NEW YORK UNIVERSITY
STERN SCHOOL OF BUSINESS
FINANCE DEPARTMENT

Working Paper Series, 1996

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FIN-96-18

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We thank Antoine Bergheim for providing the data. We thank Jian Zhang for data analysis.

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ABSTRACT

We examine the performance of the offshore hedge fund industry over the period 1989 through 1995 using a database that includes defunct as well as currently operating funds. The industry is characterized by high attrition rates of funds and little evidence of differential manager skill. We develop endogenous style categories for relative fund performance measures and find that repeat-winner and repeat-loser patterns in the data are largely due to style effects in that data.

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Abstract

We examine the performance of the off-shore hedge fund industry over the period 1989 through 1995 using a database that includes defunct as well as currently operating funds. The industry is characterized by high attrition rates of funds and little evidence of differential manager skill. We develop endogenous style categories for relative fund performance measures and find that repeat-winner and repeat-loser patterns in the data are largely due to style effects in that data

I. Introduction

A few highly successful managers over the past two decades have brought attention to the relatively small but interesting class of investment vehicles known as hedge funds. The largest of these, the multi-billion dollar Quantum Fund managed by George Soros, boasts compounded annual returns exceeding 30% for more than two decades. These superior returns have attracted both institutional and private investors. Hedge funds are similar to mutual funds in that they are actively managed investment portfolios holding positions in publically traded securities. Unlike mutual funds, they have broad flexibility in the types of securities they hold and the types of positions they take. Hedge funds can invest in international and domestic equities and debt, and the entire array of traded derivative securities. They may take undiversified positions, sell short and lever up the portfolio.

Perhaps the most interesting feature of hedge funds is that they are thought of as nearly pure "bets" on manager skill. Hedge funds were conceived as market-neutral investment vehicles that pursued strategies akin to "arbitrage in expectations."[1] Hedge fund managers seek to identify and exploit mispricing of securities in the market through the range of financial instruments available to them. Their product is superior performance, rather than tracking a passive benchmark. As a result, the compensation structure within the industry is highly performance-based. Compensation terms typically include a minimum investment, an annual fee of 1% - 2%, and an incentive fee of 5% to 25% of annual profits. The incentive fee may or may not be benchmarked against against an index such as the U.S. or U.K. treasury rate. This compensation structure may also include a "high water mark" provision that add past unmet thresholds to current ones. This asymmetric payoff to the manager has obvious implications for manager incentives: he or she is rewarded when the fund does well, and receives a baseline compensation when it does poorly, in effect, up to a quarter of an at-the-money call option on the portfolio every year, plus a fixed fee to cover operating expenses. Clearly, hedge fund operators are paid to take risks, and the further implication is that investors believe that the manager has the skill to offset the cost of the option. The downside to managing hedge funds is that they frequently disappear. The rate of attrition of hedge funds is relatively high and few funds -- and fund managers, survive more than three years.

In this paper we examine the performance of the universe of offshore hedge funds over the period 1989 though 1995. Most major hedge funds in the United States commonly have an offshore vehicle which is set up to invest alongside U.S. based limited partnerships, *pari passu*. The offshore structure provides Non-U.S. investors the opportunity to avoid taxation, and also allows U.S. based tax-exempt organizations some relief from taxation of unrelated business income tax. While the offshore hedge fund universe is smaller than the entire universe of U.S. hedge funds, it contains most of the major hedge funds and managers, and is thus fairly representative of the industry. Using a database of annual offshore fund returns which includes defunct funds as well as funds currently in operation, we investigate the basic issue of hedge fund performance.

A fundamental challenge is to identify a meaningful benchmark for the funds which are not intended to track a broad index. In addition, unlike mutual funds which typically advertise themselves as "Growth" or "Income" managers, hedge funds do not always have explicit categories, and thus are difficult to classify. While there is no broad consensus, the investment industry classifies hedge fund managers into groups such as "Opportunistic," "Event-Driven," "Futures & Currency Arbitrage" "Market-Timing," and ""Global/Macro" styles. As an alternative to these imprecise categories, we use a returns-based classification algorithm which groups managers into broadly similar styles according to how they performed, rather than what they claimed they did.

We find that the average annual return to offshore hedge funds was 13.26 % from 1989 through 1995, compared to the S&P 500 return of 16.47% over the same time period. This lower index return was accompanied by lower standard deviation (9.07 % compared to the S&P's 16.32%) and lower systematic risk with respect to the U.S. stock market. The equally-weighted offshore fund index had a S&P beta of .36 over the seven years -- reflecting the fact that, on average, hedge fund managers at least partially live up to their reputation as market-neutral risk-takers. Thus, while offshore hedge funds as a group have done relatively well on a risk-adjusted basis, as a group, they could not be characterized by the stellar returns reported by George Soros' Quantum fund.

A key question about hedge funds is whether there is evidence of manager skill. One class of hedge funds has developed explicitly to exploit supposed skill differential. Vehicles termed "Fund-of-funds" seek to allocate investor dollars into winning hedge funds, presumably by picking winners based upon past track records. We explore the profitability of picking winners via tests of relative and absolute performance persistence. We find no evidence of performance persistence in raw returns or risk-adjusted returns, even when we break funds down according to their returns-based style classifications. One possibility is that a few major managers have skill and the rest do not. To test for this we break performance into finer categories, explore whether fund size forecasts superior returns, and consider pre-fee performance. None of these yields evidence of relative performance persistence. In contrast to the mounting evidence of differential manager skill in the mutual fund industry, the hedge fund arena provides no evidence that past performance forecasts future performance.[2] This would seem to make it particularly difficult to expect a fund selector, commonly called a "fund-of-funds" to produce superior returns.

II. Data and Performance

I.1 Annual Hedge Fund Database with Defunct Funds

The U.S. Offshore Funds Directory is an annual guide to offshore hedge funds that has been published since 1990. It provides information on most of the offshore funds in operation at the beginning of the year of publication. In some cases, the publisher, Antoine Bernheim, has chosen to drop funds from the directory due to lack of data, or quality of data, and in some cases funds have asked to be removed from the directory. We hand-collected data from each volume of the directory for the 1990 through 1996 editions. We obtained the fund name, the date the fund started, net asset value of the fund, net asset value per share, dividends paid in the year, total return calculation (after fee),[3] the annual fee, the incentive fee, the name of the investment advisor(s) and the name of the principal(s). There are drawbacks and benefits to the use of annual data. The drawbacks are that covariances with benchmarks are poorly estimated, and thus risk-adjusted returns are calculated with a high level of uncertainty. In addition, we are unable to observe funds that disappear within the year, and thus survival biases are greater than would be expected with more frequently observed data. The benefit of annual returns is that it is impossible in most cases to calculate after-fee returns on a

monthly basis. Most funds have an incentive fee structure that is quarterly, and thus net returns are only valid on a quarterly basis. Thus, while annual or quarterly data would be useful, monthly data might be misleading. Finally, the Offshore Hedge Fund Directory, published annually, is one of the few sources of hedge fund data that contains defunct fund data. As we will show, this makes an enormous difference in *ex post* observed performance.

Table 1 reports the annual summary statistics about the data. The number of funds grew from 78 in 1989 to 399 at the end of 1995. The capitalization grew from $4.7 Billion to $40.3 Billion over the same time period. The equal-weighted mean return of 13.36% lagged the S&P 500 returns of 16.47% over the period, however the value-weighted return of 24.71% since 1990 beat the market. The value-weighted return largely represents the results of the biggest fund in the sample, Quantum Fund. Note that the rate of attrition for funds is about 20% per year. If funds disappear due to poor returns, then the average annual returns each year are upwardly biased. In other words, the returns we report each year are conditional upon surviving the entire year.[4] On average, hedge funds appear to have maintained a positive exposure to the stock market: up years for the S&P were also up years for the equal-weighted hedge fund index. Of course, averaging across fund managers masks a range of potential manager strategies, from high-leverage market bets to investment in zero-beta assets such as exchange rate instruments, to pure hedged bets on security mis-pricing.

II.2 Raw and Risk-Adjusted Performance

Table 2 reports the time-weighted arithmetic and geometric mean returns for equal-weighted and valued weighted portfolios of offshore hedge funds, as well as for equal-weighted portfolios subject to the selection conditions described above. The equal-weighted index underperformed the

S&P index in raw returns, while the value-weighted portfolio (dominated by the Quantum fund) outperformed the index in raw returns. This performance differential was matched by a risk differential: equal-weighted index was less volatile than the S&P 500, while the value-weighted index was more volatile. None-the-less, both equal-weighted and value-weighted indices had Sharpe ratios exceeding that of the S&P 500. The S&P 500 betas for the value-weighted and the equal-weighted indices are .43 and .33 respectively, and Jensen's alpha using arithmetic annual returns is .166 and .057 respectively. Both would seem to indicate positive risk-adjusted performance of the offshore hedge fund portfolio over the 1989-1995 period.

Were these positive risk-adjusted returns achievable? Only if one knew *ex ante* each year which funds would survive the year and which would not. Unfortunately, we are unable to follow the investment performance of dollars in funds that disappeared within each year. Unlike mutual funds, if hedge funds are merged into other funds we know neither the date nor the terms of the mergers. This limitation of the data imparts a "look-ahead" bias of unknown magnitude in the raw and risk-adjusted returns.

Survival conditioning is a particularly important issue in the evaluation of past performance of hedge funds. Table 2 reports statistics for funds subject to two types of conditioning. The first conditioning requires that a fund survive the entire seven year history. Notice that there are very few funds that meet this criterion. Despite the fact that the first hedge funds began in the 1950's, there are only 25 surviving of the original 108 offshore funds that were listed in 1990.[5] The second type of conditioning is the requirement that a fund be extant in the last period of the sample. This is the typical conditioning one would find in a commercially available database which is only designed to offer information about existing funds. The conditioning effects here are also strong. The sample of

funds extant in 1995 dominates the full sample, *ex post*, for each year of analysis. On average, the conditioning upon existence at the end of the period imparts a bias in raw returns of almost 3% per year. We calculate the bias as simply the average over all funds in the index, but it is more severe for individual funds in the sample. Brown, Goetzmann and Ross (1995) show that bias due to survival conditioning is positively related to variance. Thus, the higher the fund volatility, the greater is likely be the difference between *ex post* observed mean and *ex ante* expected return.

While it is useful to have information about defunct funds, collecting this data is not a control for survival biases. Notice the time-series of minimum returns for the survived sample in Table 2 and the whole sample in Table 1. In each case, there are much lower minimum returns for the set including defunct funds. Poor performers tend to drop from the sample. When they drop from sample during the year, we will not have a record of their poor performance in the final year of their life. This presents problems in the interpretation of returns and Sharpe ratios in Table 2. The performance reported in the table is probably an upper bound on the performance realized by an investor in offshore hedge funds during the period. An accurate estimate of performance requires intra-year data and/or the estimation of unconditional returns. Figure 1 compares the performance of the three different indices: an equal-weighted index using the full sample, an equal-weighted index using those that were extant in the last sample year, and an equal-weighted index of those funds that survived the entire seven year period. The S&P 500 is provided as a benchmark.

Funds regularly disappear from the sample, but so do fund managers. We estimate survival curves for funds and managers in our sample to determine the probability of long-term survival for each. Figure 2 shows these curves. For managers and for funds, the probability of a fund or manager surviving seven years is less than 20%.[6] It is interesting to note that the probability of a manager surviving seven years is greater that the survival probability of a fund, although this differential is not statistically significant.[7] This suggests that managers tend to shut down funds more often than funds fire managers. The compensation contract for funds is a powerful motivator to shut down under-performers. High-water mark provisions imply that a losing fund is far out of the money, and thus the manager would be better off rolling the investors into another fund. While high water mark provisions mean that past losses are carried over from quarter to quarter, they do not guarantee that the manager will not shut down the fund. In fact the fund is likely to be far out of the money before a manager risks giving up the implicit call represented by the compensation contract in exchange for an unknown probability of investors accepting an alternative fund investment.

In sum, the analysis of a database that includes defunct as well as surviving funds suggests that the survival conditioning has important effects upon the *ex post* observed historical performance. Investors using past track records will find that historical returns may be expected to exceed *ex ante* expected future returns. In addition, investors who buy past performance are also likely to be buying future volatility. High water mark provisions imply a strong correlation between poor intra-year performance and fund closure. This is turn is likely to increase the survival bias in *ex-post* observed data.

III. Individual Fund Style and Performance

Due to the nature of hedge fund market-neutral positions, the S&P 500 is not necessarily the appropriate benchmark for fund performance. By the same token, industry classifications such as "Opportunistic" provide little guidance for appropriate risk adjustment. To address the problem of benchmarking fund performance, we use a method developed in Brown and Goetzmann (1996). The

Generalized Stylistic Classification [GSC] algorithm is a generalization of a class of widely-used clustering algorithms that sort multi-variate observations into discrete classes, conditional upon a given number of classes.[8] This approach differs from the style analysis used by Sharpe (1995) and Ibbotson (1996) to control for styles effects in repeat-winner analysis. Both authors use a set of passively managed funds as regressors in a constrained regression limiting the coefficients to sum to one and the weights to be non-negative. Given the limited degrees of freedom for the typical hedge fund in our sample, such control was infeasible.

In the case of the annual hedge fund data, the GSC algorithm uses fund return histories as multi-variate observations: for each fund, the return each year is a variable. Thus, the GSC algorithm groups funds according to their proximity in past return space. The appealing intuition of this method is that funds that moved together in the past are identified as a group. As a consequence, funds that pursued similar strategies such as correlated market timers, or situational managers who bet on the same situations will be grouped within the same style. We condition upon funds having three or more years of history for inclusion in the clustering procedure. This, of course, imparts a possible upward bias in the mean returns of each style group, however clustering on any lower dimension might be expected to yield poor results.[9]

III.1 Manager Styles

The GSC algorithm identifies nine fund categories. Table 3 reports the summary statistics about indices of style categories formed by equal-weighting all funds in each style each year. Note that the requirement that fund survive three years is likely to induce a positive bias in the performance due to survival conditioning, however this table is reported to indicate how the different styles behave relative to the market. Also note that the market betas range from more than 1.3 to less than -.4, suggesting that some hedge fund manager styles encompass aggressive market exposure, while others appear to be un-hedged short-sellers. Category 8, for instance, had an average annual return of 16.9%, with a beta of 1.4 over the 1989 - 1995 period yielding a slightly positive alpha, and a Sharpe ratio less than that of the S&P (.7). GSC style 6 is evidently the short-seller category, with a beta of less than -.4, a slightly positive alpha, and a Sharpe ratio of .186. In fact, Table 5 indicates that returns of funds in this style classification are negatively correlated with many popular benchmark portfolio returns. In total, two fund styles have negative market exposures, and seven have positive exposures. George Soros is virtually in a category by himself. Three of the four Soros-managed offshore funds in the sample, including the Quantum Fund, belong to category 9 -- the best performing style. Category 9 includes 8 funds in total. The fourth Soros fund belongs to category 8. We find some evidence that managers appear to group in the same style categories, suggesting that skill might be style-specific. Using these categories allows us to estimate "style-alphas." We benchmark fund performance by the equal-weighted returns across all members of the fund.

IV. Performance Persistence

A number of recent studies have found evidence of differential skill among money manager in the mutual fund industry (see, for instance, Grinblatt and Titman, 1988 and 1992, Hendricks, Patel and Zeckhauser, 1993, Goetzmann and Ibbotson, 1994, Brown and Goetzmann, 1995, Malkiel, 1995, Carhart, 1996, and Elton, Gruber, Das and Blake, 1996, Edwards and Park, 1995). The hedge fund arena would seem to be the ideal place to look for evidence of manager skill, because hedge fund managers do not seek to track a benchmark, but rather seek to exploit mispricing. Thus it is striking to find absolutely no evidence of differential skill among offshore hedge fund managers. In the

following sections, we show the various forms of tests applied to examine performance persistence.

IV.1 Raw Fund Returns

The simplest persistence test is a year-by-year cross-sectional regression of past returns on current returns. Figure 3 shows six scatter plots with OLS regression lines indicating the regression slopes for each of these tests. Three years have positive slopes and three years have negative slopes. Slopes for the last four years in the sample are significant at standard confidence levels, suggesting that there is persistence in year to year returns. Results reported in Table 5 show that winners follow winners in 1991-92 and 1992-93. However, the pattern reverses in 1993-94 and 1994-95. Winners lose. This suggests that an unidentified factor, such as a "styles effect" may be driving the systematic positive, then negative dependence. The figures are useful to examine, because they show no evidence of a few consistently outstanding funds.

Perhaps a few large funds, like Soros' Quantum fund, are consistently successful. In fact, we might expect the largest funds to out-perform the smaller funds if investors had any ability to choose superior funds, *ex ante*.[10] To test this proposition, we examined the relationship between fund size and future return. Table 6 suggests that size is a poor forecaster of future returns. Log NAV is used to forecast whether a fund was a winner or loser in the following period -- size apparently is unrelated to superior relative performance, with the possible exception of the period 1991-92[11]. This result follows whether we examine regressions of subsequent period performance against size, or whether we look at the performance of large funds relative to small funds where "large" and "small" are defined relative to median NAV. Big funds do no better than small funds in the current sample. Perhaps managers repeat, rather than funds. Creating manager returns by equal-weighting all funds for which they were named as advisor yields results almost identical to those reported in Table 6. There is no evidence that managers, rather than funds, repeat.

Perhaps performance persists on a pre-fee basis, but that managers are able to extract their full value-added through fees. To test this proposition, we estimated pre-fee returns to funds. These results are reported in Table 7. The results are not at all sensitive to the exclusion of fees from the performance comparison. This results suggests that performance fees are unrelated to future performance. High performance fees are characteristic of hedge funds. Yet, results reported in Table 8 suggest that higher-fee funds perform no better than lower-fee funds.

IV.2 Style Adjusted Returns

The scatter plots of Figure 3 give the style designation of repeat performers. Not surprisingly, funds we were unable to classify (category "0") because they were in the database for less than three years congregate in the Loser-Loser (lower left quadrant) and Winner-Loser (lower right quadrant) in each of the figures. Poor performance is predictive of failure (or at least to non-reporting of results in our data source). However, there does appear to be some congregation of particular styles in each of the other quadrants. This observation is consistent with the view that manager skill is style-specific. As a particular example, the Soros funds (marked by an "S" in the scatter plots) appear predominantly in the upper right quadrants that are associated with the Winner-Winner category.

The first panel reported in Figure 4 appears to support this position. Classifications 1 and 7 show little evidence of persistent success, and more of their share of managers who consistently lose relative to the median hedge fund managers in each year. On the other hand, Classifications 2, 5 and 9 appear to show persistent success, and little evidence of consistent losses. In fact, Classification 9 had no managers who lost relative to the median manager two years in a row. To what extent can

we attribute this performance to managers within each group who were particularly successful, or to what measure can we ascribe this success to the fact that they specialized in sectors of the market which happened to do well *ex post*?

In Table 9, we re-define winners as hedge-fund managers whose return exceeded the style classification benchmark in any given year. In this Table we find that there is almost no persistence evident in style adjusted alphas. The already weak evidence of persistence of returns is further weakened when we account for these.style benchmarks. This evidence is also summarized in the second panel of Figure 4. Now there is no evidence of skill defined as a persistent ability of managers in a particular style classification to earn returns in excess of their style benchmark.

Brown and Goetzmann [1995] and Ibbotson [1996] suggest that the persistence and reversals in sequential manager returns might be due to style effects that are not completely captured by standard stylistic classifications. If a subset of managers are oriented to small firms, they will all do well when small firms do well, and poorly when this sector of the market underperforms. Such manager returns will persist when small firms do well, and reverse when they do poorly. The same argument would apply to other style classifications. In Table 10 we report regression results from a cross-section regression of sequential size benchmark returns, and compare these results with the corresponding regression of sequential manager returns and manager style alphas. The style benchmark returns show the same evidence of persistence and reversals that manager raw returns do. Extracting the style benchmarks from returns eliminates all evidence of persistence and reversals. Therefore, we conclude that the evidence of persistence, such as it is, is more a matter of high *ex post* returns in particular sectors, than of the particular skill of managers in being able to select securities and investment strategies within these sectors of the markets.

V. Conclusion

We examine the performance of the off-shore hedge fund industry over the period 1989 through 1995 using a database that includes defunct as well as currently operating funds. The industry is characterized by high attrition rates of funds, poor before-fee and after-fee performance relative to the S&P 500 over the same period. There is reasonably little public information available about the investment strategies and specialization of these managers. However, it is possible to apply a returns-based procedure to classify managers and determine some basic correlates of performance and to devise relevant benchmarks for comparison. Neither on the basis of raw returns nor on the basis of style adjusted benchmarks is there much evidence of differential manager skill.

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Table 1: Annual Summary Statistics For Offshore Hedge Funds

Year	Number of Funds	Number of Advisors	Number of dropped or defunct funds	Number of new funds	Total Capitalization in U.S. Dollars	Arithmetic Equal-weighted Mean Return	Arithmetic Value-weighted Mean Return	Median Return	Cross-sectional Standard Error	Maximum Return	Minimum Return	Average Annual Fee	Average Incentive Fee
1988-89	78	98			4,721,256,000	18.08	NA	20.30	2.04	57.3	-33.6	1.744	19.755
1989-90	108	137	17	47	6,153,900,000	4.36	16.37	3.80	2.04	85.9	-30.7	1.647	19.519
1990-91	142	155	19	53	11,466,358,100	17.13	36.95	15.90	2.45	94.6	-53.4	1.786	19.548
1991-92	176	210	27	61	18,876,303,000	11.98	36.99	10.70	1.26	92.4	-24.4	1.809	19.344
1992-93	265	316	23	112	39,064,117,965	24.59	41.94	22.15	1.54	155.6	-30.3	1.621	19.096
1993-94	313	363	58	108	35,419,454,000	-1.60	-7.03	-2.00	0.89	105.1	-49.8	1.644	18.753
1994-95	399	450	65	152	40,345,412,365	18.32	23.05	14.70	1.43	296.9	-40.3	1.551	18.497

Notes: Fund returns are reported after fee. Average annual incentive fee is typically paid as percentage of positive returns each year, although in some instances it is paid as a percentage of returns in excess of the treasury rate.

Table 2: Survival Conditioning Effects

Summary statistics for funds that survived the whole period

Year	N	MEAN	MED	STDERR	MAX	MIN
1989	19	23.681	22.2	2.623	49.5	5.6
1990	25	2.045	2.7	3.031	29.23	-26.5
1991	27	24.133	22.7	3.791	56.8	-16.2
1992	29	13.005	9.8	2.877	68.448	-15.7
1993	29	18.139	17.9	3.578	61.923	-30.3
1994	29	-0.925	0.4	2.082	31.2	-24.5
1995	28	18.056	19.25	2.847	40.5	-22.7

Summary statistics for funds that existed at the last period

Year	N	MEAN	MED	STDERR	MAX	MIN
1989	19	23.681	22.2	2.623	49.5	5.6
1990	37	5.963	3.9	2.833	47.5	-26.5
1991	55	21.905	18.8	2.876	75.4	-36.1
1992	104	16.083	13.9	1.592	92.4	-15.7
1993	159	26.467	23.6	2.012	155.6	-30.3
1994	231	-0.293	-0.8	1.031	105.1	-49.8
1995	368	18.323	14.7	1.429	296.9	-40.3

Survival Effects on Estimates of Mean Returns

	Time-Weighted Mean Return For Value-Weighted Index	Time-Weighted Mean Return For Equal-Weighted Index	Time-Weighted Mean Return For Funds Surviving Entire Period	Time-Weighted Mean Return For Funds Extant at Last Period	Time-Weighted Mean Return For the S&P 500 Index
Arithmetic	24.71	13.27	14.02	16.02	16.47
Geometric	23.48	12.94	13.63	15.65	15
Std. dev.	16.72	8.40	9.23	9.06	15.11
Sharpe Ratio	1.19	0.94	0.94	1.17	0.73

Table 3: Performance of Offshore Hedge Funds by GSC Categories

	1	2	3	4	5	6	7	8	9
Average Return	0.04	0.129	0.06	0.119	0.184	0.03	0.07	0.169	0.315
Standard Deviation	0.08	0.151	0.135	0.21	0.203	0.154	0.125	0.26	0.231
Beta	0.239	0.842	0.35	0.982	0.75	-0.48	-0.16	1.393	0.395
Alpha	0.01	0.03	0.03	0.01	0.101	0.08	0.09	0.01	0.272
Sharpe ratio	0.534	0.844	0.475	0.566	0.91	0.196	0.58	0.649	1.363

Notes: Average return and Standard Deviation refers to the sample statistics of annual return for each GSC style formed by equal-weighting all funds in the category, over the period 1988-1995. Beta refers to the market regression coefficient of the fund style index over the period, alpha is the market residual, and the Sharpe ratio is the return in excess of the annual return on 30 day Treasury Bills relative to the standard deviation of this quantity. Funds were required to have three years of returns to be included in the stylistic classification algorithm. This may induce positive bias in performance due to survival conditioning.

Table 4: Correlates of GSC Style Returns

	1	2	3	4	5	6	7	8	9
S&P500 Total Return	0.497	0.882	0.410	0.741	0.586	-0.495	-0.200	0.850	0.270
U.S. LT Gvt TR	0.453	0.826	0.666	0.509	0.690	-0.659	0.298	0.826	0.630
Gold Total Return	0.298	0.218	0.539	-0.102	0.095	-0.065	0.192	-0.161	0.354
Refco CTA	-0.340	-0.110	0.133	-0.416	0.311	-0.366	0.893	0.195	0.315
MSCI EAFE TR	0.763	0.670	0.563	0.583	0.337	-0.117	-0.415	0.308	0.244
S&P/BARRA Growth TR	0.366	0.742	0.199	0.683	0.512	-0.433	-0.243	0.820	0.088
S&P/BARRA Value TR	0.606	0.952	0.620	0.732	0.606	-0.521	-0.123	0.794	0.465
MAR Advisor Mkt Cap Wtd	-0.016	-0.128	0.291	-0.253	0.264	-0.340	0.801	0.183	0.538
MAR Fund/Pool Mkt Cap Wtd	-0.090	0.070	0.384	-0.254	0.466	-0.223	0.697	0.135	0.398
SB Non-US$ Bnd (Wtd)	0.557	0.114	0.293	0.130	0.036	-0.667	0.467	0.520	0.525
GS Commodity Cap App	-0.563	-0.088	-0.363	-0.499	-0.414	-0.068	0.088	-0.271	-0.506
MSCI Europe TR	0.469	0.873	0.692	0.483	0.659	-0.175	-0.176	0.393	0.285
MSCI Pacific TR	0.783	0.532	0.462	0.553	0.198	-0.030	-0.500	0.204	0.168
MSCI World TR	0.785	0.839	0.567	0.734	0.456	-0.296	-0.399	0.573	0.283

Notes: The elements in this Table give the correlation coefficients between returns on GSC style portfolios and returns on a variety of benchmark portfolios for the period 1989-95

Table 5: Repeat-Winner Test Results

Year	Coefficient	t-stat	R^2	WW	LW	WL	LL	log-odds	Z
1989-90	0.158	1.01	0.024	10	10	11	12	0.087	0.142
1990-91	-0.206	-1.4	0.028	13	21	21	14	-0.885	-1.793
1991-92	0.223	3.21	0.113	25	16	16	26	0.932	2.066
1992-93	0.422	3.62	0.085	45	24	25	50	1.322	3.755
1993-94	-0.121	-2.88	0.043	29	65	65	30	-1.58	-5.033
1994-95	-0.603	-5.91	0.133	49	66	65	51	-0.54	-2.034
Total				171	202	203	183	-0.27	-1.857

Notes: Winners and Losers are defined relative to the median manager return in each comparison year. WW denotes successive winners, LW denotes Losers in the first year and Winners in the second comparison year, WL reverses this order, and LL denotes successive Losers. Log-odds are defined as ln((WW*LL)/(LW*WL)) which is asymptotically distributed as Normal, with mean zero and standard error given as the square root of the sum of the reciprocals of these cell counts. The Z score refers to the log-odds expressed relative to this measure of standard error. The Coefficient, t-stat and R^2 columns refer to the regression coefficient, t-value and R^2 regressing manager returns in one year against manager returns in the previous year where returns are reported for the manager in both years.

Table 6: Size and Relative Performance

Year	Coefficient	t-stat	R^2	Large Winners	Small Winners	Large Losers	Small Losers	log-odds	Z
1989-90	-2.2	-1.53	0.04	12	13	17	15	-0.205	-0.384
1990-91	1.57	0.83	0.01	23	20	20	22	0.235	0.541
1991-92	2.89	3.21	0.09	32	26	27	28	0.244	0.646
1992-93	2.71	2.53	0.04	52	27	31	43	0.983	2.939
1993-94	-1.3	-2.27	0.02	40	50	66	48	-0.542	-1.903
1994-95	-0.9	-0.9	0	68	65	65	46	-0.301	-1.16
Total				227	201	226	202	0.009	0.068

Notes: Winners and Losers are defined relative to the median manager return in each comparison year. Defining large funds as funds with NAV at or greater than the median fund size, and small funds as those that had NAV less than that of the median fund, large funds in one year that won in the second year are denoted Large Winners. Small funds that subsequently won are denoted Small Winners. Large Losers and Small Losers are defined similarly.. Log-odds and Z scores are defined as in the previous Table, and the Coefficient, t-stat and R^2 columns refer to the regression coefficient, t-value and R^2 regressing manager returns in one year against ln(NAV) recorded in the previous year.

Table 7: Pre-fee Fund Persistence

Year	Coefficient	t-stat	R^2	WW	LW	WL	LL	log-odds	Z
1989-90	0.22	0.89	0.033	9	5	4	7	1.147	1.368
1990-91	-0.27	-1.667	0.059	13	12	15	6	-0.836	-1.333
1991-92	0.21	2.509	0.094	21	11	13	18	0.972	1.867
1992-93	0.48	3.627	0.118	36	14	17	33	1.608	3.705
1993-94	-0.1	-2.061	0.03	24	45	49	21	-1.476	-4.064
1994-95	-0.56	-5.324	0.116	61	60	58	40	-0.355	-1.294
Total				164	147	156	125	-0.112	-0.678

Notes: Numbers in this Table correspond to numbers reported in Table 5, except that returns are measured on a pre-fee basis

Table 8: Fees and Relative Performance

Year	Coefficient	t-stat	R^2	High Fee Winners	Low Fee Winners	High Fee Losers	Low Fee Losers	log-odds	Z
1989-90	2.31	1.932	0.09	4	15	1	19	1.623	1.387
1990-91	-6.48	-0.617	0.01	3	26	5	24	-0.591	-0.754
1991-92	-1.25	-1.874	0.04	4	40	10	34	-1.079	-1.696
1992-93	0.19	0.224	0	8	45	9	44	-0.14	-0.265
1993-94	-0.02	-0.051	0	8	70	12	67	-0.449	-0.922
1994-95	-0.39	-0.683	0	8	90	18	83	-0.892	-1.976
Total				35	286	55	271	-0.506	-2.178

Notes: Winners and Losers are defined relative to the median manager return in each comparison year. Defining high fee funds as funds with base fees at or greater than the median fee, and low fee funds as those that had fees less than that of the median fund, high fee funds in one year that won in the second year are denoted High Fee Winners. Low fee funds that subsequently won are denoted Low Fee Winners. High Fee Losers and Low Fee Losers are defined similarly.. Log-odds and Z scores are defined as in the previous Table, and the Coefficient, t-stat and R^2 columns refer to the regression coefficient, t-value and R^2 regressing manager returns in one year against fees recorded in the previous year.

Table 9: Style Adjusted Alpha Repeat Winners

Year	Coefficient	t-stat	R^2	WW	LW	WL	LL	log-odds	Z
1989-90	0.59	1.54	0.08	9	7	4	10	1.168	1.502
1990-91	-0.04	-0.19	0	15	11	12	13	0.39	0.692
1991-92	0.09	0.63	0.01	18	14	15	17	0.376	0.749
1992-93	-0.17	-1.28	0.02	29	19	21	31	0.812	1.988
1993-94	-0.07	-1.07	0.01	23	29	32	28	-0.365	-0.96
1994-95	0	0.01	0	20	23	24	29	0.049	0.12
Total				114	103	108	128	0.271	1.439

Notes: Winners and Losers are defined relative to a style adjusted alpha of zero in each comparison year. WW denotes successive winners, LW denotes Losers in the first year and Winners in the second comparison year, WL reverses this order, and LL denotes successive Losers. Log-odds are defined as $\ln((WW*LL)/(LW*WL))$ which is asymptotically distributed as Normal, with mean zero and standard error given as the square root of the sum of the reciprocals of these cell counts. The Z score refers to the log-odds expressed relative to this measure of standard error. The Coefficient, t-stat and R^2 columns refer to the regression coefficient, t-value and R^2 regressing style adjusted alphas in one year against corresponding alphas in the previous year where alphas are reported for the manager in both years.

Table 10: Regression of Sequential Annual Returns, Benchmarks and Alphas

	Raw Returns			Style Benchmarks			Style alphas		
Year	Coefficient	t-stat	R^2	Coefficient	t-stat	R^2	Coefficient	t-stat	R^2
1989-90	-0.08	-0.18	0.005	0.158	1.01	0.024	0.59	1.54	0.08
1990-91	-0.32	-0.79	0.083	-0.206	-1.4	0.028	-0.04	-0.19	0
1991-92	0.39	1.32	0.2	0.223	3.21	0.113	0.09	0.63	0.01
1992-93	0.87	4.82	0.768	0.422	3.62	0.085	-0.17	-1.28	0.02
1993-94	-0.31	-1.69	0.289	-0.121	-2.88	0.043	-0.07	-1.07	0.01
1994-95	-1.28	-1.49	0.242	-0.603	-5.91	0.133	0	0.01	0

Notes: Raw Returns regressions correspond to those reported in Table 5. Style alphas regressions correspond to those reported in Table 9. Style Benchmark regressions correspond to a cross sectional regression of annual style benchmark returns on the corresponding returns for the previous year.

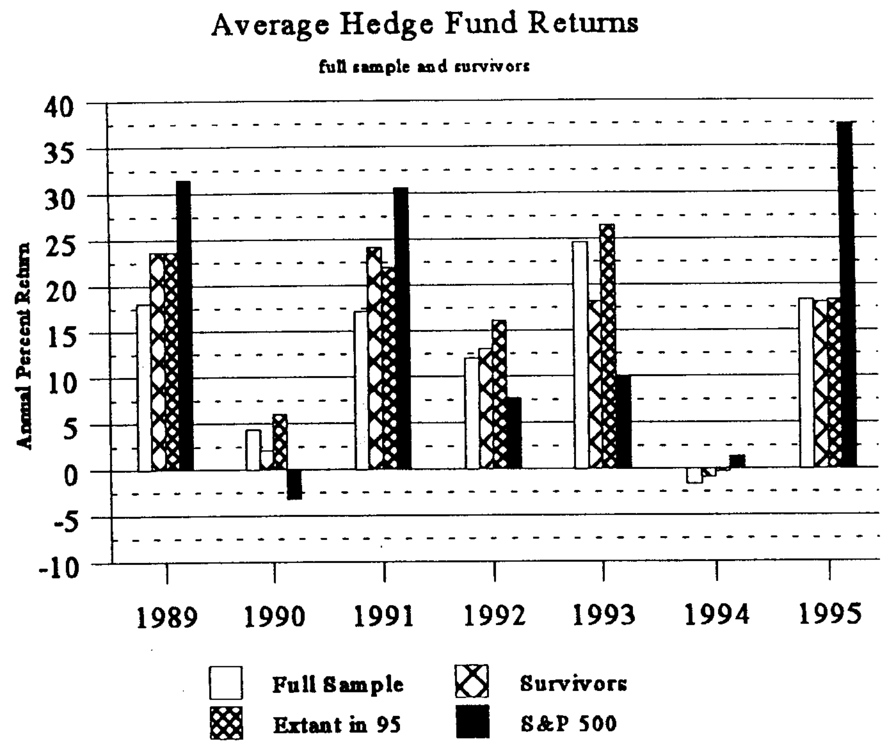
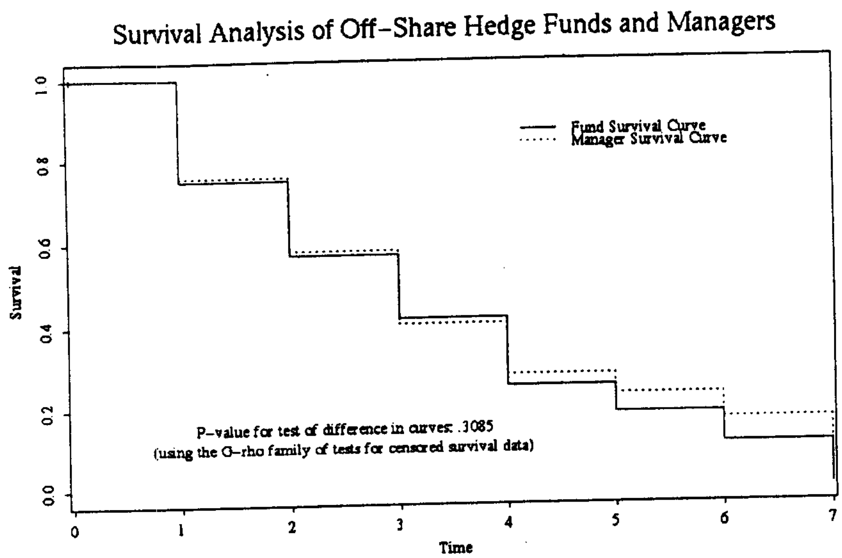


Figure 1

Figure 2



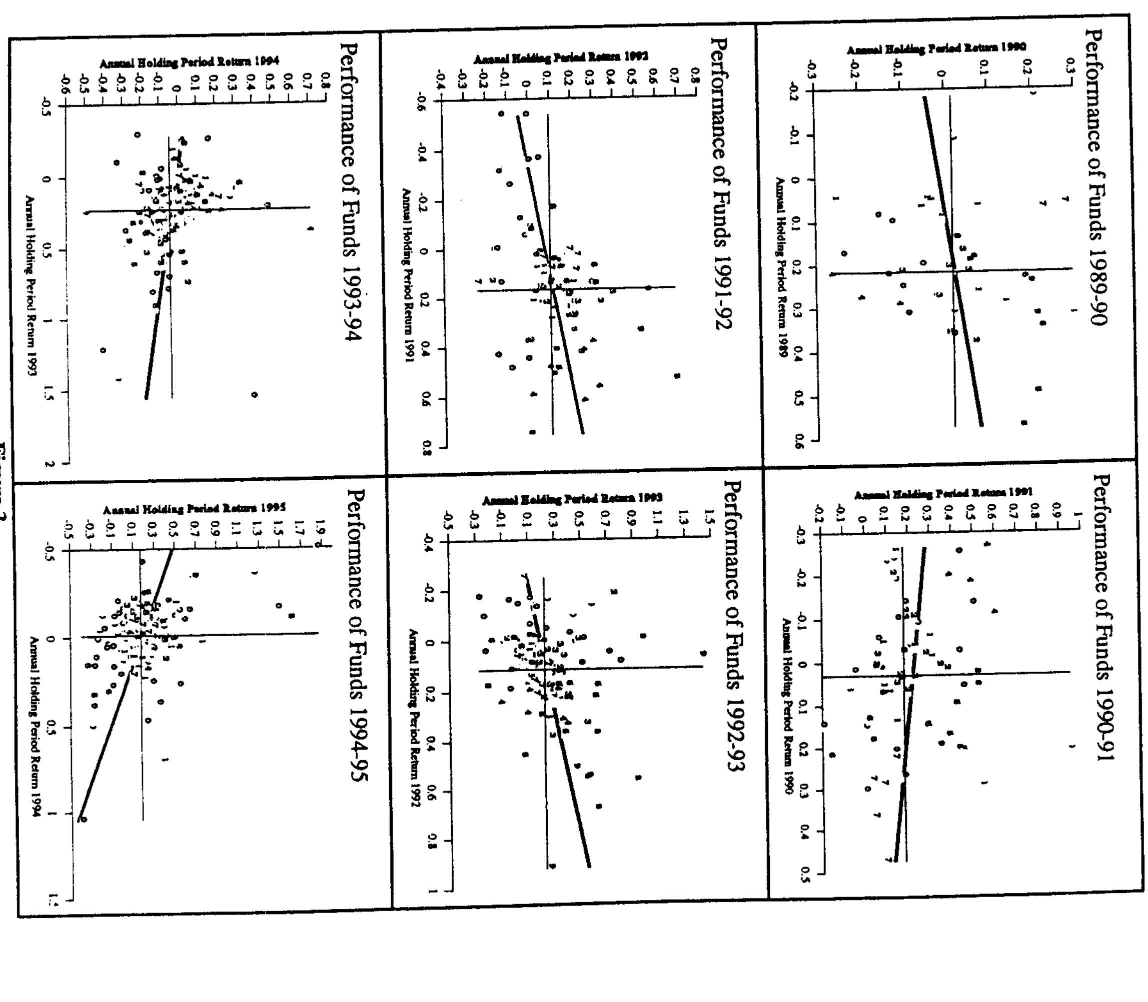


Figure 3

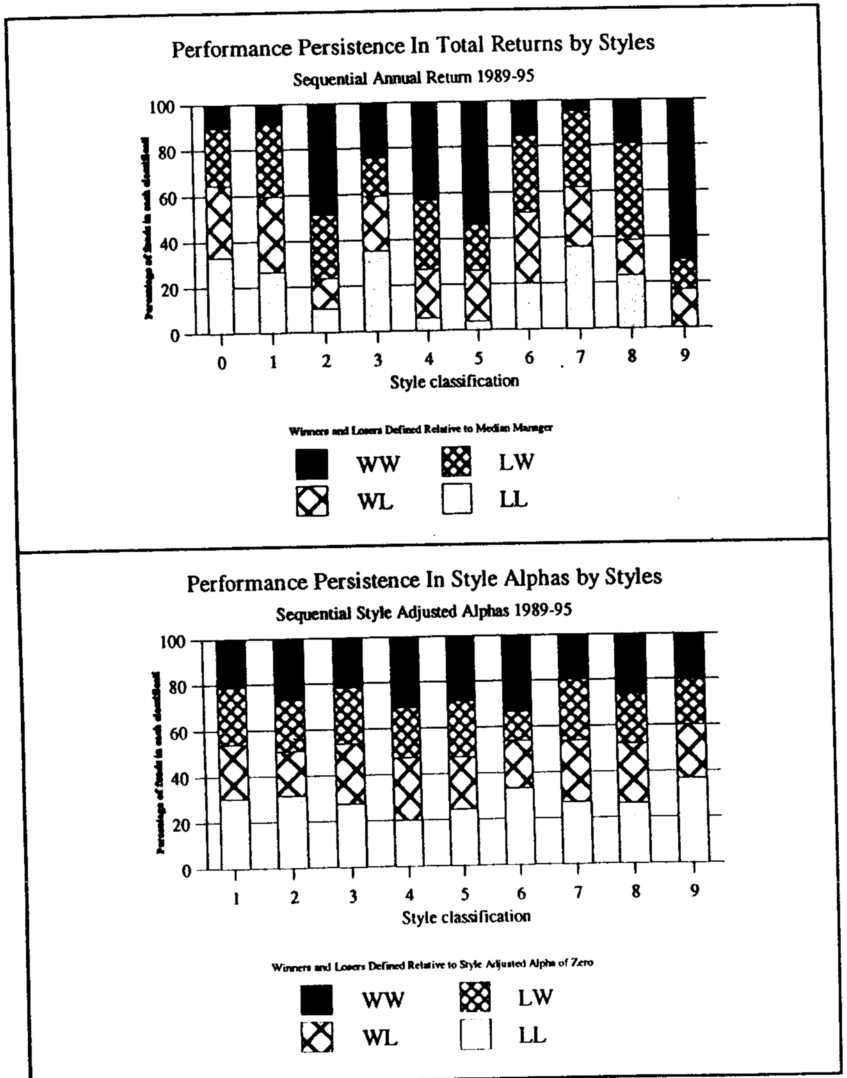


Figure 4

Notes

1.Caldwell, Ted, 1995, "Introduction: The Model of Superior Performance," in Lederman, Jess and Klein, eds. *Hedge Funds*, New York, Irwin Professional Publishing.

2.For evidence of performance persistence in mutual funds, see Grinblatt and Titman, 1988 and 1992, Hendricks, Patel and Zeckhauser, 1993, Goetzmann and Ibbotson, 1994, Brown and Goetzmann, 1995, Malkiel, 1995, Carhart, 1996, and Elton, Gruber, Das and Blake, 1996.

3.Including dividends assuming re-investment on the date of payment.

4. We are currently working on methods for estimating the unconditional mean returns each year.

5. Funds and returns for 1989 are taken from the 1990 volume. Thus we have only limited information about fund returns, since this group includes funds that began within the year 1989. This explains the number of funds, 19, for which we have return dat in the first year. Funds without return data are not included in the return calculation. This is, of course, another possible source of conditioning for return calculations. Funds occasionally fail to report annual results to the Offshore Hedge Fund Directory. It is unlikely that strong positive returns would go unreported.

6.The analysis assumes right-censored data

7.We examined the significance of the difference in survival curves for funds vs. managers using the G-rho family of tests. We found the P-value for the null of equality of curves to be 31%.

8. We address the question of the appropriate number of styles via a procedure akin the AIC criterion for time-series analysis, we decrease the number of classifications from large to small, and stop when the degrees of freedom adjusted explained sum of squares changes dramatically. See Brown and Goetzmann (1996) for details.

9. In Brown and Goetzmann (1996) we found that 24 months of mutual fund data were sufficient to endogenously generate styles that one could reject as due to chance, and within which fund membership persisted to a significant degree. Goetzmann and Wachter (1995) similar clustering methods were applied to a time-series of eight annual returns in metropolitan housing markets, and random associations among markets were rejected. While the robustness of groups using annual data depends upon the cross-sectional characteristics of the data, short time-series data is not necessarily problematic for application of clustering methods. The intuition for this is that we are not estimating second moments.

10. Gruber (1996) and Zheng (1996) find evidence that new money flows into mutual funds forecast positive relative performance. Niether Brown and Goetzmann (1995) nor Zheng (1996) find evidence that capital-weighted indices of funds outperform equal-weighted indices of funds or a risk-adjusted benchmark. Thus, while "hot money" may be smart in mutual funds, money alone is not.

11.Regressions of returns on previous period logged and unlogged fund NAV yielded similar results