Original Article

The performance persistence of equity long/short hedge funds

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PRACTICAL APPLICATIONS Investors often allocate capital to specific hedge funds on the basis of the funds' track records, which implies that they expect some persistence in the funds' performance. In this context, large-scale studies analysing the performance persistence of hedge funds provide important insights on the expected success probability of such investment behaviour. From a practical point of view, the methodological approach chosen in this paper, which consists of repeatedly forming a portfolio based on observable information and then tracking it for the next period, represents a trading strategy that is conceptually easily implementable. However, lockup and redemption periods impede the implementation of such trading strategies. Consequently, an annual frequency of reforming the portfolios makes the strategies more feasible with respect to transaction costs and lockup periods, especially for funds of funds which often face more favourable conditions than individual investors.

ABSTRACT **This paper examines the persistence of raw and risk-adjusted returns for equity long/short hedge funds using the portfolio approach of Hendricks et al Only limited evidence of persistence is found for raw returns. Funds with the highest raw returns last year continue to outperform over the subsequent year, although not significantly, while there is no persistence in returns beyond 1 year. In contrast, we find performance persistence based on risk-adjusted return measures such as the Sharpe Ratio and in particular an alpha from a multifactor model. Funds with the highest risk-adjusted performance continue to significantly outperform in the following year. The persistence does not last longer than 1 year except for the worst performers. Funds with significant**

risk-adjusted returns show less exposure to the market and have high raw returns and low volatility. These results are robust to adjustments for stale prices and sub-period analysis.

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INTRODUCTION

Studies examining the persistence of hedge fund performance vary greatly in their conclusions owing to different methodologies, databases, investigation periods and performance measures.[1] This paper does not consider various approaches to clarify the picture, but, instead, focuses on a particularly flexible one. Every period, hedge funds are sorted into portfolios according to characteristics in the last period, and the portfolios are then tracked for the next period. After the tracking period, the sorting is repeated. This approach has been used in the mutual fund literature by Hendricks *et al*[2] and Carhart,[3] among others, and has several advantages. First, portfolio betas may be more stable than betas of individual funds because time-varying betas can offset each other on the portfolio level. This is particularly relevant for hedge funds: as they have fewer restrictions on borrowing, shorting, the use of derivatives and so on, they typically follow highly opportunistic strategies that lead to time-varying risk exposures. Secondly, beta measurement is more precise owing to diversification of idiosyncratic risk and long time series for the portfolio returns. Finally, suppose there is only a very small autocorrelation in fund returns. Given the high return variance, it is difficult to detect this correlation by looking at individual funds. As in the case of momentum strategies, we have to buy a portfolio of last period's winners, not just one fund, to find persistence.

This paper extends the current literature in several directions. First, by restricting the sample to equity long/short hedge funds, the number of (risk) factors can be greatly reduced while the explanatory power of the factor models is maximised. In fact, the widely used factor models generally exhibit a very high explanatory power for the equity long/short strategy – in absolute terms as well as relative to other strategies.[4–6] Given only monthly observations of hedge fund returns, a low number of parameters is desirable, as it renders inference more robust owing to conservation of degrees of freedom and mitigation of multicollinearity problems. Secondly, and related, prior studies generally pool different hedge fund strategies and analyse them jointly.[7,8] This approach can be susceptible to the problem of model misspecification: alpha portfolios may contain funds of the same strategy because neglected risk factors for this strategy show up as alpha. Hence, results focusing on one particular strategy may be more robust. Thirdly, possible nonlinear market exposure is accounted for by including option returns as risk factors. Agarwal and Naik[5,9] find that the systematic risk exposure of hedge funds can include option-based strategies. No such exposure has been found, however, for equity long/short hedge funds on the aggregate level.[5,6] Individual funds, on the other hand, may well show nonlinear market exposure and it may be important to account for nonlinearities when evaluating performance. Finally, we consider

sorts based on regression coefficients. In order to examine the nature of return persistence, it is important to know whether the momentum loading of funds persists and whether these funds outperform.

The analysis in this paper is interesting for several reasons. First, repeatedly forming a portfolio based on observable information and tracking it for the next period represents a trading strategy that is conceptually easily implementable. Practically, however, the typical investor faces lockup periods prohibiting him from exploiting these strategies. Still, they may be interesting for funds of funds that are able to waive lockup periods.[7] Secondly, performance persistence may be more important for hedge funds than for mutual funds owing to their higher attrition rates.[10] By looking at funds' transition probabilities of moving from one portfolio to another and by tracking a portfolio over not only 1 year, but over several years, one gets a clearer picture of the persistence.

After a short overview of the literature, the factor model is introduced and applied on the index level. Next, we present the data set and sample selection procedures. The discussion of the results is the main part and focuses on the persistence of raw returns as well as risk-adjusted performance measures. In order to mitigate spurious results, various robustness tests are performed before a conclusion is reached.

LITERATURE OVERVIEW

Although the performance of mutual funds has been extensively studied in the academic literature, there is a growing body of literature on hedge fund performance persistence. Even more than in the mutual fund literature, there is a large variance in the conclusions drawn by the studies examining the persistence of hedge fund performance. A recent overview of the literature on persistence of hedge fund performance is provided by Eling.[1] He shows that these studies differ widely in methodology, database, investigation period, performance measures and conclusions. To obtain a clearer picture, at a minimum, persistence of raw returns and risk-adjusted returns has to be distinguished.

Harri and Brorsen[11] report short-term persistence of 3–4 months, with the biggest effect in the first month based on simple regressions of returns on lagged returns. Over the quarterly horizon (portfolios are reformed quarterly), Boyson and Cooper[7] obtain a monthly return spread of more than 1.14 per cent using a pool of all hedge fund strategies. For the annual horizon, Baquero *et al*[12] find an insignificant spread of an annual 4.9 per cent and an annual spread of 11.5 per cent at the quarterly horizon. Clearly, the smaller the horizon, the stronger the persistence in performance as measured by raw returns. Overall, the literature is in favour of short-term persistence over horizons of up to 6 months, but is mixed with respect to annual persistence.[1]

The evidence on the persistence of risk-adjusted performance is particularly mixed as there are various methods and performance measures. Amenc *et al*[13] show that different models strongly disagree on the risk-adjusted performance of hedge funds because there is a large dispersion of alphas across models. Still, they generally tend to rank the funds in a similar way. Common factor choices for hedge fund (risk) factors are the three Fama–French factors; Carhart's[3] momentum factor; commodity, bond and volatility factors; and factors representing returns to technical trading strategies such as the Fung and Hsieh[14] primitive trend-following

factors[15] or the Agarwal and Naik[5] option factors.[16] Persistence can be examined using simple autoregressions, Spearman's rank correlation, and contingency tables as the most prominent methods. The evidence is mixed, however. For example, while Agarwal and Naik[9] find no persistence beyond the quarterly horizon, Kosowski *et al*[17] and Edwards and Caglayan[18] report annual persistence.

One prominent method introduced by Hendricks *et al*[2] and used in the mutual fund literature[3,19] consists of repeatedly forming portfolios of funds based on lagged characteristics and tracking them for the next period. Boyson and Cooper[7] sort on characteristics other than returns or alpha for hedge funds. Although they find no persistence when sorting on past performance alone, considering manager tenure as well leads to the finding of quarterly persistence. The persistence is mainly concentrated in the poor performers. Considering all hedge fund strategies jointly, however, they use up to 20 factors to end up with an R^2 of around 0.75. Capocci[8] sorts portfolios based on additional properties of the return distribution. He finds that portfolios of funds with the highest lagged Sharpe Ratio deliver positive alpha. The same holds for funds with the lowest volatility and, to a lesser extent, funds with low market beta. Sorting portfolios based on higher moments of the return distribution or lagged alpha, however, does not detect a significant alpha spread between top and bottom portfolios.

MODEL

Portfolio formation

Our approach to form portfolios is based on Hendricks *et al.*[2] On 1 January of each year, portfolios of hedge funds are formed based on specific characteristics during the formation period and are tracked for the subsequent year. The portfolios are then reformed. The portfolios are numbered from 1 to 10, where portfolio 1 contains the 10 per cent of funds with, for example, the highest lagged returns, and portfolio 10 contains the 10 per cent of funds with the lowest lagged returns. The weights of the funds in the portfolios are equal and readjusted whenever a fund disappears during the tracking year. To provide additional information, the deciles 1 and 10 are further subdivided into terciles, indicated by capital letters A, B and C. Also, a portfolio that is long in portfolio 1 and short in portfolio 10 (long 1A and short 10C) is analysed.

In this paper, the tracking horizon is 1 year for two reasons. First, quarterly or even monthly reforming of a portfolio would be difficult to implement as a trading strategy owing to lock-in periods. Secondly, because of illiquidity or managed prices, hedge fund managers have leeway in marking their positions for month-end reporting. This flexibility can be used to artificially reduce return volatility or market beta. The resulting returns spuriously show short-term autocorrelation known as 'stale prices',[20,21] which shows up as short-term persistence in returns. Frequent portfolio reforming may therefore just take up this autocorrelation. Focusing on the 1-year horizon alleviates this problem. In the robustness section, we also explicitly control for 'stale prices'.

Factor benchmark and alpha

The investment flexibility of hedge funds makes performance assessment more difficult. Style-drift and exposure to a wide range of asset

classes, possibly even nonlinear, must be accounted for. Given the limited amount of data, this task can only be dealt with on a rudimentary level. Possible nonlinearities are accounted for by including option-based strategies, using a rolling-window approach, and performing an analysis of sub-periods, which may mitigate the effects of style-drift.

As hedge funds typically employ dynamic strategies, the static CAPM is an inappropriate benchmark. For equity long/short funds, Fung and Hsieh[6] show that the overall market and the spread between large and small cap stocks account for over 80 per cent of return variation on the index level. Combined with a momentum factor, they find it unlikely to have omitted an important risk factor. Hence, equity long/short returns can be well captured using the Fama–French factors and a momentum factor. Agarwal and Naik[5] and Fung and Hsieh[14] show that hedge funds can have exposure to option returns on standard asset classes. Specifically, Agarwal and Naik[5] use returns of rolling-over put and call options on the S&P 500 index. Hence, we extend our factor model by including Agarwal and Naik's out-of-the-money call and out-of-the-money put option factors on the S&P 500 index. This can be represented with the following model that extends Carhart's[3] four-factor model.

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i &+ \beta_{i,RMRF} RMRF_t + \beta_{i,SMB} SMB_t \\ &+ \beta_{i,HML} HML_t + \beta_{i,MOM} MOM_t \\ &+ \beta_{i,OTMC} OTMC_t + \beta_{i,OTMP} OTMP_t \end{aligned}$$

The left-hand side is the excess return of portfolio i in month t. *RMRF* is the excess return on the market portfolio, proxied by the value-weighted return on all NYSE, AMEX and NASDAQ stocks minus the 1-month Treasury Bill rate. *SMB* is the excess return of the factor-mimicking portfolio for size, *HML* is the excess return of the factor-mimicking portfolio for book-to-market equity and *MOM* is the excess return of the factor-mimicking portfolio for 1-year momentum.[22] Finally, *OTMC* and *OTMP* are the out-of-the-money call and out-of-the-money put option factors on the S&P 500 index as used in Agarwal and Naik.[5,23]

The option factors turned out to be hardly significant in all of our regression specifications, did not increase the model's explanatory power and showed no specific pattern. In addition, their inclusion only had minor effects on the other coefficients for all the regressions reported. As the option factors are currently available only until January 2005 and would therefore shorten our sample period by 11 months, we excluded them from our factor models, as reported in the tables (with the exception of Table 1). All regressions on the portfolio as well as the single fund level, however, turned out to be robust to the inclusion of these option factors.

In unreported tests, we also attempt to control for market timing abilities by including a squared term of the market factor[24] or option-like factors as in Henriksson and Merton.[25] These additional factors are, however, hardly ever statistically significant and do not affect the other coefficients in our factor model. Therefore, we do not report results based on the alternative risk models in the tables.

Performance at the index level

The CISDM equity long/short index shows the median performance of equity long/short hedge funds reporting to the CISDM database. The hedge fund index is not investable, however, and may suffer from various biases, which are

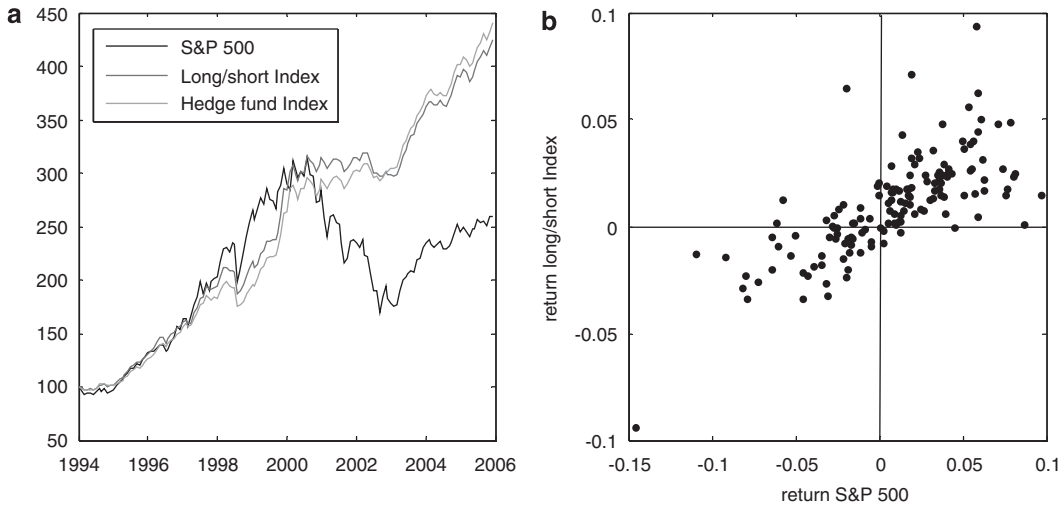

Figure 1: (a) Performance of equity long/short strategy
The figure shows the S&P 500 and the CISDM long/short index and overall hedge fund index. All indices are normalised to 100 in the beginning of 1994.
(b) Equity long/short versus market returns.
The scatterplot shows the S&P 500 monthly return versus the CISDM long/short index return from 1994 until the end of 2005.

discussed below. Figure 1(a) compares its performance to the S&P 500. Obviously, the average equity long/short hedge fund shows strong market exposure until the year 2000, where it was smart to reduce the exposure. After the market downturn, the hedge funds again took advantage of rising stock prices. The performance of the long/short strategy matches very closely the performance of the average hedge fund across all strategies. This reflects the dominance of equity long/short hedge funds in the database, as other strategies performed much differently. Overall, the strategy clearly outperformed the market benchmark and had a long exposure to the market, as Figure 1(b) shows.

As argued above, the market is an inappropriate benchmark. Applying the factor model above shows that the index outperforms the more demanding multifactor benchmark. Panel A of Table 1 displays a monthly outperformance of 0.33 per cent. The factor loadings show significant exposure to the market, small stocks and last year's winner stocks. The exposure to value stocks is very small, as the marginally significant *HML* loading shows. These coefficients are consistent with Agarwal and Naik[5] and Fung and Hsieh.[6] The option factors are not able to capture any nonlinear market exposure, however. For comparison reasons, we re-estimate the same regression equation without the option factors. In fact, the results in Panel B of Table 1 show that the alpha and all factor loadings remain basically unchanged.[26]

DATA

Data on hedge fund returns were obtained from CISDM. The CISDM database contains returns for both surviving and defunct funds. Two

Table 1: Long/short index of CISDM database

	Alpha	*RMRF*	*HML*	*SMB*	*MOM*	*OTMC* ($\times 10^{-3}$)	*OTMP* ($\times 10^{-3}$)	$R^2_{adj.}$
Panel A: Including option-based factors								
Long/short index	0.33★★★	0.41★★★	0.06★	0.20★★★	0.07★★★	0.57	−0.94	0.82
Panel B: Excluding option-based factors								
Long/short index	0.34★★★	0.45★★★	0.06★	0.20★★★	0.07★★★	—	—	0.82

The excess returns of the equity long/short index from CISDM are regressed on the following factors over the period 1994–2005: *RMRF*, *HML* and *SMB* are the Fama–French[27]factors for the market proxy and factor-mimicking portfolios for book-to-market and size. MOM is a factor-mimicking portfolio for 1-year momentum. The first regression (Panel A) additionally includes two option-based factors, *OTMC* and *OTMP*, which are the out-of-the-money call and out-of-the-money put option factors on the S&P 500 index as used in Agarwal and Naik.[5]Newey–West[28] corrected *t*-values are represented by ★★★, ★ for 99%, 90% significance, respectively.

thousand two hundred and ten (901 for equity long/short) non-active funds are included out of a total of 4390 (1693 for equity long/short), excluding funds of funds. It is well known that fund databases suffer from various biases. This paper tries to mitigate a survivorship bias by including defunct funds in the analysis and by excluding data before 1994, when CISDM did not keep track of defunct funds.[29] For the resulting sample period from January 1994 to December 2005, a total of 1649 funds are classified as equity long/short funds. To mitigate the backfill bias, we use the standard procedure and delete the first 12 observations for each fund in the database.

CISDM includes monthly net-of-fee returns, assets under management, inception date, self-declared strategy, and more fund characteristics. Many characteristics are only rarely provided by the funds. The following list shows the selection criteria for the funds that are included in our final sample.

— Funds that appear multiple times were deleted. This was considered to be the case when funds had the same name and company ID. In addition, only the funds in USD were kept in the sample, resulting in the deletion of 85 funds.
— The period considered ranges from January 1994 until December 2005, resulting in 144 monthly observations. Only data from 1994 onwards are used, as CISDM had not started to keep track of either life or defunct funds before this. This results in the exclusion of 35 funds that have no observations during this period.
— To correct for the backfill bias, the first 12 observations of every fund are excluded. In addition, at least 12 observations are needed to sort the funds in the formation period. Hence, 423 funds with less than 2 years of data for the time period considered are deleted.

This results in a sample of 1150 funds. The time span is long enough to cover more than a business cycle and contains a variety of different

market environments: the bull market in the 1990s, the bear market from 2000 until 2003, and events such as the Asian crisis in 1997 and the collapse of LTCM in the wake of the Russian financial crisis in 1998.

EMPIRICAL RESULTS

Persistence of raw returns

An important question for hedge fund investors is that of whether past performance is indicative of future performance. So far, private and institutional investors clearly allocate more funds to past good performers. For mutual funds, Sirri and Tufano[30] find large inflows into last year's winners and large withdrawals from last year's worst performers. For hedge funds, Fung *et al*[31] document that alpha funds attract more capital inflows than beta-only funds and Agarwal *et al*[32] find that ' … funds with persistently good (bad) performance attract larger (smaller) inflows compared to those that show no persistence' (p. 2). Hence, in the presence of performance persistence, an investor may be able to realise superior performance.

Table 2 reports the performance persistence in raw returns based on 10 portfolios of funds that are sorted according to their lagged 1-year raw returns. The table reveals significant variation in mean returns. The mean returns tend to decrease in portfolio rank, resulting in an annualised spread of 4.78 per cent between portfolios 1 and 10. This spread is not significant, however, with a monthly mean of 0.39 per cent and standard deviation of 0.50 per cent. Moreover, the mean returns do not decrease monotonically. Because of the tendency for winners to remain winners, there seems to be weak evidence for 'hot hands'[2] in equity long/short hedge funds for the 1-year horizon. This value is smaller than Carhart's[3] annual 8 per cent spread for mutual funds and Capocci *et al*'s[10] 7.6 per cent obtained by pooling all hedge fund strategies.

Our results indicate that, assuming normality for simplicity, the probability that last year's winners exhibit a positive return over the next month is $P(X>0) = 1-\phi((0-0.92)/0.46\sqrt{T}) = 0.57$, where T is equal to 132. Moreover, the extreme portfolios have a higher return variance than portfolios in the inner deciles, possibly because of higher leverage or generally riskier strategies. This is consistent with Herzberg and Mozes,[33] who find that the funds with the highest past returns have the highest volatility.

When we alternatively adjust the raw returns for risk by using an alpha from a Carhart[3] four-factor model, the spread in performance disappears. In fact, portfolio 10 has a (insignificantly) higher alpha than portfolio 1. It is interesting to see that the significant alphas are located in the inner deciles (portfolios 3, 4, 6 and 9), whereas the portfolios of last year's winners do not outperform against the benchmark model. Instead, they show more return variation, which eventually places them in more extreme deciles. The alpha portfolios, however, show relatively little return variance. This indicates that, on average, alpha funds are characterised not only by high returns, but also by low volatility.[34] In fact, portfolios 3, 4 and 6 have the three highest Sharpe Ratios, and portfolio 9 the sixth highest Sharpe Ratio (not reported).

Looking at the factor loadings, the coefficient on *RMRF* is around 0.5 and shows no specific pattern. With respect to *HML*, there seems to be a tendency of last year's winners to be more growth-oriented, whereas other deciles have

Table 2: Portfolios of hedge funds formed on lagged 1-year raw returns

Portfolio	*Excess return (s.d.)*	*Alpha*	*RMRF*	*HML*	*SMB*	*MOM*	$R^2_{adj.}$
1A	0.95 (0.65)	0.10	0.73***	−0.45***	0.48***	0.54***	0.64
1B	0.69 (0.50)	−0.08	0.73***	−0.09	0.34***	0.25**	0.49
1C	1.09 (0.38)	0.58**	0.52***	−0.11	0.47***	0.23***	0.66
1 (high)	0.92 (0.46)	0.22	0.68***	−0.20*	0.44***	0.35***	0.69
2	0.93 (0.34)	0.29*	0.63***	−0.06	0.32***	0.20***	0.82
3	0.99 (0.24)	0.43***	0.50***	0.08	0.23***	0.14***	0.75
4	0.93 (0.23)	0.41***	0.42***	0.02	0.24***	0.13***	0.83
5	0.76 (0.24)	0.20	0.50***	0.14**	0.21***	0.07**	0.72
6	0.78 (0.21)	0.33***	0.47***	0.09***	0.18***	0.05**	0.74
7	0.59 (0.23)	0.10	0.45***	0.16***	0.25***	−0.02	0.81
8	0.50 (0.22)	0.17	0.37***	0.06	0.18***	−0.07***	0.76
9	0.60 (0.23)	0.31**	0.42***	0.14**	0.18***	−0.14***	0.68
10 (low)	0.53 (0.36)	0.26	0.61***	0.10	0.21***	−0.26***	0.63
10A	0.62 (0.35)	0.31	0.62***	0.17	0.18**	−0.23***	0.55
10B	0.56 (0.30)	0.30	0.51***	0.15	0.18***	−0.14**	0.38
10C	0.38 (0.54)	0.16	0.70***	−0.01	0.25***	−0.42***	0.56
1–10	0.39 (0.50)	−0.04	0.07	−0.30	0.23*	0.60***	0.48
1A–10C	0.56 (0.72)	−0.06	0.04	−0.43	0.23	0.96***	0.51

Each January from 1995 until 2005, decile portfolios based on lagged 1-year returns are formed. Portfolio 1 contains funds with the highest 1-year returns, portfolio 10 funds with the lowest 1-year returns. Portfolios 1 and 10 are further divided into terciles. The portfolios are equally weighted and the weights are readjusted whenever a fund is delisted. *RMRF*, *HML* and *SMB* are the Fama–French[27] factors for market proxy and factor-mimicking portfolios for book-to-market and size. *MOM* is a factor-mimicking portfolio for 1-year momentum. Newey–West[28] corrected *t*-values are represented by ***, **, * for 99%, 95%, 90% significance, respectively.

more of a value focus, though coefficients are generally small and insignificant. More revealing is the pattern of the *SMB* coefficients. All portfolios have positive exposure, which confirms earlier findings that long/short funds are small cap-oriented.[5,6] Last year's winners are strongly exposed to small cap stocks. This exposure decreases in the decile numbering but remains positive. The spread between portfolios 1 and 10 is marginally significant and explains some of the spread in raw returns: some funds continue to earn higher returns because they are more exposed to small stocks and capture their premium. The largest spread, however, is in the momentum loadings. There is a monotonic decrease from 0.35 for portfolio 1 to −0.26 for portfolio 10, with the extreme portfolios 1A and 10C showing the strongest exposure. Given the monthly return spread of 0.39 per cent and the mean of the momentum factor of 0.84 per cent,

the spread in the loading of 0.6 more than accounts for the difference in returns. The momentum factor explains the return spread by identifying last year's winners as the holders of last year's winning stocks. The identified patterns for *SMB* and *MOM* are very similar to mutual funds, where Carhart[3] reports a spread of 0.30 for *SMB* and 0.38 for *MOM* between portfolios 1 and 10.

Overall, the model does a good job at explaining the returns of portfolios based on lagged fund returns. The R^2 ranges from 0.63 to 0.83 for the decile portfolios. This is lower than Carhart's four-factor model for mutual funds, where the R^2s are above 0.9. This is not surprising, however, given the diversity of individual hedge fund strategies for this particular style.

When a fund has been sorted into a portfolio and tracked for a year, it can either stay in that portfolio, move to another portfolio or it may have stopped reporting during the year. To visualise the probability of a fund to move to portfolio *j* (or stop reporting), given that it is in portfolio *i*, we construct a contingency table, which is presented in Figure 2(a). The figure shows that in general winners tend to remain winners and losers tend to remain losers. Last year's winners are, however, after portfolio 10, the most probable group to move to the loser portfolio. The same is true for last year's losers: They are, after portfolio 1, the most probable group to end up as this year's winners. This is in accordance with the high return variance of the extreme portfolios. There is also the tendency of the inner decile funds to remain in the inner

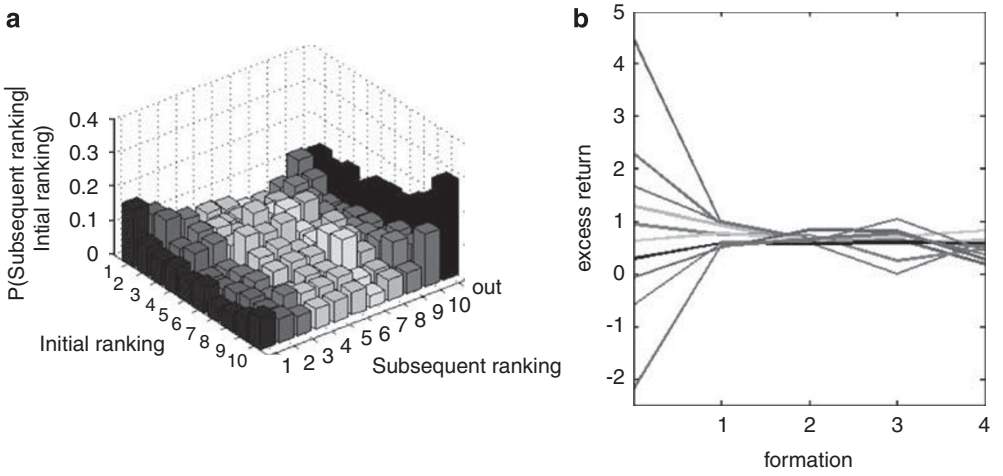

Figure 2: (a) Contingency table of initial and subsequent ranking (lagged returns).
Each year, funds are sorted into decile portfolios based on their past 1-year return. The bars indicate the transition probability of a fund moving from decile *i* into decile *j* or stop reporting.
(b) Postformation returns of portfolios sorted on lagged 1-year returns.
Each year, funds are sorted in decile portfolios based on lagged 1-year returns. The figure shows the monthly excess returns of these portfolios in the formation year and subsequent years.

deciles, which is consistent with their low return variance. The probability of stopping to report shows an increasing pattern with respect to last year's ranking and is highest for last year's losers. This is in line with Liang,[35] Brown *et al*,[36] and Baquero *et al*[12] who find that hedge funds with low past performance are likely candidates for liquidation. Overall, however, hedge funds move a great deal between portfolio deciles and the detected patterns are not very strong.

If funds move frequently lot between portfolios, one expects the persistence to be short-term in nature. Figure 2(b) shows the average return of the portfolios in the years following the formation period. The return spread shrinks drastically in the first year after ranking. This is the weak 'hot hands' effect as identified in the table. Following the portfolios beyond 1 year shows no persistence at all, not even for the bad performers.

Detection and persistence of alpha

Forming portfolios based on lagged returns does not seem to be a useful way to detect alpha portfolios. Instead, one would like a characteristic that provides a monotonic change of alpha across the deciles. Hence, we alternatively sort funds into portfolios based on lagged alphas. To provide reasonable estimates, alpha is calculated using the past 24 months of data. Table 3 provides the regression results for the decile portfolios, with portfolio 1 containing the funds with the highest lagged alpha and portfolio 10 containing the funds with the lowest lagged alpha.

This sorting is able to identify a sizeable and significant alpha spread of a monthly 0.79 per cent. Although the pattern is not perfectly monotonic, significant alphas are clearly located in the portfolios containing the funds with high lagged alpha. Persistence in alpha is especially pronounced for the extreme portfolios 1A and 10C. Portfolio 1A, however, seems to be poorly explained by the factors.

The table also shows that the portfolios with significant alphas have the highest returns. In fact, sorting based on lagged alpha produces a larger return spread than sorting based on lagged returns. The spread is a significant monthly 0.52 per cent compared to an insignificant 0.39 per cent for the portfolios based on lagged returns. Hence, lagged alpha seems to provide more information about both future alpha and future raw returns. With respect to factor exposure, alpha portfolios are generally less exposed to the market. This is also shown by the 1-minus-10 portfolio at the bottom of Table 3, where the difference in the *RMRF* coefficient is reported to be negative and significant at the 1 per cent level.

Alternatively, we sort the funds based on lagged 3-year alphas. The alpha spread between portfolios 1 and 10, however, decreases to an insignificant 0.44 per cent. There are at least two potential explanations for this decrease. First, by requiring funds to have at least 3 years of data to estimate 3-year alphas, the portfolios contain fewer funds and the estimates become less precise. In fact, the R^2 for portfolio 1 becomes as low as 0.44. Secondly, a fund's alpha 3 years ago may provide little information about today's alpha. Sorting on lagged 1-year alpha, on the other hand, gives a significant 0.67 per cent spread in alpha between portfolios 1 and 10. The funds' alphas are estimated very imprecisely, however, and the portfolio alphas show no monotonic pattern. This suggests that alpha persistence is only a short-run phenomenon. The following passage takes a closer look at this.

Table 3: Portfolios of hedge funds formed on lagged 2-year alpha

Portfolio	*Excess return (s.d.)*	*Alpha*	*RMRF*	*HML*	*SMB*	*MOM*	$R^2_{adj.}$
1A	1.38 (0.41)	1.37***	0.32**	−0.23*	0.02	−0.08	0.24
1B	0.80 (0.40)	0.44	0.35***	−0.14	0.34***	0.15**	0.43
1C	1.23 (0.36)	0.75***	0.66***	0.16**	0.28***	−0.05	0.67
1 (high)	1.02 (0.32)	0.71***	0.48***	−0.03	0.24***	−0.01	0.63
2	0.82 (0.27)	0.40***	0.44***	0.04	0.29***	0.08**	0.71
3	0.85 (0.25)	0.47***	0.49***	0.10**	0.23***	−0.00	0.78
4	0.71 (0.23)	0.31***	0.42***	0.10**	0.24***	0.06**	0.74
5	0.51 (0.26)	0.10	0.47***	0.06	0.27***	0.05**	0.79
6	0.41 (0.26)	0.09	0.45***	0.03	0.24***	−0.03	0.78
7	0.74 (0.25)	0.23*	0.54***	0.18***	0.23***	0.07***	0.80
8	0.79 (0.26)	0.42***	0.51***	0.08*	0.16***	0.00	0.75
9	0.42 (0.29)	−0.11	0.60***	0.14***	0.25***	0.06*	0.81
10 (low)	0.51 (0.42)	−0.08	0.80***	0.03	0.25***	0.06	0.77
10A	0.68 (0.36)	0.07	0.64***	0.18*	0.23***	0.12*	0.55
10B	0.78 (0.40)	0.33	0.68***	0.09	0.26***	−0.06	0.59
10C	−0.19 (0.69)	−0.95***	1.18***	−0.24*	0.24***	0.17*	0.69
1–10	0.52 (0.24)	0.79***	−0.32***	−0.06	−0.01	−0.07**	0.23
1A–10C	1.57 (0.60)	2.32***	−0.85***	0.01	−0.22*	−0.25***	0.41

Each January from 1996 to 2005, decile portfolios based on lagged 2-year alphas are formed. Portfolio 1 contains funds with the highest 2-year alpha, portfolio 10 funds with the lowest 2-year alpha. Portfolios 1 and 10 are further divided into terciles. The portfolios are equally weighted and the weights are readjusted whenever a fund is delisted. *RMRF*, *HML* and *SMB* are the Fama–French[27] factors for market proxy and factor-mimicking portfolios for book-to-market and size. *MOM* is a factor-mimicking portfolio for 1-year momentum. Newey–West[28] corrected *t*-values are represented by ***, **, * for 99%, 95%, 90% significance, respectively.

Figure 3(a) shows the transition probabilities of funds between portfolios sorted on lagged alphas. There is a strong trend for funds to remain in the same portfolio or to move to adjacent portfolios. This is particularly true for the extreme deciles. Portfolio 1, containing the funds with the highest lagged alphas, keeps over 30 per cent of its funds in the following year. This confirms the results of Jagannathan *et al*,[37] who find that approximately 20 per cent of abnormal performance relative to the style benchmark over a 3-year period spills over to the next 3-year period. This persistence is stronger among top funds than among bottom funds. Moreover, the figure shows that it is very unlikely for a high-alpha fund to become a low-alpha fund in the subsequent year or vice versa. This stands in sharp contrast to high-return funds, as shown above. The probability that a fund stops reporting decreases in lagged alpha.

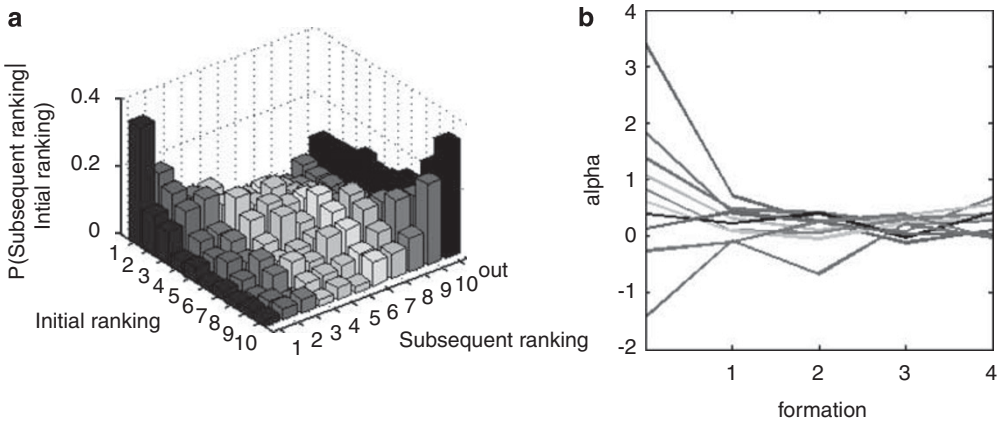

Figure 3: (a) Contingency table of initial and subsequent ranking (lagged alpha).
Each year, funds are sorted into decile portfolios based on their past 2-year alphas. The bars indicate the transition probability of a fund moving from decile *i* into decile *j* or stop reporting.
(b) Postformation alpha of portfolios sorted on lagged 2-year alpha.
Each year, funds are sorted in decile portfolios based on lagged 2-year alphas. The figure shows the monthly excess returns of these portfolios in the formation year and subsequent years.

This confirms the findings of Fung *et al*,[31] who show that alpha funds exhibit substantially lower liquidation rates than beta-only funds.

Figure 3(b) shows the alphas of the portfolios over several years. Similar to sorting portfolios based on lagged returns, the spread decreases after the formation period, though not as strongly. There is clearly more persistence in alpha than in raw returns for the first year. As in Kosowski *et al*,[17] abnormal performance is significant and persists over 1 year. While much of the persistence in alpha is gone after 1 year, the worst performers continue to underperform for 2 years. The alpha spread even widens to 0.97 per cent. But both the winner and loser portfolios have alphas insignificantly different from zero after the tracking year and the alpha spread is only significant at the 5 per cent level. Hence, portfolios based on lagged alphas should be reformed annually, as there is no outperformance 2, 3 and 4 years after picking the high-alpha funds.

The results are similar when we alternatively sort the funds based on the *t*-value of lagged alphas, which is the same as sorting based on the appraisal ratio. This sorting procedure identifies a highly significant alpha spread of 0.84 per cent and a return spread of 0.58 per cent. Carhart,[3] however, argues that using the same model for sorting and performance evaluation can pick up a model bias. For example, if the factor exposures are estimated too low or too high for a fund, this shows up as persistent over- or underperformance relative to the factor model. The problem is similar to an omitted factor. Hence, it is important to keep in mind this potential shortcoming when interpreting the results reported in this section.

Persistence of the Sharpe Ratio

Finally, we sort the funds into portfolios based on lagged Sharpe Ratios. The results in Table 4 show that this does a better job at detecting alpha portfolios than sorting based on raw returns or return variance. The results based on alpha sorting as reported in Table 3 are, however, substantially stronger. Table 4 shows that for portfolios 1–6, the alpha is positive and significant, whereas it is insignificant for portfolios 7, 8 and 10. In addition, portfolio 1 generates the highest alpha, whereas portfolios 7, 8 and 10 generate the lowest alphas. For space reasons, we do not report the transition probabilities of funds between portfolios sorted on lagged Sharpe Ratios or the Sharpe Ratios of the portfolios over several years (equivalent to Figure 3(a) and (b) for the alpha persistence).[38]

Table 4: Portfolios of hedge funds formed on lagged 1-year Sharpe Ratio

Portfolio	*Excess return (s.d.)*	*Alpha*	*RMRF*	*HML*	*SMB*	*MOM*	$R^2_{adj.}$
1A	0.69 (0.18)	0.49***	0.15***	−0.02	0.10**	0.09***	0.23
1B	0.72 (0.19)	0.35**	0.25***	0.04	0.28***	0.12***	0.62
1C	1.01 (0.24)	0.63***	0.36***	−0.03	0.18***	0.16***	0.51
1 (high)	0.79 (0.17)	0.45***	0.25***	0.02	0.19***	0.12***	0.60
2	0.97 (0.23)	0.44***	0.41***	0.02	0.23***	0.18***	0.76
3	0.81 (0.24)	0.26**	0.49***	0.05	0.22***	0.14***	0.78
4	0.90 (0.26)	0.43***	0.50***	−0.00	0.26***	0.09***	0.77
5	0.88 (0.28)	0.36***	0.50***	−0.01	0.31***	0.13***	0.82
6	0.92 (0.27)	0.31**	0.56***	0.13***	0.28***	0.08**	0.76
7	0.64 (0.31)	0.07	0.70***	0.05	0.29***	0.02	0.86
8	0.54 (0.31)	−0.03	0.60***	0.09	0.27***	−0.02	0.81
9	0.71 (0.29)	0.35**	0.56***	0.10	0.19***	−0.12**	0.67
10 (low)	0.48 (0.29)	0.18	0.47***	0.13	0.20***	−0.18***	0.63
10A	0.86 (0.36)	0.59**	0.62***	0.07	0.07	−0.12*	0.51
10B	0.23 (0.37)	0.11	0.43***	0.09	0.17**	−0.25**	0.39
10C	0.32 (0.31)	−0.02	0.44***	0.29***	0.22***	−0.18***	0.38
1–10	0.31 (0.28)	0.26	−0.26***	−0.12	−0.01	0.30***	0.43
1A–10C	0.37 (0.35)	0.50	−0.30***	−0.31***	−0.12	0.27***	0.26

Each January from 1995 until 2005, decile portfolios based on lagged 1-year Sharpe Ratios are formed. Portfolio 1 contains funds with the highest 1-year Sharpe Ratio, portfolio 10 funds with the lowest 1-year Sharpe Ratio. Portfolios 1 and 10 are further divided into terciles. The portfolios are equally weighted and the weights are readjusted whenever a fund is delisted. *RMRF*, *HML* and *SMB* are the Fama–French[27] factors for market proxy and factor-mimicking portfolios for book-to-market and size. *MOM* is a factor-mimicking portfolio for 1-year momentum. Newey–West[28] corrected *t*-values are represented by ***, **, * for 99%, 95%, 90% significance, respectively.

ROBUSTNESS CHECKS

Sub-period analysis

In order to assess the robustness of these results, we conduct the analyses for sub-periods. Prior research examines the relation between hedge fund performance and market conditions. Using a conditional benchmark, Kat and Miffre[39] conclude that abnormal performance is counter-cyclical. Capocci *et al*,[10] however, find that hedge funds show stronger outperformance in bullish times. Here, March 2000 is set as the cut-off point that divides the sample into a bull market period from January 1994 to March 2000 and a period with a bear market from April 2000 to December 2005. This also allows the factor loadings to vary between these two samples. In fact, Kosowski *et al*[17] find a breakpoint in the year 2000 for most hedge fund return indices.

The results for lagged 2-year alpha sorts are shown in Table 5 and confirm the previous findings for the sub-periods. Alpha portfolios have generally higher returns and lower factor exposures, especially for the market. Again, alpha persistence is much stronger than return persistence (not reported) over the 1-year horizon. Buying funds with the highest lagged alpha and reforming annually delivers high returns, relatively low market exposure and positive alpha. For example, while the mean monthly market return over the second sub-period was −0.16 per cent, portfolio 1 with low market exposure earned a monthly return of 0.4 per cent and positive (but insignificant) alpha. In addition, Table 5 shows that, looking at the excess returns, hedge funds have clearly performed much better in the bull-market period. Given their net long market exposure, this is not surprising.[40]

Correction for 'stale prices'

The presence of 'stale prices' because of hard-to-price assets or managed prices can artificially

Table 5: Sub-period analysis of portfolios of hedge funds formed on lagged 2-year alpha

Portfolio	*Excess return (s.d.)*	*Alpha*	*RMRF*	*HML*	*SMB*	*MOM*	$R^2_{adj.}$
1996:1–2000:3							
1 (high)	1.87 (0.47)	1.15***	0.45**	−0.14	0.19**	0.07	0.48
10 (low)	1.62 (0.64)	0.32	1.00***	0.06	0.23**	0.09	0.69
1–10	0.25 (0.42)	0.83**	−0.55***	−0.21	−0.04	−0.02	0.27
2000:4–2005:12							
1 (high)	0.40 (0.42)	0.26	0.50***	0.11***	0.25***	−0.04	0.76
10 (low)	−0.32 (0.53)	−0.43*	0.76***	0.08	0.28***	0.04	0.81
1–10	0.72 (0.27)	0.69***	−0.26***	0.04	−0.04	−0.09	0.17

Each January from 1996 to 2005, decile portfolios based on lagged 2-year alphas are formed. Portfolio 1 contains funds with the highest 2-year alpha, portfolio 10 funds with the lowest 2-year alpha. The portfolios are equally weighted and the weights are readjusted whenever a fund is delisted. *RMRF*, *HML* and *SMB* are the Fama–French[27] factors for market proxy and factor-mimicking portfolios for book-to-market and size. *MOM* is a factor-mimicking portfolio for 1-year momentum. Newey–West[28] corrected *t*-values are represented by ***, **, * for 99%, 95%, 90% significance, respectively.

reduce fund statistics such as volatility or beta. If, for example, the market falls near the end of the month and an illiquid asset does not trade, the drop in price will not show up until the following month. In addition, the lack of market prices may leave hedge funds with 'flexibility' in how they mark such positions for (month-end) reporting. Consequently, both illiquidity and managed prices can lead to asynchronous price reactions. This can spuriously show up as alpha because the contemporaneous factors will lose explanatory power. As equity long/short hedge funds invest in listed stock, this problem is expected to be of minor importance for the results in our study. Nevertheless, we check the robustness of our results with respect to stale

Table 6: Portfolios of hedge funds formed on lagged 2-year alpha

Portfolio	*Excess return (s.d.)*	*Alpha*	*RMRF*	*HML*	*SMB*	*MOM*	$R^2_{adj.}$
1A	1.34 (0.43)	1.33***	0.34**	−0.26*	−0.01	−0.06	0.23
1B	0.74 (0.36)	0.36	0.39***	0.07	0.35***	0.03	0.36
1C	1.22 (0.41)	0.75***	0.67***	−0.01	0.31***	0.01	0.68
1 (high)	0.98 (0.33)	0.66***	0.50***	−0.06	0.24***	0.00	0.65
2	0.87 (0.27)	0.43***	0.46***	0.09*	0.30***	0.06	0.70
3	0.83 (0.24)	0.43***	0.49***	0.13***	0.23***	0.00	0.81
4	0.70 (0.25)	0.31***	0.44***	0.05	0.25***	0.06**	0.75
5	0.68 (0.26)	0.28***	0.46***	0.02	0.25***	0.07**	0.81
6	0.26 (0.30)	−0.12	0.53***	0.06	0.27***	−0.03	0.73
7	0.70 (0.26)	0.22**	0.53***	0.11***	0.23***	0.08***	0.83
8	0.79 (0.27)	0.37**	0.55***	0.09*	0.17***	0.01	0.75
9	0.47 (0.29)	−0.08	0.63***	0.15***	0.22***	0.08**	0.82
10 (low)	0.45 (0.44)	−0.13	0.83***	−0.03	0.26***	0.07	0.79
10A	0.28 (0.38)	−0.26	0.66***	0.07	0.27***	0.08	0.60
10B	1.15 (0.41)	0.69**	0.65***	0.06	0.22***	0.00	0.50
10C	−0.26 (0.71)	−0.99***	1.20***	−0.30**	0.21**	0.18*	0.71
1–10	0.53 (0.25)	0.80***	−0.33***	−0.03	−0.02	−0.07**	0.25
1A–10C	1.59 (0.62)	2.32***	−0.86***	0.04	−0.22*	−0.24***	0.40

The fund returns are modified according to the Getmansky *et al*[21] correction that accounts for 'stale prices'. Each January from 1996 to 2005, decile portfolios based on lagged 2-year alphas are formed. Portfolio 1 contains funds with the highest 2-year alpha, portfolio 10 funds with the lowest 2-year alpha. The portfolios are equally weighted and the weights are readjusted whenever a fund is delisted. *RMRF*, *HML* and *SMB* are the Fama–French[27] factors for market proxy and factor-mimicking portfolios for book-to-market and size. *MOM* is a factor-mimicking portfolio for 1-year momentum. The fund returns are modified according to the Getmansky *et al*[21]correction that accounts for 'stale prices'. Newey–West[28] corrected *t*-values are represented by ***, **, * for 99%, 95%, 90% significance, respectively.

prices by aid of the procedure proposed by Getmansky *et al*,[21] which allows adjustment of the raw return series for potential smoothing. We estimate their MA(2) model for all equity long/short hedge funds in the CISDM database to obtain the smoothing parameters (or teta coefficients) based on which we construct 'unsmoothed' return series. The results are reported in Table 6 for the alpha sorts, and show that the correction leaves the results qualitatively unchanged.[41]

CONCLUSION

This paper investigates the performance persistence of equity long/short hedge funds. We find returns to show very little persistence at the annual horizon, irrespective of the length of the formation period. In addition, the observed persistence can be fully explained by factor exposures. In fact, it is mainly driven by holdings of last year's winner stocks. Hence, funds with the highest return last period are generally no-alpha funds. Moreover, best and worst performing funds tend to switch their places often, as they are very volatile.

There are, however, more promising criteria to select outperforming funds. Sharpe Ratio, market beta, and, in particular, alpha are more useful characteristics to sort funds because they are more persistent than raw returns. Although not reported in the paper, we find that sorting on lagged Sharpe Ratio identifies portfolios with the highest Sharpe Ratio, which are also more likely to have alpha. Sorting on lagged market beta or alpha identifies the largest and most significant alpha spread over the subsequent period. Past alpha also provides the most information about future returns by discovering the most significant spread in raw returns.

These selection strategies are associated with less risk than selection based on raw returns. Funds with high alpha are very unlikely to have a low alpha in the next period: instead, they will likely stay in the same or adjacent portfolio. Also, there is more persistence in alpha at the annual horizon. No persistence in alpha has, however, been detected for longer horizons except that funds with the lowest alpha continue to have the lowest alpha for 2 years.

There are at least three reasons that render such trading strategies impractical though. First, the option of going short a portfolio of hedge funds to get the alpha spread is not available. Secondly, the transaction and administrative costs of implementing such a strategy may outweigh its benefits. Thirdly, lockup or redemption periods imposed by funds can make frequent disinvestment impossible. Selecting funds with the highest lagged alpha, however, already produces a significant monthly alpha of 0.71 per cent, whereas the spread between portfolios 1 and 10 is 0.78 per cent. Going short portfolio 10 is therefore not necessary to get most of the benefit.[42] Secondly, the annual frequency of reforming the portfolios is relatively low. This makes the strategies more feasible with respect to transaction costs and lockup periods, especially for funds of funds facing more favourable conditions than individual investors.

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