
WORKING PAPERS

“Working Papers” provides a review of significant working papers in investment management. This section draws from recent research in order to highlight an area of topical interest. In selecting papers pertinent to a prominent topic, “Working Papers” acknowledges current trends in the investment management business, while simultaneously directing the reader to interesting and important recent work.

“HEDGE” FUNDS

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A casual survey of the extant literature on hedge funds suggests that the term itself might be a misnomer. However, a more careful reading lends credence to the nomenclature. In the past few years a vast and insightful literature has built up around the hedge fund business. This literature may be classified into the following major areas of inquiry.¹

1. What does investing in a hedge fund do for a typical portfolio? What is the evidence on hedge fund diversification and performance?
2. What are the various hedge fund strategies and styles? Is there some sort of classification that appears to be emerging within the literature?
3. What are the unique risks in hedge funds, how is capital adequacy maintained, and risk management carried out?
4. What is special about hedge fund fee structures? How have hedge funds performed? Do

fee structures lead to distortions in manager behavior and performance?

We take up each of these in turn.

1 Portfolio impact

Keynes once stated that diversification is protection against ignorance. Is this true for hedge funds? Long–short positions effect a dramatic change in the return distributions of equity portfolios, resulting in diversification in the mean–variance or “beta” sense.

In an empirical study, Kat and Amin [17] find that introducing hedge funds into a traditional portfolio results in substantial improvements in the mean–variance risk–return trade-off. However, this comes at a cost in terms of negative skewness, and enhanced kurtosis in portfolio returns. Hence, it is not clear whether every investor’s portfolio will be well-suited to an addition of the hedge

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fund asset class. They also find that much more than a small fraction of the additional hedge fund position is required to make a material difference to the portfolio, an aspect that might encounter risk or regulation limits in implementation. Similar results are obtained in a study by Amenc and Martellini [2], who find that return variances are lower out-of-sample as well.

Measurement of the diversification effect is traditionally carried out by regressing hedge fund returns on the market return. A low β in the regression signifies minimal realized systematic risk. Asness *et al.* [3] empirically establish that the illiquid nature of hedge fund assets leads to an understatement of the β . This arises because illiquidity causes the returns of assets to be asynchronous to the benchmark market index, resulting in a lower β , often by a third as much as the true β . Therefore, investors need to be aware that their positions in hedge funds might be less market-neutral than they empirically appear.

A limiting case of diversification through hedge funds comes from the relatively new concept of a fund of funds (FOF). The comprehensive paper by L'Habitant and Learned [21] examines many aspects of FOFs. Diversification across fund style yields greater benefits than diversification by fund selection within style, though it remains hard to find accurate information for the purposes of classifying hedge funds. There are many benefits to the FOF structure. First, less monitoring of individual funds is required. Second, the FOF offers investors better oversight and access to funds they would not otherwise be able to invest in. Third, the authors find that as the number of funds increase, (a) the variance of returns declines, while the mean return does not, and (b) downside measures such as maximum monthly loss and VaR are lower. However, as more funds are added to the FOF, positive skewness is reduced, and negative skewness structures become worse. Kurtosis also increases, hence the tails of

the distribution worsen, no doubt on account of the high degree of concurrent idiosyncratic risk in down markets. Moreover, as the number of funds increases, the β of the FOF increases as well, implying that there is an optimal level to the extent of diversification from the addition of hedge funds to the mix. The authors submit that this optimal number ranges from five to 10 funds, which mitigates what they term "diversification overkill" that arises from including too many funds. Another drawback of the FOF model is that fees multiply. Brown *et al.* [9] look at whether the higher fees paid are more than offset by the informational advantage of FOFs—they find that this is not the case.

Another form of portfolio impact arises in the serial correlation of returns. Whereas hedge funds are designed to be market neutral, Getmansky *et al.* [14] show that these market-neutral portfolios may indeed experience greater serial correlation in returns than long-only portfolios. Their research finds empirical support for illiquidity exposure as the source of this serial correlation.

2 Strategies and styles

Not surprisingly, the literature finds that identifying hedge fund styles is more complicated than in the case of mutual funds. Hedge funds may be affected by factors different from those impacting mutual funds, which may not have been uncovered in extant empirical research. The presence of myriad portfolio techniques and the use of derivatives results in non-linear effects, which may not lend themselves well to deciphering styles using the same techniques as those for mutual funds. Fung and Hsieh [11] provide a useful approach to understanding the empirical characteristics of hedge fund returns. Maillet and Rousset [25] develop a classification approach using Kohonen maps. While it may appear that non-linearities make style analysis difficult, as well as complicate performance

measurement, Pfliederer [26] writes that the nonlinearities are in fact only weak, and that linear (factor) models may still be used.

Differing styles amongst hedge funds complicates performance measurement. Fung and Hsieh [12] find five dominant hedge fund styles. Two of these correspond to standard buy and hold equity and high-yield bond classes of funds, while three are typified by dynamic trading strategies over many asset categories. To form a unified set of styles for mutual and hedge funds, they suggest a 12-factor model with nine buy–hold asset classes and three distinct dynamic trading strategies as a basis. It is important to note that the degree to which mutual fund returns are explained by style is still far higher than the extent to which hedge fund returns are (the reported R^2 s are approximately double). There are many hedge funds that did not fall within the ambit of the five styles delineated by Fung and Hsieh. Brown and Goetzmann [8] find that the number of styles has grown as the hedge fund industry has grown, and that there are now many more than just the basic few market-neutral styles. Their empirical work determines that about 20% of the difference in performance in the cross-section of hedge funds can be attributed to style differences.

Survivorship bias causes further complexity in fitting styles. Different styles perform differentially during certain economic epochs, and some styles drop out of favor. We do not seem to have much of a framework for handling this kind of econometric problem. Baquero *et al.* [4] study the impact on this issue of “look-ahead” bias, or *ex-post* conditioning that affects estimates of performance persistence. They find that this effect is severe and should be accounted for carefully in persistence studies. Bares *et al.* [6] employ genetic algorithms to determine the impact of survivorship on portfolio choice—they find that portfolio weights are significantly impacted if this effect is accounted for. Survivorship also impacts the higher moments of hedge fund

return distributions (see Barry [7] who examines this issue with an interesting look at the data on defunct funds).

3 Risk measurement and management

A popular tool for measuring hedge fund portfolio risk is VaR (value-at-risk). A recommended approach is to use a factor technique. In a recent paper, L’Habitant [22] develops a simple factor model which is then subsequently used for determining VaR. Using a sample of close to 3000 funds, he finds that the factor-based VaR approach is a useful way to detect styles and proves to be a good risk approach in- and out-of-sample. For a comparison of different risk measures such as VaR, Drawdown-at-Risk, with mean absolute deviation, maximum loss and market-neutrality approaches see Krokmal *et al.* [20].

The efficacy of VaR as a risk assessment device obtains further confirmation in the work of Gupta and Liang [16], who examine more than 2000 hedge funds to determine the extent of undercapitalization. Roughly 3% of funds appear to be poorly capitalized, though undercapitalization is a diagnostic for funds that fail, evidenced in 7.5% of dead funds. VaR is computed off the empirical distribution as well as via the use of extreme value theory. The authors conclude that the results are robust to both approaches, which are also found to be consistent with each other.

While some of the literature finds VaR to be a useful measure, there are arguments against its use. Lo [24] reasons thus on several counts. One, the factors for the VaR analysis may be less clear, since there is a poorer understanding of hedge fund styles. VaR does not include features of event risk, liquidity, default, etc., which are more important than merely price risk in the case of hedge funds. Third, since much less is known about the distribution

of hedge fund returns, and we are especially certain that drastic non-normality is present, using a purely statistical measure based on standard assumptions may be egregiously erroneous.

Koh *et al.* [19] in a survey of hedge funds, summarize alternate risk measures that may be broadly categorized as "downside" metrics, which are likely more appropriate for hedge funds and which display return distributions with substantial departures from normality. They highlight the use of the Sortino and Price [27] ratio, which modifies the standard Sharpe ratio in both numerator and denominator. The numerator contains a modified excess return, i.e. the return on the portfolio minus a minimum acceptable return (MAR), which may be set to zero, the risk-free rate, or another low barrier chosen by the investor. The denominator is modified by replacing the return standard deviation with the downside standard deviation. Another ratio that has attained much popularity is the "d-ratio" described by Lavinio [23]. This ratio is as follows: $d = |l/w|$, where l is the average value of negative returns, and w is the average value of positive returns. This may be intuitively thought of as a skewness risk measure.

4 Performance and fee structures

The recent declining market environment has proven fruitful for market-neutral trading strategies, and hedge funds have performed well in relation to their mutual fund brethren. Can some of this performance also be attributed to manager skill, over and above fund structure? Edwards and Caglayan [10] study the performance of funds over most of the past decade, and assert that while 25% of hedge funds earn significantly positive returns, the persistence of these returns over time suggests that skill is a factor in explaining the differences between funds. Another aspect that supports the presence of skill is that the better performing funds paid their

managers richer contracts *ex-ante*, consistent with the idea that these funds attracted better talent.

To measure the persistence of returns, the popular Hurst [18] ratio is often invoked, and is prescribed in Koh *et al.* [19]. This is based on the rescaled range (R/S) statistic, defined over return random variables x_1, x_2, \dots, x_n , with mean μ_x and standard deviation σ_x . The R/S statistic is

$$Q = \frac{1}{\sigma_x} \left[\max_{1 \leq k \leq n} \sum_{i=1}^k (x_i - \mu_x) - \min_{1 \leq k \leq n} \sum_{i=1}^k (x_i - \mu_x) \right].$$

The Hurst ratio, $H = (\ln Q / \ln n)$, for large n , has the following relationship to return persistence. When $H = 0.5$, returns are non-persistent, i.e. random walks. When $H < 0.5$, there is negative persistence, i.e. mean reversion, and when $H > 0.5$, there is positive return persistence. For an analysis of long- and short-term persistence, see the work of Bares *et al.* [5], who find some evidence of short-term persistence, but none over the long-term.

Traditional linear factor models are unsatisfactory approaches to the measurement of hedge fund performance. Agarwal and Naik [1] develop a model that uses factors formed from excess returns on option-based and buy-hold strategies as benchmarks for performance. They are able to explain a substantial portion of variation in hedge fund returns with a few simple strategies, and also find that hedge fund performance was high in the early 1990s and tapered off in the latter half of that decade. Hedge fund benchmarks are problematic in the performance attribution process. Fung and Hsieh [13] argue that indices built from individual hedge funds contain noise, as measurement errors in the performance of individual funds propagate

with aggregation. Instead, they suggest the use of indices based on FOF performance.

Hedge fund strategies, such as long–short portfolios and non-linear returns from the use of derivatives lead to distortions in performance measures. The Sharpe ratio has been the focus of attention of the literature that assesses these distortions. Goetzmann *et al.* [15] develop a strategy to obtain the optimal Sharpe ratio, and suggest that managers with possible upward distortions in their Sharpe ratios should be evaluated against the maximal Sharpe ratio instead. It is posited that Sharpe ratio distortions may in fact lead to portfolios with exaggerated kurtosis, leading to sharp portfolio crashes.

5 Conclusion

The advent of hedge funds has livened up the investing landscape. As covered in this abstract, there are issues relating to diversification and portfolio impact, style and performance evaluation, fee structures and risk management. It has resulted in pushing the envelope on the theory and practice of investing. Hedge funds have lived through an up and down cycle by now. The future promises to be even more illuminating.

Notes

- ¹ Caveats: this classification is *ad hoc*, and several others may accommodate the extant literature. The classification depends on the working papers reviewed too, and hence is not necessarily representative of all papers in the field. Many thanks to Robert Hendershott and Meir Statman for their comments on this article.

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