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Time-varying exposures and leverage in hedge funds[1]

Style analysis shows that as market conditions change so do the investment strategies of hedge funds. It also provides a simple indicator of hedge fund leverage that varies over time. The indicator suggests that leverage tended to be high in 1997–98 but lower more recently.

JEL classification: G11, G12.

Hedge funds are said to be nimble. They can quickly take large positions in various asset markets, only to unwind them as market conditions change. This flexibility and the ability to leverage positions are arguably the distinguishing characteristics that drive hedge fund returns but are also said to potentially add to market volatility. At the same time, little is known about hedge funds' actual strategies. While some information about their assets under management and returns on equity is available, far less is known about their portfolios and use of leverage. Under what market conditions do hedge funds change their investment positions? How does the leverage employed by the funds change as market conditions evolve? This article provides tentative answers to these questions, with a particular focus on the period surrounding the peak in equity markets in 2000.

We first investigate how hedge fund risk exposures vary over time. Our primary empirical tool is "regression-based style analysis", an established technique used to uncover the risk factors that drive portfolio returns. A rolling application of this technique across hedge fund style families yields time-varying measures of exposure to a variety of risk factors which can, at a relatively broad level, shed light on changing investment tactics. The results confirm that hedge funds change investment tactics often. Further, they also suggest that hedge funds which reportedly belong to different style families, and thus presumably follow different investment strategies, have at least some commonality in their risk exposures. For example, the three broad fund families under consideration here, even those that are supposedly market neutral,

[1] We are grateful to Dimitrios Karampatos for outstanding research assistance. The views expressed in this article are those of the authors and do not necessarily reflect those of the BIS.

experienced similar changes in their risk exposures in the period surrounding the equity market peak in 2000.[2]

We then use this empirical framework to develop a rough time-varying indicator of leverage. Broadly, greater leverage can amplify returns, but at the expense of greater risk to hedge fund investors as well as to the counterparties that transact with the funds. However, even simple balance sheet measures of leverage cannot be constructed directly because hedge funds generally do not disclose their balance sheet positions. Moreover, much of what is called leverage in hedge funds arises not through outright borrowing but through off-balance sheet derivatives positions. Our indicator is based on a simple reinterpretation of the regression equation in style analysis, and captures the degree to which returns on assets are amplified in the returns on equity in hedge funds. Consistent with anecdotal evidence, this indicator suggests that leverage was at its highest in late 1997 and early 1998 for the hedge fund style families we consider. It reached a local high in 2000 around the peak in equity prices, but has been lower over the past few years.

Tracking growth with limited data

Imperfect data on hedge funds ...

Painting a comprehensive picture of the hedge fund industry is virtually impossible given the data available. Hedge funds do not face the same disclosure requirements as other investment vehicles available to the retail investor, such as mutual funds. As a result, the main source of information on hedge funds is a small number of commercially available databases containing data which are *voluntarily* provided by the funds, presumably to publicise their track record and to attract additional capital. The performance information in these databases is typically limited to monthly returns (net of fees) and total assets under management (AUM). In most cases, there is no information on portfolio allocation, or measures of risk and leverage. This paper relies on the Hedge Funds Research (HFR) database, which represents, at best, 25–30% of the estimated total number of funds in existence.

... include investment styles ...

The hedge funds are classified into (loosely defined) investment styles on the basis of their self-described investment strategy. This classification, made at the time the fund is entered in the database, rarely changes to reflect subsequent shifts in the fund's investment philosophy. For the purposes of the analysis below, the classifications provided by HFR are aggregated into broader investment style families (Table 1). Equity-focused funds concentrate on equity market investments, while directional funds reportedly follow strategies that represent bets on the direction of markets. By contrast, market neutral funds follow strategies that focus on hedged bets and arbitrage, and

[2] Ennis and Sebastian (2003) conduct a similar analysis using an index of fund of funds returns. See also IMF (2004) for an analysis of hedge funds' risk exposures during emerging market currency crises.

Number of hedge funds and assets under management[1]						
Investment style family	1996		2000		2004	
	Number of funds	Assets under management	Number of funds	Assets under management	Number of funds	Assets under management
Directional	101	5.6	231	15.0	295	18.6
Market neutral	307	19.7	886	68.0	1,500	144.6
Equity long/short	284	18.8	818	57.0	1,145	88.4
Funds of funds	166	9.8	520	32.7	1,079	101.2
All hedge funds[2]	815	51.1	2,253	157.7	3,671	325.7

[1] The number of funds and total assets under management as listed in the compiled HFR monthly data files, as of end-January of each year. [2] The totals across hedge fund style families do not sum to the total reported under "All hedge funds" because some sub-types (as classified by HFR) are not included in the four broad style families listed above.

Sources: HFR; BIS calculations. Table 1

thus their performance should be independent of the direction of the overall market.[3]

… and indicate substantial growth

Extrapolating from the sample of funds in the HFR database can be helpful in tracking the broad growth patterns in the hedge fund industry. Table 1 lists the number of funds and AUM in each of the family styles considered here. Overall, total AUM for all hedge funds in the HFR database was roughly $326 billion in January 2004, considerably less than the industry estimates of $0.6–1 trillion for all existing hedge funds. To the extent that the HFR sample is representative of the industry as a whole, the data imply that the number of directional funds more than doubled between January 1996 and January 2004, while the total AUM in these funds more than tripled. Even more exceptional growth is implied by the figures for market neutral and equity-focused funds. By January 2004, AUM in market neutral funds had risen to more than seven times its January 1996 value; in equity-focused funds, AUM was almost five times greater.

Time-varying risk exposures

Do funds in different style families indeed follow different investment strategies? Do they react similarly to common market events? Tracking the sensitivity of hedge fund returns to the returns on various asset markets can help in identifying changes in investment strategies. To this end, we use "regression-based style analysis", a technique first proposed by Sharpe (1992) in an application to mutual funds. Simply put, it involves the attribution of portfolio returns to a series of risk "factors", typically represented by the returns

[3] These broad style families are aggregates of sub-families classified by HFR. Directional funds include the sub-families equity no-hedge, macro, market timing and short selling funds. Market neutral funds include distressed securities, equity hedge, event driven, market neutral and four arbitrage strategy sub-families. Equity funds include four emerging market focused sub-families, six equity sector-specific sub-families, equity hedge and equity no-hedge sub-families.

Box 1: Hedge fund databases and regression-based style analysis

Biases in hedge fund databases

The commercially available databases on hedge funds, including the HFR database used in this article, are based on information that is *voluntarily* reported by hedge funds. This gives rise to several biases that can cloud the interpretation of any empirical analysis based on these databases.[1] First, hedge funds typically report to only one database vendor, implying that no one database provides a comprehensive picture of the industry (sample selection bias).[2] Second, since the databases are assembled for the purpose of attracting new capital, they include historical performance only for the funds in existence during the last reporting period. This introduces a survivorship bias, since funds that stopped reporting at some point in the past are dropped. We have tried to partially correct for this by merging the monthly editions of the HFR database over the December 2001–November 2004 period. This preserves the information about funds that were included at one point in time during this period, but clearly does not distinguish between the various potential reasons for fund disappearance. Poor performance (or outright closure) is a frequent cause for a cessation in reporting, implying that the database would tend to flatter the overall performance of the industry. Conversely, larger funds may decide to close to new investors and thus cease reporting. This could bias downwards the performance information in the database if funds tend to close to new investors after a sustained period of good performance that attracts more AUM than can be profitably invested. Finally, funds that do report usually do so after a period of strong performance. Selective reporting of their past history will tend to overstate funds' average experience, and hence the average performance in the database (instant history bias).

Style analysis

In order to estimate the exposures of hedge funds to different asset classes, we have relied principally on "regression-based style analysis". The technique uses a linear regression to attribute the observed performance of a portfolio (or a fund) to exposures to a set of underlying risk factors. Its basic premise is that the pattern of sensitivity of returns to the underlying risk factors would reveal to an outside analyst the unobserved pattern of portfolio exposures.

The technique can be illustrated by reference to a portfolio with allocations to *k* (known) assets. The overall portfolio return can be written as the weighted average of the returns on the individual assets, with the weights being the share of total funds invested in each asset:

$$R_t = w_1 F_t^1 + w_1 F_t^2 + \ldots + w_k F_t^k$$

If the fund is fully invested, the sum of the portfolio shares should be equal to 100%. Analysts that do not know the portfolio weights (w) can infer them in the form of regression coefficients of the portfolio returns on asset returns. Typically, the analyst is also not aware of the exact set of securities in the portfolio. Thus, style analysis regressions are estimated using (as right-hand side variables) an array of broad market returns for the asset classes that are *thought to be* in the portfolio. Regression coefficients are then interpreted as exposures of the fund to these market risk factors. Moreover, since active management can produce excess returns over the broad market factors the regression is estimated with a constant term that captures the value of active management (if positive). Finally, because the fund could also have long or short cash positions the regression is estimated using returns in excess of the risk-free rate for both the dependent and independent variables:

$$\left(R_t - r_t^f\right) = \alpha + \beta_1\left(F_t^1 - r_t^f\right) + \ldots + \beta_k\left(F_t^k - r_t^f\right) + \varepsilon_{i,t}$$

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[1] See Fung and Hsieh (2000, 2002b) for discussion of these biases. [2] Agarwal et al (2004) compile the databases from three different commercial providers and find only a 10% overlap.

We estimate time-varying sensitivity parameters (β's) for each hedge fund style family in a two-stage procedure. Our analysis is run on (unbalanced) panels of monthly returns for the funds belonging to each family across the January 1996–October 2004 time period. In the first stage, a stepwise regression is used to select from the universe of asset classes those that are relevant for the specific investment style. The selection criterion is based on the statistical significance of the excess returns on the factors (in Table 1) in explaining the excess returns of the group of funds over the entire sample period. The second stage involves rolling fixed window regressions for each of these panels of funds.[③] Each of these regressions is based on the *fixed set* of factors identified in the first stage. The estimated coefficients from these rolling regressions enable us to inspect the time-varying properties of the sensitivity to each of the risk factors through time.

③ We have used six-, eight-, 12-, 18- and 24-month rolling windows with little impact on the qualitative nature of our results, although the estimated coefficients tend to be more volatile as the horizon shortens.

on asset classes that are *thought to be* potentially in the portfolio, by means of linear regression. The resulting regression coefficients measure the sensitivity of portfolio returns to changes in the returns on the underlying assets (for a more detailed discussion see the box on page 62).

Style analysis applied to hedge funds ...

A number of previous studies have applied variations of this technique in trying to characterise hedge fund investment strategies and in analysing the exposures of funds to particular asset classes.[4] However, the characteristics of the hedge fund business model present some empirical complications. In particular, hedge funds tend to shift exposures more frequently than mutual funds, take larger short positions and make more extensive use of strategies resulting in non-linear payoffs relative to movements in market risk factors. We attempt to deal with these complications by slightly modifying the technique.

... with rolling windows

In particular, to account for frequent shifts in strategy, we estimate the regressions for panels of funds that belong to the same style family over *rolling estimation windows* (through time), which yields time-varying exposure estimates. The cross-sectional dimension of the panel of individual hedge fund returns enriches the degrees of freedom in the estimation (and hence the precision of the estimated coefficients). The second modification we make to Sharpe's analysis is to allow for the sensitivity coefficients to take negative values in order to account for funds' short positions on particular asset classes. Finally, we follow Fung and Hsieh (2001) and Agarwal and Naik (2004) and include the returns on derivatives positions among the risk factors that can explain hedge fund performance.

We apply this rolling style analysis to several style families of hedge funds, and use as independent variables the risk factors listed in Table 2.[5] The analysis is conducted using an 18-month rolling window on monthly data over

4 Examples include Fung and Hsieh (2001), Brown et al (2002), Agarwal and Naik (2004) and Brunnermeier and Nagel (2004).

5 Agarwal and Naik (2004) include the excess returns on *both* the at-the-money (ATM) and one strike price out-of-the-money (OTM) put and call options on the S&P 500 futures contract. For both puts and calls, the calculated returns on the ATM and OTM contracts are virtually identical. Our regressions include only the returns on the OTM contracts, as these had a marginally higher variance than those on the ATM contracts.

the 1996–2004 period, allowing us to investigate changing risk exposures around the equity market peak. Overall, the average (across funds and time) of excess returns over the sample period was roughly 9%, better than the 4% average excess returns on the S&P 500.[6] Although different style families presumably follow different investment strategies, the average excess returns (and the volatility of these excess returns) for the broad families we consider here co-move to a considerable degree (Graph 1), suggesting commonalities in their risk exposures.

Style analysis results

Estimated risk exposures are similar across style families ...

The results from this style analysis can be summarised as follows. First, while there does appear to be heterogeneity in investment styles across hedge fund families, there are also striking similarities in the sensitivity of hedge fund returns to several of the risk factors. In particular, consistent with the Agarwal and Naik (2004) results, the excess returns on call and put options on the S&P 500 futures turn out to be some of the most qualitatively important risk factors. Second, the variation over time in the sensitivity to these option factors follows a similar pattern across hedge fund style families. For each style family, the estimated sensitivities suggest that hedge funds had increasing exposure to the stock market prior to the peak, but cut this exposure during the downturn. Specifically, the estimates are consistent with a strategy of being long call options (and short put options) on the S&P 500 during the period of rising equity prices in the late 1990s. Following the market downturn, the sensitivity to call options on the S&P 500 diminished greatly, while the sensitivity to the

Risk factors

Option factors	Bond market factors
Out-of-the-money call options	Salomon Brothers World Government Bond Index[1]
Out-of-the-money put options	Salomon Brothers Govt & Corp Bond Index
	Lehman Brothers US High Yield Corporate Index
Equity market factors	Lehman Brothers US High Yield (C to D)-rated Index
Russell 3000 Index	Moody's Baa vs three-month US-TBills spread
MSCI World ex US Equity Index	Moody's Baa vs 10-year US-TNotes spread
MSCI Emerging Markets Equity Index	
Fama-French Small-Minus-Big (SMB) factor[2]	Other factors
Fama-French High-Minus-Low (HML) factor[2]	Fed competitiveness weighted dollar index
Fama-French Momentum factor[3]	Goldman Sachs Commodity Index
	Gold price

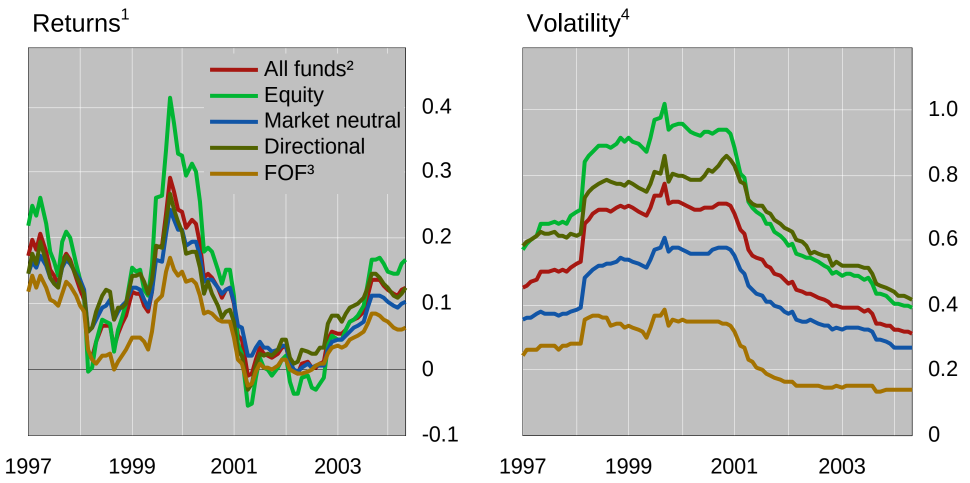
[1] All maturities, in US dollar terms. [2] The SMB factor is defined as the average return on three small portfolios minus the average return on three big portfolios. The HML factor is defined as the average return on two value portfolios minus the average return on two growth portfolios. See Fama and French (1993) for a complete description of these factors. [3] The momentum factor is defined as the average return on two high prior return portfolios minus the average return on two low prior return portfolios.

Sources: Bloomberg; Datastream; Tuck School of Business; BIS calculations. Table 2

[6] The return figures for hedge funds should be interpreted with caution because of well known biases in the databases on hedge fund performance. These biases are discussed in the box on page 62.

Excess returns and volatility by hedge fund strategy

Based on an 18-month rolling window



[1] Average annualised excess return across hedge funds; over the three-month US Treasury bill yields. [2] Includes equity, market neutral and directional style families. [3] Funds-of-funds. [4] Annualised average standard deviation of returns across hedge funds.

Sources: HFR; BIS calculations. Graph 1

return on put options on the index turned positive. Interestingly, this pattern is particularly clear for hedge funds classified as market neutral.

... such that returns tend to peak together

These points are further highlighted in Graphs 2, 3 and 4. As the left-hand panel of each graph shows, excess returns on the S&P 500 Index peaked in March 2000, as did the excess returns for each of the three style families. In each case, the sensitivity of excess hedge fund returns to the excess returns on the call option increased at least up to March 2000, consistent with a strategy of increasing exposure to equity prices. This sensitivity fell dramatically following the peak in equity prices in March 2000.[7] For equity and market neutral funds, this fall was accompanied by a reversal of the estimated exposure to the returns on put options; the sensitivities imply a shift from a position equivalent to selling puts on the S&P 500 Index to buying insurance against further market declines.[8]

Funds were bullish on small cap stocks prior to the equity market peak ...

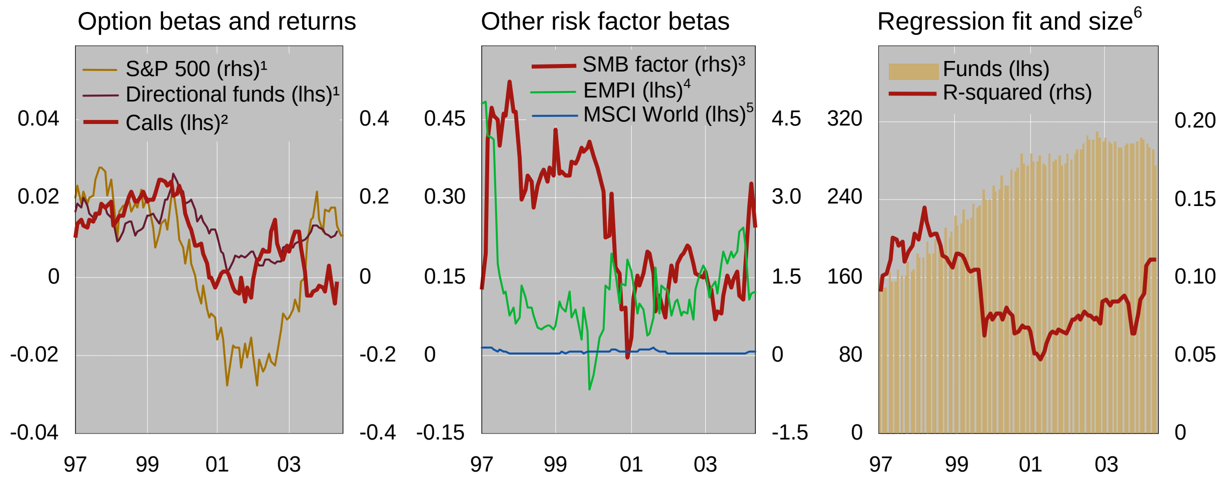
Exposure to other equity-based risk factors seemed to be common across style families as well. For example, the sensitivities to the so-called Fama-French SMB factor – which captures the difference in returns on small capitalisation stocks over large capitalisation stocks – is particularly

[7] The variation over time in the statistical significance of these risk factors is consistent with this overall pattern. The t-statistic on the call option factor in the rolling regressions prior to March 2000 was statistically significant in virtually every individual window, averaging 5.26 for directional funds, 7.47 for equity funds and 6.79 for market neutral funds. After March 2000, this regressor was rarely significant, with average t-statistics of 1.02, 1.58 and 1.26 respectively.

[8] The rolling beta for the put option factor is not included in Graph 2 on directional funds because this risk factor did not meet the criteria for inclusion into the regression specification in the first stage stepwise regression.

Risk exposures of directional funds

Based on an 18-month rolling window



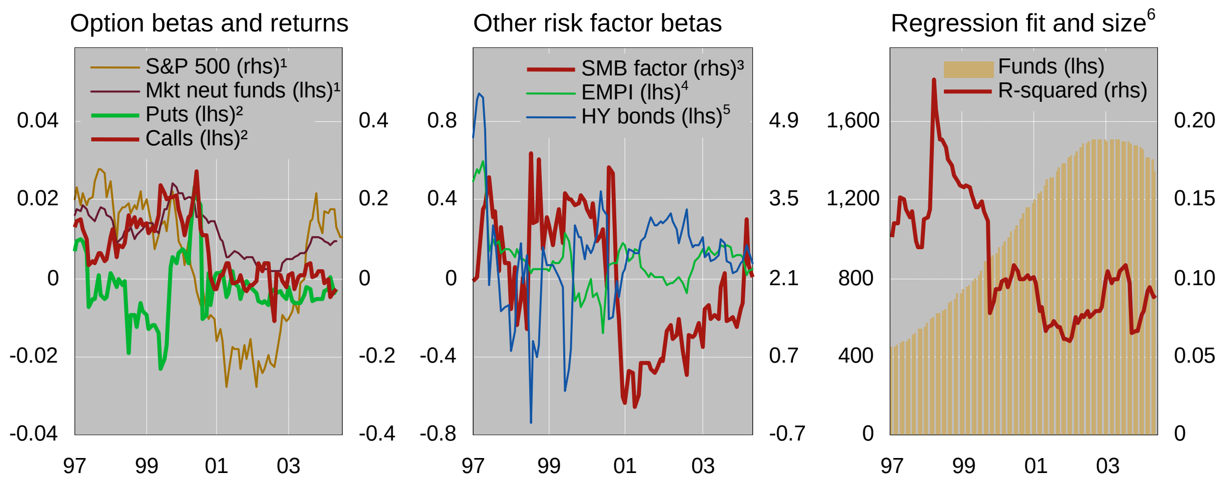
[1] Moving average of excess returns; over three-month US Treasury bills. [2] Coefficient on the excess returns on one strike out-of-the-money call option contracts on the S&P 500 futures. [3] Fama-French SMB factor. [4] MSCI emerging markets equity index. [5] MSCI world ex US equity index. [6] R-squared and number of funds for the rolling regressions of the directional family.

Sources: Datastream; HFR; Tuck School of Business; BIS calculations. Graph 2

noteworthy. Prior to the peak in equity prices, directional funds seemed to follow strategies similar to a long position vis-à-vis this factor, implying greater exposure to smaller capitalisation stocks (Graph 2, centre panel). This is consistent with hedge fund investment in technology stocks and startup companies during the dotcom boom. Sensitivity to this factor turned negative following the market decline. Hedge funds following market neutral and equity-

Risk exposures of market neutral funds

Based on an 18-month rolling window

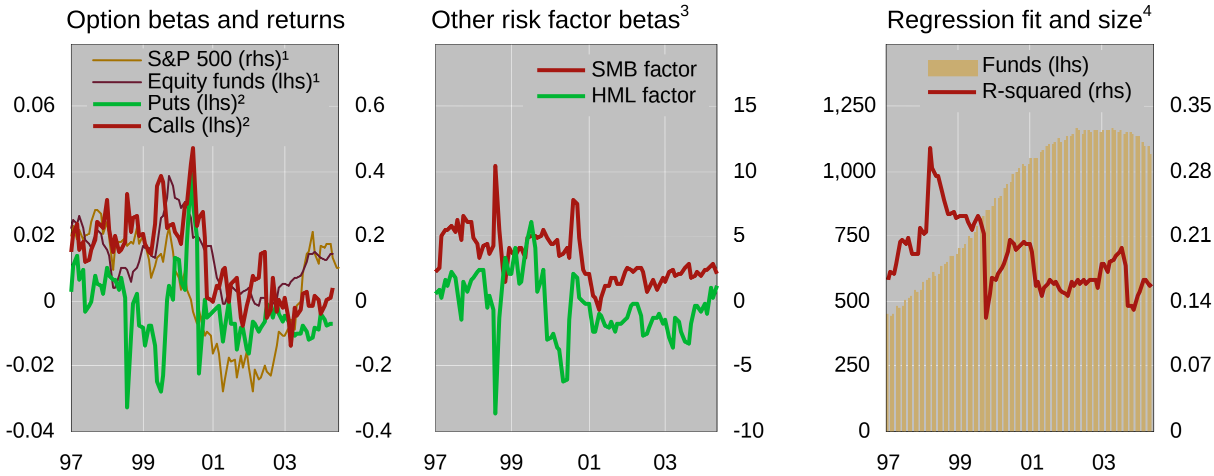


[1] Moving average of excess returns; over three-month US Treasury bills. [2] Coefficient on the excess returns on one strike out-of-the-money option contracts on the S&P 500 futures. [3] Fama-French SMB factor. [4] MSCI Emerging Markets Equity Index. [5] Lehman Brothers US High Yield Corporate Index. [6] R-squared and number of funds for the rolling regressions of the market neutral family.

Sources: Datastream; HFR; Lehman Brothers; Tuck School of Business; BIS calculations. Graph 3

Risk exposures of equity-focused funds

Based on an 18-month rolling window



[1] Moving average of excess returns; over three-month US Treasury bills. [2] Coefficient on the excess returns on one strike out-of-the-money option contracts on the S&P 500 futures. [3] Fama-French SMB and HML factors. [4] R-squared and number of funds for the rolling regressions of the equity-focused family.

Sources: Datastream; HFR; Tuck School of Business; BIS calculations. Graph 4

focused strategies displayed similar risk exposures; both style families appeared to be long the Fama-French SMB factor prior to the market downturn, as shown in the centre panels of Graphs 3 and 4. The sensitivities to this factor remained positive after March 2000, although at roughly half the value in both cases.[9]

... yet differed in exposures to interest rate risk

In addition to these common exposures, there does appear to be some degree of heterogeneity in the significant risk factors across style families. For example, exposure to fixed income market risk factors – as captured by the Lehman Brothers US High Yield Corporate Index, the Salomon Brothers World Government Bond Index and the Salomon Brothers Govt & Corp Bond Index – proved to be more important for market neutral and equity funds than for directional funds. The estimated sensitivity parameters on these risk factors seem to imply fluctuating long and short positions over the sample period.[10] In addition, the excess returns on the Goldman Sachs Commodity Index and the Fed competitiveness weighted dollar index entered as significant risk exposures for these fund families as well.

Overall, these results allow for some tentative but broad conclusions. First, hedge funds that supposedly follow different investment strategies

[9] The excess returns of all the style families tended to be sensitive to the returns in other equity markets as well, as captured by the MSCI World ex US Equity Index and the MSCI Emerging Markets Equity Index.

[10] For market neutral funds, the coefficient on the excess returns on the Lehman Brothers US High Yield Corporate Index was significant beyond the 5% level in 73% of the regression windows, with an average t-statistic of 4.59, while that on the Salomon Brothers World Government Bond Index was significant in 72% of the windows, with an average t-statistic of 4.09. The results for these risk factors for equity-focused funds were significant only slightly less often with somewhat smaller average t-statistics.

appear to have, to some degree, similar risk exposures. The similarity in the pattern of exposure of directional funds and market neutral funds to the US equity market over the sample period is particularly striking. Second, while it seems that option-based risk factors aid in the consistent estimation of sensitivity parameters, the US equity market-based options that have been incorporated into the empirical literature thus far seem to be less important after March 2000.

Time-varying leverage

Leverage amplifies sensitivity to market returns ...

Leverage is an integral part of a hedge fund's investment strategy. A fund can achieve leverage in two complementary ways. The first involves outright borrowing. Taking on debt boosts the potential return to the investors in the fund, because returns are earned on a portfolio of assets that is larger than the funds they contributed (ie the AUM).[11] We refer to this as *balance sheet leverage*. Second, the fund can take off-balance sheet positions, such as derivatives and structured notes. These positions can amplify returns by allowing exposures to underlying assets without requiring a cash outlay equal to the value of the assets. We refer to this type of leverage as *instrument leverage*.[12]

... either through borrowing or derivatives positions

To fix ideas, suppose for simplicity that the risk-free rate is zero and initial AUM is 10. Suppose further that the hedge fund borrows 90 to finance the purchase of a security for 100. If the value of the index at the end of the period moves to 105, the return on AUM is 50%. Alternatively, the hedge fund can obtain *an equivalent exposure* by placing the AUM of 10 as initial margin, and buying 100 worth of exposure to the equity index through futures contracts. In this simple example, the return on AUM is again 50% if the equity index moves to 105 by the end of the period.[13]

The question we ask in this section is whether the data on hedge fund returns can be used to construct an indicator of leverage. Since leverage in either of the forms considered can amplify returns to investors in equivalent ways, one way to measure it would be to measure the degree to which the movement in fund returns is amplified compared to the movement in the underlying market risk factors. Style analysis provides such a measure. Our indicator is based on the premise that the sensitivity parameters estimated in our style regression for an *unlevered* portfolio would add up to unity (as they would do for a mutual fund in Sharpe's original application of the technique). In contrast, the returns on a *leveraged* portfolio can be thought of as the returns

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[11] Clearly, this strategy also amplifies the potential losses in the case of portfolio underperformance.

[12] Anecdotal evidence suggests that it is increasingly the case that hedge funds take large positions by entering into derivatives contracts, with various counterparties. The capital that funds collect from investors is used primarily as collateral for these transactions.

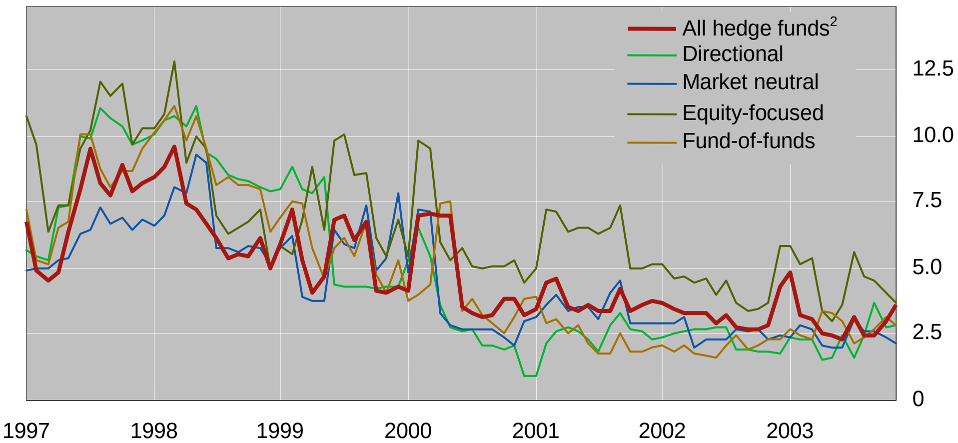
[13] In the example, the price of the underlying security and the price of the derivative (eg the futures contract) move in lockstep. More generally, movements in the prices of derivatives are related in a non-linear way to movements in price of their underlying assets.

on the unlevered portfolio scaled up by a leverage factor. In short, our indicator is the sum of the sensitivity parameters from the style regression and is compatible with both types of leverage (see the box on page 70 for a more detailed discussion).[14] Its level can be interpreted in a similar way to the ratio of the total size of the fund's asset portfolio to its AUM. For example, a value of 1 would imply no leverage, while a value of 2 would imply a total portfolio equal to twice the investors' capital.

Option factors complicate the interpretation

While the relationship of our indicator to the balance sheet form of leverage is fairly direct, the link with instrument leverage is less straightforward. As explained in the box on page 70, the explanatory variables in the style regression are typically returns on broad market indices. To the extent that hedge funds engage in investments that have payoffs that resemble derivative instruments, their returns will be non-linearly related to the returns on the underlying market risk factors. This non-linearity would be reflected in higher estimated sensitivity of the fund's returns on these factors. For this reason, the value of our leverage indicator depends on the ability of our set of risk factors to adequately capture the investment positions of hedge funds.[15] Clearly, the better the explanatory variables in the regression capture the return characteristics of the instruments in which the fund is invested, the lower the instrument leverage incorporated in our indicator. Indeed, we believe that the indicator is most useful as a gauge of trends in leverage over time rather than a cardinal measure of the level of leverage at any given point in time.

Estimated leverage measures[1]



[1] Based on a 24-month rolling regression window. [2] Includes equity-focused, market neutral and directional style families.

Sources: HFR; BIS calculations. Graph 5

[14] For the case of hedge funds, this is not strictly true since we need to make some modifications to the factor betas prior to summing.

[15] As indicated in the right-hand panel of Graphs 2–4, the goodness-of-fit measures are not particularly high, implying that a significant amount of variation in returns is left unexplained.

Box 2: Using style regressions to build an indicator of leverage

Our indicator of leverage is based on a modification of the style analysis framework detailed in Box 1 and a reinterpretation of the estimated coefficients. The first equation in that box describes the returns on a fund with long positions only in spot instruments and without any balance sheet leverage. If the same fund were to finance its portfolio by debt that represents a λ multiple of investors' funds (AUM) the return to its investors would be equal to:

$$R_t = -\lambda r_t^f + (1+\lambda) * (w_1 F_t^1 + \ldots + w_k F_t^k)$$

In this case, the *w*'s are the share of the overall portfolio invested in each (non-cash) asset. If an analyst knew the securities in the fund portfolio, and were to run the style regression as described in Box 1, the sum of the estimated coefficients (β's) should be equal to $(1+\lambda)$. Thus the difference between the sum of the estimated coefficients and unity would produce a measure of the fund's balance sheet leverage.

Of course the case of hedge funds presents a number of additional complications. Not only is the exact set of securities in the portfolio unknown, but it is also likely to include instruments that are non-linearly related to the underlying risk factors that are typically included in the style regression. In fact, the extent to which the ratio between the return on the non-linear strategy Φ_t^j and the return on the underlying factor F_t^j exceeds 1 could proxy for the degree of non-linearity. The average degree of non-linearity in the strategy of a fund can be represented as a common multiplier across the different asset classes in which the fund is invested. In style regression terms, this would be an additional scaling factor on the sensitivities of the hedge fund returns to the returns on the underlying broad market risk factors. On this basis, the sum of the estimated coefficients from the style regression would yield:

$$\sum \beta_i = (1+\lambda)\,\zeta \sum_i w_i = (1+\lambda)\,\zeta$$

where ζ stands for the average degree of non-linearity across all instruments in the fund's portfolio. The estimated coefficients are now interpreted as measuring the amplification effect of the two types of leverage. Clearly, without more assumptions we cannot distinguish between the two.

A further complication arises from the fact that hedge funds often take short positions in the underlying assets. This would clearly appear as a negative estimated coefficient in the style regression. Short positions, however, are another form of instrument leverage since the downside risk is theoretically unlimited. To account for this possibility, our indicator is the sum of the absolute values of the estimated coefficients. While this is only an approximate correction, it is necessary to account for the first-order measurement error introduced by using (long only) market indices as risk factors.

A value of the indicator greater than 1 suggests that the combined effect of the two types of leverage increases the sensitivity of fund returns to the returns on the market factors. The only slight modification we make to the calculation of this indicator is to include in the sum only those coefficients that are statistically significant beyond the 10% level.

Estimated leverage has declined

With these caveats in mind, we apply this measure to the data. Graph 5 presents the extracted leverage indicators for the different fund styles based on the set of risk factors discussed in the previous section.[16] While the indicators appear quite noisy, the broad movements over time seem to be at least consistent with anecdotal evidence on the evolution of leverage in the hedge fund industry. Leverage seems to have been at its highest in 1997–98. It

[16] These estimates are based on 24-month rolling regressions; the indices estimated with shorter window lengths are choppier, but follow roughly similar patterns.

reached a local high around the equity market peak in 2000, but has been relatively low more recently.[17]

Conclusion

By relating portfolio returns to pre-specified market risk factors, style analysis can capture important aspects of the investment strategies of hedge funds. We apply this technique in rolling regressions to a large panel of individual hedge fund returns in an effort to better understand these dynamic strategies. Our results suggest that while there is considerable diversity in investment strategies among hedge fund style families, there are also striking similarities in their risk exposures. The most qualitatively significant risk factors in this regard seem to be those that replicate options on the S&P 500 Index.

Style analysis also yields a time-varying indicator of the leverage of hedge funds. This rough indicator, which tracks the degree to which the returns on risk factors are amplified in the returns on capital held by hedge funds, depends critically on the ability of the supposed risk factors to fully capture the true exposure of hedge funds. When estimated with a limited set of market risk factors, it appears to be quite noisy, at least relative to what anecdotal evidence would suggest. Nonetheless, its longer-term movements seem reasonable on average. More broadly, the framework outlined here for measuring leverage can be built upon as better risk factors are identified in the literature.

References

Agarwal, V, N D Daniel and N Naik (2004): "Flows, performance and managerial incentives in hedge funds", working paper presented at the Gutmann Center Symposium on Hedge Funds, University of Vienna, 29 November.

Agarwal, V and N Naik (2004): "Risks and portfolio decisions involving hedge funds", *The Review of Financial Studies*, Spring, vol 17, no 1, pp 63–98.

Brown S, W Goetzmann and J Park (2002): "Hedge funds and the Asian currency crisis", *The Journal of Portfolio Management*, Summer, 6(4), pp 95–101.

Brunnermeier, M K and S Nagel (2004): "Hedge funds and the technology bubble", *The Journal of Finance*, vol LIX, no 5, October, pp 2013–40.

Committee on the Global Financial System (1999): *A review of financial market events in autumn 1998* ("The Johnson Report"), Bank for International Settlements, http://www.bis.org/publ/cgfs12.pdf.

[17] If interpreted strictly as measuring balance sheet leverage, our estimate implies that, on average, leverage for the sample of hedge funds as a whole across the 1996–2004 time period was 4.9 times equity.

Ennis, M and M D Sebastian (2003): “A critical look at the case for hedge funds”, *The Journal of Portfolio Management*, Summer, pp 103–12.

Fama, E and K French (1993): “Common Risk Factors in the Returns on Stocks and Bonds”, *Journal of Financial Economics*, vol 33, no 1, pp 3–56.

Fung, W and D Hsieh (2000): “Performance characteristics of hedge funds and CTA funds: natural versus spurious biases”, *Journal of Financial and Quantitative Analysis*, 35, 291–307.

——— (2001): “The risk in hedge fund strategies: theory and evidence from trend followers”, *The Review of Financial Studies*, Summer, vol 14, no 2, pp 313–41.

——— (2002a): “Asset-based style factors for hedge funds”, *Financial Analysts Journal*, September/October, pp 16–27.

——— (2002b): “Hedge-fund benchmarks: information content and biases”, *Financial Analysts Journal*, January/February, pp 22–34.

International Monetary Fund (2004): *Global Financial Stability Report*, April, pp 146–8.

Sharpe, W (1992): “Asset allocation: management style and performance measurement”, *The Journal of Portfolio Management*, winter, pp 7–19.