

## **Changes in the Factor Exposures of Hedge Funds**

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**January 2001**

The views expressed in this paper are those of the authors and do not necessarily represent those of the Bank of England.

## **I. Introduction**

Recent years have seen considerable interest in the activities of hedge funds, commodity trading advisors (CTAs), and the proprietary trading desks of commercial and investment banks. Part of this interest represents a need to understand the investment policies and performance of an important sector of the asset management industry, but the activities of hedge funds have also raised issues of public policy. For example, the decision by George Soros's Quantum Fund to sell sterling short in the fall of 1992 is widely believed to have brought significant pressure on the currency and to have hastened its departure from the ERM. In 1997 hedge funds again attracted adverse publicity when the prime minister of Malaysia protested that sales by hedge funds of Asian currencies were responsible for the depreciation of the ringitt. Some critics of hedge fund activity argue that not only may the funds deal in thin markets in substantial volume, but they are also guilty of herding, or even of collusion and manipulation.

Other concerns about the activities of hedge funds were prompted by the near-failure of LTCM in the fall of 1998. Many of these worries centered on the degree of leverage employed by hedge funds. For example, the President's Working Party report on hedge funds concluded "The central public policy issue raised by the LTCM episode is how to constrain excessive leverage more effectively. As events in the summer and fall of 1998 demonstrated, the amount of leverage in the financial system combined with aggressive risk taking can greatly magnify the negative effects of any event or series of events. By increasing the chance that problems at one financial institution could be transmitted to other institutions, leverage can increase the likelihood of a general breakdown in the functioning of financial markets." The potentially disruptive effect of leverage on markets may be accentuated by the feedback trading that may result from the need to liquidate positions to meet the need for additional margin or collateral.

One response to these concerns has been to argue for greater transparency for hedge fund exposures. For example, at the IMF/World Bank meetings in September 2000 the G24 group of emerging market countries complained: "Standards in the area of transparency

are being pressed upon developing countries without a commensurate application of corresponding obligations for disclosure by financial institutions, including currently unregulated highly-leveraged institutions.” However, not only may it be difficult to obtain agreement to increase disclosure, but the multiplicity of factors to which hedge funds are potentially exposed makes it difficult to specify what information would be useful or how it could be produced in a digestible and timely form.

The concerns about the activities of hedge funds have not been universally accepted. For example, there is some evidence that hedge funds did not in fact take large short positions in Asian currencies ahead of the devaluations (with the possible exception of the Thai baht) and did not make profits from these devaluations.<sup>1</sup> Other apologists draw on Milton Friedman’s argument that, rather than being destabilizing, profitable speculation drives prices towards their equilibrium value. On this view the price disturbances that followed the near collapse of LTCM were a consequence of a shortage of speculative capital rather than the reverse.

This paper seeks to shed light on the factor exposure of hedge funds by examining the loading of the returns of a sample of hedge funds on a number of explanatory factors. We look both at a fund’s average exposure to different factors and we then examine how the exposure varies across time. We look at these changing exposures for individual funds and we examine how far funds make parallel changes in their positions.

The paper is organized as follows. Section II reviews the literature and Section III provides a description of our methodology and a discussion of our empirical results. Section IV summarizes and concludes the paper.

## **II. Literature Review**

We are not the first to analyze the factor exposure of hedge funds. Fung and Hsieh (F&H 1997) apply Sharpe’s style analysis (Sharpe 1992) to a large sample of hedge funds and

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<sup>1</sup> See, for example, Eichengreen et al, (1998), Brown, Goetzmann, and Park (1998), and Fung, Hsieh, and Tsatsaronis (1999).

CTA pools. They assume that fund returns are linearly related to the returns on a number of factors and measure the factors by 8 mimicking portfolios. For each fund they regress monthly returns on the 8 factor portfolios and find that the regressions have little explanatory power. F&H suggest that the low  $R^2$  is due to the funds' trading strategy, since hedge funds may vary their factor exposure and may have at different times long or short positions in the same asset class. In this case the coefficients in the F&H regressions should be interpreted as measures of a fund's average exposure to each asset class.

Brown, Goetzmann and Park (BGP 1998) employ a similar style-analysis to examine the returns on a sample of hedge funds during the 1997/98 Asian crisis. However, since they wish to test whether hedge funds prompted the crisis by taking short positions in the Asian currencies, they recognize the possibility of shifts in the factor weights and estimate fund exposures to these currencies over a succession of 4-month periods. Thus BGP work with the returns on a sample of ten global hedge funds and undertake a series of rolling 4-month regressions of fund returns on changes in the Malaysian ringitt/dollar exchange rate. Not surprisingly given the small number of observations, these regressions suggest that the aggregate exposure of the funds to the ringitt varied considerably. For example, in February 1996 the trailing 4-month exposure was a short position of over \$200 billion, while one year later the funds had an estimated long position in the ringitt of about \$100 billion. BGP find no relationship between the estimated changes in fund exposures and changes in the value of the currency and observe that during the sharp fall in the value of the ringitt from June to September 1997, hedge funds appeared to be buying the ringitt.

In a second paper (F&H 2000) Fung and Hsieh also seek to infer hedge fund positions from fund returns. For example, using daily data for the Quantum Fund they note that net asset value rose substantially when sterling and the lira dropped out of the Exchange Rate Mechanism, while it was largely unaffected by the peso crisis in December 1994. Using monthly data for a sample of 27 funds, they observe that most global-macro funds had sizable gains in July 1997 when the Thai baht was devalued. Since the U.S. equity

market also had sizeable gains that month, the high returns achieved by hedge funds could simply reflect (amongst other possibilities) a common long position in the U.S. equity market rather than a short position in the baht. Therefore F&H regressed the monthly returns on the 27 funds on both the baht and the S&P Index for the last 6 months of 1997. The coefficient on the S&P was significant and positive in 17 of the regressions, while the baht was significant and negative in only 4. Thus F&H concluded that the performance of the S&P was a much stronger determinant of fund returns than the baht (though this leaves open the question of whether fund activity in the baht was sufficiently large to have exerted a strong impact on prices). To examine in more detail fund exposure to Asian currencies, F&H collected daily or weekly returns for 12 funds and then used stepwise regression to estimate fund exposures to a sample of possible factors. Again they found no evidence of a substantial short position in the baht in July 1997.

Agarwal and Naik (A&N 1999) employ a linear factor model to examine persistence in fund performance. They extend this analysis of hedge fund performance in a subsequent paper (A&N 2000) by recognizing that funds may follow dynamic non-linear trading strategies. They use stepwise regression to identify the independent variables, and find that a put or call option on an underlying variable is the most significant factor in the case of 54 percent of their funds. Their finding is therefore consistent with changes over time in factor loadings.

### III. Methodology and Empirical Results

Our paper is closely related to those of F&H, BGP, and A&N. Like them we estimate factor exposure for a sample of hedge funds by regressing monthly fund returns on the corresponding returns of a set of mimicking portfolios. However, in contrast to the F&H (2000) and BGP papers we are not concerned with estimating factor exposures at the time of particular crises. Instead our interest is in the broader issue of how well data on fund returns can be used to measure *changes* in factor exposure. Thus we seek to provide evidence on the following questions that concern fund managers, investors, and regulators:

- How risky are hedge funds?
- To which asset classes are the different categories of hedge funds exposed?
- Do hedge funds hold active or passive portfolios?
- Can changes in fund exposures be estimated?
- Do hedge funds herd?

#### III. 1. Data Sample

The universe from which we select our funds consists of Tass Management's database of returns for hedge funds.<sup>2</sup> We included in our sample all hedge funds which were not simply "funds of funds" and which had a record of continuous observations of monthly returns ending in September 1999 and beginning no later than January 1994. This resulted in a sample of 146 funds.

In a number of cases two funds are managed by the same manager and appear to follow almost identical investment policies. For example, there were 18 pairs of funds whose returns were correlated .95 or greater and who shared the same manager. To avoid double-weighting what are essentially identical funds, we omit one of each of these duplicate funds.<sup>3</sup> Thus our final sample consists of 128 funds with an average of 124 monthly return observations for each fund.

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<sup>2</sup> The Tass database includes both hedge funds and futures pools run by commodity trading advisors (CTAs). We include both in our analysis and use the term "hedge fund" to refer to both types of fund.

<sup>3</sup> Where there are duplicate pairs of funds, our criteria for inclusion are successively (a) the length of the return series, (b) dollar funds and (c) alphabetical.

The requirement that funds should have a continuous record introduces survivorship bias into our sample, which is likely to bias upwards our estimate of the mean return on hedge funds. There is less reason to suspect bias in measures of the covariance structure, though funds are more likely to have survived if they had positive exposure to those factors that offered the highest returns.

### **III.2. How Risky Are Hedge Funds?**

Tass Management categorizes funds according to their investment strategy. A description of these strategies is given in Appendix 1, together with the abbreviations used in this paper.

The first two columns in Table 1 show for each category the total number of funds in our final sample. The third column of Table 1 shows the mean annualized standard deviation of returns by category of fund for the 69 months for which there are common data (Jan 1994-Sep 1999). Not surprisingly, there is considerable variation across different categories of fund, with emerging market funds the most risky group and fixed interest funds at the other extreme. While one fund (Sperry Futures Fund) had an annualized standard deviation of 73 percent, the overall mean level of variability at 17.1 percent does not support the popular view that hedge funds are an unusually risky investment.

The extent to which the actions of hedge funds can exert a major impact on the market depends to a large extent on the degree to which these actions are correlated. We therefore calculate the correlation between the returns of each pair of funds for the 69 months for which there are common data. The results are summarized in the final column of Table 1. The mean correlation between funds is .13 and in 31 percent of the cases the estimated co-efficient is negative. The average correlation between funds in the same category is .36 and that between funds in different categories is .08, which suggests that the categories tend to contain funds with similar investment policies. That said, there is a considerable difference in the degree of homogeneity of individual categories. For example, for funds in the emerging market and short-selling categories the within-

category correlations are respectively .68 and .61, whereas for non-directional funds the correlation is .05.

Table 1 Number of funds by category and correlation between fund returns.

(See Appendix 1 for abbreviations)

	No. of funds	Mean Annualised Standard Deviation of % Returns	Mean Correlation Between Fund Returns
EM	18	27.5	.68
EUREQ	3	13.6	.19
EVT	24	8.1	.40
FI	3	5.1	.42
FOREX	9	16.2	.26
FUT	44	20.9	.32
GLEQ	6	14.1	.25
GLMC	8	19.3	.24
NOND	9	6.8	.05
SHT	4	20.2	.61
Within categories	--	--	.36
Ex categories	--	--	.08
All funds	128	17.1	.13
S&P Composite	--	13.7	--
Nikkei Index	--	24.4	--

### III.3. To Which Asset Classes Are the Different Categories of Hedge Funds Exposed?

We now turn to the factor exposures of hedge funds. We view the returns on each fund as generated by a linear multi-index model of the form:<sup>4</sup>

$$r_{jt} = \alpha_{jt} + \sum \beta_{kjt} I_{kt} + \varepsilon_{jt} \quad (1)$$

where

$r_{jt}$  = return on fund  $j$  in month  $t$

$I_{kt}$  = return on index  $k$  in month  $t$

$\alpha_{jt}$  and  $\beta_{kjt}$  = regression coefficients which may vary over time

$\varepsilon_{jt}$  = a zero mean error term uncorrelated with  $I_{kt}$

We assume initially that the coefficients in (1) are constant over time and we use OLS to estimate the regressions for each fund. The estimated coefficients can be viewed as measures of the fund's *average* exposure to each market.

For each group of funds we identify the principal factors to which the funds are likely to be exposed. Since a zero coefficient may reflect varying long and short exposures to that factor, we cannot use the estimated coefficients to discard irrelevant factors. Instead we rely on our priors to select plausible factors. For certain categories of fund there are some fairly obvious candidates. However, other groups, such as global-macro funds and non-directional funds, may follow a variety of quasi-arbitrage strategies, and in these cases our choice of factors is restricted both by a desire for parsimony and the availability of data. The factors and the indexes,  $I_k$ , that we use to measure the factor returns are listed in Appendix 2. The prices used to calculate both fund and factor returns are stated in dollars. Appendix 3 provides some descriptive statistics on the factor returns for the period for which there is common data.

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<sup>4</sup> This assumption of a linear structure is open to criticism. For example, Agarwal and Naik (2000) argue that hedge funds follow option-like strategies with non-linear payoffs. In the interests of parsimony we do not allow for possible non-linearities, though we do allow fund returns to be a function of asset volatility.

When providing data to Tass Management, funds report those regions or asset classes in which they invest. We use this information to divide funds into several subcategories. We partition emerging market funds into general funds or those that specialize in a particular region. Futures funds are partitioned into those that claim to invest only in commodities, those that invest only in financial futures, and those that invest in both. In general, there is a high degree of correspondence between the factor loadings and their reported investment policies. However, since funds may misreport their investment policies or change them over time, we also test formally for omitted variables and use the information to reclassify some funds. Thus in the case of those funds which report that they invest only in commodity futures, we find four instances where we can reject at the 5 percent significance level the hypothesis that the slope coefficients on financial futures markets are jointly zero. We therefore include these four funds in the broader subcategory of “commodity and financial futures” funds.

To estimate the average exposure of funds to each market, we regress the returns on each fund on the relevant factor portfolios. Table 2 summarizes the exposure of each group of funds to these factors, while Table 3 shows the number of funds with statistically significant coefficients at the 5 percent level.

**Table 2 Mean estimated factor loadings**

	EM General	EM Rgnal *	EUREQ	EVT	FI	FOREX	FUTC	FUTF	FUT	GLEQ	GLMC	NOND	SHT
No. of funds	10	7	3	24	3	9	36	1	7	4	8	9	4
Equities:													
SP								.18	.87	-.09			-.14
VAL				.15							-.04		-.34
GTH				.03							.31		-.65
NIK				.00				.42	.01	.00	.09	-.01	
FTSE			.32	.02				.19	.07	.13	.07	.05	
CAC			.10										
DAX			-.11					.13	-.02	.11	-.01	.04	
NORD			.14										
EUR			.59										
COMP										.14	.00	.05	
ASIA	.21	.68											
EMEA	.18												
LAT	.37	.87											
VOL													.08
Fixed Int:													
BUND													-.02
GILT													.08
JGB													-.05
TREAS													-.07
TERM													-.12
SWAP													-.12
Currencies:													
DM													-.10
STG													.02
YEN													.02
PESO													.06
ASFX													.08
Commodities:													
GRAIN													.23
MEAT													.23
SOFT													.07
ENGY													.05
PREC													.25
BASE													.10
r-bar sq	.68	.51	.36	.20	.15	.01	.05	.83	.20	.30	.20	.07	.43

\* Entries refer separately to funds specializing in the relevant region. One fund, which specializes in 2 regions, is omitted.

**Table 3 Number of significant coefficients at 5% level**

No. of funds	EM General	EM Rgnal *	EUREQ	EVT	FI	FOREX	FUTC	FUTF	FUT	GLEQ	GLMC	NOND	SHT
	10	3+4	3	24	3	9	36	1	7	6	8	9	4
Equities:													
SP									5	2		3	3
VAL				8							1		1
GTH				4							0		4
NIK				0					0	3	3	0	
FTSE			2	0					1	2	1	1	
CAC			2										
DAX			1						2	1	0	0	
NORD			1										
EUR			3										
COMP										4	2	3	
ASIA	9	3											
EMEA	10												
LAT	9	4											
VOL				14								0	
Fixed Int:													
BUND					0								
GILT					1								
JGB					1								
TREAS					0						0		
TERM				3	2						1	0	
SWAP				0							1	0	
Currencies:													
DM				5		0					3	1	
STG				0		1					1	0	
YEN				0		0					2		1
PESO						0							
ASFX						0							
Commodities:													
GRAIN							13		1				
MEAT							8		0				
SOFT							0		1				
ENGY							3		2				
PREC							8		0				
BASE							3		0				

\* One fund, which specializes in 2 regions, is omitted.

The bottom row of Table 2 shows that there is considerable variation across fund categories in the explanatory power of these regressions. For example, while the three regional emerging market indexes explain on average over two-thirds of the variation in the returns of emerging market funds, the returns on five currencies or currency baskets account for only 1 percent of the variation in the returns of currency funds. We provide some evidence below on whether a low explanatory power reflects a reluctance by funds to take directional bets or whether (as we might expect in the case of currency portfolios) the funds vary over time between long and short positions.

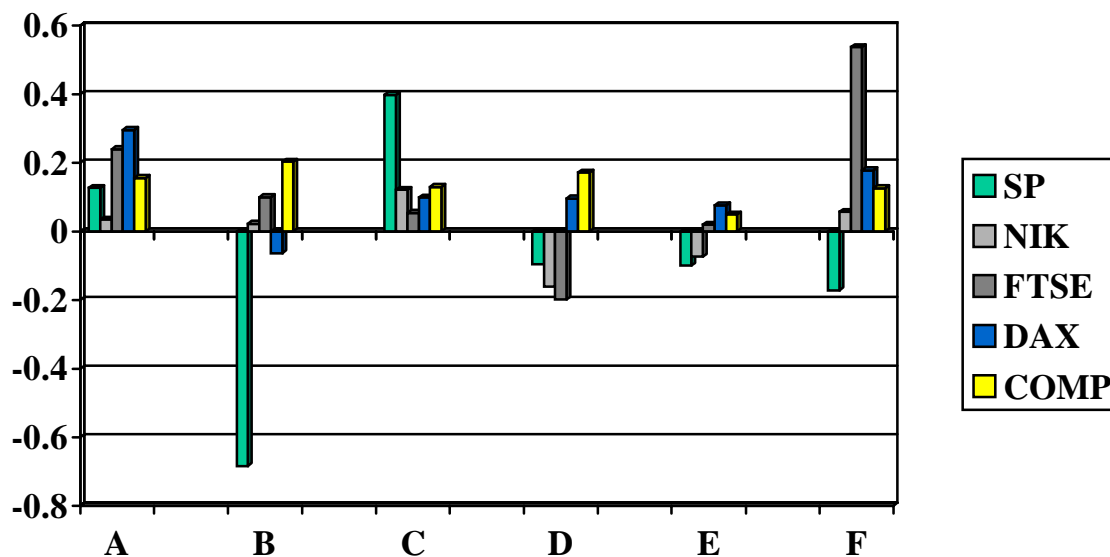
The factor loadings fit broadly with our priors. For example, the coefficients of emerging market funds on the three regional emerging market indexes are all positive and with only two exceptions highly significant. Similarly, European equity funds load, for the most part significantly, on the principal European equity markets.

Given the negligible explanatory power for currency funds, it is not surprising that the coefficients on the five currency measures are insignificant. However, some of the global- macro (and to a lesser extent, event-driven) funds appear to have taken long-term positions in currencies and in particular have had strong short positions in the deutschmark. In the case of the futures funds more than three quarters of the estimated slope coefficients were positive and in 16 percent of the cases they were significantly so (notably for grains, meats and precious metals). This does not fit well with the traditional view of commodity speculators that they are equally prepared to take on risk from both long and short hedges. A number of categories of funds had large exposures to U.S. equities. In the case of event-driven driven funds (but not non-directional funds) returns are significantly and negatively affected by changes in equity market volatility. In addition to placing directional bets on the U.S. market, event-driven and short-selling funds were both relatively long (less short) of value rather than growth stocks,

Table 2 hides the fact that there is considerable heterogeneity in fund exposures within each category, only part of which can be attributed to estimate error. For example, Figure 1 shows the estimated exposures of six global equity funds to major equity markets.

Notice that Fund B has a negative estimated beta of  $-.69$  on the S&P index, while fund C has a positive beta of  $.4$ . And, while C has a long position in each of the five markets, fund D is short in three of them.

Fig. 1 Funds in the same category often have very different factor loadings. This figure shows the estimated loadings of 6 global equity funds (A - F) on different equity indexes.



#### III.4. Do Hedge Funds Hold Active or Passive Portfolios?

We noted above that, if funds are changing their factor exposures, the loadings summarized in Tables 2 and 3 should be viewed as average values. Thus a coefficient that is close to zero may indicate that the fund does not take directional positions or that it is long and short with similar frequency. Hedge funds are characteristically active investors and the non-linearities observed by Agarwal and Naik (2000) suggest that they may be following a variety of dynamic trading strategies.

We, therefore, turn now to consider the stability of the loadings on the market indexes shown in Tables 2 and 3. We employ recursive least squares where for each fund we use the first  $k+1$  observations to obtain the first estimate of the slope coefficients and then repeatedly add one observation to the data set to revise the estimate. At each step the last estimates of the regression coefficients are used to provide a one-step ahead forecast of

the dependent variable and the recursive residual is calculated as the forecast error from this prediction scaled by its standard error. If the coefficients are stable then the recursive residuals will be independently and normally distributed with zero mean and constant variance.

To test for stability in the coefficients, we employ a cumulative sum of squares (CUSUM) test (Brown, Durbin and Evans 1975). This test sums the first  $n$  values of the squared recursive residuals and divides by the sum over all observations of the squared residuals. The expected value of this ratio under the hypothesis of parameter stability is  $n/N$ , where  $N$  is the total number of observations.<sup>5</sup> The test gives a picture of the evolution of an estimated relationship as the sample is extended one observation at a time. If the cumulative sum strays beyond the confidence bounds, the hypothesis of parameter stability is rejected. The test is general in the sense that we do not require prior specification of the break time as in the case of Chow tests, but the test has low power compared with the Chow tests and does not determine the time or the number of structural breaks.

The power of the test to reject the hypothesis of parameter stability is likely to be influenced by the number of factor portfolios that we have specified. For example, an emerging market fund may change its exposure to different countries within the region while leaving its exposure to the region as a whole unchanged. In this case we would only be able to reject the hypothesis of parameter instability if we included country indexes in the regressions

Table 4 shows that for most groups of funds the null hypothesis of stable coefficients is strongly rejected. For the total sample the null is rejected in 75 percent of the cases and only in the case of European equity, currency, and global-macro funds does the proportion not exceed 50 percent.

Table 4 CUSUM test of parameter stability. Table shows the number of funds for which the null hypothesis of parameter stability is rejected at the 5% level		
	Total no. of funds	No. significant
EM – general	11	10
EM – regional	7	7
EUREQ	3	0
EVT	24	20
FI	3	2
FOREX	9	4
FUTC	36	29
FUTF	1	1
FUT	7	6
GLEQ	6	4
GLMC	8	4
ND	9	5
SHT	4	3
Total	128	95

Some caution is needed in interpreting this apparent instability. One reason that coefficients may vary over time is that fund managers are indeed making active buy and sell decisions. However, a second possibility is that the sample of assets in the index and the method for computing the index has changed. This is particularly important in the case of emerging market funds, since the IFC emerging market indexes have been periodically broadened to include new countries. For example, the number of countries represented in the Europe, Middle East and Africa (EMEA) index has trebled since 1992. Furthermore, since 1996 adjustments have been made to the IFC indexes for cross-holdings of shares.

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<sup>5</sup> An alternative would be to test for structural breaks in the relationships. Recent examples of studies that have studied breaks in financial data include Chen and Gupta (1997), Ang and Bekaert (1998), and Pastor and Stambaugh (2000).

Even if there are no changes to the shares included in the index, a value-weighted index will be characterized by time-varying weights as relative prices change, so that an emerging market fund following a passive buy-and-hold strategy will have changing exposures to the regional components. The effect of changing weights and index composition shows up if we regress the returns on the IFC Composite Index on the returns of the regional indexes. Although the Composite returns are simply a weighted average of the returns on the three regional indexes, the r-squared of the regression is .94 rather than unity. Moreover, the CUSUM test rejects at the 5 percent level the hypothesis that the slope coefficients for the IFC Composite Index are stable.

The recursive residuals from the regressions are equivalent to the errors from one-step-ahead forecasts. The effect of changing weights on these recursive residuals depends on both the current weight of each asset class relative to past weights and the relative returns on the asset classes in that month. For example, the 1997/98 Asian crisis resulted in a sharp decline in the market weight of the Asian index within the Composite. Following that decline, high positive returns in Asian markets had a smaller impact on the Composite index than formerly, so that when the Composite Index is regressed on its component parts, there is a negative residual in these months.

There is some evidence that changing market weights partly account for the changing exposures of the emerging market hedge funds. To illustrate this, we regress the returns on the IFC Composite index on the regional return indexes and then examine the correspondence between changes in the estimated (non-standardized) slope coefficients and changes in the corresponding coefficients for general emerging market hedge funds. The average correlation between the coefficient changes for general emerging market hedge funds and the IFC Composite index varied between .10 and .11. This tendency for hedge funds and a composite index to make parallel changes in their exposures cannot be due to active management decisions and points to the need to be cautious in interpreting shifts in fund exposures as indications of speculative decisions.

Changes in index composition are not easily dealt with, but it is possible to consider how far the instability in coefficients is due to changing weights. Suppose that at time 0 a fund invests proportions  $w_{10} \dots w_{N0}$  in assets 1...N and thereafter follows a buy-and-hold policy. At time 1 the fund weights will have changed to  $w_{10} \cdot r_{11}/r_{F1} \dots w_{N0} \cdot r_{N1}/r_{F1}$ , where  $r_{j1} = 1 + \text{return on asset } j \text{ in period } 1$  and  $r_{F1} = 1 + \text{return on fund in period } 1$ . More generally, the proportion invested in asset  $j$  at time  $T$  will be  $w_{j0} \cdot \prod r_{jt} / \prod r_{Ft}$ . Since the market weights are changing, a regression of fund returns on individual asset returns will not generally produce constant coefficients. However, we can write the fund return in each period as the sum of the asset returns weighted by the amounts invested at the beginning of each period:

$$r_{Ft} = \sum w_{jt-1} \cdot r_{jt}$$

A regression of fund returns on these weighted asset returns should yield stable coefficients of unity.

Although we cannot directly observe a hedge fund's portfolio at a particular point in time, the time-series regression of fund returns on asset returns does provide an estimate of the average proportion invested in each asset. Since we know how the asset proportions change over time for a fund that follows a buy-and-hold strategy, this information on the average weights may be used to back out an estimate of the weights at the end of each month conditional on the fund following such a strategy.

To assess how far coefficient instability is due simply to changing index weights, we repeat the CUSUM stability test for general emerging market funds using estimates of the weighted asset returns,  $\sum w_{jt-1} \cdot r_{jt}$ , as the independent variables rather than the raw returns. The  $R^2$  are only negligibly affected, the coefficients on the weighted returns are significantly different from unity, and the CUSUM test continues to reject the hypothesis of stable coefficients for 10 out of 11 funds.<sup>6</sup>

While this adjustment for changing weights has little effect on our stability tests, occasional large changes in market prices may well induce a marked shift in a fund's exposures and create the impression of concurrent speculative activity by the fund. For example, we estimate that if a passive emerging market fund had average weights in the three regions,<sup>7</sup> its loading on the Asian market would have declined from .39 to .24 in a space of 6 months in 1997. This points to the need for caution in interpreting changes in factor loadings during major market movements as stemming from active management.

### **III.5. Can Changes in Exposures be Estimated?**

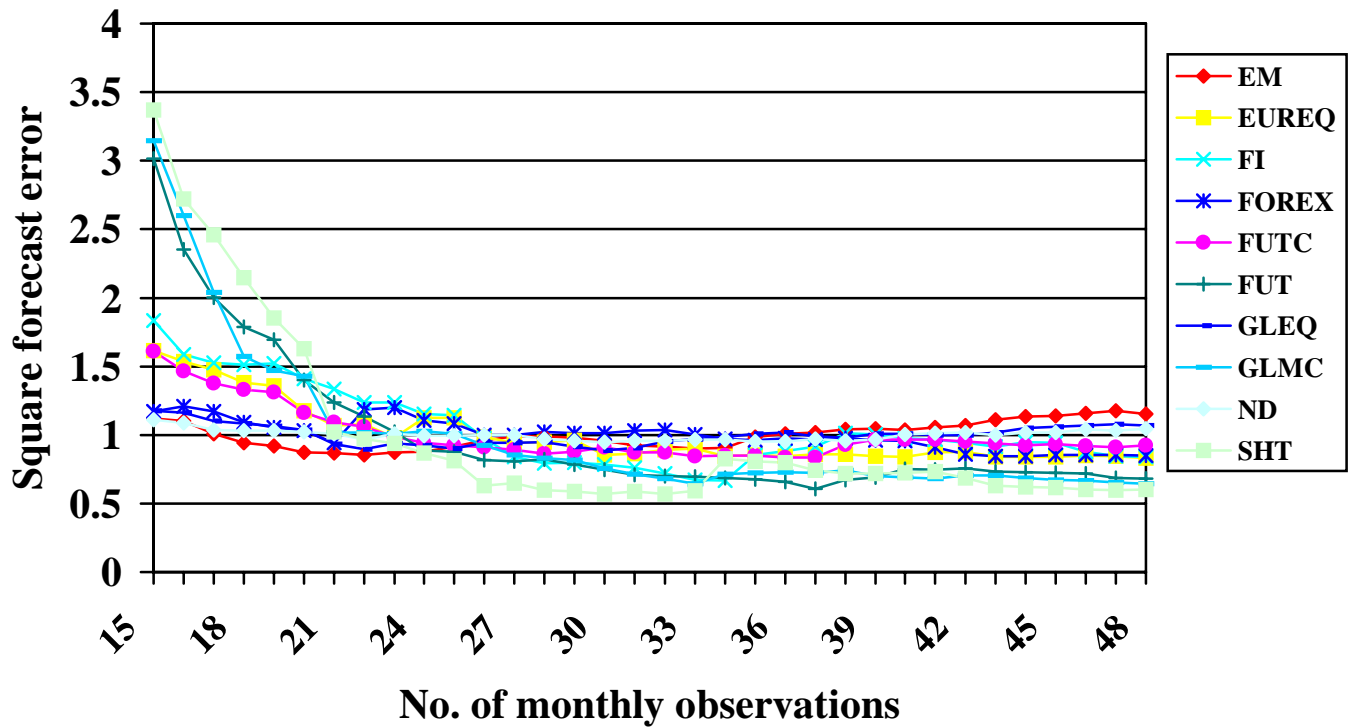
We have seen that the CUSUM test provides evidence of widespread instability in the factor loadings, only a small part of which seems to be due to changing market weights. This suggests that more recent returns data may be more informative about the loadings than earlier data. To illustrate the trade-off between employing a larger number of observations rather than more recent data, we undertake a series of rolling regressions of fund returns on index returns. Each set of regression coefficients is used to make one-step-ahead forecasts of the fund return conditional on knowledge of the future factor returns. We repeat these rolling regressions using different numbers of observations to estimate the coefficients and we examine how the mean square forecast error changes as the number of observations in the regressions changes. The mean square errors for each fund were standardized to have an average value of unity and then averaged across all funds in a given category. The results are plotted in Figure 2.

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<sup>6</sup> We noted above that a regression of the IFC Composite Index on its three component parts resulted in unstable betas. This instability is partly due to changes in index composition and therefore persists even when the adjustment is made for the effect of differential returns on the market weights.

<sup>7</sup> "Average weights" in this context means the estimated weights for the IFC Composite Index.

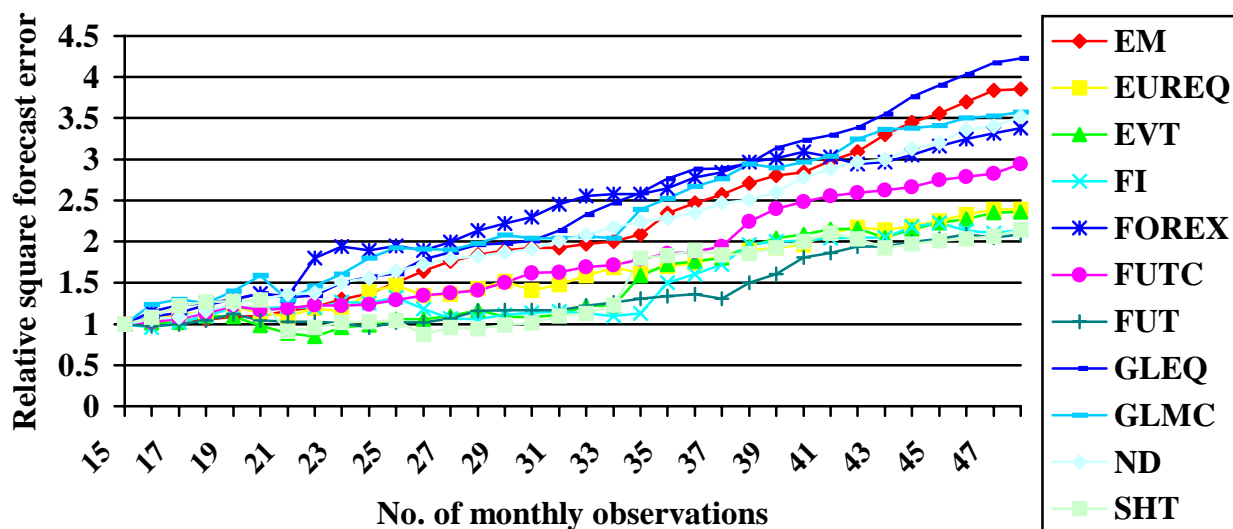
Fig 2. Mean one-month-ahead square forecast error as a function of the number of months used to estimate regression coefficients.



While the squared forecast errors in Figure 2 initially decline as the number of observations is increased, they typically reach a minimum with about 36 months of observations. Beyond this point the advantage of adding more observations is generally outweighed by the disadvantage of using more dated information. The exceptions are the European equity, forex and global-macro funds, where additional observations continue to improve the forecasting accuracy. This is consistent with the results of the CUSUM test, which provided weaker evidence of parameter instability for these funds.

If the coefficients are stable, the mean square error should decline in proportion to the number of degrees of freedom. Therefore, in Figure 3 we show the squared forecast errors relative to the values that would be expected under the assumption of stability.

Fig 3. Mean one-month-ahead square forecast error as a function of the number of months used to estimate regression coefficients. Error is shown relative to expected error under null hypothesis of stable coefficients



Thus, if the coefficients are stable, the values in Figure 3 should be unity for all numbers of observations. The steep upward sloping lines indicate that the errors consistently decline less rapidly than under the stability assumption and generally (as Figure 2 shows) begin to increase beyond a certain point.

While Figures 2 and 3 are consistent with considerable instability in the factor loadings, our results provide small comfort for anyone wishing to estimate short-term variations in fund exposures. There is relatively little benefit from shortening the interval over which the factor loadings are measured, and, since the ratio of noise to signal increases sharply for small numbers of observations, it is impossible to make useful statements about short-term changes in fund positions using monthly data.

### **III.6 Do Hedge Funds Herd?**

From the viewpoint of public policy, we may be more concerned about changes in factor exposures if they are correlated across funds. Indeed, hedge funds have been accused of implicit and explicit collusion in their trading activities.

Inspection of the monthly changes in the estimated recursive coefficients provides evidence of a cross-sectional relationship. For each fund we compute the estimated recursive coefficients from regressions of fund returns on the selected indexes. We standardize these coefficients by their standard errors, calculate for each fund the monthly differences in the standardized coefficients and for each pair of funds compute the correlations between these monthly differences. The first two columns of data in Table 5 show the mean pairwise correlation and the proportion of positive correlations. Considering the large estimate errors in measuring coefficient changes, the evidence of correlated changes in fund exposures is surprisingly strong.

Further evidence is provided by an analysis of the recursive residuals, which are equivalent to errors in the one-step return forecasts derived from data up to the end of the previous month. The last two columns of Table 5 indicate that these forecast errors are also for the most part positively correlated.

Public policy concerns about herding commonly center on currency speculation particularly in emerging markets, where it is often asserted that under fixed exchange rates there may be an incentive for speculators to imitate each other's actions and so induce a change of parity. Table 5 does indeed contain evidence of such herding in both currency and emerging market funds, but it is not clear that it is more marked than for other categories of fund.

While this association between changes in the recursive coefficients and in the forecast errors suggests common changes in fund exposure, we should note that it is impossible to date these changes with any degree of accuracy. Any changes in the factor exposures

will not be apparent as long as the factor returns are close to their means; it is only when there are large changes in factor returns that the structural breaks in the relationship will show up as jumps in the estimated recursive coefficients. The result is that funds will appear to make large changes in their exposures during periods of crisis when there are large changes in factor returns.

Table 5 Tests of fund “herding.” The first 2 columns of data show the mean pair wise correlation and the percentage of positive correlations between changes in the recursive residuals and the total number of correlations; the final 2 columns show the mean pair wise correlation and the percentage of positive correlations between forecast errors.

	Changes in recursive coefficients		Forecast errors	
	Mean correlation	% positive (N)	Mean correlation	% positive (N)
EM	.14	69 (165)	.18	86 (153)
EUREQ	-.02	33 (15)	-.03	67 (3)
EVT	.11	67 (2771)	.27	92 (276)
FI	.46	100 (15)	.44	100 (3)
FOREX	.17	75 (180)	.28	94 (36)
FUTC	.29	91 (3780)	.38	95 (630)
FUT	.06	66 (210)	.12	67 (21)
GLEQ	.14	61 (70)	.21	73 (15)
GLMC	.11	69 (336)	.20	86 (28)
ND	.04	58 (396)	.03	53 (36)
SHT	.35	92 (12)	.46	100 (6)

#### IV Summary and Conclusion

In recent years the activities of hedge funds and other highly leveraged institutions have attracted considerable criticism. They have been accused of taking large speculative positions in emerging markets that have led to, or accentuated, an economic crisis in these countries. Other critics have been concerned that the high degree of leverage

employed by hedge funds can oblige them to liquidate large positions in falling markets, which may result in both volatile prices and threaten the solvency of the lending banks. In the words of the Chairman of the House Committee on Banking and Financial Services, hedge funds “are seen by some to be run-amok, casino-like enterprises, driven by greed that with their sheer size can control markets and, in certain circumstances, even jeopardize the viability of sovereign states.”

Our data provide some limited reassurance on these issues. The risk of the average hedge fund in our sample was broadly comparable with that of the U.S. equity market. Moreover, the extent to which hedge funds are likely to impact a particular market is limited by the heterogeneous nature of these funds. Thus, the mean correlation between the returns of each pair of funds in our sample was only .13.

High within-category correlations between funds were generally associated with a common loading on major factors. For example, general emerging market funds all exhibited a marked exposure to Asian, Latin American, and Europe/Middle East/African emerging market indexes. On the other hand, despite worries that hedge funds take substantial directional bets on currencies, the returns on a sample of currencies did little to explain the returns on our sample of foreign exchange funds.

Hedge funds are commonly thought to make frequent changes in their exposures. If that is so, estimated factor loadings need to be interpreted as measures of a fund’s average exposure over the estimation period. Our tests of the stability of factor loadings rejected the null hypothesis of stable coefficients at the 5% level in the case of three quarters of the funds.

This instability in the coefficients implies that there is a trade-off between increasing the number of data points used to estimate the loadings and using more dated information. With monthly data, conditional forecasts of fund returns typically minimized the variance of the forecast error with about three years of data, though the benefits from using the more recent data were generally modest. Thus, while funds do change their exposure to

different markets, monthly data are not sufficient to pick up short-term variations. Much more frequent reporting of fund values would be needed to provide any up-to-date information on fund exposures.

We presented evidence that within each category funds tend to make similar changes to their factor exposures. But we also drew attention to two difficulties in interpreting changes in factor loadings. First, these changes are more likely to become apparent when there is a large shift in the independent variable, so that it is impossible to date the changes with any precision. Second, it is difficult to distinguish changes in loadings that result from active fund management from those that would characterize even a passive portfolio. These problems confront any attempt to measure whether speculative activities by hedge funds have been associated with market crashes.

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## **Appendix 1 Definitions of Fund Categories (Category abbreviations are shown in parentheses)**

*Emerging Market (EM)*: Funds invest in equity and/or debt securities in emerging markets.

*European Equity (EUREQ)*: Funds take long/short positions in European equities on a directional (as opposed to market neutral) basis.

*Event Driven (EVT)*: Equity-oriented funds designed to capture price movement generated by an anticipated corporate event. Includes funds specialising in risk/merger arbitrage, distressed securities, or special situations.

*Fixed Income Directional (FI)*: Funds take long/short positions in fixed income securities around the world.

*Pure Currency (FOREX)*: Dedicated currency funds.

*Pure Managed Futures (FUT = funds investing in commodity and financial futures; FUTC = funds investing in commodity futures; FUTF = funds investing in financial futures)*: Funds invest only in the global commodity & financial futures markets.

*Global Equity (GLEQ)*: Funds take long/short positions in global equities on a directional (as opposed to market neutral) basis.

*Global Macro (GLMC)*: Funds invest opportunistically in the global equity, currency, fixed income and commodity markets.

*Non-directional (NOND)*: All relative value and arbitrage strategies (except merger arbitrage) are included in this category, e.g., fixed income arbitrage, convertible arbitrage, statistical arbitrage etc.

*Dedicated Short Seller (SHT)*: Funds aim to be net short at all times. Funds are active primarily in the U.S. equity market.

## Appendix 2

### Definition of factors (all prices are converted to U.S. dollars)

Market	Definition
<b>Equities:</b>	
SP	Standard & Poor's Composite Index
VAL	Wilshire Large Value Stock Index
GTH	Wilshire Large Growth Stock Index
NIK	Nikkei 225 Index of Japanese stocks
FTSE	FTSE 100 Index of UK stocks
CAC	CAC 40 Index of French stocks
DAX	Xetra Dax Index of German stocks
NORD	FT/S&P World Nordic Stock Index
EUR	Residual from regression of returns from FTSE World Europe Index on the above four European stock indexes
COMP	IFC Composite (Investable) Return Index
ASIA	IFC Asia (Investable) Return Index
EMEA	IFC Europe, Middle East and Africa (Investable) Return Index
LAT	IFC Latin America (Investable) Return Index
VOL	Standard deviation of daily returns over month on S&P Composite Index
<b>Fixed Interest:</b>	
BUND	Index of medium-term German government bonds
GILT	Index of medium-term UK government bonds
JGB	Index of medium-term Japanese government bonds
TREAS	Salomon index of 7-10 year Treasury bond returns
TERM	Monthly change in difference between yields on 10- and 3-year U.S. Treasuries
SWAP	Monthly change in 2-year \$U.S. swap spread
<b>Currencies:</b>	
DM	Deutschmark
STG	UK pound
YEN	Japanese yen
PESO	Mexican peso
ASFX	Basket containing equal dollar investment in Korean won, Thai baht and Indonesian rupee
<b>Commodities:</b>	
GRAIN	MLM Grain Index
MEAT	MLM Meats Index
SOFT	MLM Softs Index
ENGY	JPMCI Energy Sub Index
PREC	JPMCI Precious Metal Sub Index
BASE	JPMCI Base Metal Sub Index



## For reference only

Table 4a 1-step-ahead forecast errors as a function of the length of the estimation period

Months	EM	EUREQ	EVT	FI	FOREX	FUTC	FUT	GLEQ	GLMC	ND	SHT
15	1.12	1.62	2.77	3.32	1.17	1.61	3.02	1.18	3.15	3.37	1.11
16	1.10	1.53	2.25	2.85	1.21	1.47	2.35	1.16	2.60	2.72	1.09
17	1.01	1.48	1.88	2.71	1.17	1.38	2.00	1.10	2.04	2.46	1.04
18	0.95	1.38	1.74	2.32	1.09	1.33	1.79	1.08	1.58	2.15	1.03
19	0.92	1.36	1.52	1.98	1.05	1.31	1.69	1.06	1.47	1.85	1.03
20	0.87	1.18	1.21	1.75	1.03	1.16	1.40	1.04	1.43	1.63	1.02
21	0.87	1.07	0.98	1.51	0.94	1.09	1.24	0.93	1.02	1.02	1.01
22	<b>0.86</b>	1.08	0.86	1.38	1.19	1.06	1.14	0.89	1.02	0.97	0.97
23	0.87	0.98	0.89	1.31	1.20	0.99	1.02	0.93	1.01	0.94	1.01
24	0.88	1.12	0.84	1.21	1.11	0.94	0.89	0.93	1.03	0.87	0.99
25	0.92	1.12	0.84	1.17	1.08	0.93	0.88	0.90	1.01	0.81	0.99
26	0.96	0.98	0.78	1.04	1.00	0.91	0.82	0.94	0.92	0.63	1.00
27	0.99	0.94	0.77	0.94	1.00	0.89	0.81	0.94	0.86	0.65	1.00
28	0.99	0.95	0.76	0.94	1.02	0.86	0.82	0.95	0.83	0.60	0.97
29	0.98	0.96	0.67	0.89	1.02	0.88	0.78	0.91	0.82	0.59	0.96
30	0.96	0.85	0.63	0.80	1.01	0.91	0.75	<b>0.89</b>	0.76	<b>0.57</b>	<b>0.95</b>
31	0.92	0.86	0.61	0.74	1.03	0.87	0.71	0.90	0.71	0.59	0.95
32	0.92	0.89	0.64	0.74	1.03	0.87	0.70	0.95	0.68	0.57	0.96
33	0.90	0.90	<b>0.61</b>	0.70	1.01	0.85	0.69	0.97	0.64	0.59	0.97
34	0.91	0.84	0.77	0.71	0.97	0.85	0.69	0.98	0.712	0.83	0.97
35	0.98	0.85	0.79	0.74	0.96	0.85	0.68	1.01	0.72	0.81	0.95
36	1.08	0.85	0.78	0.72	0.97	0.84	0.66	1.02	0.73	0.80	0.95
37	1.02	0.86	0.77	0.70	0.97	<b>0.83</b>	<b>0.61</b>	0.99	0.72	0.74	0.97
38	1.04	0.86	0.80	0.73	0.98	0.93	0.67	0.98	0.74	0.72	0.96
39	1.05	0.85	0.81	0.71	0.96	0.96	0.69	1.01	0.70	0.72	0.97
40	1.04	0.84	0.80	0.68	0.96	0.97	0.75	1.01	0.69	0.72	1.00
41	1.05	0.87	0.79	0.66	0.91	0.97	0.75	1.00	0.68	0.73	1.01
42	1.07	0.88	0.77	0.65	0.86	0.95	0.76	1.00	0.71	0.68	1.02
43	1.11	0.84	0.71	0.63	<b>0.85</b>	0.94	0.73	1.02	0.70	0.63	1.00
44	1.13	0.84	0.72	0.63	0.85	0.93	0.73	1.05	0.69	0.62	1.02
45	1.14	0.84	0.73	0.63	0.85	0.93	0.72	1.06	0.67	0.62	1.02
46	1.16	0.85	0.72	0.58	0.86	0.92	0.72	1.07	0.67	0.60	1.04
47	1.18	0.85	0.72	0.56	0.85	0.91	0.67	1.08	0.65	0.60	1.03
48	1.15	<b>0.83</b>	0.71	<b>0.54</b>	0.85	0.93	0.68	1.07	<b>0.64</b>	0.60	1.04