Competing Risks in Hedge Fund Survival

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Abstract

Institutional investors want long-term investments in hedge funds, but are troubled by premature liquidation. Current survival studies have treated all funds that exit the database as liquidated. We apply a competing risks model to account for the different exit types that hedge funds experience, which avoids blurring the effect of predictor variables. Predictor variables are treated as time dependent variables, which allows their impact to be measured at every instant of life. Separating exit types leads to estimates of attrition that are lower than previously thought. The results will help investors avoid the large capital losses associated with liquidation.

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1 Introduction

Traditionally, most of the money held by hedge funds has been from private accounts held by wealthy individuals. The amount of money being allocated to hedge funds is growing substantially, and in particular, much of this new money is from corporate and public pension plans, insurance companies, and other defined benefits plans. In the long term, investment in capital markets will likely produce returns that are high enough to meet beneficiary obligations to pensioners. Short term volatility in these markets, however, can put reliable payment streams at risk (Mirabaud (2003)). Consequently, institutional investors are rushing to hedge funds, and the absolute returns these funds generate, to make their pension portfolios more efficient. Their enthusiasm has been dampened by well-publicized hedge fund liquidations, such as that of LTCM, and the large capital losses that often accompany these liquidations.

The outlook for the hedge fund industry, however, remains bullish. Recent evidence suggests that institutional investors are planning their investments into these funds on a long-term basis, and are seeking funds that will not liquidate prematurely. They want to build ongoing relationships with their hedge fund managers, and are demanding funds with increased transparency, with robust business models and disciplined investment strategies, with a culture of integrity, and with thorough risk management practices (Casey, Quirk & Acito and The Bank of New York (2004)). Hedge funds that meet these requirements are likely to survive the longest and avoid liquidation.

Selecting hedge funds that are likely to produce consistent returns and remain in operation for a long time is therefore important for institutional investors. Survival analysis can help them in this regard, since it can provide an additional tool with which investors can perform due diligence on a group of hedge funds. In particular, it can help them select funds with characteristics associated with a long lifetime, and avoid those that are likely to liquidate. Hedge funds with longevity can ease investor concerns regarding illiquidity of these funds, namely their long lock-up period on new capital and infrequent redemption. To address this issue, we present a model that allows investors to estimate the risk of hedge fund liquidation and identify funds with longevity.

Hedge fund databases provide information on both live and dead funds (exited funds), making a survival analysis of their lifetimes possible. Fung and Hsieh (2002) point out that many funds exiting these databases have not liquidated, but have simply stopped reporting to the database vendor, for a variety of reasons. Most academic studies of hedge fund lifetimes, however, have treated all funds exiting the database as having liquidated, and have not made the distinction between the different types of exits that hedge funds experience. Furthermore, these studies have treated all predictor variables as fixed variables, when in reality many of these variables change over time. In this paper we show that predictor variables should be treated as time dependent variables whenever possible.

The aggregation of exit types into a single group can lead to at least five distortions when survival analysis is applied to hedge fund lifetimes. First, the effect of predictor variables on survival becomes blurred, since the variables are attempting to predict a heterogeneous group of exits. Second, it leads to distorted estimates of survival time, since many funds that are not liquidated but counted as dead, should be counted as censored instead. Third, it does not allow for survival time to be defined in terms of liquidation only – the only exit type that is of concern to investors (Baquero, ter Horst, and Verbeek (2005)). Other exits, such as those occurring when the hedge fund ceases to report performance figures to the database vendor, or those occurring when the fund is closed to new investment, do not have dire consequences for investors and are therefore of little economic concern. Fourth, it may produce mortality estimates that are artificially inflated, since some funds counted as dead in these estimates are in fact live funds. Fifth, it may underestimate survivorship bias, since non-liquidated funds in the dead pool often have good returns.

The survivorship bias in hedge funds databases is well documented. Most studies estimate the annual bias at 200 to 300 basis points. The annual survivorship bias in mutual funds, however, is usually estimated at 100 basis points or less. Thus, despite the fact that some exiting hedge funds have very good returns, estimates of survivorship bias are high. This suggests that hedge funds that liquidate do so with very poor returns. The results of this paper highlight the need for estimates of survivorship bias based on liquidated funds only, and for models that can reliably predict hedge fund liquidation.

Predictor variables whose values change over time, such as returns, volatility, or assets under management, are best treated as time dependent variables, rather than as fixed variables as is done in current studies of hedge fund survival. Indeed, the former approach is an *ex-ante* measure of performance, but the latter is an *ex-post* measure since performance can only be assessed after all the hedge funds are failed or censored. In current studies, performance is typically measured one or two years prior to the fund exiting, rather than over its entire lifetime. Time dependent variables, on the other hand, allow the performance of a group of hedge funds to be compared at each point in time and at the same age, rather than at the end of their lifetimes. It is more informative to assess how the performance of a failing fund compares to the performance of its peers, that is, of funds still alive at the same instant. This avoids comparing performance at two points in time that are substantially different, as would be the case when the performance of short-lived funds and long-lived funds is compared using fixed variables.

In this study we show how survival analysis can serve as a new tool for due diligence of hedge funds. Before committing any money to a hedge fund, investors should be able to estimate how long the fund is likely to survive, and whether the fund is at risk of liquidation. By avoiding hedge funds that are likely to liquidate, investors in general, and pension fund managers in particular, can avoid the large capital losses that often accompany liquidation. In order for this to be done accurately, liquidation must be separated from the other exit types that hedge funds can experience. We apply a competing risks survival model, in which the different exit types are treated separately, and allow for predictor variables whose values change over time to be time varying, rather than fixed. We extend the model of Brown, Goetzmann, and Park (2001) in a competing risks framework with time dependent variables. We also estimate survivorship bias by including only liquidated funds in the dead pool of funds. Consistent with previous studies of hedge fund survival, we apply logistic regression to model hedge fund survival status on predictor variables. We also apply multinomial logistic regression, which allows for different exit types rather than one single group of exits. This allows us to better identify the cross-sectional determinants of hedge fund liquidation. We also isolate exit types to estimate the attrition rate of hedge funds over the 1994 to 2003 period. Finally, we use a Weibull accelerated failure time (AFT) model under a competing risks framework to estimate the median survival time of funds, based on values of predictor variables such as returns, minimum investment, hurdle rate, and fees.

The results of this study can be summarized as follows. We find that funds no longer reporting performance figures to the database vendor have good returns and a large asset base, and thus resemble live funds more than they do liquidated funds. We find returns volatility to be a much more important predictor of fund liquidation than of the other exit types, and that the presence of a highwater mark can hasten liquidation. We also find that the effect of predictor variables in the Brown, Goetzmann, and Park (2001) model changes when competing risks and time dependent predictor variables are introduced. We find survivorship bias to be very high when only liquidated funds are used to define the pool of dead funds. We also find that isolating liquidation from the other exits leads to yearly attrition rates that are roughly one-half those obtained when all exits are used to define dead funds. Finally, we find that hedge fund lifetimes depend on a number of predictor variables, and that isolating liquidation leads to expected lifetimes that are roughly twice as long as those estimated when exits are aggregated.

2 Literature Review

The liquidation of Long-Term Capital Management (LTCM) has drawn attention to hedge fund liquidations and the large capital losses that investors suffer following liquidation, and has also opened up the possibility that hedge funds could be exposed to systemic risk. The success of LTCM spawned a number of imitator hedge funds, and as explained by MacKenzie (2003), this created a superportfolio within the industry since many of LTCM's positions were also being held by its imitators. The Russian government's default on its ruble-denominated debt triggered not only LTCM's liquidation but those of its imitators and other hedge funds investing in emerging markets, as investors began a flight to quality. Chan, Getmansky, Hass, and Lo (2005) develop a returns generating model that allows for systemic risk among hedge funds and banks. They show how uncorrelated returns can suddenly become very high when the returns of both institutions are in a phase-locking regime. Ineichen (2001) describes warning signals for investors who want to avoid investing in funds likely to suffer from premature liquidation.

The widely-varying estimates of survivorship bias encountered in the literature has prompted researchers to investigate factors driving hedge fund mortality and liquidation probabilities, in an attempt to understand factors driving survivorship bias. One small group of studies has estimated the attrition rate of hedge funds from databases or their fifty percent survival time. Another group of studies has applied multivariate analysis to identify factors linked to hedge fund survival time, defined as the time until a hedge fund exits the database. This paper refines these studies by isolating liquidation from the other exits hedge funds experience.

Estimates of survivorship bias in hedge fund databases range from as little to 0.16 percent per year, as obtained by Ackermann, McEnally, and Ravenscraft (1999), to as high as 7.70 percent per year, as obtained by Malkiel and Saha (2004). In most studies, such as those by Brown, Goetzmann, and Ibbotson (1999), Fung and Hsieh (2000), Liang (2000, 2001), Barès, Gibson, and Gyger (2001), Edwards and Caglayan (2001), and Barry (2002), survivorship bias is estimated at 2 to 4 percent per year.

Estimates of the attrition rate of hedge funds from databases range from 2.0 percent per year by Amin and Kat (2003) to 30.7 percent by Getmansky, Lo, and Mei (2004). Most other studies estimate yearly attrition at 5 to 15 percent, including those of Liang (2000, 2001), Barry (2002), Barès, Gibson, and Gyger (2001), and Baquero, ter Horst, and Verbeek (2005). These estimates are dependent on the database used and the time period under consideration. All studies, however, point to one consistent pattern. The attrition rate of hedge funds was high during late 1998, following the Asian crisis of 1997 and the near collapse of Long Term Capital Management in September, 1998. Many hedge funds died during that period, and few were born. Getmansky, Lo, and Mei (2004) and Amin and Kat (2003) show that the attrition rate of hedge funds has increased over the 1994 to 2004 period. Amin and Kat (2003) argue that this increase could reflect managers closing down faster nowadays than one decade ago. It could also reflect an influx of mediocre funds, or the limited investment and arbitrage opportunities available to hedge fund managers.

Estimates of the fifty percent (median) survival time of hedge funds are also varied. Brown, Goetzmann, and Park (2001) estimate it to be 2.5 years, Amin and Kat (2003) to be 5.0 years, while Gregoriou (2002) and the Securities Exchange Commission (2003) each estimate it to be 5.5 years. Barès, Gibson, and Gyger (2001), however, estimate it at over 10 years, much higher than that found in other studies.

Some authors have used probit regression to link hedge fund survival status (live versus dead) to predictor variables. Liang (2000) finds that funds with poor performance, low assets, low incentive fee, high leverage, young age, and low manager personal investment, are at increased risk of death. Baquero, ter Horst, and Verbeek (2005) use probit regression on liquidation only, and find that funds with poor performance, low assets, high incentive and management fees, and young funds, to be at increased risk of liquidation. These results presented in both studies are consistent with the findings of Brown, Goetzmann, and Park (2001) that funds with negative returns over a holding period one and two years prior to the last month of reporting are at increased risk of death, as are young funds and those with low excess returns. Chan, Getmansky, Hass, and Lo (2005) find also that funds with large capital inflows are at decreased risk of death.

Studies that have applied the Cox proportional hazards model to hedge fund lifetimes have pointed to a number of predictor variables related to survival. Brown, Goetzmann, and Park (2001) find that funds with low returns and young funds are at increased risk of failure. Their results suggest that while managers with returns below their highwater mark may have an incentive to increase volatility to bolster future returns, this incentive is mitigated by the increased risk of fund failure with rising volatility. Gregoriou (2002) finds mean returns, assets under management, and minimum purchase, to be positively related to survival. Boyson (2002) finds manager attributes, such as age or education, to be linked to survival, even after adjusting for returns and volatility.

The results of these studies suggest common predictor variables related to hedge fund survival in a Cox model. Estimates of attrition, of survival time, and of survivorship bias, however, vary substantially. One possible explanation could be that the models employed have treated all hedge fund exits as a single group, and have not attempted to isolate liquidation from the other exit types. For example, funds exiting because they are closed to new investment may have good returns, while liquidated funds have poor returns. By aggregating these exits together, the effect of returns on survival becomes unduly mitigated. Among studies of survivorship bias, only those by Ackermann, McEnally, and Ravenscraft (1999) and Baquero, ter Horst, and Verbeek (2005), have attempted to isolate the effect of different exit types on survivorship bias. In this paper we argue that the different estimates of survival, attrition, and survivorship bias encountered in the literature can be partly explained by the heterogeneous composition of dead funds.

3 Data

We use 2,371 live funds and 1,224 dead funds from the Hedge Fund Research, Inc. database (HFR), covering the period January 1994 to December 2003. The lifetime of a hedge fund is defined as the time elapsed from the date of inception to the date it exits the database. In the HFR database, funds exit for three reasons (1) they are liquidated, (2) they are closed to new investors, or (3) they have simply stopped reporting to HFR. We assume stationarity in the lifetimes of hedge funds, which implies that their calendar date of inception has no effect on how long they survive. This assumption is necessary, since methods of survival analysis translate all lifetimes to a unique, common origin.

We examine the following hedge fund variables to determine which are useful predictors of fund liquidation:

- Performance measures: monthly return (net of all fees) and assets under management (AUM) are treated as time dependent predictor variables. At each point of a hedge fund's lifetime, the mean and standard deviation of these variables twelve months prior to the point will be assessed.

- General features: management and incentive fees, minimum investment, hurdle rate, highwater mark. Since hedge funds rarely change these features during the course of their operations, these variables are treated as fixed.

- Trading parameters: leverage, redemption period. Hedge funds are likely to vary the amount of leverage they employ. Unfortunately, HFR contains only one single value of leverage, either a binary variable (yes/no), a range of values, or the maximum amount of leverage employed. Hence, despite that leverage is a time dependent variable, it is treated as a fixed dichotomous variable. Redemption period is treated as a fixed polytomous variable.

- In our cross-sectional models of survival, we also include the fund's age as a predictor variable.

The underlying feature of all methods of survival analysis is their ability to handle censored lifetimes. When all funds can be observed until failure, there is no censoring and ordinary methods to analyze the dependency of their lifetimes on predictor variables, such as OLS or GMM, can be employed. Hedge fund databases, however, always include censored (live) funds because they always include both dead and live funds. Ignoring censored funds, and including only dead funds in estimation, leads to biases since the censored lifetimes also contribute information about the survival experience of all funds in the database.

Insert Table I here

Table I presents the number of live and dead funds experiencing each exit type, and the mean and standard deviation of their returns during their entire history over the 1994 to 2003 period, and during the last twelve and six months preceding exit. During the last twelve and six months, liquidated funds suffer from negative returns and high volatility, but funds no longer reporting have good returns. Liquidated funds and funds closed to new investment experience a drop in assets during their last year, but funds no longer reporting remain large. The three groups of exiting funds are clearly not homogenous in their returns, volatility, or assets, especially during the last year and six months of existence. This provides the initial justification for treating these exits separately in subsequent analyses.

4 Methods and Results

In this section we describe the competing risks model we use to analyze hedge fund liquidation times, the multinomial logit model for liquidation probabilities, hedge fund attrition rates and survivorship bias, and a Weibull model for estimating hedge fund lifetimes. We also extend the model of Brown, Goetzmann, and Park (2001) to allow for multiple exits and time dependent predictor variables and compare the performance of the extended model to their original model.

4.1 Competing Risks Survival Model

Survival analysis is usually applied by defining a single lifetime as a non-negative random variable, T, and estimating the survival function $S(t)$ or the hazard function $\lambda(t)$. In this study we apply a competing risks model, a multivariate survival model in which only $T = \min(T_1, \cdots, T_m)$ is observed. Equivalently, the joint distribution of (T, J) is observed, where T is a non-negative random variable for survival time, and J is a discrete random variable with finite support corresponding to the jth failure type. We assume that once a fund has exited the database it can never re-enter, so that the competing risks model is the most appropriate model among the multivariate failure time models. This is because once a hedge fund exits the database with a particular failure type, the other failure times are never observed. If one allows for hedge funds to re-enter the database, however, then other multivariate models, such as the Markov model, are more appropriate.

We use the Cox proportional hazards model with time dependent predictor variables under competing risks with $m = 3$. In this model, each of the three exits is treated as a separate failure type. For the jth failure type $(j = 1, 2, 3)$ the model assumes a hazard function of the form

$$\lambda_j\left(t; \beta_j, Z(t)\right) = \lambda_{j0}(t) \exp\left(Z(t)^T \beta_j\right), \tag{1}$$

where $Z(t)$ is a vector of predictor variables containing the entire history of the variables up to time

t, and where for each failure type, $\lambda_{j0}(t)$ is a latent baseline hazard function and β_j is a vector of coefficients. Estimation of β_j is done with the partial likelihood. For failure type j, we observe k_j ordered lifetimes $t_{j1} < t_{j2} < \cdots < t_{jk_j}$. The partial likelihood under competing risks is then

$$L_P\left(\beta_1, \beta_2, \beta_3\right) = \prod_{j=1}^{3} \prod_{i=1}^{k_j} \frac{\exp\left(Z_{ji}(t_{ji})^T \beta_j\right)}{\sum\limits_{r \epsilon R(t_{ji})} \exp\left(Z_r(t_{ji})^T \beta_j\right)} \tag{2}$$

where $Z_{ji}(t_{ji})$ is the value at time t_{ji} of the vector of predictor variables for the ith hedge fund experiencing a failure of type j at time t_{ji}, and $R(t_{ji})$ is the risk set at time t_{ji}, namely the set of funds still alive immediately prior to t_{ji} (Kalbfleisch and Prentice (2002)).

For each predictor variable the Cox model produces a hazard ratio (HR), which represents the percent change in the hazard rate of the fund brought on by a one-unit increase in the value of the predictor variable. When $HR > 1$ the variable increases the hazard (decreases survival), and when $HR < 1$ the variable decreases the hazard. The percent change in the hazard rate of the fund due to the variable is given by $(HR - 1) \times 100\%$. Hazard ratios can be defined for binary predictor variables, such as leverage or hurdle rate, or continuous predictor variables, such as returns or volatility. Suppose that β_{ij} is the coefficient for variable i acting on failure type j. For a binary variable the hazard ratio is defined as $HR = \frac{\exp(\beta_{ij} \times 1)}{\exp(\beta_{ij} \times 0)} = \exp(\beta_{ij})$, so HR represents the change in hazard brought on by the presence of the variable. For a continuous variable, $HR = \frac{\exp\left(\beta_{ij} Z_k(t)\right)}{\exp\left(\beta_{ij} Z_m(t)\right)} = \exp\left(\beta_{ij}\left[Z_k\left(t\right) - Z_m\left(t\right)\right]\right)$, where $Z_k\left(t\right)$ and $Z_m\left(t\right)$ are two different values of the variable, so that $HR = \exp(\beta_{ij})$ represents the change in hazard brought on by a one-unit increase in the variable (when $Z_k(t) - Z_m(t) = 1$). For both types of variables, the values of the remaining variables are kept the same, so these cancel out of the expression for the hazard ratio.

4.2 Competing Risks Analysis of Hedge Fund Lifetimes

Table I indicates that the group of exited funds does not constitute a homogeneous group. Funds that stop reporting have good returns and are large, while liquidated funds have poor returns and are small. Consequently, the effect of performance and size predictor variables on survival would become blurred if the exit types were aggregated as a single group and a univariate survival model applied. To correct for this possibility we fit the Cox proportional hazards model for each exit type separately in a competing risks framework. For comparison with existing studies, we also aggregate the exits and apply a conventional univariate Cox model on all exits combined. We treat returns and assets under management as time dependent predictor variables, rather than as fixed variables. We also fit the model of Brown, Goetzmann, and Park (2001), and extend their model by allowing for competing risks and time dependent predictor variables. To make our results comparable, and to minimize backfill bias (Ackermann, McEnally, and Ravenscraft (1999)), we use only funds born on or after January 1st, 1994.

Insert Table II

Hazard ratios (HR) from the Cox model under competing risks, and from the conventional Cox model on all exits combined, are presented in Table II. The results point to differences in the predictive nature of the variables on liquidation, compared to other exit types. The effect of many predictor variables is different when each exit type is treated separately, and the effect tends to cancel out when exits are combined. Hence, high volatility in returns and in assets are strongly associated with liquidation, and high returns are more protective of liquidation than of the other exits. For example, the hazard ratio of 1.058 for all exits combined suggests that every $100M increase in asset volatility increases the risk of exit by 5.8 percent. In fact, asset volatility increases the risk of liquidation only, but not of the other exits. Moreover, the effect of asset volatility on liquidation is much higher than that suggested by the hazard ratio corresponding to all exits. Indeed, the hazard ratio of 1.243 indicates that every $100M increase in asset volatility increases the risk of liquidation by 24.3 percent (Table I suggests that a $100M variation in asset base can be expected). Investors are therefore much more at risk of fund liquidation by high asset volatility than the hazard ratio for all exits suggests.

Examination of the other hazard ratios further illustrates how the effect of explanatory variables becomes blurred when all exits are aggregated. Every one percent increase in monthly returns decreases the hazard of all exits by 6.9 percent, but decreases the hazard of liquidation by 9.6 percent. Investors are therefore more protected of liquidation by high returns than the aggregated hazard ratio suggests. For funds closed to new investment, the effect of incentive fee is strongest, as is the effect of average assets under management. This is consistent with the argument of Fung and Hsieh (2002) that good managers can charge high incentive fees, build up their assets base, and close their funds to new investors when a target asset size is reached. Unlike Gregoriou (2002) or Liang (2000), we find no effect of leverage or redemption period on survival. We exclude these two variables to keep the model parsimonious.

The results in Table II indicate also that high management fees are associated with a decreased risk of fund liquidation, which suggests that good managers can charge high management fees and still avoid liquidation. The highwater mark imposed by hedge funds, however, can increase the risk of liquidation. This reflects the argument of Brown, Goetzmann, and Ibbotson (1999) and Liang (2000) that once losses are incurred, it is difficult for some managers to recuperate losses, attain their highwater mark, and avoid liquidation. Managers incurring a loss and subjected to a highwater mark may have no incentive to continue operating the fund, and may be motivated to simply liquidate its assets (Scholes (2004)). We find no effect of minimum investment on the risk of any type of exit, which indicates that the effect of fund size on survival is better proxied by assets under management than by minimum investment. We also find that funds with a hurdle rate tend to survive longer, regardless of which exit type is used to define the lifetime.

The hazard ratios for liquidation in Table II can be used to assess the impact of predictor variables on liquidation only. Hazard ratios corresponding to the other exits are not as important, since those exits do not have dire consequences for investors. Assessing the impact of predictor variables on the other exits does not provide warning signals about possible capital losses. We include these latter hazard ratios, however, and those corresponding to aggregated exits, to illustrate arguments in the literature regarding voluntary hedge fund closure, and to illustrate how the effect of the predictor variables on liquidation can become blurred if liquidation is not analyzed separately from the other exits. Indeed, the p-values reported in the last column suggest that the effect of some of the variables is not the same across exit types.

4.3 Extension of the Brown, Goetzmann, and Park (2001) Model

In this section we modify the model of Brown, Goetzmann, and Park (BGP) (2001) using the methodologies outlined previously, and we show how these modifications lead to a refinement of their model. Table III presents hazard ratios from the Cox model of BGP (2001), and from the model extended by allowing for multiple exits and for time dependent predictor variables. The left side of Panel A presents the BGP (2001) model estimated with our data. It indicates that negative returns over the last year of life and a high standard deviation increase the risk of failure, while high risk-adjusted returns over the last year of life decrease the risk of failure. These findings are similar to those of BGP (2001). The right side of Panel A presents the BGP model with time dependent predictor variables. It indicates that the effects of returns and volatility on fund exit are present at each instant of a hedge fund's existence, and not only during its last year. This is an important distinction. It is obvious from Table I that, *ex-post*, returns and volatility during the last year of life are strong predictors of liquidation. What is less obvious is how returns and volatility can affect liquidation during the entire span of a fund's lifetime. That these variables remain significant when treated as time dependent variables shows that they are stronger predictors of liquidation than suggested when they are treated fixed variables.

Extending the BGP (2001) model to multiple exit types allows the effect of the predictor variables to be assessed for each exit type separately. Panel B of Table III indicates that negative returns, captured by the Under_Quart, Under_Year, and Under_2Year variables, are strongly linked to liquidation. This is consistent with the results of Table II, and with the finding in Table I that liquidated funds have returns substantially lower than those of surviving funds. Panel B also indicates high returns volatility to be associated with an increased hazard of any exit type.

When volatility is treated as time dependent, however, the results change. Panel C presents the BGP (2001) model with time dependent variables and multiple exits. The results indicate that increased volatility at each instant of the fund's lifetime leads to an increased risk of liquidation, but not of other exits. Hence, persistent volatility is an important predictor of liquidation. The results show also that the predictive effect of negative returns is strongest for funds liquidating

($HR = 3.809$), and weakest for funds no longer reporting and closed to new investment ($HR = 1.400$ and $HR = 1.405$ respectively). High returns, as indicated by the performance variable Alpha(t), leads to a decrease of the reporting time of funds and of fund closure, but has no effect on the time to liquidation of hedge funds.

Insert Table III

The results of Table III further highlight the need to separate exit types and treat predictor variables as time dependent whenever possible. When exits are aggregated, the effect of negative returns appears weak. When exits are separated, however, the effect of negative returns on liquidation becomes much more evident. When variables are treated as time dependent, we see that their effects are present at each instant of a hedge fund's lifetime, and not only during last the quarter, year, or two years of existence.

4.4 Cross-Sectional Determinants of Liquidation

Several studies, such as those by BGP (2001), Liang (2001), Malkiel and Saha (2004), and Baquero, ter Horst, and Verbeek (2005) model cross-sectional determinants of survival by using a probit model, where the dependent variable is a binary variable corresponding to whether a fund is alive or dead. If longitudinal models of hedge fund survival are hampered by the aggregation of exit types into a single heterogeneous group, however, then cross-sectional models of survival ought to suffer the same fate. Among these studies only Baquero, ter Horst, and Verbeek (2005) address this issue. They run a probit model on fund liquidation only, and define funds experiencing other exits as live funds. This approach assumes that all non-liquidated funds exiting the database are in fact alive.

We apply a multinomial logit regression model with four possible outcomes for hedge funds: alive, liquidated, closed to new investment, or no longer reporting. This model presents a refinement over existing models. The group of exits is separated, so each exit type is given a separate outcome, and liquidation can be isolated. According to the multinomial logit model, the probability of fund i experiencing exit type $j = 1, 2, 3$ is given by

$$\pi_{ij} = P(Y_i = j) = \frac{\exp\left(Z_i^T \beta_j\right)}{\sum_{k=1}^{3} \exp\left(Z_i^T \beta_k\right)} = \frac{1}{\sum_{k=1}^{3} \exp\left[Z_i^T \left(\beta_k - \beta_j\right)\right]} \tag{3}$$

where β_j is a set of coefficients associated with exit type j, and Z_i is a set of predictor variables for the ith hedge fund (Agresti (2002)). We use the live outcome as the baseline outcome, so the probability of fund i being in the live category is $1 - \sum_{j=1}^{3} \pi_{ij}$. For each variable in the multinomial model, we present contrasts for the beta coefficient across the failure types. For comparative purposes we also run a logistic regression model that combines all exits into a single group.

Insert Table IV

The results of the multinomial and logistic models are presented in Table IV. Panel A indicates that liquidation is the exit type that is most affected by negative returns over one quarter, one year, and two years prior to fund exit. This reflects the finding presented in Panel B of Table III. Over the short term (one quarter) negative returns are more likely to lead to funds being closed to new investment than to the other exits. In the long term, however (one and two years), negative returns affect the probability of liquidation more than they affect the other exits, as evidenced by the large and significant coefficients of Under_Year and Under_2Year for liquidation. Panel B indicates also that the effect of volatility is similar across failure types, since none of the contrasts is significant. Similar to Brown, Goetzmann, and Park (2001), Liang (2000), Baquero, ter Horst, and Verbeek (2005), Chan, Getmansky, Hass, and Lo (2005), and Malkiel and Saha (2004), we find that young funds, funds with low returns, and funds with high returns volatility, are at increased risk of any exit type from the database. This reflects the argument of Brown, Goetzmann, and Park (2001) that seasoned managers of well-established funds benefit from a long experience in the industry, and are likely to survive longer. Our multinomial model indicates that long-term risk adjusted returns, as proxied by Alpha(Year), decrease the probability of fund closure and of funds no longer reporting, but have little effect on liquidation.

4.5 Estimates of Survivorship Bias

The widely-varying estimates of survivorship bias encountered in the literature could partly be due to the heterogeneity of the dead pool of funds, in particular, to the finding of Fung and Hsieh

(2002) and Liang (2000) that some dead funds have very good returns and are alive and well. To address this issue, we calculate survivorship bias as the difference in returns between live and dead funds, and vary the composition of the pool of dead funds. Table V indicates that varying the dead pool can substantially change estimates of survivorship bias. Including all dead funds leads to a yearly upward bias of 1.51 percent in returns, which is consistent with the estimates of Liang (2001), Edwards and Caglayan (2001), and Amin and Kat (2003). This estimate is misleading, because when funds no longer reporting are excluded from the dead group, the estimate jumps to 3.28 percent, which is similar to that obtained by Brown, Goetzmann, and Ibbotson (1999) and Fung and Hsieh (2000). This finding is consistent with the notion that funds no longer reporting experience good returns. When liquidated funds are excluded, it drops to -0.36 percent. This reflects the argument of Liang (2001) that poor performance is the main reason for fund liquidation. Panel B indicates that treating funds no longer reporting as live funds produces a yearly bias of 3.35 percent. Again, most of this bias can be attributed to liquidated funds, because when liquidated funds only constitute the dead group, the estimate increases to 4.60 percent. Baquero, ter Horst, and Verbeek (2005) refer to this as "liquidation bias", and estimate it at 1.52 percent yearly. Our annual estimate of 4.60 percent is higher, and higher than most other estimates found in the literature, but lower than the 7.40 percent found by Malkiel and Saha (2004).

Insert Table V

4.6 Hedge Fund Attrition Rates

Several studies have pointed to an increase in the attrition rate of hedge funds over the last decade. Getmansky, Lo, and Mei (2004) find the attrition rate to increase from 3.0 percent in 1994 to 10.7 percent in 2003, with a high of 11.4 percent in 2001. Amin and Kat (2003) find annual attrition to increase from 2.2 percent in 1995 to 12.3 percent in 2000. These estimates, however, could be inflated because no effort was made to separate liquidation from the different exits that hedge funds experience.

We estimate yearly attrition as a proportion, with denominator defined as the number of funds alive at the beginning of the year, and numerator as the number of funds liquidating during the year. We also estimate attrition by redefining the numerator as the number of closed funds, funds no longer reporting, liquidating plus no longer reporting, liquidating plus closed, and no longer reporting plus closed. To compare our attrition rates with those of current studies, we also define the numerator as the number of all exited funds during the year. The estimates in Table VI indicate that when exits are aggregated, the rates of attrition are close to those obtained by Getmansky, Lo, and Mei (2004), except in 1998, during which time we find an attrition rate of 16.16 percent, substantially higher than the 9.5 percent found by these authors.

Insert Table VI

We find the attrition rate of funds closing to new investment to have increased from 0.17 percent in 1994, to 1.47 percent in 2003. This supports the argument of Amin and Kat (2003) that fund managers are closing down faster nowadays than one decade ago. The overall increase in attrition can therefore be partially attributed to the increase in funds no longer reporting to HFR over the 1994 to 2003 period. When liquidation only is considered, attrition is estimated at 3 to 5 percent annually, with no apparent increase. Table I indicates that the returns and assets of funds closed to new investment resemble those of liquidated funds. If we suppose that closed funds are liquidated also, then attrition is roughly 5 to 6 percent year, again with no apparent increase (second to last column of Panel B). All of our estimates of attrition, however, point to an marked increase in 1998. The results of this analysis suggest that the increase in attrition found in previous studies is blurred by the different exits hedge funds experience, and that the rate of attrition may not be increasing as dramatically as previously thought. Overall, we find that yearly attrition rates based on liquidation only are roughly one-half as large as those based on all exits combined.

4.7 Hedge Fund Survival Time

In this section we adopt the view of a prospective investor who wishes to commit money to a hedge fund, and show how survival analysis can help the investor select funds that are likely to survive a long time and avoid liquidation. To estimate the survivor function $S(t)$ we use the Kaplan-Meier estimator given by

$$\widehat{S}(t) = \prod_{j:t_j<t} \left(1 - \frac{d_j}{n_j}\right), \tag{4}$$

where n_j is the number of funds alive at the instant immediately preceding time t_j and d_j is the number of funds liquidating at time t_j. For comparative purposes we also fit the Kaplan-Meier estimator by defining d_j to be all funds exiting at time t_j. From the Kaplan-Meier estimator we obtain the mean survival time given by $\widehat{\mu} = \int_0^\infty \widehat{S}(t)dt$. We repeat this analysis on large and small funds in the different hedge fund styles in the HFR database.

Insert Figure I

Figure I presents the Kaplan-Meier estimates of $S(t)$ for liquidation (solid line) and for all exits (dashed line). Treating liquidation separately leads to a marked increase in survival time, a finding that is consistent with the decreased attrition shown in Table VI. The mean survival time until liquidation is 8.3 years, while the mean survival time until any exit is 6.5 years. Hence, isolating liquidation leads to a upward revision of almost two years in mean survival time. The latter estimate of 6.5 years is comparable to the fifty percent survival time of 5.5 years found by Gregoriou (2002) and the Securities and Exchange Commission (2003). Hence, we are confident that the increase in survival is due to isolating liquidation, and not to differences in database composition.

Insert Table VII

Table VII presents the mean survival time of hedge funds by style, where survival is defined in the Kaplan-Meier estimator as the time until exit from the database (Panel A) and the time until liquidation (Panel B). It also presents the mean survival time for large and small funds in each style and the p-value for the Log Rank test of equal survival between the large and small funds. Large (small) funds are those with assets larger (smaller) than the median assets for all hedge funds in that style. In general, the mean survival times in Panel B are longer than those in Panel A, which indicates that the time until liquidation is longer than the time until the fund exits the database, and which reflects the multiple types of exits that hedge funds undergo. Hence, mean survival times based on all exits will be biased downwards. Investors can expect longer survival times than those suggested by models that aggregate exits into a single group.

Panel B of Table VII provides an idea of how long newly-launched funds can be expected to survive before liquidation. An investor randomly selecting a fund in the Distressed Securities style, for example, can expect the fund to survive 5.25 years before liquidation. Choosing a large fund will increase expected survival time to 5.45 years, while a small fund will decrease it to 5.00 years, but this difference is not significant ($p = 0.0949$). On the other hand, a newly-launched Fixed Income hedge fund will survive 7.36 years before liquidation. A large Fixed Income fund will survive slightly longer, 7.81 years, while a small fund will survive three years less, 4.12 years, a significant difference ($p = 0.0224$). The results of Panel B indicate that, in every category except Merger Arbitrage, large funds outlive small funds. This is consistent with the finding in Table II that a large asset base is associated with longevity.

Having identified which investment categories are associated with longevity, an investor may then wish to estimate the expected survival time of a hedge fund, based on its characteristics and performance. The Cox model does not usually provide estimates of survival time, only of the impact of predictor variables on the hazard function, via hazard ratios. To estimate hedge fund lifetimes we use the accelerated failure time (AFT) Weibull regression model, which uses the following specification for the log of survival time

$$\log(T) = \alpha + z^T\beta + \sigma W \tag{5}$$

where z and β denote vectors of predictor variables and regression coefficients, respectively, σ denotes a scale parameter, and W follows the extreme value distribution (but T follows the Weibull distribution). Estimates of α, β and σ are obtained by maximum likelihood, and an estimate of the 50th percentile of the distribution of $Y = \log(T)$ at values $z = z_0$ of the explanatory variables is given by $\widehat{Y}_{50} = \widehat{\alpha} + z_0^T\widehat{\beta} + \widehat{\sigma}W_{50}$, where $W_{50} = \log(\log 2)$ is the 50th percentile of the extreme value distribution. Exponentiation of $\widehat{Y}_{50}$ produces an estimate of the median survival time for a hedge fund with values z_0 of the predictor variables (Kalbfleisch and Prentice (2002)). To simplify the notation we exclude the subscript j on T, Y, α, β and σ, for $j = 1, 2, 3$.

Insert Table VIII

Table VIII presents estimates of the Accelerated Failure Time (AFT) Weibull regression model under competing risks. In this model a positive (negative) coefficient leads to an increase (decrease) in survival time. The results are consistent with those of the Cox proportional hazards model presented in Table II. The effects of returns and assets under management (mean and standard deviation) are strongest for liquidation. High returns and a large asset base, and low volatility in returns and assets, increase the time to liquidation, leading to longevity. The presence of a hurdle rate increases the time until each exit type, and of all exits combined, while high incentive fees have the opposite effect. We find high management fees to decrease the time until fund closure, but as in Table II we find no effect of minimum investment on any of the exits. The results of Table VIII support the idea that the factors driving liquidation are different from those driving the other exits that hedge funds can experience. It also highlights the need to isolate liquidation from the other exit types if those factors are to be accurately identified and measured.

Insert Table IX

Based on the estimates of the AFT model in Table VIII, we can estimate the average time that a hedge fund with certain characteristics can be expected to survive. Table IX presents the median survival time of four hypothetical hedge funds. Fund 1 has a an average return of one percent with volatility of two percent over the last twelve months of observation, no highwater mark or hurdle rate, incentive and management fees of twenty percent and one percent respectively, a minimum investment of $500,000 and mean and volatility of assets over the last twelve months of observation of $500M each. Table IX indicates that an investor can expect such a fund to survive 2.7 years before exit from the database, but 6.7 years before liquidation. Fund 2, which is identical to Fund 1 except that its incentive fee is ten percent, can be expected to survive 7.4 years before liquidation. The results of two other hypothetical funds are also presented. In all four cases, the time to liquidation is roughly twice as long as the time to all exits. This suggests that estimates of hedge fund lifetimes based on models that aggregate exits are misleading, since investors can except lifetimes roughly twice as long as those suggested by aggregated models.

5 Discussion

The results of this paper raise several issues that merit discussion. Ackermann, McEnally, and Ravenscraft (1999) attribute low survivorship bias to two performance effects acting in opposite directions. Poor returns from liquidated funds will cancel out good returns from closed funds and funds no longer reporting, to yield a net bias that is close to zero. A low survivorship bias implies that investors need not be concerned about the performance of their portfolios when hedge funds exit the database. This sense of security is justified when funds exit because they are no longer reporting. Our results indicate, however, that when funds exit because of liquidation, investors will experience very poor performance. Survivorship bias and survival are therefore linked: since most of the bias results from liquidated funds, it is important for investors to avoid investing in funds that are likely to liquidate. Our results suggest that investing in funds that subsequently close to new investment or that stop reporting, will likely not severely affect the long term performance of their portfolios.

In this study we argue that longitudinal survival models such as the Cox proportional hazard model or the Weibull AFT regression model, are preferable to cross-sectional survival models such as the probit model. Longitudinal models can provide an estimate of how long a fund can be expected to survive before liquidating, whereas cross-sectional models can only provide estimates of the probability of fund liquidation. In our Cox model we use time dependent predictor variables, rather than fixed predictor variables, on variables whose values change over time, such as returns. Previous studies have attempted to capture the effect of returns by considering returns during the last six or twelve months of life. This is an *ex-post* approach because returns can only be measured after a hedge fund has liquidated, and is therefore of little use for predicting a fund's lifetime. For example, when observing a fund at any month, it is impossible to ascertain whether the last six months of returns being observed are the fund's final six months of returns, or simply the most recent six months of returns. That distinction can only be made the next month, conditional on whether the fund lives or dies. With time dependent variables, however, the effect of returns at every month during a fund's lifetime can be assessed, without having to condition on fund survival status each month. Time dependent variables, therefore, constitute an *ex-ante* approach for measuring the effect of explanatory variables whose values change over time.

It is likely that macroeconomic conditions are related to fund liquidation. Hedge funds may perform poorly during bad economic times, such as during periods of slow economic growth or during recessions. Smaller funds may have an insufficient asset base to withstand hard times for an extended period, which could lead to their liquidation when economic conditions deteriorate. Hence, lagged economic indicators may prove to be useful predictors of liquidation. We leave this issue open for possible future research.

We exclude funds born before 1994 because we wish to minimize backfill bias in the HFR database. This can lead to underestimates of survival, because long-lived funds born before 1994 and either (*i*) dying after 1994, or (*ii*) still alive at the end of the observation period, are not included in the sample. This potential bias is mitigated by short-lived funds that were born and died before 1994, since those funds are not included in HFR. By analyzing funds born after 1994 only, we exclude both long- and short-lived funds from the sample, but it is impossible to ascertain what potential impact such an exclusion has on our estimates of hazard ratios and survival time. Barès, Gibson, and Gyger (2001) do not exclude funds born prior to 1994 and find a fifty percent survival time of over ten years. Many short-lived hedge funds that do poorly, however, never report to databases, which implies that the estimate of that study is biased upwards. Nevertheless, it is possible that hedge funds live much longer than some studies, including this study, suggest.

We have not assessed the impact on survival of investor capital flows to and from hedge funds. Funds that experience large outflows of capital may find it difficult to meet their overhead costs, even if they charge high yearly management fees to cover those costs. The effect of outflows would be even more dramatic for funds that have poor returns, fall under their highwater marks, and cannot charge their incentive fee. It stands to reason that capital flow, modeled as a time dependent variable, might be a strong predictor of liquidation. Inflows and outflows are partly reflected in the assets under management of each fund, so it is likely that the effect of capital flows can be captured by assets under management. In a logit model, Chan, Getmansky, Hass, and Lo (2005) find capital flows to be a stronger predictor of hedge fund exit than assets under management, but most of their effect was attributed to the last twelve months prior to exit from the database and that study did not separate liquidation from the other exit types. Funds that exit because they are closed to new investment may experience lower capital flows simply because they are refusing new investors. Ineichen (2001) points out that funds should return capital gains to existing investors once their optimal asset base has been reached. In this study we find that a large asset base significantly decreases the risk of fund liquidation. As pointed out by Hachemian (2005), one reason for the demise of small hedge funds is that they do not generate sufficient fees to hire administrative staff.

Their managers spend too much time with administrative duties, and not enough time attending to their investments.

We have assumed that liquidation is always an undesirable outcome. Yet some hedge funds liquidate simply because their managers wish to cease operations. In that case, investors redeem their money and do not suffer losses. Most liquidations, however, are associated with large capital losses, such as the liquidations of LTCM and Tiger Funds. The findings in Table I suggest that liquidated funds lose money during their last year of operation, and that liquidation is usually undesirable.

6 Conclusion

With the increasing number of hedge funds available, and the long lock up period and infrequent redemption that these funds impose, institutional investors are demanding funds likely to remain in operation for many years and avoid liquidation, so that the large capital losses that often result from liquidation can be avoided. The recent popularity of hedge funds offering portfolio insurance and capital guarantees is testimonial to this new trend. Survival analysis can serve as a tool for due diligence of hedge funds, since it can help investors identify fund characteristics that are associated with longevity and help them select hedge funds less likely to liquidate. Our estimates of survivorship bias indicate the differential in returns that investors can expect in the long run, within a cohort of selected funds, between funds that live and those that die. Most studies of hedge fund survival and of survivorship bias are incomplete because they do not separate liquidation from the other exit types that hedge funds can experience. It is important to isolate liquidation from the other exits and identify determinants of liquidation solely, since other exits have little economic consequences for investors.

The main contribution of this paper is to treat the different types of exits that hedge funds can experience separately, and in particular, to isolate liquidation from the other exits and provide estimates of survival and mortality that are more economically meaningful than those produced in previous studies of hedge fund survival. We fill a gap in the existing literature because we produce more representative estimates of hedge fund survival, attrition rates, and of survivorship bias. By treating predictor variables of survival as time dependent rather than fixed, we evaluate their impact on survival at each instant of hedge fund lifetimes, rather than during the last months or year of their life. The results of this paper provide investors with a new method with which to evaluate and screen hedge funds, complementing studies on performance persistence, diversification, and asset pricing already at their disposal in the literature.

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Table I. Number of Failure Types of Dead Funds, with Mean and Standard Deviation of Returns and Assets During Their Entire History, and During the Last Twelve and Six Months of Reporting

PANEL A: Number of live funds and exited funds for each exit type, with the mean and standard deviation of their returns. PANEL B: Number of live funds and exited funds for each exit type, with the mean and standard deviation of the assets under management. Returns and assets are calculated over their entire history (first set of columns), over the last twelve months before exit (second set), and over the last six months before exit (third set).

Panel A: Returns (%)		Entire History		Last 12 months		Last 6 months	
	# Funds	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Live	2,371	1.07	4.95	1.37	3.42	1.32	3.03
No Reporting	522	1.28	7.13	0.85	8.66	0.64	9.60
Liquidated	513	0.71	7.45	−0.06	8.30	−0.14	8.52
Closed	189	0.72	6.81	0.37	7.36	0.42	7.58
Panel B: Assets ($M)		Entire History		Last 12 months		Last 6 months	
	# Funds	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Live	2,371	93	357	125	508	137	576
No Reporting	522	105	572	93	498	93	496
Liquidated	513	54	315	58	354	57	356
Closed	189	65	416	59	354	48	256

Table II. Hazard Ratios from the Cox Proportional Hazards Model Under Competing Risks and With Time Dependent Predictor Variables

Hazard ratios for the competing risks Cox proportional hazards (PH) model estimated for each exit, and for the conventional Cox PH model for all exits combined. The model for the exits Liquidated (2st column), Closed to New Investment (3rd column) and No Longer Reporting (4th column) treated simultaneously is the competing risks model with time dependent predictor variables, with hazard function $\lambda_j\left(t; Z\left(t\right)\right) = \lambda_{0j}(t)\exp\left(Z(t)^T\beta_j\right)$ for $j = 1, 2, 3$. The model for all exits combined (5th column) is the conventional Cox PH model with time dependent variables, with hazard function $\lambda(t; Z(t)) = \lambda_0(t)\exp\left(Z(t)^T\beta\right)$. Avg_Ret($t$) and StdDev_Ret($t$) are time dependent predictor variables for the mean and standard deviation of returns over one year, respectively, each expressed as a monthly percentage. Highwater and Hurdle are fixed binary predictor variables taking on the value one if the fund has a highwater mark and a hurdle rate, respectively. IncFee and ManFee are fixed predictor variables for incentive fee and management fee respectively, each expressed as a percentage. MinInv is a fixed predictor variable for minimum investment, expressed in \$M. Avg_AUM(t) and StdDev_AUM(t) are time dependent predictor variables for the mean and standard deviation of assets under management over one year, respectively, expressed in \$100M. A hazard ratio greater than one increases the risk of failure, while a hazard ratio less than one decreases the risk of failure. Hazard ratios significant at the 0.1, 1, and 5 percent level are denoted with ***, ** and *, respectively. For each variable, the p-value is from a likelihood ratio (LR) test that the predictor variable is identical across exit types, where the LR is obtained from only that variable included in the model. For all variables included, the LR test p-value is $<.0001$.

Variable	Liquidated	Closed	No Reporting	All Exits	LR p-value
Avg_Ret(t)	0.904^{***}	0.918^{***}	0.959^{***}	0.931^{***}	0.0007
StdDev_Ret(t)	1.031^{***}	0.964^{*}	1.013^{***}	1.022^{***}	0.6838
Highwater	1.716^{**}	1.062	1.030	1.238^{*}	0.0213
Hurdle	0.253^{***}	0.165^{***}	0.248^{***}	0.236^{***}	0.3010
IncFee	1.013	1.022^{*}	1.019^{*}	1.016^{**}	0.7831
ManFee	0.863^{*}	0.976	0.857^{*}	0.881^{**}	0.0564
MinInv	0.939	1.035	0.946	0.977	0.1236
Avg_AUM(t)	0.634^{***}	0.587^{**}	0.994	0.910^{***}	$<.0001$
StdDev_AUM(t)	1.243^{***}	1.085	1.019	1.058^{**}	0.0837

Table III. Hazard Ratios for the BGP (2001) Cox Proportional Hazards Model, and for the Model Extended With Multiple Failure Types and With Time Dependent Predictor Variables

Hazard ratios for the Brown, Goetzmann, and Park (2001) Cox proportional hazards model, and for the model extended with time-dependent variables and multiple failure types. PANEL A: BGP model with fixed predictor variables, with hazard given by $\lambda(t;z) = \lambda_0(t)\exp\left(z^T\beta\right)$, and BGP model with time dependent predictor variables, with hazard given by $\lambda\left(t;Z(t)\right) = \lambda_0(t)\exp\left(Z(t)^T\beta\right)$. PANEL B: BGP model with multiple exit types under competing risks, with hazard given by $\lambda_j(t;z) = \lambda_{0j}(t)\exp\left(z^T\beta_j\right)$ for $j = 1,2,3$. PANEL C: BGP model with multiple exit types and time dependent predictor variables, with hazard given by $\lambda_j(t;Z(t)) = \lambda_{0j}(t)\exp\left(Z(t)^T\beta_j\right)$. Under_Quart, Under_Year, and Under_2Year are binary variables for negative returns over three months, one year, and two years preceding failure. Alpha(Quart) and Alpha(Year) are the returns divided by the standard deviation, obtained over the quarter and year preceding failure, respectively. Time is a time trend, StdDev is the standard deviation over the last twelve months preceding failure. Under(t) is a time dependent binary predictor variable for negative returns over one year, Alpha(t) and StdDev(t) are time dependent predictor variables for the returns divided by the standard deviation over nine months, and for the standard deviation of returns over one year, respectively. Hazard ratios significant at the 0.1, 1, and 5 percent level are denoted ***, ** and *, respectively. For each variable, the p-value is from a likelihood ratio (LR) test that the predictor variable is identical across exit types, where the LR is obtained from only that variable included in the model. For all variables included, the LR test p-value is <.0001.

Panel A. Allowing for time dependent predictor variables			
Fixed variable		Time dependent variables	
Under_Quart	1.383^{**}	Under(t)	2.463^{***}
Under_Year	1.335^{*}		
Under_2Year	1.018		
Alpha(Quart)	1.098	Alpha(t)	0.915^{***}
Alpha(Year)	0.108^{***}		
Time	1.060^{**}	Time	0.942^{***}
StdDev	1.067^{***}	StdDev(t)	1.001^{**}

Table III. Hazard Ratios for the BGP (2001) Cox Proportional Hazards Model, and for the Model Extended With Multiple Failure Types and With Time Dependent Predictor Variables (Continued)

Panel B : Allowing for multiple exit types				
	Liquidated	Closed	No Reporting	LR p-value
Under_Quart	1.285	1.672	1.349	0.0336
Under_Year	1.873^{***}	1.018	1.039	<.0001
Under_2Year	1.669^{***}	0.849	0.565^{**}	<.0001
Alpha(Quart)	1.103	1.153	1.040	0.0332
Alpha(Year)	0.257^{*}	0.014	0.106^{***}	0.0003
Time	1.081^{**}	1.191^{***}	0.993	0.0135
StdDev	1.068^{***}	1.045^{**}	1.074^{***}	<0.0001
Panel C : Allowing for time dependent predictor variables and multiple exit types				
	Liquidated	Closed	No Reporting	LR p-value
Under(t)	3.809^{***}	1.405	1.400^{**}	<.0001
Alpha(t)	0.940	0.101^{***}	0.895^{**}	<.0001
Time	0.937^{*}	1.052	0.911^{**}	0.0135
StdDev(t)	1.001^{**}	1.000	1.000	0.8057

Table IV. Logistic Regression and Categorical Modeling of Hedge Funds

PANEL A: Estimated regression coefficients from the logistic model (grouping all failures together) and from the multinomial logit model (keeping failures separate). Under_Quart, Under_Year, and Under_2Year are binary variables for negative returns over three months, one year, and two years preceding failure. Alpha(Quart) and Alpha(Year) are the returns divided by the standard deviation, obtained over the quarter and year preceding failure, respectively. Age is the age of the fund, and StdDev is the standard deviation over the last twelve months preceding failure. Coefficients significant at the 0.1, 1, and 5 percent level are denoted ***, ** and *, respectively. In the logistic model the probability of hedge fund i experiencing exit (all exits types combined) is given by $\pi_i = \left[1 + \exp\left(-Z_i^T \beta\right)\right]^{-1}$. In the multinomial logit model the probability of hedge fund i experiencing exit type j is given by $\pi_{ij} = \exp\left(Z_i^T \beta_j\right) / \sum_{k=1}^{3} \exp\left(Z_i^T \beta_k\right)$ for $j = 1, 2, 3$. PANEL B: Contrasts to compare coefficients from the multinomial logit model across failure types. For exits i and j, the contrast is defined as $\beta_i - \beta_j$, and its standard error is given by $Var(\beta_i) + Var(\beta_j) - 2Cov(\beta_i, \beta_j)$. The two-tailed test that each contrast is zero is conducted assuming normality. Contrasts significant at the 0.1, 1, and 5 percent level are denoted ***, ** and *, respectively.

Panel A : Coefficients estimated from the Logistic and Multinomial Models

Variable	Logistic All Failures	Multinomial Logit Liquidated	Multinomial Logit Closed	Multinomial Logit No Reporting
Intercept	-0.2573^{*}	-1.1127^{***}	-2.0887^{***}	-1.2364^{***}
Under_Quart	0.4346^{***}	0.3768^{***}	0.4824^{***}	0.4579^{***}
Under_Year	0.3800^{***}	0.4986^{***}	0.1979	0.3178^{**}
Under_2Year	0.0438	0.2894^{**}	-0.0243	-0.2533^{*}
Alpha(Quart)	0.4695^{*}	0.3788	0.6842	0.4492
Alpha(Year)	-1.9708^{***}	-1.0805	-4.3587^{***}	-2.0293^{***}
Age	-0.2346^{***}	-0.2322^{***}	-0.1529^{***}	-0.2736^{***}
StdDev	0.2322^{***}	0.2385^{***}	0.1994^{***}	0.2378^{***}

Panel B: Constrats $\beta_i - \beta_j$ from the Multinomial Model

Variable	Liquidated − Closed	Liquidated − No Reporting	Closed − No Reporting
Intercept	0.9760^{***}	0.1237	-0.8523^{***}
Under_Quart	-0.1056	-0.0810	0.0246
Under_Year	0.3008	0.1808	-0.1199
Under_2Year	0.3137^{*}	0.5427^{***}	0.2290
Alpha(Quart)	-0.3054	-0.0704	0.2350
Alpha(Year)	3.2782^{***}	0.9488	-2.3293^{*}
Age	-0.0793	0.0414	0.1207^{*}
StdDev	0.0391	0.0006	-0.0385

Table V. Mean Monthly Returns of Live and Dead Funds and Estimates of Survivorship Bias

PANEL A: Estimates of monthly and yearly survivorship bias obtained by defining live funds as those alive at December 2003, and dead funds as no longer reporting, liquidated, or closed to new investment. PANEL B: Estimates of monthly and yearly survivorship bias obtained by defining live funds as those alive at December 2003 plus those no longer reporting, and dead funds as liquidated funds and funds closed to new investment. Bias/Month is the difference between Live Returns and Dead Returns. Bias/Year is Bias/Month multiplied by twelve.

Panel A: Live Group = Alive at Dec 2003				
Dead Group	Live Return	Dead Return	Bias/Month	Bias/Year
No Reporting + Liquidated + Closed	1.043	0.917	0.126%	1.51%
Liquidated + Closed	1.043	0.770	0.273%	3.28%
No Reporting + Liquidated	1.043	0.900	0.143%	1.72%
No Reporting + Closed	1.043	1.073	−0.030%	−0.36%
Liquidated	1.043	0.667	0.376%	4.51%
Closed	1.043	0.999	0.044%	0.53%
No Reporting	1.043	1.103	−0.060%	−0.72%
Panel B: Live Group = Alive at Dec 2003 + No Reporting				
Dead Group	Live Return	Dead Return	Bias/Month	Bias/Year
Closed + Liquidated	1.050	0.771	0.279%	3.35%
Liquidated	1.050	0.667	0.383%	4.60%
Closed	1.050	1.000	0.050%	0.60%

Table VI. Hedge Fund Attrition Rates

PANEL A: Number of existing funds at the beginning of each year, funds entering the database during the year, and funds experiencing each type of exit (liquidation, closed to new investment, and no longer reporting) during the year. PANEL B: Mortality rates, expressed as a proportion of hedge funds experiencing each type of exit (liquidation, closed to new investment, and no longer reporting), experiencing liquidation or no reporting (third to last column), experiencing liquidation or closure (second to last column), and experiencing no reporting or closure (last column).

Panel A: Existing Funds, Funds Entering at Mid-Year, and Exiting Funds					
Year	Existing Funds	Funds Entering	Liquidated Funds	Closed Funds	Funds Not Reporting
1994	1,153	336	13	2	9
1995	1,464	474	33	2	29
1996	1,875	459	104	8	79
1997	2,314	449	92	20	103
1998	2,370	463	117	37	229
1999	2,442	536	91	39	112
2000	2,729	508	121	36	216
2001	2,852	606	101	56	134
2002	3,175	638	129	51	111
2003	3,535	519	140	52	121

Panel B: Annual Mortality Rates (%)							
Year	All Exits	Liquidate	Closed	No Report	Liquidate +NoRep	Liquidate +Closed	NoRep+ Closed
1994	2.08	1.13	0.17	0.78	1.91	1.30	0.95
1995	4.37	2.25	0.14	1.98	4.23	2.39	2.12
1996	10.19	5.55	0.43	4.21	9.76	5.97	4.64
1997	10.07	4.31	0.94	4.83	9.14	5.25	5.76
1998	16.16	4.94	1.56	9.66	14.60	6.50	11.22
1999	9.91	3.73	1.60	4.59	8.31	5.32	6.18
2000	13.67	4.43	1.32	7.91	12.35	5.75	9.23
2001	10.20	3.54	1.96	4.70	8.24	5.50	6.66
2002	9.17	4.06	1.61	3.50	7.56	5.67	5.10
2003	8.85	3.96	1.47	3.42	7.38	5.43	4.89

Table VII. Mean Survival Time of Hedge Funds, by Style and Size

Estimated mean survival time in years, defined as $\widehat{\mu} = \int_0^\infty \widehat{S}(t)dt$, where $\widehat{S}(t)$ is the Kaplan-Meier estimator of the survival function, along with the standard error for $\widehat{\mu}$ (S.E.). Large and small hedge funds are those with mean assets over the 1994 to 2003 periods that are above and below the median assets of all hedge funds with the same style. The Log Rank p-value is for the Log Rank test for equality of the survival functions between large and small funds. PANEL A: Survival time is defined as the time until exit from the database (all exits aggregated). PANEL B: Survival time is defined as the time until liquidation. Cells marked n/a refer to strata with insufficient liquidations to obtain the required estimates.

PANEL A: All Exits	All Funds		Large Funds		Small Funds		Log Rank
	Mean	S.E.	Mean	S.E.	Mean	S.E.	p-value
Convertible Arbitrage	5.19	0.17	5.38	0.19	4.76	0.33	0.0356
Distressed Securities	4.38	0.22	5.11	0.21	3.73	0.32	<.0001
Emerging Markets	5.18	0.20	5.80	0.24	4.55	0.30	0.0005
Equity Hedge	6.89	0.16	7.69	0.20	5.60	0.20	<.0001
Equity Market Neutral	5.46	0.26	6.40	0.32	3.36	0.19	<.0001
Equity Non-Hedge	5.10	0.27	5.81	0.36	3.50	0.22	0.0091
Event Driven	5.62	0.21	6.24	0.22	4.62	0.29	0.0055
Fixed Income	5.91	0.23	6.52	0.29	5.44	0.38	0.0105
Fund of Funds	7.10	0.13	6.82	0.10	5.97	0.21	<.0001
Market Timing	4.50	0.33	4.89	0.43	3.62	0.38	0.3348
Merger Arbitrage	4.85	0.23	5.11	0.28	3.65	0.23	0.4663
Relative Value Arbitrage	6.18	0.38	5.39	0.27	5.55	0.518	0.0205
Sector	4.79	0.19	5.43	0.25	3.88	0.23	0.0020
Short Selling	3.83	0.26	4.14	0.29	2.12	0.11	0.6799

Table VII. Mean Survival Time of Hedge Funds, by Style and Size (Continued)

PANEL B: Liquidation	All Funds		Large Funds		Small Funds		Log Rank
	Mean	S.E.	Mean	S.E.	Mean	S.E.	p-value
Convertible Arbitrage	3.54	0.06	n/a	n/a	3.35	0.13	n/a
Distressed Securities	5.25	0.15	5.45	0.13	5.00	0.27	0.0949
Emerging Markets	6.51	0.19	6.73	0.22	6.16	0.32	0.0439
Equity Hedge	6.62	0.08	7.00	0.09	5.62	0.13	<.0001
Equity Market Neutral	7.12	0.25	7.78	0.27	4.22	0.20	0.0003
Equity Non-Hedge	7.68	0.31	8.53	0.36	4.70	0.23	0.0015
Event Driven	4.56	0.09	4.79	0.07	3.67	0.13	0.0122
Fixed Income	7.36	0.21	7.81	0.25	4.12	0.14	0.0224
Fund of Funds	6.47	0.06	6.12	0.04	6.03	0.12	<.0001
Market Timing	5.28	0.29	5.59	0.36	4.51	0.40	0.3415
Merger Arbitrage	4.02	0.10	3.73	0.10	4.01	0.18	0.6753
Relative Value Arbitrage	4.56	0.12	4.67	0.11	4.36	0.21	0.2464
Sector	5.52	0.14	5.47	0.14	5.16	0.24	0.0083
Short Selling	4.36	0.19	4.50	n/a	1.33	n/a	0.7948

Table VIII. Accelerated Failure Time (AFT) Weibull Regression Model Under Competing Risks

Model for survival time T is $\log(T) = \alpha + z^T\beta + \sigma\varepsilon$, where z and β denote vectors of variables and of regression coefficients, respectively, α is the intercept, σ denotes a scale parameter, and ε follows the extreme value distribution. Mean Return and StdDev Return are mean and standard deviation of returns expressed as a percent, respectively, during the last 12 months of observation, Highwater Mark and Hurdle Rate are each binary variables for the presence of a highwater mark and a hurdle rate, respectively, Incentive Fee and Management fee are expressed in percent, Minimum Investment is expressed in \$100K, Mean AUM and StdDev AUM are mean and standard deviation of assets under management expressed in \$M, respectively, during the last 12 months of observation. To simplify notation we exclude the subscript j from T, α, β, and σ, for $j = 1, 2, 3$.

	Estimated Regression Coefficient			
Variable	Liquidation	Closed	No Reporting	All Exits
Intercept	2.1127***	2.4588***	1.9135***	1.5143***
Mean Return	0.0292***	0.0231	−0.0038	0.0119*
StdDev Return	−0.0082***	0.0328**	0.0026	−0.0033*
Highwater Mark	−0.2207*	0.1497	0.0228	−0.0476
Hurdle Rate	0.8601***	1.1502***	0.9248***	0.9235***
Incentive Fee	−0.0103*	−0.0202**	−0.0139**	−0.0131***
Management Fee	−0.0413	−0.1304*	0.0282	−0.0340
Minimum Investment	0.0014	−0.0013	0.0021	0.0006
Mean AUM	0.0016***	0.0007	0.0001	0.0006***
StdDev AUM	−0.0011***	−0.0001	−0.0003	−0.0006***
Scale Parameter ($\widehat{\sigma}$)	0.5819	0.5900	0.5996	0.5925

Table IX. Estimates of Median Survival Time from AFT Weibull Model Under Competing Risks

Estimates of median survival time T_{50} for hedge funds, given by exponentiating $\log(T_{50}) = \widehat{\alpha} + z^T\widehat{\beta} + \widehat{\sigma}W_{50}$, where $\widehat{\alpha}, \widehat{\beta}$ and $\widehat{\sigma}$ are from Table VIII and $W_{50} = \log(\log(2))$ is the median time of the extreme value distribution, and z are specified values of the variables. Fund 1 has mean and standard deviation of returns over the last 12 months of observation of 1% and 2% respectively, no highwater mark or hurdle rate, incentive and management fees of 20% and 1% respectively, minimum investment of $500K, and mean and standard deviation of assets over the last 12 months of observation of $500M each. Fund 2 is identical to Fund 1, except that its incentive fee is 10%. Fund 3 has mean and standard deviation of returns over the last 12 months of observation of 1% and 5% respectively, a highwater mark and a hurdle rate, incentive and management fees of 35% and 1% respetively, a minimum investment of $250K, and mean and standard deviation of assets over the last 12 months of observation of of $250M each. Fund 4 is identical to Fund 3, except that it has no hurdle rate. To simplify notation we exclude the subscript j from $T_{50}, \widehat{\alpha}, \widehat{\beta}$, and $\widehat{\sigma}$, for $j = 1, 2, 3$.

	All Exits	No Reporting	Liquidation	Closed
T_{50} for Fund 1	2.7 years	3.9 years	6.7 years	7.6 years
T_{50} for Fund 2	3.1 years	4.5 years	7.4 years	9.3 years
T_{50} for Fund 3	5.4 years	8.6 years	9.5 years	20.9 years
T_{50} for Fund 4	2.1 years	3.4 years	4.0 years	6.6 years

Figure I. Estimator of Survivor Function, Liquidation Versus All Exits

Kaplan-Meier estimates of survival time given by $\widehat{S}(t) = \prod_{j:t_j<t} \left(1 - \frac{d_j}{n_j}\right)$ where d_j is the number of liquidations or exits at time t_j and n_j is the risk set at time t_j. The solid line is the estimate of $\widehat{S}(t)$ for liquidation only, while the dashed line is an estimate of $\widehat{S}(t)$ for all exits combined. The horizontal axis is time in years and the vertical axis is the survival probability $\widehat{S}(t) = \Pr(T > t)$.