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Discussion paper

Survival, Look-Ahead Bias and the Persistence in Hedge Fund Performance

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Abstract

Hedge funds databases are typically subject to high attrition rates because of fund termination and self-selection. Even when all funds are included up to their last available return, one cannot prevent that ex post conditioning biases affect standard estimates of performance persistence. In this paper we analyze the persistence in the performance of U.S. hedge funds taking into account look-ahead bias (multi-period sampling bias). To do so, we model attrition of hedge funds and analyze how it depends upon historical performance. Next, we use a weighting procedure that eliminates look-ahead bias in measures for performance persistence. The results show that the impact of look-ahead bias is quite severe, even though positive and negative survival-related biases are sometimes suggested to cancel out. At horizons of one and four quarters, we find clear evidence of positive persistence in hedge fund returns, also after correcting for investment style. At the two-year horizon, past winning funds tend to perform poorly in the future.

Jel-codes: G11, G12, G23

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1 Introduction

During the last decade, hedge funds have gained tremendous popularity, particularly in the USA. Hedge funds are similar to mutual funds in that they provide actively managed portfolios in publicly traded assets. Unlike mutual funds however, they have a broad flexibility in the type of securities they hold and the type of positions they take. They can invest in international and domestic equities and debt, and the entire array of derivative securities. They may take undiversified positions, sell short and lever up the portfolio (see, e.g., Fung and Hsieh, 1997, Liang, 2000). According to Brown and Goetzmann (2001), hedge funds are best defined by their freedom from regulatory controls stipulated by the Investment Company Act of 1940. Especially these non-standard features make hedge funds an interesting investment alternative with potential diversification benefits for the existing portfolio.

The question whether hedge funds show persistence in their performance receives much attention in the recent literature (see, e.g. Agarwal and Naik, 2000). The underlying idea behind these studies is that investors usually invest more in funds that recently performed well in the expectation that these funds will continue to do so in the future. However, many empirical studies concerning mutual funds show that active selection, on average, underperforms passive investment strategies. Testing whether an active selection strategy makes sense is even more relevant in the hedge fund industry because hedge fund investors are often confronted with lockup periods, that may be as long as one year, during which the invested money cannot be withdrawn. Moreover, many funds apply a redemption notice period of up to 90 days.

A major problem in evaluating hedge fund performance and its persistence is the relatively high attrition rate. For example, Brown, Goetzmann and Ibbotson (1999) report an attrition rate of about 14% per year over 1987-1996. If fund survival (directly or indirectly) depends upon historical performance, it is well known that standard methods of analysis may lead to biased results (see, e.g. Brown et al., 1992, Carpenter and Lynch, 1999, or Ter Horst, Nijman and Verbeek, 2001). Spurious persistence patterns may arise, the form of which depends upon the survival process and the underlying heterogeneity in fund characteristics. While most studies attempt to eliminate survivorship bias by taking fund returns into account until the moment of disappearance, a second ex-post conditioning bias, the so-called look-ahead bias, is usually not accounted for. This bias arises because the employed methodology implicitly or explicitly conditions upon survival over a number of consecutive periods. When analyzing performance persistence, for example, the fact that funds dissolve in a nonrandom way during the ranking or evaluation period may cause a bias (see, e.g. Carhart, 1997). As stressed by ter Horst, Verbeek and Nijman (2001), the elimination of look-ahead bias requires that the methodology be adjusted. An essential step in the correction procedure is to model the survival process of hedge funds and how it relates to their (historical) performance.

As noted by Fung and Hsieh (1997, 2000) and Liang (2000), practical problems may complicate this issue. Because the hedge fund industry is highly unregulated, and data sets may be subject to backfilling biases, a careful analysis is required. A wide range of empirical problems need to be taken into account in order to prevent biased results (see, e.g. Fung and Hsieh, 1997, Ackermann, McEnally and Ravenscraft, 1999, Agarwal and Naik 2000). One of these potential biases is a self-selection bias that arises due to the fact that hedge funds voluntarily report to a data vendor. Since hedge funds are not allowed to advertise publicly, these data vendors serve as an important distribution channel. Thus, self-selection bias exists either because underperfomers do not wish to make their performance known, because funds that performed well have less incentive to report to data vendors to attract potential investors, or because funds do not wish intervention in case SEC interprets reporting as illegal advertising. Ackermann, McEnally and Ravenscraft (1999) suggest that the previously mentioned survivorship bias and the self-selection bias cancel out. While it may be the case that, e.g., average fund returns are more or less unaffected by the joint operation of endogenous self-selection and liquidation, it is not possible, in general, that these two processes leave the cross-sectional and time-series distributions of returns unaffected Whether or not self-selection bias arises and whether or not it cancels out look-ahead bias will therefore necessarily depend upon the focus of study and the methodology used.

In this paper we empirically analyze the persistence in the performance of hedge funds that report returns in US$ over the period 1994-2000. To correct for ex post conditioning biases, we apply the methodology proposed in ter Horst, Nijman and Verbeek (2001). This approach requires a well-specified model that explains survival of hedge funds and how it depends upon historical performance. We extend the model of Liang (2000) by allowing for a flexible impact of historical returns, by incorporating aggregate time effects to capture economy-wide shocks that affect survival rates of all hedge funds, and by carefully testing for potential sources of misspecification. Next, we analyze the persistence in hedge fund performance during this period, correcting for look-ahead bias.

The remainder of this paper is organized as follows. In Section 2 we describe the sample of hedge funds that we employ and describe the potential biases that could arise. In Section 3 we model the survival process of hedge funds. Section 4 examines persistence in performance for a sample of hedge funds over the period 1994 - 2000, taking into account the potential biases that might be present. Finally, Section 5 concludes.

2 Hedge funds data

Hedge funds seek to deliver high absolute returns and typically have features such as hurdle rates and incentive fees with high watermark provision. Investors in hedge funds are often confronted with lockup periods and redemption notice periods. Such restrictions on withdrawals imply smaller cash fluctuations, and give fund managers more freedom in setting up long-term or illiquid positions. However, investors that follow an active selection strategy of investing in funds that recently performed well might be negatively affected by this lockup period.

Agarwal and Naik (2000) distinguish 'non-directional' and 'directional' hedge funds. Non-directional funds are characterized by having a low correlation with the market (market-neutral), while directional funds are highly correlated with the market. These categories are divided in ten popular strategies (fixed-income arbitrage, event driven, equity hedge, restructuring, event arbitrage, capital structure arbitrage, macro, long, hedge, short), which prove to be dramatically different from those of mutual funds as they are not based on static asset allocation but on dynamic exposures to passive indices. As mentioned above, U.S. based (onshore) hedge funds are free from regulatory controls stipulated by the Investment Company Act of 1940. Since 1996 the number of U.S. investors allowed in unregulated funds is 500. Moreover, domestic hedge funds can accept money from "qualified investors", who have at least $5 million to invest and have "sophisticated understanding" of financial markets. In addition they can accept money from pension funds that have at least $25 million in capital. A distinction is made between onshore and offshore funds, where the latter type of funds is typically developed to raise capital from non-US investors. Offshore hedge funds are non-U.S. corporations, typically registered in a tax-haven and as such they are not regulated by the SEC. The number of net worth investors is not limited and participation from U.S. investors is still restricted. As mentioned by Liang (2000) it is common practice that onshore funds report only returns, while offshore funds might report both assets and returns.

These distinctive features, particularly the low level of regulation and the long lockup periods, give hedge funds large flexibility in the types of positions they can take, by using short selling, leverage and derivatives. It allows them to have a dynamic position by holding diverse asset categories and moving quickly across them. Besides unregulation, strong managerial incentives constitute a second important feature characterizing this industry. Such incentives are largely based on performance. On average, fund managers receive around 20% of annual profits, as well as an annual management fee of about 1%. There is no incentive fee until the fund has recovered past losses (i.e. returns have to surpass a threshold or "high water-mark"). This incentive structure could lead to excessive risk taking, although this is often dampened by a substantial managerial investment in the fund and the fact that managers may incur in liabilities as general partners.

In this paper we use hedge fund data from TASS Management Limited. In principle, the TASS database goes back to 1979, although the initial years typically contain very few funds. By the beginning of the 1990s, about 200 funds were in the database. The fact that by 1998 more than 1400 (living) funds are available illustrates the increased importance of the hedge fund industry. Information on defunct funds is available only for funds that attrited in 1994 or later. For the empirical results we shall therefore concentrate on the period 1994-2000.

Below we shall focus on hedge funds reporting returns in US$. This results in a total of 1797 funds, of which 1185 are active in the first quarter of 2000. This corresponds with an average annual attrition rate of 8.6% from 1994 to 2000[1], very close to the rate of 8.3% that was reported for 1994-1998 by Liang (2000) (using a similar data set). Table 1 provides detailed information on the numbers of funds that enter and leave our data set in each quarter. For example, in the first quarter of 1997, 69 funds enter the sample, while 30 attrite. Given that 1069 funds were present at the beginning of the quarter, this corresponds to an attrition rate of 2.81%. Recall that attrition is caused by both self-selection and fund termination.

In Table 2 we provide average quarterly returns for different subsets of funds, as well as the returns on the S&P 500 index. The column labelled 'all' refers to all funds that were present in a given quarter, the column 'alive' refers to funds that are still active in the first quarter in 2000, while 'dead' refers to funds that had left the database by the end of our sample period. Clearly, the table indicates that average returns of dead funds are substantially below those of active funds. For example, the average return in the first quarter of 1995 of funds that are still active in 2000 is 4.0%, while the average return is only 2.5% for funds that have attrited by 2000. Combining both subsets produces an average quarterly return in the first

[1]The average annual attrition rate is computed as four times the (unweighted) average quarterly attrition rate.

Quarter	**Funds entering**	**existing**	**leaving**	**attrition rate**
1994-I	50	577	0	0.00
1994-II	38	627	0	0.00
1994-III	60	665	2	0.30
1994-IV	55	723	5	0.69
1995-I	64	773	3	0.39
1995-II	47	834	14	1.68
1995-III	52	867	14	1.61
1995-IV	53	905	10	1.10
1996-I	67	948	18	1.90
1996-II	51	997	23	2.31
1996-III	63	1025	34	3.32
1996-IV	44	1054	29	2.75
1997-I	69	1069	30	2.81
1997-II	56	1108	26	2.35
1997-III	65	1138	28	2.46
1997-IV	46	1175	17	1.45
1998-I	68	1204	27	2.24
1998-II	41	1245	31	2.49
1998-III	57	1255	58	4.62
1998-IV	32	1254	38	3.03
1999-I	49	1248	27	2.16
1999-II	26	1270	40	3.15
1999-III	34	1256	45	3.58
1999-IV	13	1245	52	4.18
2000-I	20	1206	41	3.40
overall			612	2.16

Table 1: Numbers of US hedge funds entering and leaving TASS database 1994-2000

Quarter	**all funds**	**alive funds**	**dead funds**	**S&P 500**
1994-I	-0.018	-0.015	-0.022	-0.035
1994-II	0.011	0.009	0.014	0.008
1994-III	0.017	0.026	0.004	0.042
1994-IV	-0.011	-0.010	-0.013	0.002
1995-I	0.034	0.040	0.025	0.100
1995-II	0.041	0.054	0.021	0.097
1995-III	0.039	0.049	0.025	0.069
1995-IV	0.041	0.042	0.041	0.065
1996-I	0.031	0.036	0.023	0.067
1996-II	0.060	0.063	0.054	0.040
1996-III	0.019	0.024	0.011	0.025
1996-IV	0.057	0.066	0.039	0.081
1997-I	0.045	0.046	0.044	0.030
1997-II	0.051	0.054	0.044	0.178
1997-III	0.075	0.080	0.063	0.077
1997-IV	-0.010	-0.004	-0.024	0.020
1998-I	0.048	0.058	0.019	0.146
1998-II	-0.012	-0.006	-0.033	0.040
1998-III	-0.049	-0.049	-0.049	-0.138
1998-IV	0.051	0.061	0.006	0.251
1999-I	0.031	0.039	-0.010	0.056
1999-II	0.078	0.086	0.023	0.071
1999-III	0.005	0.007	-0.012	-0.068
1999-IV	0.129	0.136	0.024	0.138
2000-I	0.060	0.063	-0.018	0.038
overall	0.033	0.038	0.012	0.056

Table 2: Average returns of US hedge funds 1994-2000

quarter of 1995 of 3.4%. Over the entire sample period, average returns of surviving funds are about 2.1% (per annum) above the average returns of all funds, a number which Malkiel (1995), Liang (2000) and others refer to as the "survivorship bias". This estimate is between the 1.5% of Fung and Hsieh (2000) and the numbers presented by Brown, Goetzmann and Ibbotson (1999) [3%] and Liang (2000) [2.24%].

While it is commonly accepted that funds with a relatively bad performance are more likely to be dissolved, it is not clear a priori over which period historical returns are important to explain survival. To obtain some insight into this question, Figure 1 presents conditional attrition rates (hazard rates) by performance decile over the next eight quarters. That is, in each quarter funds are ranked on the basis of (gross, raw) returns and divided into 10 deciles. Next, for each decile, the average attrition rate is determined for one up to eight quarters after the ranking period. It is clear from the figure that in the first four quarters conditional attrition rates for loser funds (decile 1) are much higher than for winner funds (decile 10), while for the last two or three quarters the relationship is almost flat. This seems to indicate that quarterly returns are important determinants of subsequent attrition rates over the next four or so quarters, while after 8 quarters attrition rates are basically the same, independent of initial returns.

There are a number of classification methods for hedge funds' investment styles commonly used by data vendors, although none appears to be universally accepted. The TASS database employs two different classifications. The classification we use initially contains 17 styles which are mutually exclusive and closely correspond to the commonly used Tremont hedge fund style indices. It takes into account different dimensions simultaneously: asset class, geographical focus and investment bias (i.e. U.S. equity hedge funds; European equity hedge funds; Asian equity hedge funds; pure leveraged currency; fixed income directional; convertible fund (long only); etc.). However, this investment style is not available for 269 funds (of which 242 are dead funds). This represents a major drawback since we intend to study survival-related biases by investment style. In order to determine the style of this subsample of funds, we apply multiple discriminant analysis.

For all funds in the TASS database, we observe indications of their investment style through a set of 15 *overlapping* style indicators (e.g. bottom up, market neutral, fundamental, ...). On average, each fund is characterized by at least four of these styles. The subsample of funds for which we also observe a unique style classification according to the 17 styles distinguished above, is used to determine a set of discriminant functions. These

Post-formation rate of dead funds

Ranking criterion : past one-quarter excess returns

In each quarter from 01/1994 to 01/2000, funds are ranked into decile portfolios based on their previous one-quarter net excess returns. For the quarter subsequent to initial ranking and for each of the next 8 quarters after formation, the rate of dead funds as a percentage of the total number of funds still existing at the beginning of each period is determined. Thus, the bar in cell (i,j) represents the conditional probability of dying in the post-formation period i given an initial ranking of decile j.

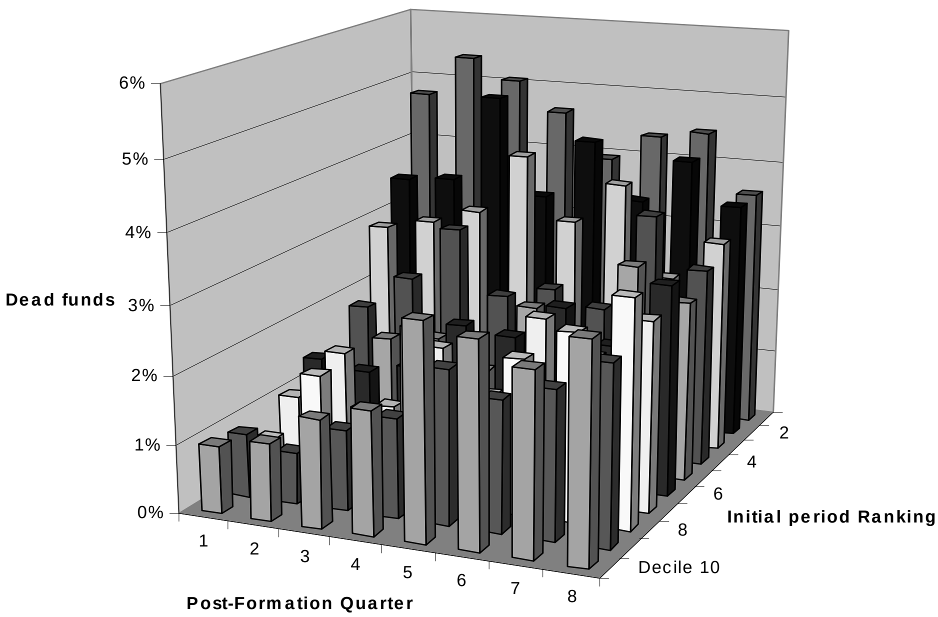

Figure 1: Conditional attrition rates, 1 to 8 quarters after initial rank

	all funds			onshore			offshore		
Investment Style	active	dead	total	active	dead	total	active	dead	total
Convertible Arb.	8	3	11	4	1	5	4	2	6
Dedicated Short Bias	11	1	12	6	0	6	5	1	6
Emerging Markets	123	91	214	17	15	32	106	76	182
Equity Market Neutral	101	59	160	38	23	61	63	36	99
Event Driven	123	33	156	61	9	70	62	24	86
Fixed Income Arb.	19	9	28	6	2	8	13	7	20
Global Macro	21	10	31	2	2	4	19	8	27
Long/Short Equity	256	108	364	124	53	177	132	55	187
Managed Futures	165	191	356	75	66	141	90	125	215
Hedge Fund Index	322	143	465	97	36	133	225	107	332
All styles	1149	648	1797	430	207	637	719	441	1160

Table 3: Numbers of active and dead US hedge funds per investment style

discriminant functions provide a set of scores for each of the 17 styles.[2] Subsequently, the discriminant functions are used to determine the scores for the subsample of funds for which the appropriate style classification is missing, after which each fund is allocated to its "most likely" style. While such a procedure necessarily is subject to classification error, its within sample performance is rather well, with 52.3 % of the funds classified correctly in one of 17 investment styles.

As mentioned above, these 17 styles closely correspond to the Tremont hedge fund benchmarks. Tremont offers a series of nine hedge fund indices, computed on a monthly basis and constructed out of hedge funds that have at least $10 million under management and provide audited financial statements (see, e.g. Lhabitant, 2001). In Table 3 we report the number of active and dead funds assigned to a Tremont index. The investment style "Hedge Fund Index" is a general hedge fund index and does not refer to a particular investment style. We assigned funds without a clear investment style, like fund-of-funds, to this category. In addition, we distinguish between offshore and onshore funds.

It appears that "Long/Short equity" and "Managed Futures" are the most popular investment styles, with 364 and 356 funds, respectively. Furthermore, the majority of the funds can be classified as offshore. A large proportion of about 53.7% of the funds with investment style "Managed Futures" have disappeared from the database by 2000. For "Emerging Mar-

[2]In fact, one of these 17 style categories (pure property) contained only one fund and was not used in the discriminant analysis.

kets", this percentage is about 42.5%, while for "Dedicated Short Bias" this percentage is only 8.3%. Clearly, this indicates that investment style might be a significant factor in explaining fund survival. We do not observe striking differences between attrition rates of offshore and onshore funds, although the first group has a somewhat larger proportion of dissolved funds.

In the next section, we present a model that explains attrition of hedge funds as a function of historical returns as well as a number of fund characteristics, including investment style.

3 Modelling the survival process

Variables that are likely to affect attrition rates of hedge funds are historical returns over a number of previous quarters, fund size, age of the fund, and the fund's investment style. To describe our survival model, let y_{it} be an indicator variable that indicates whether or not fund i has an observed return in quarter t. Our specification describes the probability of fund survival ($y_{it} = 1$) using a longitudinal probit model, such that a fund survives if an underlying latent variable, y^*_{it} is positive. That is,

$$\begin{aligned} y^*_{it} &= \alpha + \sum_{j=1}^{J} \gamma_{ij} r_{i,t-j} + \beta' x_{i,t-1} + \lambda_t + \eta_{it} \qquad (1) \\ y_{it} &= 1 \text{ if fund } i \text{ is observed in quarter } t \ (y^*_{it} > 0) \\ y_{it} &= 0 \text{ otherwise} \end{aligned}$$

where $r_{i,t-j}$ is the return of fund i in quarter $t-j$, $x_{i,t-1}$ is a vector of fund-specific characteristics, including a set of style dummies, and λ_t denote fixed time effects describing economy wide effects. The coefficients γ_{ij} indicate how survival is affected by the fund's returns, lagged j quarters. Compared to Liang (2000), who includes the average monthly return over the fund's history, this allows us to analyze the dynamic impact of historical returns upon fund survival. For the moment, we fix the maximum lag J at 6. The γ_{ij} coefficients are assumed to be equal across funds, with the exception of those cases in which less than J historical returns are available. In such a case, the γ_{ij} coefficients are set to zero if the corresponding return is unobserved (which is typically the case for funds with a recent inception date). This approach prevents that the survival model is only appropriate for funds that actually have a 6 quarter history, and thus prevents that a multi-period sampling bias affects the survival model. The model in (1) is a reduced form in the sense that it describes attrition due to both self-selection and fund termination.

Variable	mean	std.dev	min	max
offshore	0.61	0.49	0.00	1.00
Incentive Fees	16.17	7.78	0.00	50.00
Mng. Fees	1.60	1.03	0.00	8.00
Personal capital	0.66	0.48	0.00	1.00
Leverage	0.73	0.45	0.00	1.00
ln(NAV)	16.56	1.78	7.58	23.30
ln(Age)	3.52	0.92	1.10	5.62
$\ln(\text{Age})^2$	13.25	6.16	1.21	31.55
Emerging Markets	0.11	0.31	0.00	1.00
Equity Market Neutral	0.08	0.27	0.00	1.00
Event Driven	0.10	0.30	0.00	1.00
Fixed Income Arb.	0.01	0.11	0.00	1.00
Global Macro	0.02	0.14	0.00	1.00
Long/Short Equity	0.19	0.39	0.00	1.00
Man. Futures	0.21	0.41	0.00	1.00
Fund of Funds	0.19	0.40	0.00	1.00

Table 4: Summary statistics fund-specific variables.

In Table 4 we present some summary statistics of the fund-specific variables ($x_{i,t-1}$) that were included in the survival model in (1). These descriptive statistics are based on 22739 fund/period observations, while 11 of the fund-specific variables are dummies. It appears that 61% of the observations are from offshore hedge funds. These funds, while reporting in US$, are located in tax-havens like the Virgin Islands. The average incentive fee of the fund manager is about 16%, but can be as high as 50% of realized performance. Note that these incentive fees are only obtained when the fund has recovered past losses (high water-mark). The annual management fee varies from 0% to 8% (of net asset value) and has an average of 1.6%. For about 66% of the observations, the hedge fund manager invests personal capital in the fund, while 73% of the observations correspond to hedge funds that make use of leverage. The age of the funds varies between 3 months and 275 months (about 23 years), while the average age is about 34 months. The average size of the hedge funds, measured by their log net asset value is 16.56, corresponding to about 15.5 million US$. About 19% of the observations belong to so called funds-of-funds, while only 1% corresponds to hedge funds with a "fixed income arbitrage" investment style.

We estimate (1) using all investment styles, while including style dummies to capture the possibility, as suggested by the summary statistics in Table 3, that different investment styles are associated with different overall attrition

Parameters	Estimate	Std.error	Parameters	Estimate	Std. Error
intercept	2.167	0.400	ln(NAV)	0.154	0.012
$r1$	1.133	0.148	ln(Age)	-0.956	0.149
$r2$	1.117	0.176	ln(Age)^2	0.131	0.022
$r3$	1.022	0.176	Emerging Markets	-0.152	0.067
$r4$	0.477	0.176	Equity Market Neutral	-0.198	0.077
$r5$	0.265	0.146	Event Driven	0.110	0.088
$r6$	0.204	0.152	Fixed Income Arb.	-0.137	0.172
offshore	-0.067	0.044	Global Macro	-0.099	0.156
Incentive Fees	-0.010	0.003	Long/Short Equity	-0.102	0.062
Mng. Fees	-0.024	0.020	Man. Futures	-0.016	0.061
Personal capital	0.084	0.042			
Leverage	-0.029	0.047			
Loglikelihood:-2413.5076			Chi-squared test: 697.24 ($DF = 43$)		
pseudoR^2: 0.1262			($p = 0.0000$)		

Table 5: Estimation results survival model.

rates. Given the limited number of funds with investment styles "convertible arbitrage" or "dedicated short bias", no dummies are included for these styles and the funds are allocated to the general hedge fund index (reference category). In addition, the model includes time dummies to capture aggregate shocks to the survival rates. Because fund size (NAV) is not available for each period for all funds in our sample, we use the most recent observation of net asset value available from the TASS database. Observations for which NAV is missing and cannot be imputed are not used in estimation.[3] The estimation results, based on 22739 fund/period observations, are presented in Table 5, the estimates for the time effects are not reported[4]. The results show that the impact of historical returns upon fund survival is positive and highly significant: funds with high returns are much more likely to survive than funds with low returns. The impact of the individual quarters decreases with each lag. As indicated by the Chi-squared test, the variables in the model are jointly highly significant, while many of the variables are also individually significant. For example, fund size has a strong positive impact upon survival: smaller funds are, ceteris paribus, much more likely to

[3]This occurs in 7% of the cases. Because we do not want to eliminate these observations from our persistence analysis in Section 4, we also estimated a second survival model from which ln(NAV) is excluded. The estimation results are available upon request. This model, based on a smaller information set, is used to correct for look-ahead bias whenever information on net asset value is missing.

[4]The estimates for the time dummies are available upon request by the authors.

be dissolved than large funds. Further, the fact that a manager has invested personal capital in the hedge fund affects survival rates in a positive and statistically significant way. Surprisingly, the magnitude of the incentive fee for a manager affects the probability of survival in a negative and significant way, i.e. the higher the incentive fee, ceteris paribus, the more likely it is that the fund will disappear in the next quarter. Age has a significant nonlinear effect: young hedge funds have a high probability to disappear, but when funds become more mature, the non-survival probability decreases. Most investment style dummies have a significant impact on survival probabilities. The funds with style "event driven" have, ceteris paribus, the highest probability to survive, while funds classified as "equity market neutral" have the lowest survival probability. Interestingly, no significant effect is found for the "managed futures" style. Given the high attrition rate of this class of funds, as reported in Table 3, it must be the case that the other factors in the model, like historical returns, already capture this effect.

The specification reported in Table 5 is tested against a number of more general alternatives. For example, we test whether the model is significantly improved when returns lagged 7, 8 and 9 quarters are added. The value of the likelihood ratio test statistic is 9.97, which is only marginally significant at the 5% level.[5] Because of the number of observations that we would loose when we extend the survival model with these three additional lags and given the marginal rejection, we decided not to include the additional lags. Furthermore we tested the logarithmic specification in size against a more general alternative. The likelihood ratio test on the inclusion of $\ln(NAV)^2$ produces an insignificant value of 2.57. One particular alternative specification requires some explanation. It is conceivable that the value of the γ_{ij} coefficients depends upon the number of lagged returns that is available. For example, the marginal impact of last quarter's return may be larger if less historical returns are available. To test for this, we construct an alternative model in which γ_{ij} is allowed to be a function of the number of available lags. In particular, we study the significance of the additional variable $\log(J - J_i + 1)\sum_{j=1}^{J_i} r_{i,t-j}$, where J_i denotes the number of lagged returns that is available, with a maximum of J. Note that the additional variable is zero whenever J or more historical returns are observed. The likelihood ratio test statistic produces the insignificant value of 0.62. In summary, the results of the above tests do not indicate any serious shortcomings of the current specification.

In order to obtain an indication of the probability that an arbitrary hedge fund will disappear in the next quarter given its past record of returns and age, we use the estimates of (1) to compute the probability of disappearance.

[5] The asymptotic distribution is Chi-squared with 3 degrees of freedom.

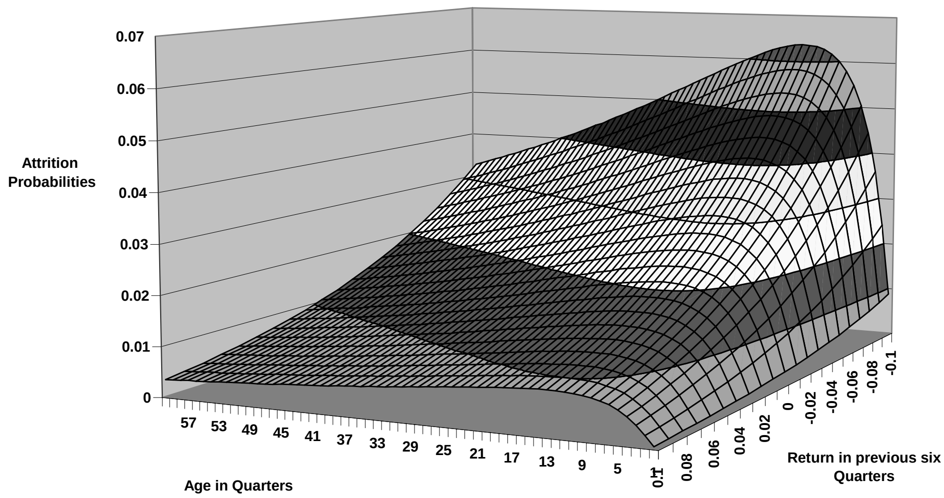

Figure 2: Attrition probabilities by fund age and previous six quarters' returns (as implied by the estimated survival model).

In Figure 2 the attrition probabilities are reported for funds with different ages (in quarters) where historical returns vary from -10% to $+10\%$ for each of the last six quarters. All other variables are fixed at their sample average. It appears that for a fund with age 12 quarters and a return record of -10% for each of the last six quarters, the probability to disappear in the next quarter is about 6.3%, while for a fund with the same age but a return record of $+10\%$ for each of the last six quarters the attrition probability is only 0.9%. It is clear that fund age affects survival nonlinearly. Apparently, survival rates of funds that recently started are less affected by a poor historical performance than those of funds that are around for several years, while older funds are also less likely to dissolve.

4 Estimating Persistence in Performance

The question whether hedge funds show persistence in their performance has received much attention in the recent literature. For example, Brown, Goetzmann and Ibbotson (1999) use annual returns of offshore hedge funds and do not find persistence in their sample. Agarwal and Naik (2000) use quarterly, half-yearly and annual (post-fee and pre-fee) returns and examine short-term as well as long-term persistence. They find that persistence is highest at the quarterly horizon and decreases when moving to a yearly horizon. However, persistence in quarterly returns could be affected by the fact that most hedge funds only report on an annual basis. The investment style of the hedge funds is not relevant for the persistence pattern found by Agarwal and Naik (2000).

In this section, we will first examine whether there is performance persistence in raw returns. Basically, we examine whether 'winning' funds, where winning is defined as exceeding the median fund return in a given period, are more likely to be winners in the next period. To obtain some indications about the probabilities that hedge funds from the top deciles remain in the top deciles, Figure 3 reports a contingency table of quarterly performance. Each quarter all funds are ranked in ten deciles, and this is compared with their ranking in the previous quarter. The table also incorporates dead funds and new funds that enter the database and is therefore not affected by look-ahead bias. Funds that are in the top decile (decile 10) have a probability of about 20% of being a top performer in the next quarter again. However, they also have a similar probability of ending up in the loser decile (decile 1). The funds that performed worst (decile 1) in the ranking period, have the highest probability of being a loser again (about 23%), but also a probability of 5% of being dead in the next quarter. Moreover, these funds have a high probability of more than 15% to end up in the winner decile. The explanation for this finding might be that funds in the extreme deciles (decile 1 and decile 10) are more risky than those in the other deciles. More risk is associated with higher average returns, but also with bigger chances of extremely good and extremely poor outcomes. Such funds are more likely to move from the winner to the loser decile or vice versa. In line with this, we observe that funds from the middle deciles are more likely to remain in the middle deciles than to move to one of the extreme deciles. The probability of being dead in the next quarter is relatively high for the lower deciles.

The previous analysis does not provide information about the levels of average returns across the different deciles. To investigate this, we rank the funds in the so-called ranking period on the basis of past average returns over the previous quarter, the previous year or the previous two years. This

Contingency table of initial and subsequent performance rankings

Ranking criterion : past one-quarter net excess returns

Hedge funds are sorted each quarter from 1994Q1 to 2000Q1 into ten rank portfolios based on their previous one-quarter net excess returns. This initial ranking is confronted to the fund's subsequent one-quarter return ranking. The bar in cell (i,j) represents the conditional probability of achieving a subsequent ranking of decile j given an initial ranking of decile i. New funds are placed in a separate category. In this case bar in cell (i,j) represents the conditional probability of achieving a ranking of decile j in the quarter subsequent to the starting-operations quarter.

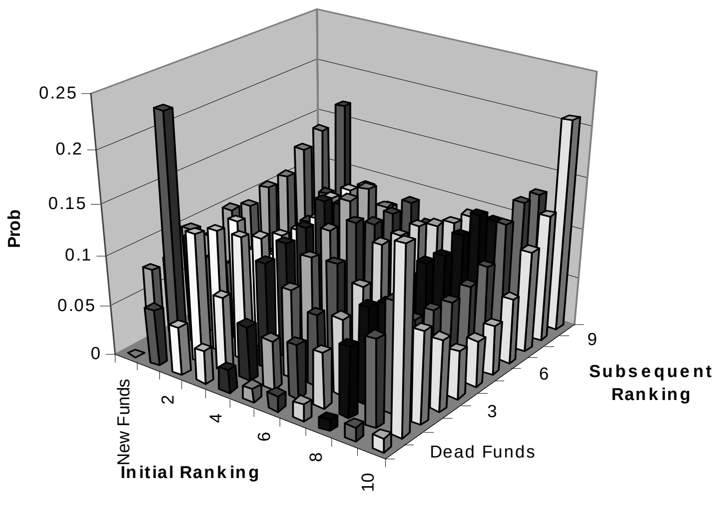

Figure 3: Contingency table of quarterly performance

ranking is broken down into ten deciles. In the subsequent evaluation period we calculate the average returns for each of these deciles. For instance, for the one year ranking period this implies that the first ranking is based on returns over the year 1994 (i.e. the first year of our sample), while the evaluation period is the year 1995. The procedure is repeated over the entire sample period, moving forward by one quarter at the time and adjusting the sample to include those funds that have a sufficiently long return history. As a result these rankings are conditional upon survival over the ranking and evaluation periods. Multi-period selection bias or look-ahead bias may thus distort the empirical results.

As is well known by now, spurious performance persistence patterns might arise that are due to look-ahead bias (Carpenter and Lynch, 1999). Following the correction procedure introduced by Ter Horst, Nijman and Verbeek (2001), we also present persistence results that are corrected for look-ahead bias. Basically, the correction method implies a multiplication of the performance measure (e.g. the average return over the ranking period) with a weight factor, which is the ratio of an unconditional survival probability in the numerator and a conditional survival probability in the denominator. The latter one can be obtained from the estimated survival process that is reported in Section 3, while the unconditional probability can be estimated by the ratio of the funds that survived the ranking period and the number of funds present in the sample at the beginning of the ranking period. The correction for the average returns over the evaluation period is similar, except that the unconditional probabilities are conditional upon the fund's decile during the ranking period (but not upon the entire return history).

Consider the case that we are interested in persistence in raw returns at a biannual horizon. This implies that we can only use information on funds that have reported returns for at least eight consecutive quarters. Let $Y_{it} = 1$ if fund i has survived during quarters t to $t + 7$ (and $Y_{it} = 0$ otherwise) and let R_i denote the entire vector of fund returns. The probability that a fund is observed in quarters t to $t + 7$, given its returns and given its characteristics X_{it} (age, management fees, investment style, net asset value), can be obtained from the survival model. Assuming that survival is independent of current or future returns, this probability is

$$P\{Y_{it} = 1|R_i, X_{it}\} = \prod_{t=s}^{s+7} P\{y_{it} = 1|r_{i,t-1,\ldots,}x_{i,t-1}\}. \qquad (2)$$

Estimates for the probabilities at the right-hand side are directly obtained from the probit model. The unconditional survival probability can easily be estimated by the ratio of the appropriate number of funds that survived from quarter t to $t + 7$ and the number of funds that was in the sample in quarter

$t-1$. As shown by Ter Horst, Nijman and Verbeek (2001), multiplying the returns for funds used in the analysis by the resulting weight factors provides the unconditional distribution of returns we are interested in.

Figure 4 presents the results at the annual frequency, while Figures 5 and 6 present persistence of raw returns at quarterly and biannual horizons, respectively. All estimates are based on the full sample of hedge funds, excluding fund-of-funds. All figures give results with and without corrections for look-ahead bias. These figures show some interesting patterns. At the annual level, we see that the persistence pattern without corrections is slightly J-shaped. Given the results of Hendricks, Patel and Zeckhauser (1997) and ter Horst, Nijman and Verbeek (2001), a pattern like this may be attributable to look-ahead bias. Correcting for look-ahead bias flattens the J-shaped pattern, but the three top deciles (deciles 8, 9 and 10) still show positive persistence in returns. Without corrections, average returns may be overestimated by as much as 6% (decile 1) which shows that the impact of look-ahead bias might be quite severe. The corrections are most pronounced for the extreme deciles, which is to be expected given that these deciles typically contain the more risky funds. The finding that look-ahead bias has a U-shaped pattern is due to the cross-sectional dispersion in fund specific risk. Funds ranked in one of the extreme deciles are more likely to be 'high risk' funds and thus less likely to survive. Conditional upon the fact that they did survive in the evaluation period, they will have made better returns than average. See Ter Horst, Nijman and Verbeek (2001) for additional discussion.

At the quarterly horizon, we clearly observe positive persistence in hedge fund returns, particularly for the best four deciles. For example, the top decile provides an average return over the next quarter of 23.5% (annualized) while the bottom decile provides only about 7.5%. This corresponds to the findings of Agarwal and Naik (2000), who also find strong persistence at a quarterly horizon over the period 1982 - 1998. However, in their study the issue of look-ahead bias is not taken into account. The corrections for look-ahead bias reduce most of the averages somewhat, although the bias is much less than in case of an annual horizon. Because this graph refers to only one quarter, it is not surprising that the look-ahead bias is less severe than at the annual level. The bias correction does not change the persistence pattern very much. When we move to the biannual level, the number of funds that can be used to construct the figure is substantially reduced. Both the corrected and uncorrected persistence patterns show a clear positive persistence, with the exception of the top decile. The subsequent 8-quarter performance of the top decile is disappointing, even without corrections for look-ahead bias. This strange effect is probably partly due to the reduced number of funds that can be used to construct this persistence graph. Approximately half of the

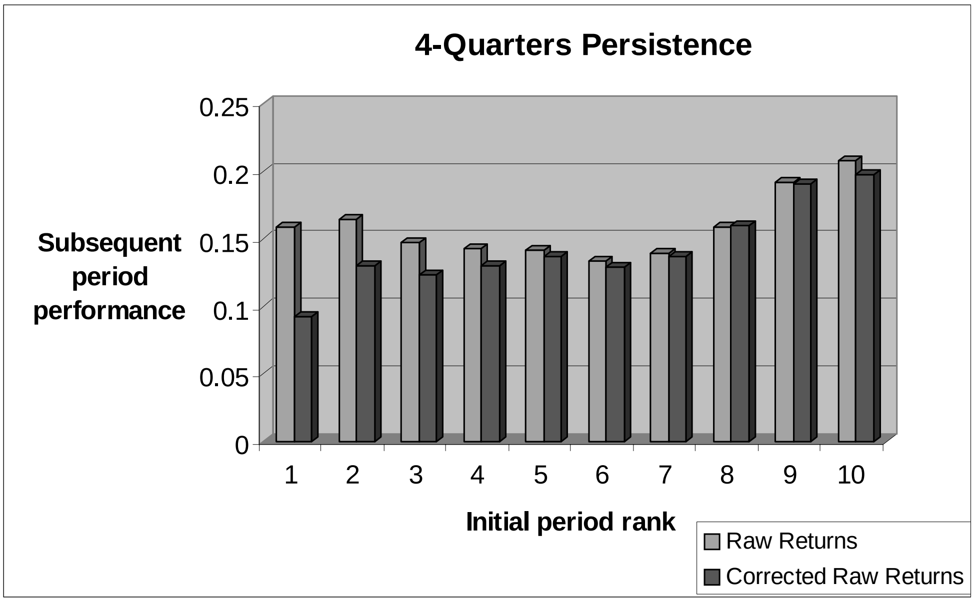

Figure 4: Annual persistence in raw returns. Returns are annualized per decile.

funds have returns for 16 consecutive quarters or more. Another explanation might be that the results are driven by a few funds that have extreme returns for one or more 2-year periods. Given that average returns are computed on the basis of overlapping samples, a few extreme returns may have a strong impact. To investigate the impact of these extreme observations, we also computed average returns in the evaluation period giving zero weight to the 1% lowest and 1% highest returns. This is expected to result in more robust estimates for the expected returns during the evaluation period. The results are presented in Figure 7 and indicate average returns, particularly for deciles 1 and 10, that are probably more reasonable. The fact that the outlier correction has a large impact for the extreme deciles indicates that the estimated returns are not very accurate. Nevertheless, it is clear from both figures that 2-year losers are expected to perform very weak during the next two years. On the other hand, 2-year winners are expected to perform poorly too in the future.

One explanation for the positive persistence in raw returns, after correcting for look-ahead bias, is the presence of cross-sectional variation in expected fund returns due to heterogeneous style or (systematic) risk characteristics. Therefore, we also examine persistence in risk-adjusted returns. For hedge

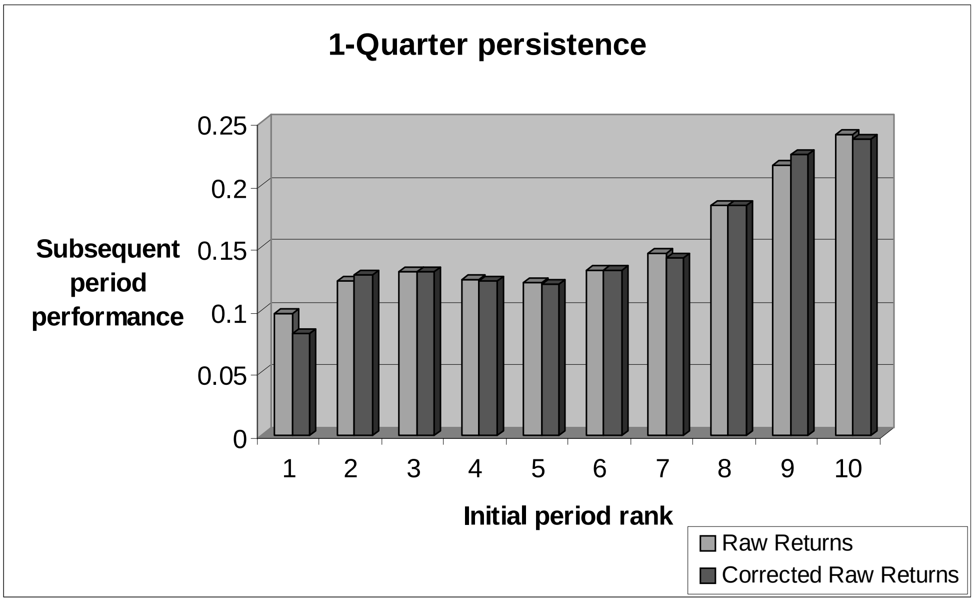

Figure 5: Quarterly persistence in raw returns. Returns are annualized per decile.

funds this is somewhat more complicated than for mutual funds. Hedge fund returns typically have low correlations with returns on standard asset pricing factors like the return on the market portfolio. This is an important feature of hedge funds and makes them an interesting investment vehicle for diversification opportunities. The reason for the low correlation is that hedge funds often follow highly dynamic investment styles, and are allowed to invest in derivatives, to take short positions or to make use of leverage. The question how to obtain risk-adjusted returns of hedge funds receives a lot of attention in the current literature. Basically, two approaches can be found, the first approach makes use of indices that have option like pay-off structures (see, e.g. Fung and Hsieh, 1997, 2001, and Agarwal and Naik, 2000), while the second approach uses peer group hedge fund indices (see, e.g. Lhabitant, 2001). The idea behind the first approach is that hedge fund strategies generate option-like returns that should be reflected in the benchmark indices. The second approach avoids the problem and simply makes use of indices constructed out of other hedge funds with the same reported style as the funds under consideration. The first approach is only suitable for very specific trading strategies, while the second approach is much more general. However, it is more appropriate to denote the obtained returns from the second approach

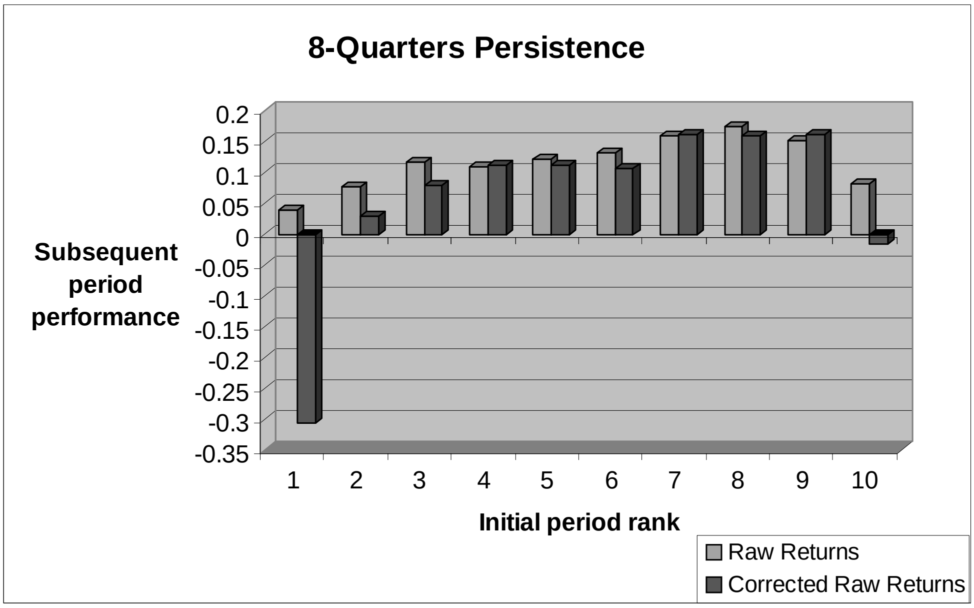

Figure 6: Biannual persistence in raw returns. Returns are annualized per decile.

as style-adjusted or relative returns instead of risk-adjusted returns. Given that in our study the focus is on persistence in hedge fund returns in general, and not for a specific investment style, we decided to follow the second approach, and examine whether hedge funds show persistence in style-adjusted or relative returns. The style benchmarks we employ are the Tremont hedge fund style indices, and correspond to the investment styles of the hedge funds in our sample (see Table 3). Basically, we subtract from the raw return of a hedge fund the return on the style benchmark the fund belongs to. Similarly to the procedure followed in case of raw returns, we examine whether there is persistence in relative returns. Figure 8 presents the results at the annual frequency, while Figures 9 and 10 present persistence of relative returns at quarterly and biannual horizons, respectively. Figure 11 presents persistence of relative returns over two-year horizons where, as before, the most extreme observations are given zero weight. All figures give results with and without corrections for look-ahead bias.

At an annual horizon we find a strong persistence pattern for the top three deciles (decile 8, 9 and 10). The funds in these top deciles, on average, outperform their style benchmark. The outperformance increases from about 1% (decile 8) to somewhat less than 6% for decile 10 at an annual basis

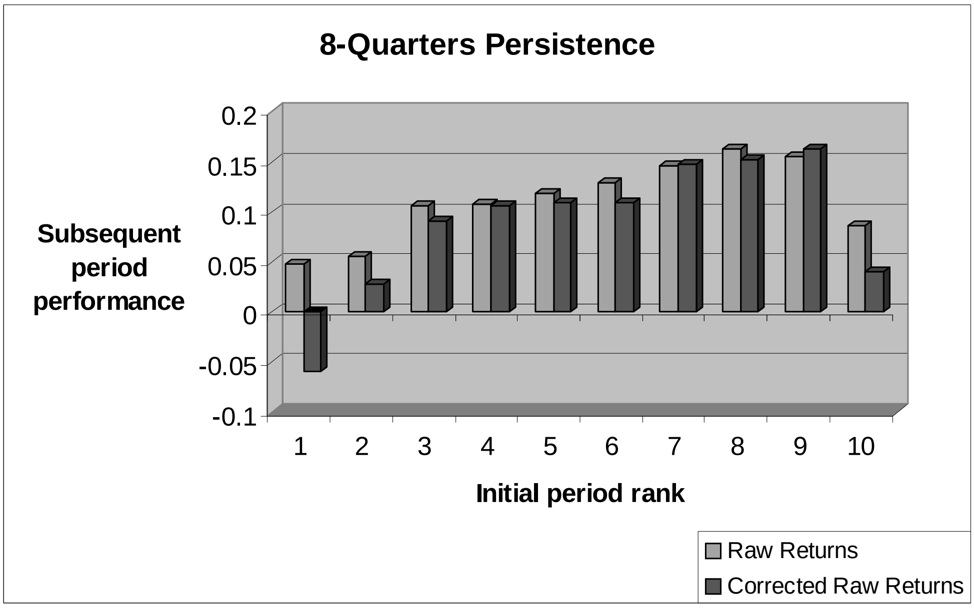

Figure 7: Biannual persistence in raw returns (robust estimates). Returns are annualized per decile.

(corrected relative returns). Underperformance and persistence of negative relative returns is found for the remaining deciles. The effect of look-ahead bias is most severe for decile 1, where the bias is about 6%. At a quarterly horizon the persistence of relative returns is even stronger. For decile 6 this outperformance is about 1% and increases to about 11% for decile 10. Similarly to the results of the raw returns, the effect of look-ahead bias is much smaller at a quarterly horizon than at an annual horizon. At a biannual horizon we do not observe any persistence of relative returns. Almost all funds show, on average, underperformance with respect to their corresponding style benchmark. When the 1% highest and lowest observations are omitted from the evaluation period, we find qualitatively similar results (Figure 11).

5 Concluding remarks

Empirical studies analyzing the performance of hedge funds are hampered by high attrition rates. The results in this paper clearly indicate that fund attrition is driven by historical returns, attrition rates being higher for funds that perform poorly. Given endogenous survival, standard ways of analyzing per-

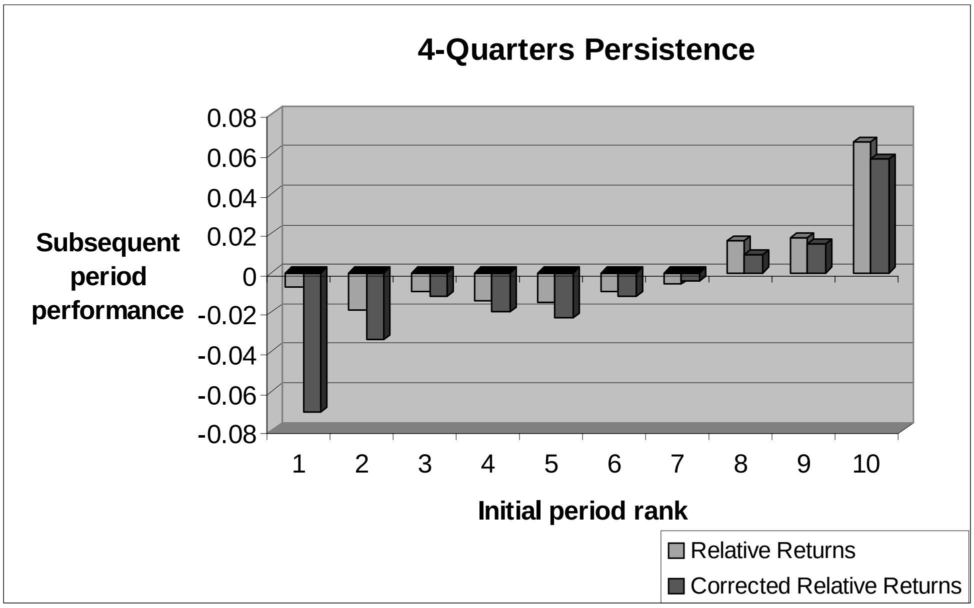

Figure 8: Annual persistence of style adjusted, relative returns. Returns are annualized per decile.

sistence in performance are affected by look-ahead bias, as one is implicitly conditioning upon the fund having observed returns for a number of consecutive quarters. To eliminate such biases, it is possible to use a weighting procedure, which requires an appropriate model that relates fund survival to fund performance and other observables.

In this paper we specified an empirical model for hedge fund survival in the US. We determined the persistence in fund returns with and without correcting for look-ahead bias, based upon the survival model and using a simple weighting procedure. The resulting graphs indicate that the look-ahead bias is quite severe. For the one quarter and four quarter horizons, the corrected results indicate positive persistence in raw fund returns. That is, the best 20 to 30% of the funds are expected to provide above average returns in the subsequent evaluation period too. As reported by Agerwal and Naik (2000), persistence is particularly strong at quarterly horizons and somewhat weaker at annual horizons. At a biannual horizon the results are ambiguous. The corrected and uncorrected average returns show strong persistence for all the deciles, except the top decile. A more robust estimate for the expected return, where the 1% lowest and highest returns got zero weight in the evaluation period, showed lower and probably more reasonable

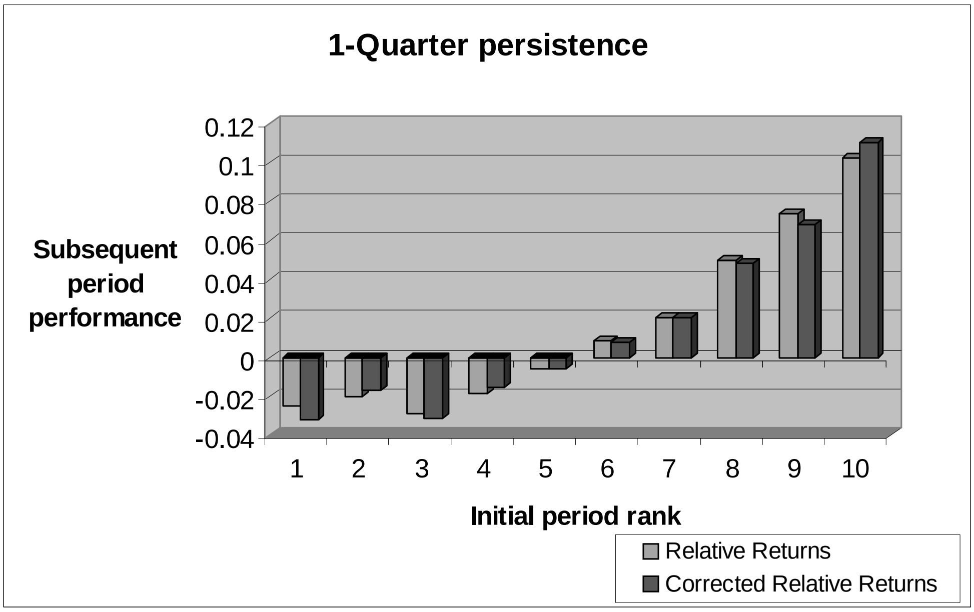

Figure 9: Quarterly persistence of style-adjusted, relative returns. Returns are annualized per decile.

average returns for deciles 1 and 10. Nevertheless, it can be expected that the losers (decile 1) continue to perform poorly at biannual horizon.

In order to check whether the presence of cross-sectional variation in expected returns due to style or risk characteristics explains the observed persistence patterns in raw returns, we examined persistence in style-adjusted or relative returns. The investment styles of the hedge funds in our sample correspond to the commonly used Tremont hedge fund style indices. By subtracting from the raw hedge fund returns the return of the corresponding style benchmark, and following the same procedure as in case of raw returns, we determined the persistence in relative returns with and without correcting for look-ahead bias. At a quarterly and annual horizon the graphs show that, on average, the top deciles outperform their style benchmark. For the top 10% of the hedge funds this outperformance is almost 6% (annualized) for an annual horizon, and even more than 11% (annualized) for a quarterly horizon. At a biannual horizon we mainly found underperformance of the hedge funds with respect to their style benchmark.

At the methodological level, the results in this paper stress the importance of correcting for look-ahead bias. The impact of this multi-period conditioning bias is quite severe, and also varies across the different horizons. The

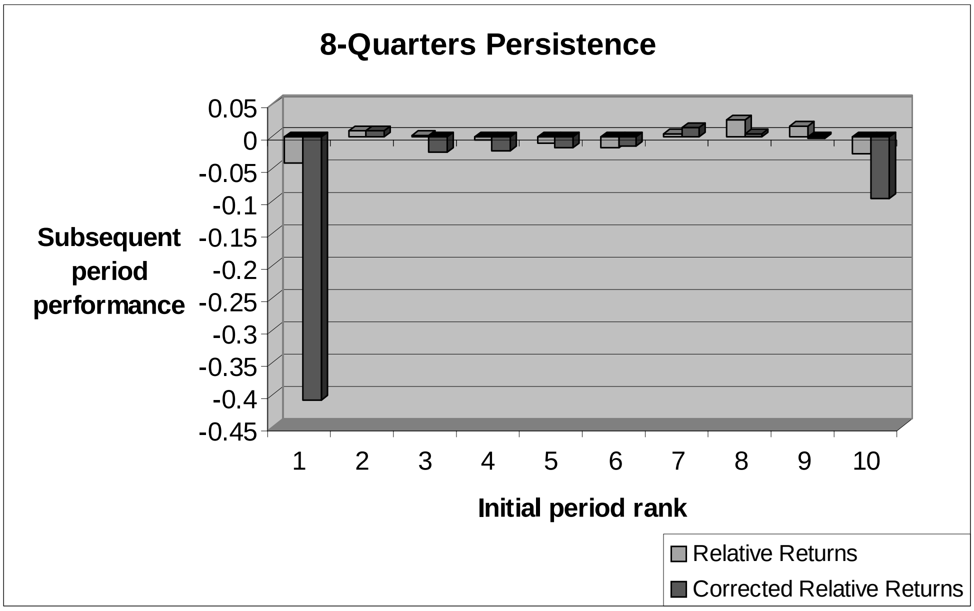

Figure 10: Biannual persistence of style-adjusted, relative returns. Returns are annualized per decile.

suggestion of Ackermann, McEnally and Ravenscraft (1999) that for hedge funds positive and negative survival-related biases may cancel out, is clearly not supported by our results.

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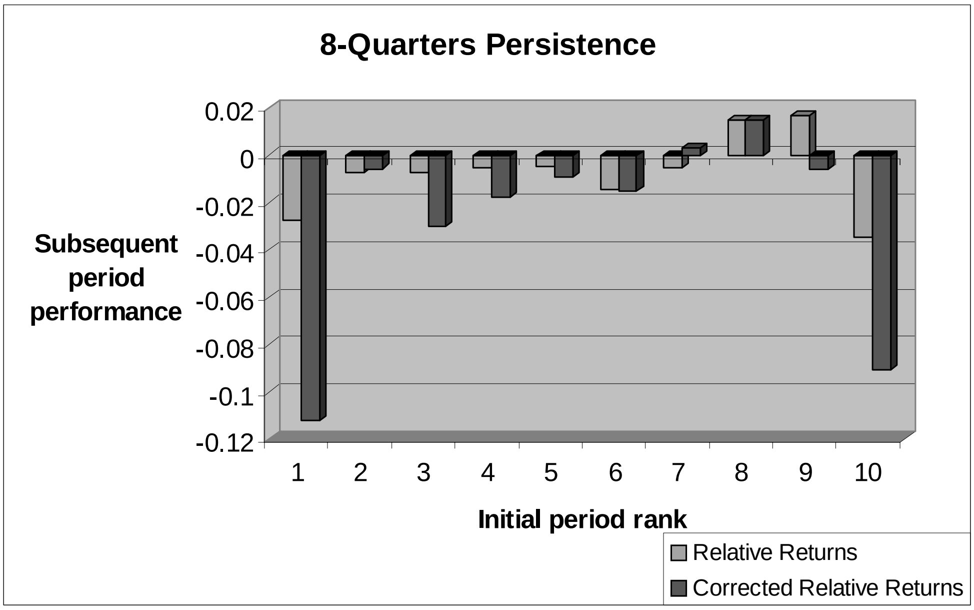

Figure 11: Biannual persistence in style-adjusted, relative returns (robust estimates). Returns are annualized per decile.

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