the abnormal performance of hedge funds identified in panel A. In other words, the abnormal performance of hedge funds as a group is not as good as once thought.

These averages conceal quite large discrepancies across styles. The conclusion, that average abnormal performance worsens when non-normality risk and time-varying parameters are explicitly modeled, sounds particularly true for managed futures, emerging markets, other and global macro. Abnormal returns of 3.77%, 3.32%, 2.11% and 1.26%, respectively, can be attributed to model misspecification. This actually means that non-normality risks and conditional asset allocation account for a staggering 40%, 87%, 29% and 27%, respectively, of the abnormal performance that was identified in table 5, panel A. On the other end of the spectrum, some styles now perform better than once thought. The abnormal performance of dedicated short bias at -0.2% in panel A was poor compared to its peers. It is comparatively better in panels B and C at 2.57% and 1.94%, respectively. A similar conclusion can be drawn for event driven and fixed income arbitrage. For these two categories, including time-varying parameters and non-normality risk in the pricing equation increases abnormal performance by 2.14% and 1.56%, respectively.

To highlight that the use of misspecified models may lead to wrong inference on the significance of the measures of abnormal performance, panels B and C of table 5 also report the percentage of funds that were misleadingly classified based on statistical significance in panel A. The last column of panel B shows that 7.28% of the funds (163 funds out of the universe of 2,239 funds) are misclassified when non-normality risk is omitted. A failure to model non-normality risk and time-varying parameters leads to wrong conclusion on the statistical significance of the abnormal performance of 676 funds in panel C (30.19% of the funds). The omission of non-normality risk and conditional information has a particularly damaging impact on the statistical significance of the measure of abnormal performance of dedicated short bias, event driven, fixed income arbitrage, global macro and long/short equity hedge. For these styles, more than 30% of the funds were misclassified in panel A.

The adequacy of the models of panels B and C relative to that of panel A is also born out by consistently higher average adjusted-R^2 for the former models. On average, the fit of the conditional model with non-normality risk factors of panel C exceeds that of the model of panel A by 14.1%. The conditional model with non-normality risk explains an average of 39.08% of the variation in hedge fund returns. Although low compared to what is traditionally found for mutual funds, these coefficients of determination resemble the ones reported in previous hedge fund studies (Fung and Hsieh (1997), Liang (1999), Agarwal and Naik (2000a), (2000b)). The average t-statistics on the measures of abnormal performance also increases substantially in panel C relative to panel A, suggesting that the inference on statistical significance is stronger within the better specified model.

Finally panel C confirms that the representative hedge fund manager, with an average α_0 at 5.54%, has superior skills.[7] Long/short equity hedge, with an average conditional alpha at 8.29%, is the style that performs the best. It is shortly followed by event driven (7.91%) and convertible arbitrage (7.30%). The styles that performed the worst are emerging market (0.48%) and dedicated short bias (1.94%). It is interesting to note also that the conditional performance of fund of funds (at 2.61%) is substantially worse than that of non-fund of funds (at 6.26%). This strongly suggests that the average fund of funds manager is unable to add enough value to make up for the fees he charges (typically 1.5% management fee plus 10% incentive fee). Finally, the last row of panel C reports $p(\alpha_0 > 0)$, the percentage of fund managers who beat their benchmark at the 5% level within the augmented conditional model. 46% of fund managers have superior skills: we cannot attribute their abnormal performance merely to luck. Only 24% of the managers that had an emerging markets style show superior skills. On the other hand, skills are more frequent among the managers who belong to the following categories: convertible arbitrage, event driven, fixed income arbitrage and other.

A note of caution is warranted at this stage. There are two reasons to suggest that the measures of abnormal performance reported in table 5 are overstated. First, the attrition rate of hedge funds is known to be high in the early stage of business. Because our analysis focuses on hedge funds with a relative long history of returns (at least 45 observations), the sample is tilted towards skillful managers and thus the abnormal performance is upward-biased. Second, the coefficients of determination of the conditional model with non-normality risks are low compared to those typically reported for mutual funds. This suggests that the model might not be completely adequate at capturing the complex and highly opportunistic nature of hedge fund strategies. This also could lead to an overstatement of the abnormal

[7] This result is consistent with earlier studies such as Brown, Goetzmann and Ibbotson (1999), Liang (1999), Agarwal and Naik (2000b) and Edwards and Caglayan (2001).

performance. These points notwithstanding, the paper highlights the importance of non-normality risks and conditional asset allocation in assessing hedge fund performance. As such, it underlines the inaccuracies of previous papers that assume normality in the distribution of hedge fund returns and constant factor loadings.

V. Conclusions

The issue of whether hedge fund managers have superior skills constitutes a quite well-documented area of research in finance. Quite often however previous authors failed to recognize the non-normality in the distribution of hedge fund returns and the highly opportunistic strategies the managers typically follow. The purpose of this article is to use a methodology that tackles these problems by jointly treating exposure to systematic skewness and kurtosis risks as potential sources of return and conditioning the measures of abnormal performance and risks on economic conditions. Then and only then, is it possible to obtain clear inference on the ability, or lack thereof, of a hedge fund manager to beat his/her benchmark.

We draw the following three conclusions. First, systematic kurtosis and systematic skewness are the two most important drivers of hedge fund returns. They enter the risk-return relationship of 69% and 66% of hedge funds, respectively. Second, information variables available at time $t-1$ model the dynamics in the risks and abnormal performance of hedge funds. Third, a failure to account for non-normality risks and conditional asset allocation leads to wrong statistical inference on performance for 30.19% of the funds and to a 1% overstatement of the average abnormal performance of hedge funds. Non-normality risks and conditional asset allocation explain, on average, 15% of the abnormal performance of hedge funds that was previously identified. In other words, the abnormal performance of hedge funds as a group is not as good as once thought.

A final note concerns the fact that although the traditional multi-factor model is a popular tool for performance evaluation amongst practitioners as well as academics, there are indications that the model might not be entirely appropriate to evaluate the performance of hedge funds. The low coefficients of determination suggest that even the conditional model with non-normality risks has difficulty capturing the complex and highly opportunistic nature of hedge fund strategies. Some of the findings from the conditional model, including the high level of abnormal performance, may therefore be biased to some extend. Clearly, these issues deserve further study.

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Table 1: Summary Statistics of Hedge Funds

The table presents summary statistics of hedge funds per and across categories. Mean and standard deviation are annualized. The percentage of funds with a mean that exceeds zero at the 5% level is reported in brackets. The reward-to-risk ratio is measured as the ratio of the annualized mean to the annualized standard deviation. *p*(*Sk*<0) (*p*(*Sk*>0)) is the percentage of funds with a negatively (positively) skewed return distribution at the 5% level. *p*(*Sk*=0) is the percentage of funds whose skewness is the same as that of the normal distribution at the 5% level. *p*(*Ku*-3<0) (*p*(*Ku*-3>0)) is the percentage of funds with platykurtic (leptokurtic) distribution at the 5% level. *p*(*Ku*-3=0) is the percentage of funds with mesokurtic distribution at the 5% level. *p*(*JB*>0) is the percentage of funds whose return distribution departs from normality at the 5% level, where *JB* is the Jarque-Bera test for normality.

Category	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Fund of Funds	Global Macro	Long/Short Equity Hedge	Managed Futures	Other	All Hedge Funds
Number of Funds	99	26	172	85	213	87	446	102	713	235	61	2,239
Mean	0.1171	0.0404	0.1422	0.0872	0.1118	0.0920	0.0838	0.1038	0.1498	0.1138	0.1173	0.1184
	[0.92]	[0.19]	[0.42]	[0.66]	[0.85]	[0.69]	[0.70]	[0.54]	[0.57]	[0.36]	[0.70]	[0.61]
Standard Deviation	0.0693	0.2390	0.2436	0.0877	0.0913	0.0913	0.0992	0.1716	0.1943	0.2268	0.1309	0.1569
Reward-to-Risk Ratio	1.6909	0.1689	0.5838	0.9942	1.2248	1.0082	0.8450	0.6050	0.7708	0.5017	0.8958	0.7542
Skewness (*Sk*)												
- Average	-0.2464	0.2554	-0.3277	0.3873	-0.3061	-2.0639	-0.0199	0.3950	0.4019	0.3771	0.0011	0.0539
- *p* (*Sk* <0)	30%	0%	33%	9%	41%	69%	23%	10%	15%	8%	30%	22%
- *p* (*Sk* =0)	54%	73%	45%	56%	36%	18%	46%	46%	45%	48%	31%	44%
- *p* (*Sk* >0)	16%	27%	23%	34%	23%	13%	31%	44%	39%	44%	39%	33%
Excess Kurtosis (*Ku* -3)												
- Average	5.5493	2.0373	6.1372	2.7477	5.4477	15.9736	4.7869	3.2887	3.5859	2.9783	6.5533	4.7201
- *p* (*Ku* -3<0)	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
- *p* (*Ku* -3=0)	38%	50%	22%	46%	21%	9%	29%	31%	35%	42%	21%	31%
- *p* (*Ku* -3>0)	62%	50%	78%	54%	79%	91%	71%	69%	65%	58%	79%	69%
Jarque-Bera Normality Test												
- Average	969.77	40.79	389.75	111.29	941.78	2,913.33	394.43	107.79	166.68	142.39	492.57	445.24
- *p* (*JB* >0)	68%	58%	80%	64%	81%	92%	75%	74%	69%	63%	79%	73%

Table 2: Summary Statistics and Correlations for the Risk Factors

Market is the return on the MSCI world equity index in excess of the US Treasury-bill rate. Bond is the excess return on an US Treasury-bond index. Commodity is the excess return on Reuters spot commodity index. FX is the excess return on the US dollar against major currency index. SMB and HML are size and value risk premia as defined by Fama and French (1993). Momentum is the return differential between two portfolios of stocks with high and low past returns, respectively. SMB, HML and Momentum are from Kenneth French's website. Skewness is the return differential between two equally-weighted portfolios of stocks with low and high systematic skewness, respectively, where systematic skewness is defined as in Kraus and Litzenberger (1976). Kurtosis is the return differential between two equally-weighted portfolios of stocks with high and low systematic kurtosis, respectively. Mean and standard deviation are annualized. The reward-to-risk ratio is measured as the ratio of the annualized mean to the annualized standard deviation. The probability value that the mean is zero at the 5% level is reported in brackets.

	Market	Bond	Commodity	FX	SMB	HML	Momentum	Skewness	Kurtosis
Panel A: Summary Statistics									
Mean	0.0760	-0.0347	-0.0293	-0.0216	0.0106	0.0231	0.0991	-0.0300	0.0449
	[0.03]	[0.00]	[0.27]	[0.13]	[0.67]	[0.43]	[0.01]	[0.30]	[0.17]
Standard Deviation	0.1517	0.0499	0.1162	0.0623	0.1111	0.1282	0.1586	0.1276	0.1457
Reward-to-Risk Ratio	0.5008	-0.6961	-0.2518	-0.3465	0.0950	0.1800	0.6250	-0.2347	0.3083
Panel B: Pairwise Correlations									
Market	1								
Bond	0.06	1							
Commodity	0.13	-0.04	1						
FX	-0.25	-0.13	-0.39	1					
SMB	0.14	-0.20	0.00	0.06	1				
HML	-0.25	0.00	0.03	0.05	-0.35	1			
Momentum	-0.08	0.16	-0.09	-0.03	-0.01	-0.53	1		
Skewness	-0.50	0.09	-0.01	-0.05	-0.54	0.19	0.32	1	
Kurtosis	0.63	-0.11	-0.03	0.04	0.56	-0.27	-0.28	-0.92	1

Table 3: Statistical Significance of the Risk Factors

The table reports the percentage of funds that have significant factor loadings at the 5% level in univariate regressions of the fund excess returns on the risk factor. Market is the return on the MSCI world equity index in excess of the US Treasury-bill rate. Bond is the excess return on an US Treasury-bond index. Commodity is the excess return on Reuters spot commodity index. FX is the excess return on the US dollar against major currency index. SMB and HML are size and value risk premia as defined by Fama and French (1993). Momentum is the return differential between two portfolios of stocks with high and low past returns, respectively. Skewness is the return differential between two equally-weighted portfolios of stocks with low and high systematic skewness, respectively. Kurtosis is the return differential between two equally-weighted portfolios of stocks with high and low systematic kurtosis, respectively. The standard errors are heteroscedasticity and serial correlation-consistent (Newey and West (1987)).

Category	Market	Bond	Commodity	FX	SMB	HML	Momentum	Skewness	Kurtosis
Convertible Arbitrage	46%	9%	11%	11%	39%	24%	13%	48%	49%
Dedicated Short Bias	96%	8%	15%	12%	85%	62%	15%	92%	96%
Emerging Markets	78%	10%	15%	10%	58%	38%	11%	76%	81%
Equity Market Neutral	32%	22%	8%	13%	27%	38%	36%	26%	28%
Event Driven	66%	7%	10%	8%	59%	21%	17%	69%	70%
Fixed Income Arbitrage	18%	23%	13%	14%	18%	16%	7%	25%	22%
Fund of Funds	64%	17%	9%	9%	64%	49%	19%	66%	69%
Global Macro	29%	25%	11%	18%	37%	27%	22%	36%	37%
Long/Short Equity Hedge	77%	20%	11%	7%	57%	55%	22%	70%	75%
Managed Futures	23%	53%	14%	18%	14%	16%	27%	32%	30%
Other	64%	16%	16%	10%	51%	48%	28%	61%	64%
All Hedge Funds	65.39%	28.41%	17.02%	15.94%	57.44%	46.90%	28.23%	65.65%	68.65%

Table 4: Statistical Significance of Conditioning Information

The table reports the percentage of funds that reject at the 5% level the hypotheses of (1) constant abnormal performance (α_1=0), (2) constant risks (β_1=0) and (3) constant parameters (α_1=β_1=0). It also reports the percentage of funds whose abnormal performance or risks are sensitive at the 5% level to either one of the information variables. The significance levels are based on Newey and West (1987) heteroscedasticity and serial correlation-consistent standard errors.

	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Fund of Funds	Global Macro	Long/Short Equity Hedge	Managed Futures	Other	All Hedge Funds
Panel A: Time Variation in Abnormal Performance												
- Default spread	0.14	0.27	0.21	0.17	0.16	0.21	0.15	0.12	0.21	0.14	0.16	0.17
- Term structure	0.17	0.27	0.33	0.13	0.24	0.20	0.18	0.12	0.19	0.17	0.16	0.19
- Own return	0.42	0.33	0.31	0.20	0.34	0.23	0.35	0.17	0.24	0.18	0.27	0.27
- $\alpha_1 = 0$	88%	50%	71%	74%	77%	71%	73%	45%	69%	49%	75%	69%
Panel B: Time Variation in Risks												
- Default spread	0.15	0.22	0.23	0.15	0.14	0.16	0.16	0.14	0.18	0.17	0.15	0.17
- Term structure	0.21	0.28	0.25	0.14	0.19	0.20	0.19	0.16	0.19	0.16	0.20	0.19
- Own return	0.17	0.18	0.22	0.13	0.16	0.19	0.19	0.15	0.19	0.19	0.16	0.18
- $\beta_1 = 0$	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Panel C: Conditional Models versus Static Models												
- $\alpha_1 = \beta_1 = 0$	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 5: The Abnormal Performance of Hedge Funds

The table reports the annualized abnormal performance α of hedge funds, averaged within categories (columns 1 to 11) and across categories (column 12). The average *t*-statistics on α are reported in parentheses. “Alpha due to non-normality risk” is the average return that was misleading attributed to stock picking in panel A, while it reflects a compensation for systematic non-normality risk. “Alpha due to non-normality risk and conditional allocation” is the average return that was misleading attributed to stock picking in panel A, while it reflects a compensation for systematic non-normality risk and conditional asset allocation. The *p*-values in brackets are for the null hypothesis that these alphas are zero at the 5% level. “Misclassified funds” is the percentage of funds that were misleadingly classified based on statistical significance at the 5% level in panel A. $p(\alpha_0>0)$ is the percentage of managers who beat their benchmark at the 5% level. The significance levels are based on Newey and West (1987) heteroscedasticity and serial correlation-consistent standard errors.

Category	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Fund of Funds	Global Macro	Long/Short Equity Hedge	Managed Futures	Other	All Hedge Funds
Panel A: Static model without non-normality risk factors												
- Average α	0.0717	-0.0020	0.0380	0.0401	0.0578	0.0410	0.0338	0.0474	0.0917	0.0949	0.0727	0.0647
	(3.63)	(-0.13)	(0.88)	(1.63)	(2.05)	(2.44)	(1.44)	(1.15)	(1.52)	(1.30)	(2.51)	(1.61)
- Average adjusted-R^2	0.1133	0.5047	0.2509	0.1407	0.1880	0.1095	0.2899	0.1252	0.3453	0.1132	0.2456	0.2501
Panel B: Static model with non-normality risk factors												
- Average α	0.0646	0.0257	0.0195	0.0392	0.0519	0.0409	0.0292	0.0449	0.0778	0.0986	0.0698	0.0576
	(3.77)	(0.44)	(0.74)	(1.67)	(1.96)	(2.50)	(1.42)	(1.16)	(1.40)	(1.37)	(2.60)	(1.57)
- Alpha due to non-normality risk	0.0071	-0.0277	0.0185	0.0009	0.0058	0.0001	0.0046	0.0024	0.0139	-0.0038	0.0029	0.0071
	[0.00]	[0.00]	[0.00]	[0.43]	[0.00]	[0.93]	[0.00]	[0.27]	[0.00]	[0.21]	[0.12]	[0.00]
- Misclassified funds	3.03%	15.38%	4.65%	2.35%	7.98%	4.60%	6.95%	4.90%	10.52%	5.53%	1.64%	7.28%
- Average adjusted-R^2	0.1633	0.5436	0.2660	0.1641	0.2086	0.1144	0.3145	0.1328	0.3732	0.1185	0.2685	0.2722
Panel C: Conditional model with non-normality risk factors												
- Average α_0	0.0730	0.0194	0.0048	0.0319	0.0791	0.0567	0.0261	0.0348	0.0829	0.0572	0.0516	0.0554
	(5.71)	(0.86)	(1.01)	(1.79)	(3.29)	(3.75)	(2.12)	(1.08)	(1.86)	(0.75)	(3.39)	(2.10)
- Alpha due to non-normality risk and conditional allocation	-0.0013	-0.0214	0.0332	0.0081	-0.0214	-0.0156	0.0077	0.0126	0.0087	0.0377	0.0211	0.0093
	[0.74]	[0.29]	[0.01]	[0.22]	[0.00]	[0.02]	[0.00]	[0.36]	[0.04]	[0.00]	[0.12]	[0.00]
- Misclassified funds	19.19%	42.31%	29.07%	23.53%	33.33%	35.63%	29.82%	30.39%	31.56%	29.79%	24.59%	30.19%
- Average adjusted-R^2	0.3823	0.6096	0.3830	0.3106	0.3195	0.3229	0.4424	0.2224	0.4856	0.1856	0.3705	0.3908
- $p(\alpha_0>0)$	0.76	0.38	0.24	0.33	0.67	0.69	0.49	0.35	0.45	0.26	0.66	0.46