Capacity Constraints and Hedge Fund Strategy Returns

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Abstract

Hedge funds have generated significant absolute returns (alpha) in the decade between 1995 and 2004. However, the level of alpha has declined substantially over this period. We investigate whether capacity constraints at the level of hedge fund strategies have been responsible for this decline. For four out of eight hedge fund strategies, capital inflows have statistically preceded negative movements in alpha, consistent with this hypothesis. We also find evidence that hedge fund fees have increased over the same period. Our results provide support for the Berk and Green (2004) rational model of active portfolio management.

Keywords: *Hedge funds*; *capacity constraints*; *alpha*; *factor models*; *performance fees*; *flows*

JEL classification: *G11, G12, G23*

1. Introduction

Hedge funds display many of the features of the 'arbitrageurs' referred to in canonical formulations of the efficient markets hypothesis. These large, relatively unregulated, highly sophisticated investors are thought to represent a strong disciplining force

in financial markets. When prices deviate from fundamental value, hedge funds are believed to commit capital to eradicate mispricing, making high and relatively riskless returns in the process. In sum, hedge funds are widely thought to hold factor neutral portfolios, and to focus on generating alpha for their investors.

Several authors have pointed out that hedge fund returns contain high systematic risk exposures. For believers in the efficient markets hypothesis, the more surprising finding is that hedge funds deliver high positive and statistically significant absolute returns over and above their systematic risk exposures.[1] This finding is remarkably robust to a variety of linear factor models, including those that contain nonlinear assets such as options[2] (see Agarwal and Naik, 2004; Fung and Hsieh, 2001, 2004). Hedge funds' significant absolute returns have also been found robust to corrections for data problems (see Liang, 2000; Getmansky *et al*., 2004).

A recent article by Fung *et al*. (2006) investigates whether the alpha generated by funds-of-hedge-funds (FoFs) has varied over time, and uses estimates of FoF alpha as a proxy for the behaviour of the industry as a whole. They find that FoF alphas have declined substantially in the most recent period in their data: the period beginning in April 2000 and ending in December 2004. Over the same period, they also record high capital flows into FoFs, especially to FoFs that have generated positive and statistically significant alpha in the past. Finally, they find evidence that high capital inflows forecast declines in future FoF alpha. They conclude that alpha production is subject to declining returns to scale. They interpret these findings as evidence of capacity constraints in the hedge fund industry *à la* Berk and Green (2004).

Fung *et al*. (2006) document the presence of capacity constraints using data on FoFs. However, their results could be driven by declines in the ability of FoF managers to select alpha-generating funds in the underlying strategies as well as by declines in the alpha opportunities available in various hedge fund strategies. This paper directly addresses the question of capacity constraints at the level of hedge fund strategies. We focus on strategy-level analysis for two main reasons. First, considering the asset allocation problem facing a hedge fund investor, it is likely that the investor decides on strategies before choosing among the individual funds within each strategy. Hence, if some strategies are more likely to experience capacity constraints than others, this may affect how capital is distributed across strategies. Second, there are pervasive factors that influence all funds within a strategy. For example, if there are no mergers taking place, this will affect investment opportunities for all merger arbitrage funds, not just a few individual funds. This suggests that it is important to identify whether capacity constraints impact the strategy-level common component of hedge fund returns.

We first show that alpha has decreased at the level of hedge fund strategies in the most recent period from 2000 to the end of 2004. We measure systematic risk using the seven-factor model of Fung and Hsieh (2004). In regressions of monthly hedge fund strategy index returns on the Fung-Hsieh factors, we find R-squared statistics of up to 90 percent. Despite this, hedge fund strategy alphas are positive and statistically significant. Using the same structural breakpoints estimated in Fung *et al*. (2006), we show that hedge fund strategy alphas exhibit the same pattern of time variation as FoFs.

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[1] Li and Kazemi (2007) find evidence of market timing in hedge fund indices. They attribute this result primarily to the propensity of hedge funds to be long volatility, and find a smaller role for manager ability.

[2] Isakov and Morard (2001) provide evidence that the use of option strategies consistently improves the performance of a portfolio.

This suggests that the Fung *et al*. (2006) results are not solely driven by declines in FoF fund selection ability.

Second, we demonstrate that for four out of eight hedge fund strategies, future strategy alpha is lower when current capital flows into the strategy are high. We first compute capital flows into the different hedge fund strategies. The flows exhibit a reverse time pattern to that observed in the alphas. In particular, flows are highest in the most recent sub-period of our data, the time period in which our estimated alphas are very low. To conduct a more in-depth analysis, we run rolling regressions of the hedge fund strategy return series on the seven-factor model. These regressions yield a decomposition of hedge fund strategy returns into systematic and absolute components. We regress the latter component on the lagged capital flows into each strategy (making sure to avoid any potential overlap). The analysis reveals that high capital flows precede statistically significant declines in alpha. However, there is interesting cross-sectional variation in these findings. Relative Value, Directional Traders, Emerging Markets and Fixed Income strategies appear to show evidence of capacity constraints, while there is little evidence that the other strategies are subject to capacity constraints.

Finally, we present evidence consistent with the second channel via which Berk and Green (2004) suggest that alpha will be zero in equilibrium – a steady increase in incentive fees in the hedge fund industry, especially in the most recent period of time.

We conclude that capacity constraints are indeed a concern for seekers of alpha in a subset of hedge fund strategies. Although this is disappointing news for investors, it is good news for the analysis of Berk and Green (2004). These authors present a rational model of active management that predicts that in an economy with competitive provision of capital and rational investors, differential managerial ability will not be detectable by an econometrician. In particular, they show that under these assumptions alpha will be zero. Our results suggest that the mechanisms they put forward may provide a consistent rationale for the declining alpha we see in our hedge fund strategy return data.

The organisation of the paper is as follows: section two describes our data, section three presents our methodology, section four discusses the results, and section five concludes.

2. Data

2.1. *Hedge fund data*

We use a large and comprehensive dataset of hedge funds. Our data are available for the period between January 1994 and December 2004. Our data (which include data on dead funds) are drawn from the union of four large databases namely HFR, TASS, CISDM (formerly ZCM/MAR), and MSCI. This enables us to resolve occasional discrepancies among different databases and to create a sample that is more representative of the entire hedge fund industry. Only funds that report assets under management (AUM) are included in the dataset. A careful filter is applied to the data. We first exclude funds-of-hedge-funds, and then eliminate any fund with flows greater (less) than 500 (100) percent of its prior month's AUM at any point in its history. This leaves us with a total of 7,610 funds.

The first panel of Table 1 shows the evolution of the aggregate AUM in the hedge fund industry. Figure 1 plots the final column of Panel 1, and confirms the many press reports about the dramatic growth of the hedge fund industry. Aggregate AUM in the industry has grown from US $ 70 billion in 1994 to US $ 740 billion in 2004.

Table 1

Summary Statistics

This table presents summary statistics for assets under management (AUM), the number of funds and capital flows across eight hedge fund strategies. The columns in panel 1 represent the strategies, and the rows show the percent of total AUM that is contained within each strategy at the end of each year. The final column presents the total AUM contained across all strategies at the end of each year in billion of US dollars. Panel 2 presents the number of funds at the end of each year for each strategy represented in columns. The final column of Panel 2 contains the total number of funds in our sample at the end of each year. Panel 3 presents the percent of total net flow into the hedge fund industry for each strategy, for each year. The final column presents the total net dollar flow in billions of US dollars.

Panel 1: Composition of total AUM

Year	Security Selection	Macro	Relative Value	Directional Traders	Multi-Process	Emerging Markets	Fixed Income	Other	Total US $BN
1994	11%	35%	5%	15%	7%	10%	5%	10%	69.257
1995	12%	30%	6%	20%	8%	9%	5%	10%	86.142
1996	13%	28%	7%	21%	8%	9%	7%	7%	135.767
1997	14%	24%	8%	19%	9%	10%	8%	7%	206.194
1998	20%	20%	10%	20%	9%	4%	10%	8%	220.332
1999	23%	16%	10%	21%	9%	4%	8%	9%	276.613
2000	24%	8%	14%	24%	10%	3%	8%	10%	292.249
2001	27%	4%	18%	19%	10%	2%	9%	10%	344.168
2002	27%	4%	19%	17%	11%	2%	10%	10%	392.965
2003	28%	5%	18%	16%	10%	3%	9%	11%	570.436
2004	26%	5%	17%	16%	13%	3%	9%	12%	739.371

Panel 2: Composition of number of funds   Number

Year	Security Selection	Macro	Relative Value	Directional Traders	Multi-Process	Emerging Markets	Fixed Income	Other	Number
1994	13%	18%	7%	15%	6%	7%	6%	27%	1115
1995	13%	17%	8%	17%	8%	9%	5%	23%	1464
1996	15%	15%	9%	20%	8%	9%	5%	18%	1954
1997	17%	14%	9%	21%	9%	10%	5%	16%	2312
1998	19%	12%	10%	22%	9%	8%	5%	13%	2523
1999	20%	11%	11%	24%	8%	7%	5%	13%	2811
2000	20%	9%	13%	27%	9%	6%	5%	12%	3075
2001	20%	7%	16%	28%	9%	4%	4%	12%	3357
2002	20%	6%	18%	27%	10%	3%	5%	11%	3713
2003	21%	6%	17%	26%	10%	3%	5%	12%	4009
2004	23%	6%	16%	22%	12%	3%	5%	13%	4091

Research by Fung and Hsieh (1997) and Brown and Goetzmann (2003) shows that there are five to eight distinct style factors in hedge fund returns. Following these insights, and the classification in Agarwal *et al*. (2005), we classify the reported hedge fund strategies into eight broad categories: Security Selection, which comprises long/short equity hedge, equity hedge and equity market neutral funds; Macro; Relative Value, which comprises merger arbitrage, convertible arbitrage and statistical arbitrage funds; Directional Traders, which includes vendor classifications such as sector, long bias and equity non-hedge; Multi-Process, which also contains event driven funds; Emerging Markets; Fixed Income, and Other, which is a catch-all category containing

Table I

Continued.

Panel 3: Composition of net flows

Year	Security Selection	Macro	Relative Value	Directional Traders	Multi-Process	Emerging Markets	Fixed Income	Other	Total US$ BN
1994	2%	4%	−2%	27%	20%	35%	11%	2%	3.069
1995	44%	−138%	154%	62%	49%	−48%	−2%	−21%	0.508
1996	10%	7%	19%	23%	17%	6%	14%	4%	8.819
1997	14%	8%	17%	16%	10%	10%	12%	13%	24.720
1998	29%	6%	20%	13%	13%	−5%	17%	7%	17.422
1999	15%	2%	36%	53%	-3%	−12%	1%	8%	9.314
2000	26%	−1%	32%	35%	10%	−1%	1%	−3%	23.889
2001	26%	3%	33%	14%	14%	0%	4%	6%	35.127
2002	25%	2%	22%	18%	14%	2%	9%	8%	37.588
2003	11%	8%	22%	20%	15%	2%	9%	14%	80.837
2004	17%	5%	14%	20%	15%	4%	11%	14%	100.829

strategies such as managed futures and discretionary trading. The first panel in Table 1 also shows the time evolution of the share of total hedge fund AUM in each strategy. There has been interesting cross-sectional variation in this time evolution, with growth in Security Selection, Multi-Process and Relative Value funds at the expense of Macro funds, and to a certain extent, Emerging Markets funds.

The second panel in Table 1 enumerates the number of funds in each of the strategies in each year of our data. The table reveals that the strategies which have experienced growth in AUM have also seen an increase in the number of funds. In thinking about capacity constraints, we are often confronted with the possibility that high return generating funds could close to new money, thus preventing constraints on alpha generation from binding. Panel 2 suggests that there may be entry of new funds into alpha-generating sectors, regardless of whether successful funds close to new money.

2.1.1. *Flows*. We compute dollar flows F_{it} for fund i during month t as follows:

$$F_{it} = A_{it} - A_{it-1}(1 + r_{it}) \tag{1}$$

Here A_{it}, A_{it-1} and r_{it} are the AUM for fund i at the end of month t, and $t-1$, and the returns accrued from month $t-1$ to t respectively. Note that we assume that the flows came in at the end of the month, subsequent to the accrual of returns. We then compute strategy level flows by aggregating individual fund flows up to the level of strategies, and scale the dollar flows by strategy-aggregated end-of-previous-month AUM:

$$f_{st} = \left(\sum_{i=1}^{N_s} F_{it} \right) \Big/ \left(\sum_{i=1}^{N_s} A_{it-1} \right) \tag{2}$$

The third panel in Table 1 shows the share of flows that have gone into each strategy in each year. There is significant cross-sectional and time-series variation in flow shares. For example, in 1995, although aggregate flows into the industry only measured US$508

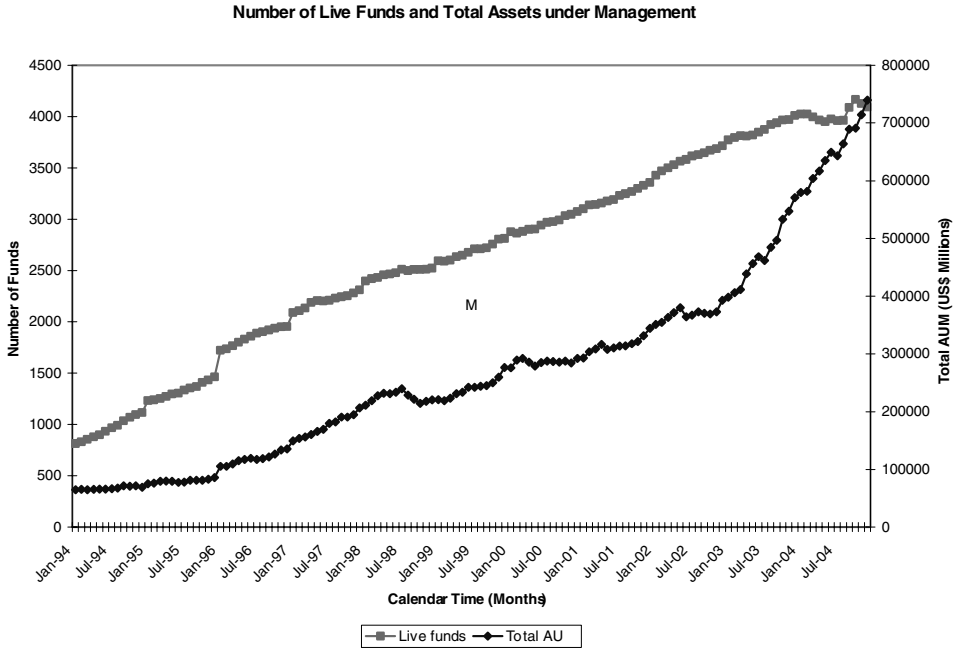**Number of Live Funds and Total Assets under Management**

Fig. 1.
Number of funds and total AUM

This figure plots the evolution of the number of hedge funds and the total AUM in our sample across time in months. The data are constructed by aggregating information from TASS, HFR, CISDM and MSCI for all funds that report AUM. The sample period begins in January 1994, and ends in December 2004.

million, this disguises a large reallocation away from Macro funds and Emerging Markets funds and towards Relative Value funds.

2.1.2. *Returns.* We compute value weighted excess return indices for each strategy. Value weighted excess returns are constructed as

$$r_{st}^{VW} = \sum_{i=1}^{N_s} \omega_{it}(r_{it} - r_{ft}) \tag{3}$$

where $\omega_{it} = A_{it-1}/(\sum_{i=1}^{N_s} A_{it-1})$ are AUM weights reconstructed each month, r_{it} is the (net of fee) return on fund i, a member of strategy s in month t, and r_{ft} is the return on the three-month US treasury bill in month t, obtained from Datastream. Table 2 shows that the annualised value weighted mean excess return lies between 2.8 and 8.4% depending on the strategy. The standard deviation of excess returns is also quite high, ranging between 2.6 and 16.4% on an annualised basis.

2.2. *Factor return data*

To calculate the systematic component of strategy index returns, we regress them on factors that have been shown to have explanatory power for hedge fund returns. These factors are drawn from the work of Fung and Hsieh (2004). They are: the excess return on the S&P 500 index (SNPMRF); a small minus big factor (SCMLC) constructed as the

Table 2

Summary statistics: returns and flows

This table presents summary statistics for hedge fund strategy returns and flows. For each strategy represented in a column, in rows we present the number of funds, the average life of a fund in years and the time series mean of total AUM across all funds in the strategy. This is followed by summary statistics for AUM weighted returns (in excess of the three-month T-bill rate) across all funds in each strategy, and total flows as a percentage of strategy AUM. The summary statistics in each case are: the annualised mean, median and standard deviation. The standard deviation is annualised by multiplying the square root of 12 under the assumption that monthly returns are iid. Strategy level flows are calculated by aggregating individual fund flows up to the level of strategies, and scaling the dollar flows by strategy-aggregated end-of-previous-month AUM.

	Security Selection	Macro	Relative Value	Directional Traders	Multi-Process	Emerging Markets	Fixed income	Other
N(Funds)	1711	796	970	1455	699	423	399	1157
Average life in years	4.0	4.4	4.4	5.1	4.7	4.4	4.3	4.7
Average AUM US $BN)	60.9	30.7	40.3	51.0	27.5	11.5	23.9	27.1
Excess returns								
μ	6.481	4.987	5.610	8.378	7.960	5.951	2.758	5.191
Median	6.077	4.824	6.225	5.893	8.883	15.127	4.960	4.301
σ	6.522	9.430	2.630	9.075	5.273	16.386	4.182	7.240
Flows								
μ	8.955	6.290	18.292	11.101	13.751	4.784	11.320	9.187
Median	7.800	3.919	18.756	10.767	12.282	5.347	9.823	8.547
σ	3.656	3.581	4.552	3.197	4.125	5.027	4.203	4.565

difference of the Wilshire small and large capitalisation stock indices; three portfolios of lookback straddle options on currencies (PTFSFX), commodities (PTFSCOM) and bonds (PTFSBD), which are constructed to replicate the maximum possible return to a trend-following strategy on the underlying asset, all in excess returns; the yield spread of the US ten-year treasury bond over the three-month T-bill, adjusted for the duration of the ten-year bond (BD10RET) and the change in the credit spread of the Moody's BAA bond over the ten-year treasury bond, also appropriately adjusted for duration (BAAMTSY).

3. Methodology

3.1. *Risk-adjusted performance evaluation*

We first estimate regressions of hedge fund strategy returns on the seven-factor model. Writing r_{st} for the value-weighted return index for strategy s at time t, we estimate:

$$r_{st} = \alpha_s + X_t \beta_s + \varepsilon_{st} \tag{4}$$

Where:

$$X_t = [SNPMRF_t \; SCMLC_t \; BD10RET_t \; BAAMTSY_t \; PTFSBD_t \; PTFSFX_t \; PTFSCOM_t]$$

A static factor analysis of the risk structure of hedge fund strategy returns is not appropriate if managers change their alpha-generating tactics over time. Therefore, we estimate equation (4) separately for three sub-periods, thus allowing for breakpoints in the relationship between strategy returns and the seven factors. The breakpoints are the same as those employed in Fung *et al*. (2006), and correspond to the collapse of Long-Term Capital Management in September 1998, and the peak of the technology bubble in March 2000. Finally, the validity of these pre-specified breakpoints is checked using the Chow (1960) test for structural breaks.

3.2. *Detecting capacity constraints*

We begin with a simple analysis of the capital flows experienced by the different strategies over the three sub-periods identified in the previous section. If capacity constraints are responsible for movements in alpha, we expect that high flows would precede reductions in alpha. This intuition is formalised by conditioning movements in alpha on flows into the various hedge fund strategies.

To construct a measure of hedge fund strategy alpha, we decompose strategy returns into systematic and absolute return components. If we ran a single regression for each strategy, we would get a static decomposition of the strategy's returns using a stable set of parameters (alpha and loadings), which do not exhibit any time variation. However, our goal is to explain time variation in alpha. This time variation is captured by running a rolling factor regression each month using a 12-month estimation window.[3]

In our analysis, we employ two different factor models: the full set of seven Fung-Hsieh factors, and a subset of these factors, the four non-options factors in the set (all except the three PTF lookback straddle option factors) to check the robustness of our results. We estimate:

$$r_{sw} = \alpha_{sw} + X_w \beta_{sw} + \varepsilon_{sw} \qquad (5)$$

Here, the w subscript represents the window over which the rolling regression is run. For example, the first such w represents the first 12 months of the available data, January 1994 to December 1994, and the second return window is February 1994 to January 1995. r_{sw} is the vector of the 12 return observations for strategy s for window w, and X_{sw} the matrix of factors over the same window. The regressions result in a series of estimated factor loadings β_{sw} corresponding to each value of w.

With each set of estimated factor loadings, we construct an out-of-sample quantitative measure of hedge fund ability, $alpha\_u_{st}$. For example, $alpha\_u_{s,Jan1995}$ for January 1995 is constructed by subtracting the product of the factor loadings estimated over the January 1994 to December 1994 window and the factor realisations in January 1995 from the return observation for January 1995.

We regress $alpha\_u_{st}$ on lagged strategy-specific capital flows and three conditioning variables. We control for size and using the total AUM contained within the strategy (using a logarithmic scale), additionally conditioning on the squared size to control for

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[3] We also use a 24-month estimation window and the results remain the same.

potential non-linearity in the relationship. We also follow the methodology in Getmansky (2004), and control for the number of funds within a strategy in the prior year, as a proxy for competition between funds in the strategy.

Fung *et al*. (2006) find that there are three distinct periods between 1994 and 2004 that are of importance to hedge funds. We therefore estimate separate regressions for each one of these periods. Finally, in our regressions, we use flows from month $t - 13$ to $t - 24$ to explain *alpha_u* for period t, thereby ensuring that there is no overlap between our *alpha_u* measures and our flow measures. Our final specification is:

$$alpha\_u_{st} = \kappa_s + \phi(f_{st-13} + .. + f_{st-24}) + \upsilon AUM_{st-12} + \lambda AUM^2_{st-12}$$
$$+ \chi\, Number_{st-12} + \zeta_{st}$$

$$(6)$$

In equation (6), we interpret a negative value of ϕ as evidence of capacity constraints in the strategy.

We also look for confirming evidence of capacity constraints in time variation in the structure of fees in the hedge fund industry. In the Berk and Green (2004) model, managers appropriate any remaining absolute return by raising their fees. As we cannot observe the fee structure each year for the funds in our data, we assume that the fee structure is the same for a fund throughout its life. We inspect the equal weighted average incentive fee and management fee for each year across all funds in each strategy.[4]

To get around the assumption that the fee structure for a fund remains the same throughout its life, we also employ another measure, the average fee across all funds born each year. If the fees reported in the database are only correct for the first year after a fund entered, and are not updated when changes occur, the data for funds born each year will provide a clearer picture.

3.3. *A note on estimation*

In our regressions, we use 12 monthly lags of flows.[5] There are lock-ups and other restrictions associated with hedge fund inflows and outflows. Therefore, in order to detect movements in alpha in response to flows, we require a sufficiently lengthy time period in our estimation. However, in order to avoid a huge number of right hand side variables in our specifications, we constrain the coefficients on lags of one to 12 months to be the same, summing these lags of the right hand side variables in our equations. Since the alphas are estimated using returns from period $t - 1$ to $t - 12$, the flows are lagged an additional 12 months, and summed over the following 12 month period, $t - 13$ to $t - 24$ in order to avoid using overlapping observations.

All our standard errors are computed using the method of Newey and West (1987). These standard errors are consistent in the presence of heteroskedastic and autocorrelated residuals. We use six lags of the dependent variables and residuals when computing the Newey-West correction in our factor regressions, and eighteen lags of the dependent variables and residuals when computing the Newey-West correction in our flow regressions. These are the maximum numbers of lags that we can use taking into account the number of observations and the sub-period breaks in our specifications.

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[4] Ackermann *et al*. (1999) find that incentive fees rarely change over a fund's life.

[5] We also do the analysis using six monthly lags, and the results are not greatly altered.

4. Results

4.1. *Alpha attenuation*

Table 3 presents the results from estimating regression (4) for the entire period as well as for the three sub-periods. The first row in each strategy shows estimates of equation (4) for the overall period, and the subsequent three rows show estimates of equation (4) for the three sub-periods. There are several features of note in the table. First, the regression R^2 statistics range between 33 and 78% across strategies over the entire sample period. Clearly, a large fraction of hedge fund returns can be explained using a linear factor model. While these R^2 statistics appear low in contrast to those observed in mutual funds (see Carhart, 1997), they are higher when we account for the change in exposures in different sample periods. Second, for five out of eight strategies, the alpha over the entire sample period is positive and statistically significant at the 5% level. These (net-of-fee) alphas range from 31 to 44 basis points per month in excess of the risk-free interest rate. Hedge funds, over the entire eleven-year period from 1994 to 2004, appear to have delivered returns in excess of their systematic risk exposures. Third, the systematic risk exposures are quite startling. For all but the 'Other' category of hedge funds, the exposure to the excess return on the market portfolio and to the small-minus-big factor is large, positive and statistically significant. An investor could take exposure to these factors far cheaper than by incurring the high management and incentive fees implicit in hedge fund investments. Exposure to the market could easily be achieved by buying an ETF, while exposure to SMB could be achieved by purchasing a small-cap mutual fund.[6]

The full-sample alpha and systematic risk exposures disguise interesting time-variation over the sample period. The three rows below the full-sample coefficient estimates present the risk exposures and alphas over the three time periods in the data, January 1994 to September 1998 (period I), October 1998 to March 2000 (period II) and April 2000 to December 2004 (period III).

First, the Chow structural break test strongly confirms the hypothesis that there are three distinct periods in the data, over which systematic risk exposures change greatly. Second, the estimated alpha is largest in period II. For example, in the Security Selection, Relative Value, Directional Traders and Multi-Process strategies, the estimated alpha in period II is greater than 80 basis points per month over the 18 month period. Third, alpha has fallen in the most recent sub-period in the data, relative to the period II alpha, as well as in contrast with period I alpha. For example, in Security Selection, Directional Traders, Fixed Income and Relative Value strategies, alpha is either far lower than that in period II, or not statistically significant. This finding echoes that found in Fung *et al*. (2006), who discover the same downtrend in alpha using data on funds-of-funds.

What has been responsible for this reduction in alpha? Table 4 presents a clue: we compute the average monthly flow as a percentage of last month's AUM at the strategy level for the three sub-periods. The table reveals that for every strategy, the flow means have been higher in the third sub-period than in the second sub-period, and in most cases, also substantially higher than those in the first sub-period. Capacity constraints may be the answer to the reduction in alpha witnessed in Table 3. For a more formal

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[6] Bams and Otten (2002) find that European small-cap funds exhibit positive post-fee alpha.

Table 3

Value weighted index: factor regressions

The left hand-side variable in each regression is the AUM weighted (net-of fee) excess return of hedge funds within a strategy. The right hand-side variables are: the excess return on the S&P500 index; the excess of small-cap over large-cap stock returns constructed using the Wilshire indices; excess returns on three portfolios of lookback straddle options on bonds, commodities and foreign exchange; the spread of Moody's BAA corporate bond returns index over the US 10-year maturity treasury bond, and finally the excess return of the US 10-year maturity treasury bond. For strategies in rows, in columns we present the intercept alpha, the slope coefficients on the seven factors and the R-squared statistic from the regression. Newey–West heteroskedasticity and autocorrelation consistent standard errors are reported (using 6 lags), two stars indicate significance at the 5% level, and one star indicates significance at the 10% level. The regression results are reported first for the overall sample and then for three sub-periods; January 1994 to September 1998 (period I), October 1998 to March 2000 (period II) and April 2000 to December 2004 (period III). The last two columns in the table present the results from testing for two sample breaks; between period I and period II and between period II and period III. Test for structural breaks are conducted using the Chow (1960) test, and is applied only to slope coefficients, not the constant term. The value of the F-statistic is shown in the table below and the critical value (alpha = 0.05) is 2.167.

Returns	α	Rm-Rf	SCMLC	PTF Bonds	PTF Com	PTF FX	BAA Spread	TCM 10 Y	R^2	I = II?	II = III?
All Funds											
Overall period	0.249**	0.259**	0.199**	−0.012	0.018	0.011**	0.177	0.168**	0.586		
Period I	0.125	0.382**	0.121**	−0.012	0.035**	0.012**	0.471*	0.022	0.675		
Period II	0.549**	0.269**	0.366**	0.063**	−0.007	−0.024*	0.753**	0.512**	0.884	2.869**	
Period III	0.147*	0.193**	0.151**	0.000	0.017**	0.012**	0.091	0.155**	0.769		22.834**
Security Selection											
Overall period	0.309**	0.303**	0.272**	−0.006	0.014	0.005	−0.038	0.098*	0.668		
Period I	0.288**	0.371**	0.293**	−0.006	0.025**	0.003	0.184	0.052	0.834		
Period II	0.916**	0.431**	0.435**	0.049**	−0.006	−0.003	0.881**	0.563**	0.891	3.114**	
Period III	0.027	0.209**	0.167**	0.000	0.024**	0.007	0.024	0.103	0.718		27.073**
Macro											
Overall period	0.087	0.266**	0.158**	−0.013	0.025	0.017	0.438	0.313**	0.335		
Period I	0.404	0.344**	−0.113	−0.029	0.043	0.023	0.775	0.143	0.424		
Period II	−0.835	0.311	0.537**	0.153**	0.001	−0.072*	1.327*	0.868**	0.725	3.168**	
Period III	−0.071	0.262**	0.183**	0.011**	0.014	0.025**	0.050	0.216**	0.718		14.376**
Relative Value											
Overall period	0.384**	0.045**	0.061**	−0.010	0.002	−0.001	0.160	0.023	0.331		

Table 3
Continued.

Returns	α	Rm-Rf	SCMLC	PTF Bonds	PTF Com	PTF FX	BAA Spread	TCM 10 Y	R^2	I = II?	II = III?
Period I	0.332**	0.091**	0.086**	−0.005	0.005	−0.005	0.574**	−0.013	0.613		
Period II	0.934**	−0.040	0.085**	0.029**	−0.001	−0.021**	0.312	0.322**	0.731	4.084**	5.457**
Period III	0.292**	0.040**	0.011	−0.003	−0.005	0.009*	0.139**	0.043***	0.390		
Directional Traders											
Overall period	0.332**	0.461**	0.393**	−0.004	0.020*	0.016**	−0.024	0.183**	0.777		
Period I	0.103	0.614**	0.363**	0.005	0.031**	0.011**	0.430*	0.035	0.871		
Period II	1.327**	0.449**	0.509**	0.017	−0.025**	0.013	0.467**	0.388**	0.928	2.232*	35.389**
Period III	0.077	0.359**	0.297**	0.007	0.033**	0.015*	0.029	0.227**	0.841		
Multi-Process											
Overall period	0.444**	0.176**	0.169**	−0.023**	0.007	0.001	0.276**	0.073*	0.600		
Period I	0.147	0.300**	0.153**	−0.014*	0.004	0.001	0.753**	−0.045	0.736		
Period II	0.826**	0.127**	0.172**	0.009	0.009	−0.027*	0.247	0.169	0.764	2.172**	6.473**
Period III	0.472**	0.114**	0.157**	−0.012**	0.007	0.005	0.273**	0.068**	0.619		
Emerging Markets											
Overall period	−0.092	0.561**	0.412**	−0.036	0.005	0.002	0.720**	0.090	0.481		
Period I	−1.279**	0.839**	0.246	−0.037	0.022	−0.002	1.429*	−0.447	0.530		
Period II	0.677	0.794**	0.651**	0.107	−0.019	−0.062**	1.260	−0.048	0.708	0.648	11.293**
Period III	0.379	0.512**	0.306**	0.000	0.042	0.003	0.470**	0.349**	0.696		
Fixed Income											
Overall period	0.039	0.121**	0.117**	−0.008**	0.005	0.000	0.349**	0.105**	0.530		
Period I	0.064	0.175**	0.062	−0.007	0.004	0.007	0.160	−0.080	0.489		
Period II	0.402**	0.018	0.122**	0.035**	0.002	−0.039**	1.107**	0.782**	0.898	5.485**	12.138**
Period III	0.030	0.127**	0.098**	−0.009	0.006	0.002	0.316**	0.137**	0.685		
Other											
Overall period	0.392**	0.031	−0.030	0.030**	0.039*	0.036**	0.089	0.221**	0.379		
Period I	0.338	0.074	−0.106	0.037**	0.105**	0.031**	−0.047	0.104	0.622		
Period II	−0.153	0.096	0.136	0.071**	−0.002	0.018	0.073	−0.064	0.367	3.175**	1.606
Period III	0.409**	0.044	0.028	0.005	0.003	0.032**	−0.135	0.236**	0.372		

Table 4

Flow Means in Sub-Samples

Table 4 presents the average monthly flow as a percentage of the previous month's assets under management at the strategy level for three sub-periods. The strategies are indicated in columns, the last column presents the mean percentage flow over all strategies, and periods are indicated in rows. The three sub-periods are January 1994 to September 1998 (period I), October 1998 to March 2000 (period II) and April 2000 to December 2004 (period III).

Flows	Security Selection	Macro	Relative Value	Directional Traders	Multi-Process	Emerging Markets	Fixed Income	Other	All
Period I	0.809	0.183	1.759	0.734	1.234	0.621	1.233	0.778	0.731
Period II	0.311	−0.029	0.817	0.719	−0.236	−1.183	0.152	0.210	0.263
Period III	0.821	1.040	1.513	1.182	1.495	0.676	0.903	0.928	1.086

analysis, we now turn to estimates of equation (6) to see whether we can detect the presence of capacity constraints in hedge fund strategies using hedge fund flows and rolling alpha estimates.

4.2. *Capacity constraints*

Table 5 presents the results of our capacity constraints regressions. First, the co-efficient on lagged flows, whenever it is statistically significant, is negative. This is true for four out of the eight strategies in the set, Relative Value, Emerging Markets, Fixed Income and Directional Traders strategy groups. The negative and statistically significant coefficients suggest the presence of capacity constraints in these strategies – when flows into the strategy have been previously high, the alpha in the subsequent period is likely to be lower. It seems intuitive that these constraints should bind for Relative Value, Fixed Income and Emerging Markets strategies, since these strategies rely on liquidity in their underlying markets (especially in the case of Emerging Markets). However, it seems less intuitive that these constraints bind for Directional Traders. One possible explanation is that there may be a lot of directional funds focusing on the same sector, creating a shortage of investment opportunities.

It is worth noting that unlike mutual funds, hedge funds may choose to close for new money. This makes it more difficult to find a relationship between flows and subsequent alpha, biasing the coefficient ϕ towards zero. Despite this bias, we are able to find evidence consistent with the presence of capacity constraints in hedge fund strategy flows and returns.

The coefficient magnitudes indicate that a 10% increase in annual flows into a strategy is associated with a decline of between 36 and 94 basis points in alpha in the subsequent month. Across all funds, the alpha over the entire period from 1994 to 2004 is estimated to be approximately 25 basis points per month from Table 3. This suggests that capacity constraints are economically important, not merely statistically significant. Taken at face value, our results suggest that if a strategy experiences steady asset growth for several years, the alpha could turn negative. In the factor regressions negative alphas are observed for some periods. Also, Aragon (2006) argues that when lock-ups are controlled for, the alpha may become negative. However, this is not a straightforward conclusion. Much would depend on how inflows are distributed across funds within a strategy, and the incidence of funds liquidating.

Table 5

Seven-factor model alpha conditional on flows

Table 5 presents coefficients from a time series regression of strategy level hedge fund alpha_u (estimated using the Fung-Hsieh seven-factor model) on lagged own-strategy flows, lagged log(AUM), the square of lagged log(AUM), and the lagged number of funds in each strategy in the previous year. The equation estimated is:

$$alpha\_u_{st} = \kappa_s + \phi(f_{st-13} + .. + f_{st-24}) + \upsilon AUM_{st-12} + \lambda AUM^2_{st-12} + \chi Number_{st-12} + \xi_{st}$$

Data are monthly and fixed period effects are included for period I (Jan 1997 to September 1998), period II (October 1998 to March 2000) and period III (April 2000 to December 2004). Strategies are in rows, and coefficients are in columns, followed by the R-squared statistic and the Durbin-Watson statistic for the residuals. Newey-West heteroskedasticity and autocorrelation consistent standard errors are employed (18 lags), two asterisks indicate significance at the 5% level, and one asterisk indicates significance at the 10% level.

	ϕ	υ	λ	χ	R^2	Durbin-Watson
Security Selection						
$alpha\_u_{st}$	0.050	9.456	−0.331	−0.006	0.041	2.10
Macro						
$alpha\_u_{st}$	0.093	4.132	−0.303	0.027	0.036	1.93
Relative Value						
$alpha\_u_{st}$	−0.036**	10.666**	−0.602**	0.007**	0.103	1.79
Directional Traders						
$alpha\_u_{st}$	−0.094*	48.817**	−2.207**	0.003*	0.091	2.27
Multi-Process						
$alpha\_u_{st}$	−0.014	−18.552	0.731	0.028	0.087	2.07
Emerging Markets						
$alpha\_u_{st}$	−0.083**	36.659	−1.801	−0.045**	0.124	2.17
Fixed Income						
$alpha\_u_{st}$	−0.058**	3.017	−0.171	0.026**	0.087	1.74
Other						
$alpha\_u_{st}$	0.009	28.284	−1.494	0.045**	0.072	2.35

In Table 5 the coefficients on size and size squared are consistent with the presence of diminishing returns to scale when significant (for two out of the eight strategies), consistent with the findings in Getmansky (2004). For a majority of the strategies, competition has a significant effect on performance. The effect is positive for Relative Value, Fixed Income, Directional Traders and Other strategies, suggesting that with higher competition, managers perform better. For Emerging Markets, however, competition has a negative effect on performance, which is in accordance with the analysis of Getmansky (2004).

Table 6 presents the results when *alpha_u* is estimated from a four-factor model rather than the seven-factor model. Our results concerning capacity constraints are robust for the Relative Value, Fixed Income and Directional Traders strategy groups, although they do not hold for the Emerging Markets strategy.

Table 6

Four-factor model alpha conditional on flows

Table 6 presents coefficients from a time series regression of strategy level hedge fund alpha_u (estimated using four factors, i.e. SNPMRF, SCMLC, BD10RET and BAAMTSY) on lagged own-strategy flows, lagged log(AUM), the square of lagged log(AUM), and the lagged number of funds in each strategy in the previous year. The equation estimated is:

$$alpha\_u_{st} = \kappa_s + \phi(f_{st-13} + .. + f_{st-24}) + \upsilon AUM_{st-12} + \lambda AUM^2_{st-12} + \chi Number_{st-12} + \xi_{st}$$

Data are monthly and fixed period effects are included for period I (Jan 1997 to September 1998), period II (October 1998 to March 2000) and period III (April 2000 to December 2004). Strategies are in rows, and coefficients are in columns, followed by the R-squared statistic and the Durbin-Watson statistic for the residuals. Newey-West heteroskedasticity and autocorrelation consistent standard errors are employed (18 lags), two asterisks indicate significance at the 5% level, and one asterisk indicates significance at the 10% level.

	ϕ	υ	λ	χ	R^2	Durbin-Watson
Security Selection						
$alpha\_u_{st}$	0.036	−0.238	0.051	−0.003	0.095	1.87
Macro						
$alpha\_u_{st}$	0.099	1.704	−0.176	0.026*	0.047	1.80
Relative Value						
$alpha\_u_{st}$	−0.013*	6.388	−0.412**	0.007**	0.173	1.63
Directional Traders						
$alpha\_u_{st}$	−0.077**	12.457	−0.533	0.000	0.156	2.07
Multi-Process						
$alpha\_u_{st}$	0.006	−29.073**	1.421**	−0.006	0.086	1.63
Emerging Markets						
$alpha\_u_{st}$	0.038	28.467	−1.693	−0.028*	0.102	1.90
Fixed Income						
$alpha\_u_{st}$	−0.026*	−4.519	0.229	0.008	0.055	2.00
Other						
$alpha\_u_{st}$	0.018	4.881	−0.334	0.027**	0.094	2.31

One potential concern is the possibility of time-trends in our measures.[7] Figure 2 plots the time-evolution of the value-weighted *alpha_u* and flows for all strategies. The figure suggests that there is no time-trend in *alpha_u* over the sample period. An augmented Dickey-Fuller test confirms that the time-series of *alpha_u* is stationary. Furthermore, there is no linear upward trend in flows, so there is no need to detrend the variable. Finally, we calculate the Durbin-Watson statistic in our regressions, and obtain values that are always close to two, indicating that the residuals are not autocorrelated.

An integral part of Berk and Green's argument is that high ability managers will benefit from increased fees. We investigate whether there is an increase in fees over our

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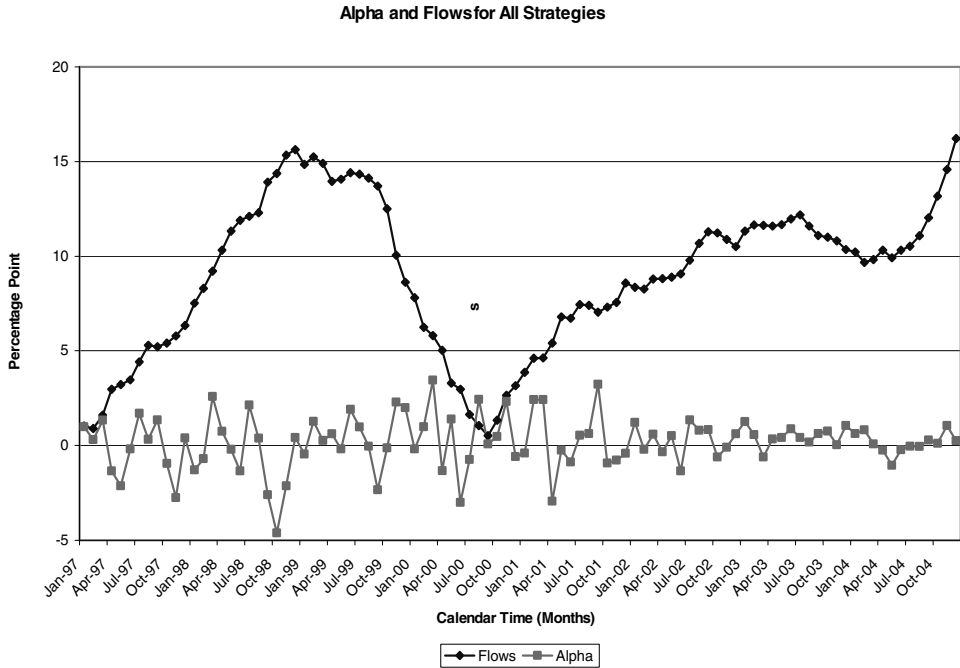[7] We thank an anonymous referee for pointing this out.

Fig. 2.
Alpha and flows for all strategies

This figure plots the evolution of the value-weighted non-systematic return and flows for all strategies in our sample across time measured in months. The data are constructed by aggregating information from TASS, HFR, CISDM and MSCI for funds that report AUM. The sample period begins in January 1997, and ends in December 2004.

sample period. Table 7 shows both AUM weighted and equally weighted incentive fees over the period from 1994 to 2004. The first half of the table reveals that there has been a near-monotonic increase in incentive fees over the period. Funds born in 2004 have an average incentive fee of 19.32%. This represents a substantial increase from 1994, when the comparable number is 15.80%. For all funds (not merely those born each year), on an equal-weighted basis, there has been an increase of approximately 152 basis points in incentive fees over the same period.

The value weighted measures in Table 7 show a similar trend, with an increase in incentive fees of approximately 200 basis points over the same ten-year period. Interestingly, there appears to be no similar trend in the management fee component. Taken together, the results in Table 7 provide additional evidence that the Berk and Green (2004) model is an accurate characterisation of the hedge fund industry.

5. Conclusion

This paper documents trends in the systematic risk exposures and alphas of hedge fund strategy index returns. The analysis reveals that alpha generation occurred primarily during the peak of the bull market period between October 1998 and March 2000. Furthermore, alpha in the hedge fund industry has severely declined in the most recent sub-period in the data, from April 2000 to December 2004.

Table 7

Performance fee structure

This table presents the evolution of performance fees over the sample period. The first two columns present the equally weighted performance fee in percent for all funds, and for all funds born each year, respectively, for the years indicated in rows. The last two columns present the same for the AUM weighted performance fee.

Year	Equally-weighted		Value-weighted	
	All funds	Funds born	All funds	Funds born
1994	17%	16%	17%	18%
1995	18%	18%	17%	17%
1996	18%	18%	18%	18%
1997	18%	17%	18%	17%
1998	19%	19%	18%	19%
1999	19%	19%	19%	20%
2000	19%	19%	19%	18%
2001	19%	19%	19%	19%
2002	19%	18%	19%	18%
2003	19%	19%	19%	17%
2004	19%	19%	19%	19%

We attempt to uncover whether capacity constraints in the hedge fund industry are responsible for the recent decline in the alpha of hedge fund strategies. We find that for four out of eight hedge fund strategies, capital inflows have statistically preceded negative movements in alpha.

Taken together, our results suggest that capacity constraints do exist at the level of hedge fund strategies, and are likely to be a concern for investors going forward.

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