The Impact of Non-Normality Risks and Tactical Trading on Hedge Fund Alphas

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ABSTRACT
Most previous tests of hedge fund performance have failed to model the exposure of hedge fund returns to systematic non-normality risks, nor have they taken the tactical asset allocation decisions of hedge funds managers into account. This paper shows that failure to account for these features leads to incorrect statistical inferences on the performance of 1 out of 4 hedge funds and overstates hedge funds' alpha by 1.54% on average. Put another way, hedge funds offer abnormal returns that are 23.1% lower than commonly accepted.

Keywords: Hedge funds, performance evaluation, alpha, systematic skewness, systematic kurtosis, tactical asset allocation.

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Over the last 10 years, hedge funds have become very popular, with private as well as institutional investors. Most hedge fund managers have substantial experience in the global capital markets, either as investment managers, investment analysts or proprietary traders. This expertise is often presented to investors as a virtual guarantee for superior performance. To verify the claim that hedge funds managers have superior skills, several studies have analyzed their performance (see for example Fung and Hsieh, 1997; Brown, Goetzmann and Ibbotson, 1999; Liang, 1999; Agarwal and Naik, 2000; Edwards and Caglayan, 2001; Capocci and Hübner, 2004). Invariably, the conclusion has been that hedge funds do indeed offer investors superior returns.

Recently, some studies have cast doubt on the ability of hedge fund managers to generate superior performance. Hedge fund databases have been shown to contain several biases (backfill, survivorship and selection), which, when not corrected for, will lead one to significantly overestimate hedge fund performance (see, for example, Fung and Hsieh, 2000; Malkiel and Saha, 2005). Kat and Palaro (2006) suggest that hedge funds managers fail to add value as portfolios that use futures to replicate the payoffs of hedge funds typically generate higher returns than the funds themselves. Likewise, Fung, Hsieh, Naik and Ramadorai (2006) report that because of new capital inflows and diminishing returns to scale, the risk-adjusted performance of funds of funds has deteriorated remarkably in recent years.

Almost without exception, hedge fund performance studies rely on traditional performance measures, such as the Sharpe ratio or factor model based alphas. However, it is now well understood that hedge fund returns can be highly non-normal, which makes traditional performance measures, which are based on the assumption of normality, unsuitable. Deviations from normality as well as every risk factor that is incorrectly specified or left out altogether, will show up as alpha, thereby suggesting superior performance where there actually may be none. A second reason to doubt the results of traditional studies of hedge fund performance is the fact that many hedge funds follow highly dynamic investment strategies. This may cause the fund return distribution to shift back and forth between parameters over time. Again, when this is not captured by the performance evaluation method, this may severely impact the traditional performance measures and lead to biased conclusions.

This paper contributes to the debate on hedge fund performance by quantifying the error arising from ignoring non-normality risks and tactical trading when evaluating hedge fund returns. We do so by evaluating hedge fund performance using a model that treats systematic non-normality risks as a potential source of hedge fund returns. In addition, we explicitly model the tactical asset allocation decisions of fund managers. We show that the arrival of public information alters the asset allocation of hedge fund managers and induces a change in the risk profile and performance of hedge funds. We find that failure to account for these two features leads to incorrect statistical inference on the performance of 1 out of 4 hedge funds and overstates their alpha by 1.54% on average. Overall, non-normality risks and tactical asset allocation explain no less than 23.1% of the commonly perceived abnormal performance of hedge funds.

**PERFORMANCE EVALUATION MODEL**

The traditional approach to performance evaluation is to regress a fund’s excess return \( r_t \) on a set of \( K \) return-generating factors \( f_t \), implicitly assuming that the fund’s returns are normally distributed and the regression parameters are constant.

\[
    r_t = \alpha + \beta f_t + \epsilon_t. \tag{1}
\]

The performance of the fund is then evaluated by testing the statistical significance of the \( \alpha \) coefficient in (1).

**Non-Normality Risk Factors**

As the distribution of hedge funds returns often departs from normality, the vector of risk factors typically used for traditional investment vehicles needs to be augmented with mimicking portfolios for systematic skewness and kurtosis risks. In line with Harvey and Siddique (2000) and Chung, Johnson and Schill (2006), we take the view that in a well-diversified portfolio, idiosyncratic skewness and kurtosis are eliminated and investors therefore only earn compensation for exposure to systematic skewness and kurtosis (also known as co-skewness
and co-kurtosis). As a result, we define a hedge fund's systematic skewness (kurtosis) as the amount by which it contributes to the skewness (kurtosis) of a well-diversified portfolio.

Option payoffs and squares or cubes of market returns are commonly employed to model the non-normality risks of hedge funds. These procedures relate hedge fund returns to either one of the following payoffs: lookback straddles (Fung and Hsieh, 2001), short puts on stock indices (Mitchell and Pulvino, 2001; Agarwal and Naik, 2004), short puts on high-yield debt (Okunev and White, 2003), quadratic and cubic market returns (Ranaldo and Favre, 2003).

Unlike previous authors, we model departures from normality with mimicking portfolios for systematic skewness and kurtosis risks, where the methodology we employ to construct the mimicking portfolios is a direct extension of that proposed in Fama and French (1993). We believe that our mimicking portfolios are superior to the non-normality risk proxies previously used, for two reasons. First, our non-normality risk factors have low correlations with passive benchmarks and therefore are better candidates for inclusion as risk factors in a multi-factor pricing model. Second, we believe that the square of the market excess returns is a questionable proxy for skewness. This factor resembles more the Treynor and Mazuy (1966) measure of market timing than the Kraus and Litzenberger (1976) or Harvey and Siddique (2000) measure of systematic skewness. The skewness factor of Ranaldo and Favre (2003) is, by construction, always positive; an unlikely outcome as the risk premium for exposure to systematic skewness would be expected to be negative in periods of high positive skewness.

### Tactical Asset Allocation

The assumption of constant parameters embedded in equation (1) implies that fund managers do not alter their asset allocation as new information arrives in the market. When it comes to hedge funds, this assumption is unlikely to be true. In reality, hedge fund managers often tactically change their asset allocation over time, tilting their portfolio towards asset classes that are expected to outperform and away from asset classes that are expected to under-perform. When doing so, a manager’s tactical asset allocation may induce changes in the risk profile and (abnormal) performance of the fund. To model the dynamics in the asset allocation of hedge fund managers, we assume, as in Christopherson, Ferson and Glassman (1998), that there is a linear relationship between the parameters in (1) and \( Z_{t-1} \), a set of \( L \) mean-zero information variables available at time \( t - 1 \). \( \alpha \) and \( \beta \) then equal

\[
\left( \alpha_t \mid Z_{t-1} \right) = \alpha_0 + \alpha_1 Z_{t-1}, \tag{2}
\]

\[
\left( \beta_t \mid Z_{t-1} \right) = \beta_0 + \beta_1 Z_{t-1}. \tag{3}
\]

where \( \left( \mid Z_{t-1} \right) \) denotes a parameter that is conditional on \( Z_{t-1} \), \( \alpha_0 \) is the average alpha of the fund, \( \beta_0 \) is a \( K \)-vector of average betas, \( \alpha_1 \) and \( \beta_1 \) 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 alpha and measures the departure from \( \alpha_0 \), the average alpha of the fund. Similarly, \( \beta_1 Z_{t-1} \) captures the variation though time in the betas and measures the departure from \( \beta_0 \), the average betas of the fund.

Replacing \( \alpha \) and \( \beta \) in (1) by \( \left( \mid Z_{t-1} \right) \) and \( \left( \mid Z_{t-1} \right) \) in (2) and (3) yields the conditional model of performance first proposed by Ferson and Schadt (1996) and Christopherson, Ferson and Glassman (1998)

\[
\begin{align*}
\epsilon_t &= \alpha_0 + \alpha_1 Z_{t-1} + \beta_0 f_t + \beta_1 f_t Z_{t-1} + \epsilon_t, \tag{4}
\end{align*}
\]

where \( \alpha_0 \) is the conditional counterpart of Jensen’s (1968) \( \alpha \). Model (4) differs from traditional performance evaluation models in two important ways. First, it treats systematic skewness and kurtosis as pervasive sources of risk. Second, it adds \( Z_{t-1} \) and \( f_t Z_{t-1} \) to the regression. These regressors pick up variations through time in the performance and risk measures of hedge funds that are related to changing economic conditions and tactical asset allocation.
Within the above framework, three hypotheses can be tested. First, we can assess the relative importance of non-normality risk factors at explaining hedge funds returns. Second, we can test whether business cycle indicators model the tactical asset allocation of hedge fund managers and whether the arrival of publicly available information induces a change in the abnormal performance and risk profile of funds. Third, we can measure the abnormal performance of hedge funds within a model, which explicitly accounts for both non-normality risks and tactical asset allocation.

**DATA AND PRELIMINARY ANALYSIS**

**Summary Statistics of Hedge Fund Returns**

The hedge fund data comes from the TASS database. As of August 2004, the database contained net-of-fee return data on 4,270 US dead and surviving hedge funds over the period January 1985 – 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, we concentrate on the 2,062 (dead and surviving) funds for which at least 50 consecutive months of returns were available. Note that as a result, our dataset suffers from selection bias and our performance measures will tend to be biased upwards.

Hedge fund investment strategies tend to be quite different from the strategies followed by traditional money managers, making extensive use of derivatives, short-selling 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, Funds of Funds, Global Macro, Long/Short Equity, Managed Futures and ‘Other’.

Table 1 reports summary statistics of returns per strategy (columns 1 to 11). The last column presents the results for the entire cross section. The table indicates that, over the period studied, hedge funds offered an annualized average return of 12% with 63% of the funds having a positive mean at the 5% level. This result, however, conceals wide differences across strategies. Average returns range from a low of 4.57% for dedicated short bias to a high of 15.27% for long/short equity. Similarly, while 92% of convertible arbitrage funds have mean returns that exceed zero at the 5% level, the mean of only 20% of dedicated short bias funds is positive and significant at the 5% level.

<table>
<thead>
<tr>
<th>Convertible Arbitrage</th>
<th>Dedicated Short Bias</th>
<th>Emerging Markets</th>
<th>Equity Market Neutral</th>
<th>Event Driven</th>
<th>Event Timing</th>
<th>Fund of Funds</th>
<th>Global Macro</th>
<th>Long/Short Equity</th>
<th>Managed Futures</th>
<th>Other</th>
<th>All Hedge Funds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.1182</td>
<td>0.0457</td>
<td>0.1373</td>
<td>0.0044</td>
<td>0.1324</td>
<td>0.0072</td>
<td>0.1204</td>
<td>0.1327</td>
<td>0.1326</td>
<td>0.1220</td>
<td>0.1200</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.9700</td>
<td>0.2387</td>
<td>0.2444</td>
<td>0.0891</td>
<td>0.0914</td>
<td>0.0692</td>
<td>0.1709</td>
<td>0.1973</td>
<td>0.2352</td>
<td>0.1283</td>
<td>0.1584</td>
</tr>
<tr>
<td>Reward-to-Risk Ratio</td>
<td>1.6304</td>
<td>0.1210</td>
<td>0.5619</td>
<td>1.2398</td>
<td>1.0378</td>
<td>0.8784</td>
<td>0.6993</td>
<td>0.7740</td>
<td>0.5125</td>
<td>0.9554</td>
<td>0.7579</td>
</tr>
<tr>
<td>Skewness (5%)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>- Average</td>
<td>-0.3697</td>
<td>0.2026</td>
<td>-0.3688</td>
<td>0.3194</td>
<td>-0.2991</td>
<td>-2.1546</td>
<td>-0.0259</td>
<td>0.3652</td>
<td>-0.4023</td>
<td>-0.0237</td>
<td>0.0411</td>
</tr>
<tr>
<td>- p(Sk&lt;0)</td>
<td>33%</td>
<td>0%</td>
<td>34%</td>
<td>10%</td>
<td>41%</td>
<td>70%</td>
<td>24%</td>
<td>10%</td>
<td>9%</td>
<td>8%</td>
<td>31%</td>
</tr>
<tr>
<td>- p(Sk&gt;0)</td>
<td>67%</td>
<td>100%</td>
<td>66%</td>
<td>90%</td>
<td>59%</td>
<td>30%</td>
<td>76%</td>
<td>91%</td>
<td>92%</td>
<td>92%</td>
<td>69%</td>
</tr>
<tr>
<td>- p(Sk=0)</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
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<td>0%</td>
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<tr>
<td>Kurtosis (5%)</td>
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<td></td>
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<tr>
<td>- p(Ku&lt;3)</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
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<tr>
<td>- p(Ku=3)</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
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<tr>
<td>- p(Ku&gt;3)</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
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<tr>
<td>Jarque-Bera Test</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Average</td>
<td>1.0524</td>
<td>39.62</td>
<td>423.59</td>
<td>117.92</td>
<td>1,036.61</td>
<td>3,123.52</td>
<td>233.33</td>
<td>106.46</td>
<td>182.45</td>
<td>147.92</td>
<td>506.33</td>
</tr>
<tr>
<td>- p(JB&lt;0)</td>
<td>71%</td>
<td>56%</td>
<td>83%</td>
<td>86%</td>
<td>91%</td>
<td>64%</td>
<td>76%</td>
<td>73%</td>
<td>72%</td>
<td>65%</td>
<td>80%</td>
</tr>
<tr>
<td>- p(JB&gt;0)</td>
<td>29%</td>
<td>44%</td>
<td>17%</td>
<td>14%</td>
<td>9%</td>
<td>36%</td>
<td>24%</td>
<td>27%</td>
<td>28%</td>
<td>35%</td>
<td>20%</td>
</tr>
</tbody>
</table>

Table 1. Summary Statistics of Hedge Fund Returns

This table presents summary statistics of hedge fund returns per and across strategies. 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(Ku<3) (p(Ku>3)) is the percentage of funds with platykurtic (leptokurtic) distribution at the 5% level. p(JB<0) (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.
Higher average returns tend to be associated with higher standard deviations. There is one exception. Dedicated short bias exhibits the second highest volatility but the lowest mean return. As a result, the reward-to-risk ratio of this strategy, at 0.1913, is the lowest across strategies. Based on the same performance measure, convertible arbitrage offers the best risk-adjusted return.

As previously reported (Fung and Hsieh, 1997, 2001; Mitchell and Pulvino, 2001; Brooks and Kat, 2002; Agarwal and Naik, 2004; Malkiel and Saha, 2005), the distribution of hedge fund returns frequently departs from normality. Across the entire cross section, 23% of the funds exhibit negative skewness at the 5% level, while 34% of the funds exhibit positive skewness. These averages again mask sharp differences across strategies though. 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 and managed futures tend to be positively skewed.

The average excess kurtosis is positive at 4.908. This suggests that the typical hedge fund has a return distribution that has more mass in the tails than predicted by the normal distribution. With 71% of the funds exhibiting an excess level of kurtosis significant at the 5% level, it appears that a lot of information regarding the distribution of returns is contained in the tails. As with skewness, there are wide differences across categories though. 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.

The Jarque-Bera test statistics confirm formally that the distribution of hedge fund returns departs from normality in 74% of the cases. Consistent with the preceding analysis, departures from normality are more frequent for fixed income arbitrage, emerging markets, event driven and ‘other’ than for dedicated short bias or managed futures.

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

The methodology to construct mimicking portfolios for systematic skewness and kurtosis risks is a direct extension of that proposed in Fama and French (1993) to form size and book-to-market value sorted portfolios. The skewness and kurtosis mimicking portfolios are based on monthly returns over the period January 1980 to August 2004 on all stocks listed on the Amex, NYSE and NASDAQ exchanges. Stocks that were delisted over the period considered are also included.

We calculate the systematic skewness of each stock using the definition of Harvey and Siddique (2000)\(^1\)

\[
SK_i = \frac{E \left( \left( r_{it} - (\alpha_i + \beta_i r_{Mt}) \right) \left( r_{it} - \bar{r}_i \right)^2 \right)}{E \left( \left( r_{it} - \bar{r}_i \right)^2 \right)}
\]  

where \( r_{it} \) denotes the return on stock \( i \) at month \( t \), \( r_{Mt} \) is the return on the S&P 500 index, \( \alpha_i \) and \( \beta_i \) are coefficients from a regression of \( r_{it} \) on \( r_{Mt} \), and \( \bar{r}_i \) is the corresponding unconditional mean (where a 60-month window is used to estimate \( \alpha_i \), \( \beta_i \) and \( \bar{r}_i \)). We sort stocks in ascending order according to \( SK_i \) and form two portfolios, a low \( SK \) portfolio \( (L_{SK}) \) and a high \( SK \) portfolio \( (H_{SK}) \), where the median skewness is used to divide stocks into \( L_{SK} \) or \( H_{SK} \).

---

1 - The Harvey and Siddique (2000) definition of skewness ensures, unlike that of Klaus and Litzenberger (1976), that the returns on the skewness mimicking portfolio have a low correlation with equity returns.
We also extend the Harvey and Siddique (2000) formula for skewness to the fourth moment and define the systematic kurtosis of a stock as

\[ K_{U_i} = \frac{E \left[ \left( r_i - (\alpha_i + \beta_i r_m) \right) \left( r_m - \bar{r} \right)^2 \right]}{\left( E \left[ (r_m - \bar{r})^2 \right] \right)^{3/2}} \]  

(6)

We split the universe of stocks into three systematic kurtosis portfolios based on the following breakpoints: 30% for the low \(KU\) portfolio (\(L_{KU}\)), 40% for the medium \(KU\) portfolio (\(M_{KU}\)) and 30% for the high \(KU\) portfolio (\(H_{KU}\)).

Following Fama and French (1993), we form six portfolios (\(L_{SK}L_{KU}\), \(L_{SK}M_{KU}\), \(L_{SK}H_{KU}\), \(H_{SK}L_{KU}\), \(H_{SK}M_{KU}\), \(H_{SK}H_{KU}\)) from the intersection of the two skewness and three kurtosis portfolios. The time \(t\) return on \(L_{SK}L_{KU}\) for example, is the equally-weighted return on a portfolio that includes, out of the 50% of stocks with the lowest systematic skewness, the 30% of stocks with the lowest systematic kurtosis.

The return on the skewness mimicking portfolio in each of the subsequent 12 months is defined as the difference in return between the three equally-weighted low skewness portfolios (\(L_{SK}L_{KU}\), \(L_{SK}M_{KU}\), \(L_{SK}H_{KU}\)) and the three equally-weighted high skewness portfolios (\(H_{SK}L_{KU}\), \(H_{SK}M_{KU}\), \(H_{SK}H_{KU}\)). Therefore, the skewness mimicking portfolio measures the difference in return of low versus high systematic skewness stocks and is largely free of market and kurtosis-bias. Similarly, the return on the kurtosis mimicking portfolio equals the difference in returns between the two equally-weighted high kurtosis portfolios (\(L_{SK}H_{KU}\), \(H_{SK}H_{KU}\)) and the two equally-weighted low kurtosis portfolios (\(L_{SK}L_{KU}\), \(H_{SK}L_{KU}\)). The kurtosis mimicking portfolio measures the difference in return of high versus low systematic kurtosis stocks and is again largely free of market and skewness-bias. Finally, the 60-month window to calculate (5) and (6) is rolled forward every 12 months to form new estimates of \(SK_i\) and \(KU_i\) and, thus, six new \(L_{SK}L_{KU}\), \(L_{SK}M_{KU}\), \(L_{SK}H_{KU}\), \(H_{SK}L_{KU}\), \(H_{SK}M_{KU}\), \(H_{SK}H_{KU}\) portfolios. This recursive approach yields a monthly time series of 236 returns for the skewness and kurtosis mimicking portfolios.

<table>
<thead>
<tr>
<th></th>
<th>Market</th>
<th>Bond</th>
<th>Commodity</th>
<th>FX</th>
<th>SMB</th>
<th>HML</th>
<th>Momentum</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0760</td>
<td>-0.0347</td>
<td>-0.0293</td>
<td>-0.0216</td>
<td>0.0106</td>
<td>0.0231</td>
<td>0.0991</td>
<td>-0.0062</td>
<td>0.0014</td>
</tr>
<tr>
<td>[0.03]</td>
<td>[0.00]</td>
<td>[0.27]</td>
<td>[0.13]</td>
<td>[0.67]</td>
<td>[0.43]</td>
<td>[0.01]</td>
<td>[0.43]</td>
<td>[0.88]</td>
<td></td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.1517</td>
<td>0.0499</td>
<td>0.1162</td>
<td>0.0623</td>
<td>0.1111</td>
<td>0.1262</td>
<td>0.1566</td>
<td>0.0510</td>
<td>0.0407</td>
</tr>
<tr>
<td>Reward-to-risk ratio</td>
<td>0.5008</td>
<td>-0.6961</td>
<td>-0.2518</td>
<td>-0.3465</td>
<td>0.0950</td>
<td>0.1800</td>
<td>0.6250</td>
<td>-0.1797</td>
<td>0.0345</td>
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Panel B: Pairwise Correlations

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<thead>
<tr>
<th></th>
<th>Market</th>
<th>Bond</th>
<th>Commodity</th>
<th>FX</th>
<th>SMB</th>
<th>HML</th>
<th>Momentum</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
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<tr>
<td>Market</td>
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<td></td>
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<td></td>
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<tr>
<td>Bond</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Commodity</td>
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<td>-0.04</td>
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<tr>
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<td>SMB</td>
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<td>0.00</td>
<td>0.06</td>
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<td>HML</td>
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<td>0.00</td>
<td>0.03</td>
<td>0.05</td>
<td>-0.35</td>
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<tr>
<td>Momentum</td>
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<td>-0.09</td>
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<td>-0.01</td>
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<td>Skewness</td>
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<td>Kurtosis</td>
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<td>-0.02</td>
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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 Datastream US Treasury-bond index. Commodity is the excess return on the 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. Momentum is the return differential between two portfolios of stocks with high and low past returns. Skewness is the return differential between two equally-weighted portfolios of stocks with low and high systematic skewness and about the same kurtosis. Kurtosis is the return differential between two equally-weighted portfolios of stocks with high and low systematic kurtosis and about the same skewness. 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.

Summary statistics for the factor risk premia are presented in panel A of table 2. Three risk factors (Market, Bond and Momentum) stand out as significant at the 5% level over the period considered. Panel B of table 2 reports pairwise correlations across the risk factors. With relatively few exceptions, the correlations do not exceed 30% in absolute terms. As a result, multicollinearity is unlikely to be a problem.
Following Fama and French (1989) we treat the first lag in the default spread (measured as the difference in yield between Moody’s BAA and AAA-rated corporate bonds) and the dividend yield on Datastream’s World Equity Index as proxies for the business cycle. Fama and French (1989) show that dividend yield and default spread take on relatively high values when an economic downturn is expected. As a result, hedge fund managers might decide to tilt their asset allocations towards more conservative asset classes or even decide to sell the market short. Two additional conditioning variables are considered. In case of persistence in performance, we condition the measure of abnormal performance on the lagged return of the hedge fund under review. Similarly, we allow the betas to change as a function of the previous month’s realization of the systematic risk factor.

THE ROLE OF NON-NORMALITY RISKS AND TACTICAL TRADING

In this section, we revisit the evidence on hedge fund performance within a setting that takes non-normality risks and tactical asset allocation into account. We start off by highlighting the importance of systematic skewness and kurtosis for explaining hedge fund returns. In addition, we show that the information variables defined above indeed capture part of the tactical asset allocation decisions of hedge fund managers.

Non-Normality Risk Factors

Table 3 reports the percentage of funds per strategy group (columns 1 to 11) and across all strategies (last column) that have significant factor loadings at the 5% level in equation (1). For example, 41% of all convertible arbitrage funds have a significant market beta, while the same is true for 57.13% of all hedge funds in our sample.

With 57.13% of market betas significant at the 5% level, market risk appears to be the main driver of performance across strategies. In order of statistical importance, it is followed by SMB, HML, and Momentum, which enter the risk-return relationship of 32.59%, 31.57%, and 30.21% of funds, respectively. Note that, as always, there are wide differences across strategies. The returns on fixed income arbitrage and managed futures, for example, are much less sensitive to the chosen risk factors than dedicated short bias and long/short equity for example.

The regressions of hedge fund returns on the 9 risk factors highlight the importance of systematic skewness and kurtosis risks in explaining hedge fund returns. Overall, systematic skewness ranks 5th (out of 9 factors) and is a significant factor behind the returns of 26.62% of all funds. Across strategies, the percentage of funds sensitive to systematic skewness ranges from as low as 13% for managed futures to as high as 36% for dedicated short bias and long/short equity. Skewness is the second most important risk factor for convertible arbitrage and the third most important risk factor for equity market neutral, fixed income arbitrage and long/short equity. Systematic kurtosis is a significant factor for 17.51% of all funds. Overall, it ranks 7th out of 9. As for systematic skewness, there are wide differences across strategies, however. For example, 24% of the returns of long/short equity have significant kurtosis loadings, while only 10% of the returns of managed futures are sensitive to kurtosis risk.
The results thus far make it clear that (1) hedge fund return distributions may exhibit quite significant departures from normality (see table 1), and (2) systematic skewness and kurtosis risks indeed explain part of the variation in hedge fund returns (see table 3). Failure to account for the systematic non-normality risks of hedge fund could therefore have important consequences on the outcome of performance evaluation studies. We will return to this shortly.

Tactical Asset Allocation

We model the tactical asset allocation decisions of hedge fund managers using a set of realized information variables. Table 4 reports the percentage of funds that show evidence of time-variation in alpha (panel A), risk profile (panel B) or both (panel C). The percentage of funds whose alpha changes with past default spread, past dividend yield and past return is also reported in panel A. For example, the default spread is a significant factor behind the alpha of 31% of convertible arbitrage funds, while for 83% of the convertible arbitrage funds the null hypothesis of a constant alpha (\( \alpha = 0 \)) is rejected at the 5% level.

The results in panel A of table 4 highlight the importance of proper modeling of the dynamics of hedge fund alphas. Across strategies, 69% of the alphas are time-dependent. The evidence is particularly strong for convertible arbitrage and event driven, but weaker for global macro, dedicated short bias and managed futures. Past returns are an important factor for 42% of all hedge funds. As such, it is the best predictor of future alpha. Default spread (dividend yield) is relevant for 31% (28%) of all funds.

Panel B of table 4 documents strong evidence of time-variation in the risk measures. The data consistently reject the proposition that fund betas are constant. Default spread and dividend yield have predictive power over 29% of the funds' betas, while past return predicts the change in betas of 28% of all funds. None of the information variables is redundant at the 5% level. Each has a role to play, either as a predictor of the risk measures or as an indicator of future alpha.

When the joint significance of \( \alpha_i \) and \( \beta_i \) is tested, panel C of table 4 provides overwhelming evidence that both alphas and betas are time-dependent. The hypothesis of constant regression parameters is rejected for all 2,062 funds. The results in table 4 confirm that hedge fund managers tend to tactically change their asset allocation over time. As a result, hedge funds' risk profile and alpha change in a predictable manner. This in turn implies that the static models traditionally employed to evaluate hedge fund performance could be seriously misspecified. Restricting alphas and betas to be constant, instead of conditioning them onto past information, could lead to misleading conclusions. This is what we turn to next.

Performance Evaluation

We proceed by demonstrating to what extent the use of misspecified models will lead one to draw incorrect conclusions with respect to the superiority of hedge fund returns. Table 5 reports the annualized abnormal performance of hedge funds, averaged within strategy groups (columns 1 to 11) and across strategies (last column) for four models. The first model, in panel A, is the conventional static model, which does not take tactical
trading into account and which excludes non-normality risk factors. This model will be used as a benchmark to assess the impact of ignoring non-normality risks and tactical trading on alpha. The second model, in panel B, is also a static model, but it does treat the non-normality mimicking portfolios as potential risk factors. The third model, in panel C, ignores non-normality risks but models the dynamics in the asset allocation of hedge fund managers through a set of conditioning variables. Finally, the last model, in panel D, accounts for both non-normality risks and tactical asset allocation.

The main result of table 5 is that the average alpha of hedge funds decreases substantially when (a) non-normality risk factors are included in the pricing model and (b) the tactical asset allocation of hedge fund managers is explicitly modeled. While the average alpha across funds stands at 6.68% a year within the conventional static model of panel A, it falls to 6.28% when non-normality risks are included in the risk-return relationship (panel B). The difference of 0.41% is commonly attributed to skill, but it is in effect compensation for exposure to an undesirable return distribution. The p-value reported in brackets in the last column of panel B shows that the 0.41% difference in alpha is significant at the 1% level. Similarly, the average alpha of 5.83% reported in panel C, is less than that of panel A. The difference of 0.85%, which is significant at the 1% level, can be attributed to time-varying parameters; namely, tactical asset allocation.

Finally, panel D shows that, when we account for both non-normality risks and tactical trading, the average alpha of hedge funds falls to 5.14%. The 1.54% difference in alpha relative to panel A is commonly attributed to skill, while it is in fact compensation for non-normality risks and tactical asset allocation. It is significant at the 1% level. This 1.54% accounts for 23.1% of the average abnormal return identified in panel A. Put simply, on average hedge funds offer alphas that are 23.1% lower than commonly accepted.

It is important to note that these averages conceal quite large discrepancies across the different strategies. The conclusion that average alpha worsens when non-normality risks and tactical asset allocation are taken into account is particularly true for managed futures, ‘other’, global macro, funds of funds and equity market neutral, where abnormal returns of 8.04%, 2.99%, 2.15%, 1.45% and 1.42%, respectively, can be attributed to model misspecification. This means that non-normality risks and tactical asset allocation account for a staggering 76%, 40%, 45%, 38% and 37% respectively, of the abnormal performance identified in panel A of table 5. On the other end of the spectrum, fixed-income arbitrage, emerging markets and dedicated short bias perform better in the new model. Their average alpha was 4.40%, 3.52% and 1.07% respectively, in panel A and is comparatively higher in panel D at 6.46%, 5.08%, and 2.60%.
To highlight that the use of misspecified models may lead to wrong inference on the significance of hedge fund alphas, panels B, C and D of table 5 also report the percentage of funds that were misclassified based on statistical significance in panel A. We call a fund “misclassified” when it produces conflicting statistical inferences on performance. For example, such a fund could have outperformed its benchmark in Panel A and underperformed its benchmark when non-normality risks and tactical asset allocation are explicitly modeled. 5.14% of the funds (106 funds out of the universe of 2,062 funds) fall into the “misclassified” category when non-normality risk factors are omitted. A failure to model tactical asset allocation leads to an incorrect conclusion on the statistical significance of the alpha of 458 funds in panel C (22.21% of the funds). When both non-normality risks and tactical asset allocation are omitted, 27.11% of the funds (559 funds out of 2,062) are misclassified based on statistical significance of their alpha in panel A. The omission of non-normality risk and conditional information has a particularly damaging impact on the statistical significance of the alpha of dedicated short bias, global macro, long/short equity and managed futures. For these strategies, more than 30% of the funds were misclassified in panel A.

The superiority of the models in panels B, C and D relative to that in panel A is also evidenced by the consistently higher average adjusted- $R^2$ for these models. On average, the fit of the conditional model with non-normality risk factors of panel D exceeds that of the model of panel A by 13.34%. The conditional model with non-normality risk explains an average of 38.38% of the variation in hedge fund returns.

Panel D confirms that, with an average $\alpha_o$ of 5.14%, the representative hedge fund manager does indeed have superior skills. With an average conditional alpha of 8.27%, long/short equity is the best performing strategy, followed by convertible arbitrage (7.89%) and fixed income arbitrage (6.46%). The strategies that perform worst are dedicated short-bias (2.60%), equity market neutral (2.42%), funds of funds (2.32%), global macro (2.63%) and managed futures (2.52%). It is interesting to note that the conditional performance of funds of funds (at 2.32%) is substantially worse than that of non-funds of funds (at 5.85%). 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% management fee plus 10% incentive fee).

Finally, the last two rows of panel D report the percentages of fund managers that beat or underperform their benchmark at the 5% level within the augmented conditional model ($p(\alpha_o > 0)$ and $p(\alpha_o < 0)$). This shows 38% of fund managers to have superior skills, while only 5% systematically underperform. Less than 1 out of 5 fund managers with emerging markets and managed futures styles show superior skills. On the other hand, skill is more prevalent among the managers in convertible arbitrage, fixed income arbitrage and ‘other’ strategies.

At this stage a word of caution is warranted. There are two reasons why the alphas reported in table 5 are likely to be overstated. First, there is the issue of survivorship bias. Since most databases only started collecting data around 1994, data from before 1994 suffer from survivorship bias. In addition, the attrition rate among young hedge funds is known to be high. Because our analysis focuses on hedge funds with a relative long history of returns (at least 50 observations), the sample is tilted towards skillful managers and thus the abnormal performance is upwardly biased. Second, the coefficients of determination of the conditional model with non-normality risks are still low compared to those typically reported for mutual funds. This suggests that even the conditional model with non-normality risks might not be very adequate in capturing the complex and highly opportunistic nature of hedge fund strategies. In other words, we could still be missing one or more compensated risk factors, which will lead to an overstatement of abnormal performance in the same way as not accounting for non-normality risks does. For these reasons, we believe that the actual performance of hedge funds is substantially worse than the 5.14% average alpha reported in table 5.

**CONCLUSION**

This paper highlights the importance of non-normality risks and tactical asset allocation in assessing hedge fund performance. As such, it underlines the inaccuracies of previous papers on hedge fund performance that ignored higher moments in the distribution of hedge fund returns and assumed constant asset allocation. Correcting
for these shortcomings, we find that failure to account for non-normality risks and tactical asset allocation on average leads to an overstatement of performance by 1.54% and to incorrect statistical inference on the performance of 1 out of 4 funds. On average, non-normality risks and conditional asset allocation explain 23.1% of the abnormal performance of hedge funds as commonly perceived.

A final note concerns the fact that although the traditional multi-factor model is a very 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 extent. Clearly, these issues deserve further study.
REFERENCES


