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Survival Analysis of Hedge Funds

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Abstract

This paper applies a survival analysis to individual hedge fund data reported in the Lipper TASS database. We use several methodologies including the non-parametric survival analysis, the Semi-parametric Cox proportional hazard analysis with shared frailty, and the logit analysis to assess the effects of both fund-specific characteristics and the dynamic performance properties on survival probabilities of hedge funds. Estimation results are summarized as follows. (i) Funds with higher returns, assets under management (AUM), and recent fund flows, and funds with lower volatilities and higher skewness of returns and AUM have higher survival probabilities. (ii) Incentive scheme matters for survival probabilities, and the directions of the effects differ depending on the measures: funds with higher incentive fees have lower survival probabilities, while those with a high water mark have higher survival probabilities. (iii) Cancellation policies as proxies for liquidity constraints matter: funds with a longer redemption notice period and a lower redemption frequency have higher survival probabilities. (iv) As the number of total hedge funds becomes larger, survival probability significantly falls. (v) On the other hand, leverage does not significantly influence survival probabilities.

Key Words: Hedge funds, High Water Mark, Incentive Fees, Survival Analysis, Panel Logit

JEL Classification: G11, G12, G13

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1. Introduction

This paper attempts to analyze factors that influence the duration of life time of hedge funds reported in the Lipper TASS database. In doing so, we attempt to test the widest range of attributes of all the existing studies using various types of hazard models. Specifically, the attributes we test include return properties, investment strategies, fund size, competitive pressure, fund flows, drawdown, leverage, incentive scheme, liquidity constraints, and minimum investment amount. The hazard models we use include the non-parametric Kaplan-Meier analysis, Cox proportional hazard model, and the panel logit model.

The hedge fund industry, one of the alternative investment sectors, has grown rapidly in recent years. As shown by Casey, Quirk & Acito and the Bank of New York [2004], about five years ago, hedge funds gathered virtually all of their assets from wealthy individuals. Currently, however, hedge funds constitute a main investment vehicle for institutional investors, including endowments and foundations and pension funds as well as for wealthy individuals, particularly among the advanced economies. Their main objectives to invest in hedge funds lie in their absolute returns and extremely low correlations with traditional asset classes, like equities and bonds. This return property, to some degree, results from unregulated and opaque investment strategies they adopt.

Owing to the increasingly available return data of hedge funds from sources, such as HedgeFund.net, HFR, and Lipper TASS, a growing number of studies have analyzed the risk-return profiles that are unique to hedge funds and their relationship to the attrition rates of hedge funds.[1] Many of these studies find that hedge fund returns tend to be uncorrelated with market indices, typically arguing that the standard methods of assessing their risk-return profiles may be misleading. For instance, Getmansky, Lo, and Makarov [2004] propose a new variant of the

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[1] For instance, Ackermann, et al. [1999], Fung and Hsieh [1997a, 1997b, 1999, 2000, 2001], Liang [1999, 2000, 2001], and Brown, Goetzmann, and Park [2000, 2001ab] are such pioneering works. In particular, Brown, Goetzmann, and Park [2000, 2001ab], Fung and Hsieh [1997ab], and Brown and Goetzmann [2003] provide detailed performance attribution based on the style analysis for hedge funds.

sharp ratio by directly focusing on the usually high degree of serial correlation in hedge-fund returns.[2]

In addition, as shown by Casey, Quirk, & Acito and the Bank of New York [2004], institutional investors wish to invest in hedge funds on a long-term basis. This is partly due to the low liquidity of hedge funds and the difficulty in processing information about new hedge funds.[3] Thus, desirable hedge funds for them are those that are likely to survive for a long time, and thus are much less likely to be liquidated, which could lead to large capital losses for investors.

Motivated by this trend in hedge fund investment, in this paper, we attempt to conduct survival analyses of individual hedge funds as rigorously as possible. More specifically, we attempt to quantitatively clarify what factors influence the survival and mortality pattern of hedge funds, using individual hedge fund data. We use the Lipper TASS database that consists of monthly returns, assets under management, and other characteristics specific to each fund for over 5,000 individual funds from February 1977 onward. The database has a significant advantage over others, in that it categorizes hedge funds into two segments, "Live" and "Graveyard" funds. The Graveyard funds are those that (i) are no longer reporting their performance data to the Lipper TASS, (ii) are liquidated, (iii) are closed to new investment, (iv) are restructured, (v) merged with other hedge funds, and so on. Thus, the funds classified as "Live" are considered to be active as of the latest survey in that the Lipper TASS successfully confirmed as active. This distinguished treatment between live and other funds substantially mitigate the so-called "survivorship bias," which arises

[2] Another important issue is the persistence of hedge-fund performance. For instance, Agarwal and Naik [2000] investigate the persistence of hedge-fund performance over quarterly to yearly intervals by focusing on the series of wins and losses for consecutive periods. They find that high persistence of performance is unrelated to the type of hedge fund strategies, such as convertible arbitrage, fixed-income arbitrage, event driven, distressed, global macro, and so on.

[3] Most institutional investors recognize that the depth of resources required to effectively source, select, and monitor hedge funds are significant and expensive. Such recognition directs them to the so-called Fund of Hedge Funds.

from the fact that typical databases do not contain funds that went out of business.[4]

Several authors have analyzed the survival rates of hedge funds so far. For instance, Chan, Getmansky, Haas, and Lo [2005] estimate the effects of fund-specific characteristics, such as age, assets under management, current and lagged returns, and the flows to and out of the funds on the likelihood of liquidation for the funds in the Lipper TASS database.[5] They show that age, assets under management, cumulative returns, and fund flows have a significantly negative impact on the liquidation probability. Also, Baquero, Horst, and Verbeek [2005] show that funds with a larger size and a higher past return are much more likely to survive, but do not find any meaningful relationship between incentive fees and survival rates. These studies use the discrete-time binary choice models such as the logit and probit models to address this issue. These types of models have an advantage of handling dynamic aspects and momentum effects by easily including time-varying covariates, but have a disadvantage, in that they cannot handle the problem of right censoring. Put differently, estimation is likely to be biased due to the fact that a non-negligible number of hedge funds are not terminated at the end of the sample period.

On the other hand, Brown, Goetzmann, and Park [2001] use the Cox semi-parametric hazard model and find that the liquidation probability rises with a rise in conventional risk measures. In particular, they find that funds with negative returns for two consecutive years have a higher risk of closing down. Also, Gregoriou [2002] estimates the Cox proportional hazard model and find that leverage matters for liquidation probability, as well as the past returns and the assets under management. The use of the so-called duration models, such as the Cox proportional hazard model, enables us to deal with the right censoring mentioned above, and at the same time, to assess the

[4] For instance, Baquero et al. [2004] find that the survivorship bias is likely to affect the mean and variance, as well as cross-moments of hedge fund returns, sometimes resulting in spurious persistence in performance.
[5] More precisely, Chan, Getmansky, Haas, and Lo [2005] do not focus on the liquidated funds in that they regard all of the Graveyard funds as liquidated funds. Also, they do not analyze the effects of incentive scheme, leverage, and cancellation policy, among others, on the liquidation probability.

effects of fund-specific characteristics on survival probabilities in a regression-like framework. However, the Cox proportional hazard model is subject to a very restrictive assumption of the proportionality of hazard ratios with respect to duration time.

Given these advantages and disadvantages, we use both types of models. We try to capture non-monotonic duration dependence by the duration models, while we assess the dynamic effects of fund attributes by both the duration models and the logit models with more computational efficiency. The simultaneous use of these models enables us to investigate the effects of a much wider range of variables on hedge fund survival probabilities in a robust manner. The variables we test include those related to the governance structure, like the existence of a high water mark, incentive/management fees, leverage, cancellation policy, such as redemption frequency, lockup period and redemption notice period, and minimum investment amount, as well as the dynamic performance measures such as current and lagged returns and fund flows.[6] We believe that this paper is the most extensive study on the survival probabilities of hedge funds in literature.

Among these, one of the most noteworthy issues in recent hedge fund industry is the effects of incentive scheme for fund managers on the liquidation probabilities. In particular, recently, incentive fees are frequently accompanied by a high water mark, which conditions the payment of the incentive upon exceeding the maximum achieved share value. Whether such an incentive scheme augments risk-taking by hedge fund managers is of particular interest to investors.

The rest of the paper is organized as follows. Session 2 describes the dataset. Section 3 reviews the empirical methodologies we adopt in this paper. Section 4 reports and discusses estimation results. Section 5 concludes the paper.

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[6] Also, we try to capture the effect of competitive pressure on the survival probability, using the total number of hedge funds, which has increased particularly since around 2000.

2. Data

In this paper, we use the Lipper TASS database, which began to track fund exits from January 1994. The Lipper TASS database consists of monthly returns, assets under management, and other fund-specific attributes, such as leverage, fee structure, and cancellation policy.[7] Table 1 shows the number of existing funds, new entries into and exits out of the database, and the attrition rates defined as new exits/liquidations divided by existing funds from 1985 to 2005.

One of the most noteworthy features of the Lipper TASS database is that it divides hedge funds into two major categories: "Live" and "Graveyard" funds. Hedge funds categorized as "Live" are active as of December 2005. Currently, the database has more than 4,000 live funds and 2,000 Graveyard funds.

It should be noted, however, that Graveyard funds are not solely liquidated funds. One of the reasons is the voluntary nature of inclusion in the Lipper TASS database. For instance, funds that have already obtained solid customer base are likely to lose an incentive to report to the Lipper TASS Database or funds that have performed well might be reborn as new investment.[8] To cope with this situation, the database further divides Graveyard funds into the following seven sub-categorizes: (i) liquidated; (ii) no longer reporting to TASS; (iii) unable to contact; (iv) closed to new investment; (v) merged into another entity; (vi) dormant; and, (vii) unknown.[9]

To analyze hedge fund liquidations, Chan, Getmansky, Haas , and Lo [2005] use the entire Graveyard funds on the ground that including the funds categorized as other than liquidated enable them to develop a broader perspective on the dynamics of the hedge fund industry. As shown by Fung and Hsieh [2000] and others, however, many Graveyard funds that are not liquidated are

[7] See Chan, Getmansky, Haas, and Lo [2005] for detailed characteristics of the database.
[8] In fact, funds that have obtained enough amount of assets under management tend to stop reporting the Lipper TASS data base.
[9] In addition, there are funds whose Graveyard status is not simply described. We call this "blank cell" in this paper.

actually alive and perform well. Table 2 reports summary statistics of monthly returns and assets under management by status: (i) live, (ii) Graveyard, and (iii) liquidated funds. Here, "all funds" denote all of the funds that reported return data at least once to the Lipper TASS database. First of all, not surprisingly, live funds performed much better than Graveyard funds in terms of means and standard deviations of monthly returns, and mean levels of assets under management (AUM) as shown in Table 2 (i) and (ii).[10] Looking in more detail by investment strategy, mean returns/standard deviations of live funds are uniformly higher than the Graveyard funds. Also, as shown in Table 2 (ii) and (iii), liquidated funds performed worse than overall Graveyard funds in terms of mean returns. This observation is mainly due to the fact that widely-acknowledged successful funds are likely to leave the database since their advertising needs for their good performance are reduced.

Judging from these both qualitative and quantitative differences between overall Graveyard funds and liquidated funds, we choose to focus on the liquidated funds in contrast with live funds. Potential biases from the use of overall Graveyard funds in survival analyses can be written as follows. First, interpretation of the coefficient estimates on covariates becomes blurred. Second, it produces faulty estimates of survival since many "dead" funds should be categorized as "live" instead. Third, it is likely to underestimate the survivorship bias since many "dead" funds actually performed well.

Although the Lipper TASS database includes a huge number of hedge funds, there are numerous blanks. Thus, we need to select sample funds that can be used in our empirical analysis. The criterion we adopt in this paper basically follows that of Chan. Getmansky, Haas, and Lo [2005]: hedge funds that have at least two years of track record and have reported all the necessary

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[10] Other return properties, such as skewness and kurtosis, show much less difference between live and Graveyard funds.

data without a break over their lifetime.[11] By interviewing many major institutional investors, such as insurance companies and pension funds, as well as data vendors, we found this selection criterion is consistent with actual practice of major institutional investors.[12] After a process of filtering, we obtain 952 live funds and 511 Graveyard funds, of which 270 funds are liquidated. As a result, our sample size of the cross-sectional analysis is 1,222, and that of the cross-sectional time-series analysis turns out to be 78,002.[13] The cross-sectional analysis covers existing fund from January 1985 to December 2005, and the cross-sectional time-series analysis covers the period from January 1994 to December 2005. The reason for the difference in the starting year between the two analyses is that since the Lipper TASS database began to track exits from January 1994, the only time-series status of sample funds between January 1985 and December 1993 is "live" for the logit model.[14] On the other hand, we should use the data prior to January 1994 for the duration models since we need the data of the length of life time.

Before proceeding to an empirical analysis, let us compare the return properties between the entire funds included in the Lipper TASS database denoted "all funds" in Table 2 and our sample funds. First, regarding the live funds reported in Table 2 (i), our sample funds show higher standard deviations of AUM, but other properties including means of return and AUM show little differences. Next, for the liquidated funds, our sample funds exhibit higher means of returns and AUM, but other return properties including standard deviations, skewness, and kurtosis, show little differences.

[11] As a robustness check, we removed the first condition of at least two years of track record. As a result, the number of sample funds increases from 1,222 to 1,642 (from 78,002 to 83,527 for the logit model), but we obtained the almost identical estimation results. The estimation results are available upon request.

[12] The second condition is important since hedge funds that lost money tend to cease reporting, which is likely to cause serious biases.

[13] For instance, Chan, Getmansly, Haas, and Lo [2005], a representative example of a logit analysis on hedge fund survival, have 12,895 observations on a yearly basis.

[14] Also, the number of funds between 1985 and 1993 is small, as suggested by Table 1.

3. Empirical Methodologies

3.1 Basic Setting

To address the questions, such as how long hedge funds survive, and to what extent and what kind of variables influence the probability of survival of hedge funds, hazard models are generally used. The basic setting is as follows. Suppose that an event time, T, is a random variable and the time to exit is a realization of the random process. A cumulative probability distribution is given as

$$F(t) = \Pr(T \le t),$$

and the survivor function is given as

$$S(t) = \Pr(T > t) = 1 - F(t),$$

where t is time, and $\Pr(T > t)$ is the probability that the timing of the event T is greater than t. Thus, the survivor function identifies the probability that a hedge fund survives past time t.

Alternatively, we can describe the time to exit using a hazard function. The hazard rate is a measure of the probability that a hedge fund will exit in time t, given that it has survived up to that time. The hazard function is defined as

$$\begin{aligned} h(t) &= \lim_{\Delta t \to 0} \frac{\Pr(T < t + \Delta t | T \ge t)}{\Delta t} \\ &= \lim_{\Delta t \to 0} \frac{F(t + \Delta t) - F(t)}{\Delta t S(t)} = \frac{f(t)}{S(t)} = \frac{-d \ln S(t)}{dt}, \end{aligned} \tag{1}$$

where $\Pr(\bullet | \bullet)$ denotes the conditional probability that the event takes place, and $f(t)$ denotes the probability density function associated with $F(t)$.

There are two classes of models for estimating a hazard model: a duration model and a discrete-time hazard model. Although both classes are very similar in a statistical sense, they have their own advantages and disadvantages, respectively, and let us briefly explain them here.[15]

First, the duration model can capture a non-monotonic relationship between the

[15] In fact, Dokusum and Gasko [1990] obtain a one-to-one correspondence between these two classes of models except for the treatment of right censoring.

probability of an exit and duration of a fund. If we introduce duration time as an explanatory variable in a discrete-time hazard model, such as a logit model, we implicitly assume that the probability of an exit, either increases, or, decreases monotonically with duration time.[16]

Second, the duration model is able to deal with the problem of right censoring. It is highly likely that some hedge funds will not exit at the end of the sample period. The logit model cannot properly handle such a right-censoring problem.

However, the semi-parametric duration model is subject to a very restricted proportional hazard assumption, which sometimes makes an estimation of robust parameters difficult. On the other hand, the logit model is not subject to this assumption and can incorporate time-varying covariates, including general economic indicators and lagged changes of their own fund flows with much more computational efficiency than the duration model. This feature enables us to easily capture the dynamic aspects of fund attributes. Given these advantages and disadvantages, we use both types of models in a mutually complementary manner with a view to capitalizing on their own strengths.[17]

3.2 Duration Model

3.2.1 Non-parametric Approach: The Kaplan-Meier Analysis

The estimator of Kaplan and Meier [1958] is a completely non-parametric approach. Under the assumption that duration samples of size n are homogeneous and no censoring is present, the empirical survivor function would simply be estimated as

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[16] For instance, Lunde, Timmermann, and Blake [1999] conducted the survival analysis about mutual funds and using both models, and found that the qualitative results of the covariate effects on the closure probability obtained by the Cox regression model are unaffected by discrete-time model, but they are biased toward zero, when the duration dependence is misspecified. More specifically, they could not find evidence in favor of linear duration dependence.

[17] Kiefer [1988] provides a comprehensive survey of duration analysis. For the discrete-time hazard model, see Maddala [1983], for instance.

$$\hat{S}(t) = \frac{\text{number of } (T \geq t)}{n}. \tag{2}$$

Under the presence of right censoring, however, the following modification is needed.[18] Let T^* be the random time of the end of a hedge fund in the absence of right censoring, and C be the censoring time. Then, the observed random variable can be written as

$$T = \min(T^*, C).$$

Now, suppose that there are k completed durations in the sample, where $k < n$ holds. Since some observations are right-censored, two or more observations are likely to have the same duration. Here, let us order the completed durations from the smallest to the largest as $t_1 < t_2 < \ldots t_k$, let d_i denote the number of funds that exit at time t_i, and m_i the number of durations censored between t_i and t_{i+1}. The set of durations that are eligible to exit at time t is called the risk set, which is defined as

$$n_i = \sum_{j \geq i}^{k} (m_j + d_j). \tag{3}$$

As shown by equation (3), the risk set n_i denotes the number of durations neither completed nor censored before duration t_i. Then, the probability of exiting in the interval $t + dt$ given that the hedge fund survives up to time t_i is given by

$$\hat{\lambda}(t_i) = \frac{d_i}{n_i}. \tag{4}$$

Thus, the corresponding estimator of the survivor function is given by

$$\hat{S}(t_i) = \prod_{j=1}^{i} (1 - \hat{\lambda}_j) = \prod_{j=1}^{i} \left(\frac{n_j - d_j}{n_j} \right). \tag{5}$$

As for hazard curves, we use the Nelson-Aalen estimator, which is known for its better

[18] Of course, we face the problem of left censoring, in that some spells are in progress when an observation period begins. Since left censoring is much harder to deal with than right censoring, researchers do not usually adjust for its effects. It turns out, however, that of 1,222 sample funds the number of left-censored funds is only 7, compared with 952 funds subject to right censoring. Hence, the effects of left censoring are likely to be much smaller than right censoring.

small-sample properties than the method that uses the Kaplan-Meier survivor functions.[19]

3.2.2 Semi-parametric Approach: The Cox Proportional Hazard Analysis

3.2.2.1 Basic Model

The semi-parametric approach potentially allows for circumventing the problems of both the non-parametric estimator (no explanatory variables) and parametric estimator (arbitrary choice). The following is the partial-likelihood approach proposed by Cox [1972, 1975].

For simplicity, we assume that all n observations are uncensored.[20] Observed durations are ordered from the smallest to the largest as $t_1 < t_2 \ldots < t_n$. The conditional probability that the first observation exits at time t_1, given that all of the n durations could have ended at time t_1, can be written as

$$\frac{h(t_1, \mathbf{x}_1, \boldsymbol{\beta}, h_0)}{\sum_{i=1}^{n} h(t_1, \mathbf{x}_i, \boldsymbol{\beta}, h_0)}, \tag{6}$$

where $\mathbf{x}$ denotes a vector of explanatory variables, $\boldsymbol{\beta}$ a parameter vector to be estimated, and h_0 the baseline hazard that means a hazard function for the mean fund.[21] Equation (6) indicates the contribution of the first observation to partial likelihood. Now, if we assume the specification:

$$h(t, \mathbf{x}, \boldsymbol{\beta}, h_0) = h_0(t)\phi(\mathbf{x}, \boldsymbol{\beta}),$$

equation (6) can be rewritten as

$$\frac{h_0(t)\phi(\mathbf{x}_1, \boldsymbol{\beta})}{h_0(t)\sum_{i=1}^{n} \phi(\mathbf{x}_i, \boldsymbol{\beta})} = \frac{\phi(\mathbf{x}_1, \boldsymbol{\beta})}{\sum_{i=1}^{n} \phi(\mathbf{x}_i, \boldsymbol{\beta})}. \tag{7}$$

Equation (7) shows that the baseline hazard $h_0(t)$ vanishes, so that (i) only the information of

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[19] The Nelson-Aalen estimator is due to Nelson [1972] and Aalen [1978].

[20] Right censoring can be easily handled in the partial-likelihood framework. A hedge fund, whose spell is censored between duration t_j and t_{j+1}, appears in the summation in the denominator of the contribution to log-likelihood of observations 1 through j, but not in any others. Censored spells do not enter the numerator of a contribution to likelihood at all.

[21] We can handle time-varying covariates in the Cox proportional hazard model. But, for notational ease, we omit time subscript in $\mathbf{x}$.

completed durations is needed to estimate parameters $\boldsymbol{\beta}$, and, (ii) we do not require an assumption on its underlying distribution.[22] Parameters $\boldsymbol{\beta}$ can be obtained by maximizing the following partial log-likelihood:

$$\ln L^{*}(\boldsymbol{\beta}) = \sum_{j=1}^{n}\left[\ln \phi(\mathbf{x}_i, \boldsymbol{\beta}) - \ln \sum_{i=j}^{n} \phi(\mathbf{x}_i, \boldsymbol{\beta})\right]. \tag{8}$$

Cox [1972, 75] showed that the estimator of $\boldsymbol{\beta}$, which maximizes the partial log-likelihood (8), is consistent and asymptotically normal, regardless of the form of the baseline hazard. A specification of ϕ in general use is $\phi(\mathbf{x}, \boldsymbol{\beta}) = \exp(\mathbf{x}'\boldsymbol{\beta})$.

Note, here, that the hazard for a hedge fund is a multiplicative replica of another so that the ratio of two hazards is constant assuming that the covariates $\mathbf{x}_j$ and $\mathbf{x}_m$ do not change over time:

$$\frac{h(t|\mathbf{x}_j)}{h(t|\mathbf{x}_m)} = \frac{\exp(\mathbf{x}'_j\boldsymbol{\beta})}{\exp(\mathbf{x}'_m\boldsymbol{\beta})}. \tag{9}$$

We test the proportional hazard assumption using the Schoenfeld [1982] residuals. The test is, in fact, a test of nonzero slope in a generalized linear regression of the scaled Schoenfeld residuals on functions of time. No specification for functions of time is optimal for all situations. We choose time itself as the time scale since we found that other specifications, such as 1 minus Kaplan-Meire product-limit estimate of the survivor function, did yield almost identical results.

3.2.2.2 Cox Proportional Hazard Analysis with Shared Frailty

The term "shared frailty" is used in survival analysis to describe the Cox proportional hazard models with random effects.[23] A frailty is a latent random effect that enters multiplicatively on the hazard function. In the context of a Cox proportional hazard model, where the data are organized

[22] In parametric models, $h_0(t)$ can be assumed to follow the Weibull, Gomperts distributions, for instance.
[23] Thus, a Cox model with shared frailty is sometimes called a random-effects Cox model. For details, see Gutierrez [2002], for instance.

as i=1,…,n groups with j=1,…,n_i observations in group i, for the jth observation in the ith group, the hazard is given by

$$h_{ij}(t) = h_0(t)\alpha_i \exp(x_{ij}\boldsymbol{\beta}). \tag{10}$$

Here α_i denotes the group-level frailty. The frailties are unobservable positive quantities and are assumed to follow the Gamma distribution with mean zero and variance θ to be estimated from the data. Note, here, that for $\nu_i = \ln\alpha_i$, the hazard can be rewritten as

$$h_{ij}(t) = h_0(t)\exp(x_{ij}\boldsymbol{\beta} + \nu_i), \tag{11}$$

so that the log-frailties ν_i are analogous to random effects in standard linear panel regressions. Put differently, shared frailty models are used to model within-group correlation in that observations within a group are correlated since they share the same frailty, and the extent of the correlation is measured by θ. The idea is that individuals or some categories of individual investors have different frailties, and those who are most frail die earlier than the others. When the null hypothesis H_0: θ =0 is rejected by the likelihood-ratio test, then within-group correlation is significantly strong, so that the Cox shared frailty model is accepted.[24] Specifically, in this paper, we attempt to control for heterogeneous effects across investment strategies since non-parametric analysis shows the relevance of those effects.

In a Cox proportional hazard model, the times at which failures occur are not relevant, but the ordering of the failures is. Thus, when subjects fail at the same time and the exact ordering of failures is unclear, we need special treatment in calculating the risk set. We adopt the Efron [1977] method for handling such cases of tied failures.[25]

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[24] Also, we can use stratified Cox proportional hazard models to control for within-group correlations. In stratified Cox analysis, the baseline hazards are allowed to differ by group, but the coefficients are assumed to be the same across different groups. The reason for the use of the Cox model with shared frailty is that we can test within-group correlations in the case of the shared-frailty models. As a robustness check, we also estimated the stratified Cox models, and we obtained very similar results to the shared-frailty models.

[25] The Efron method is an approximation to the so-called "exact marginal method," except that it adjusts the subsequent risk sets using probability weights. The Efron approximation is more accurate than other methods including the Breslow [1974] method.

3.3 Discrete-time Hazard Approach: The Logit Analysis

Let D_{it}^* be a latent variable representing the unobserved propensity to exit, conditional upon the covariates. It enables us to model the default propensity in a (panel) variance component setting as

$$D_{it}^* = \mathbf{x}_{it}'\boldsymbol{\beta} + \nu_i + \varepsilon_{it}, \tag{12}$$

where $\mathbf{x}_{it}$ and $\boldsymbol{\beta}$ are vectors of covariates and unknown parameters, respectively, as before, and ν_i and ε_{it} are panel-level random effects and pooled error terms, respectively. We assume that ν_i are normally distributed with mean zero and variance σ_ν^2, and ε_{it} are distributed as a standard logistic with mean zero and variance $\sigma_\varepsilon^2 = \pi^2/3$, independently of ν_i.

Now define

$D_{it} = 1$ if $D_{it}^* > 0$ and

$D_{it} = 0$ if $D_{it}^* < 0$,

where $D_{it} = 1$ corresponds to the time of liquidation in our estimation, and $D_{it} = 0$ corresponds to the live state. Then, the probability of $D_{it} = 1$ is given by

$$\begin{aligned}\Pr(D_{it} = 1 | \mathbf{x}_{it}) &= \Pr(D_{it}^* > 0 | \mathbf{x}_{it}) \\ &= \Pr(\mathbf{x}_{it}'\boldsymbol{\beta} + \nu_i + \varepsilon_{it} > 0), \\ &= \boldsymbol{\Omega}(\mathbf{x}_{it}'\boldsymbol{\beta} + \nu_i)\end{aligned} \tag{13}$$

where $\boldsymbol{\Omega}(\bullet)$ denotes the logistic cumulative distribution function:

$$\boldsymbol{\Omega}(\mathbf{x}_{it}'\boldsymbol{\beta} + \nu_i) = \frac{\exp(\mathbf{x}_{it}'\boldsymbol{\beta} + \nu_i)}{1 + \exp(\mathbf{x}_{it}'\boldsymbol{\beta} + \nu_i)}. \tag{14}$$

To assess whether the model is correctly specified, we use the following statistic:

$$\rho = \frac{\sigma_\nu^2}{\sigma_\nu^2 + \sigma_\varepsilon^2}. \tag{15}$$

We test the null hypothesis $\rho = 0$ by a likelihood-ratio (LR) test. If the null hypothesis is rejected, then the panel estimator is judged to be different from the pooled estimator, so that the panel estimator is accepted. In this paper, we test random effects across individual funds as well as investment strategies

4. Empirical Analysis

4.1 Explanatory Variables

Explanatory variables used in the analysis below are listed in Table 3 (i) and (ii). First, we have six categories of explanatory variables for the cross-sectional Cox proportional hazard models: (i) return property, (ii) AUM, (iii) leverage, (iv) fees, (v) liquidity, and (vi) minimum investment. The motivation for return property and AUM speaks for itself. Funds with a better performance, and with larger and more stable assets are less likely to be liquidated. Hence, we expect negative coefficients on the mean and skewness of returns, the winning ratio defined as the ratio of the number of months with positive returns to the total number of months, and the mean and skewness of AUM, while positive coefficients on the variance and kurtosis of both return and AUM.[26]

Second, hedge funds are very flexible in their investment options and one of the important such options is the use of leverage. There is a widespread perception that hedge fund returns are very volatile, due to their heavy use of leverage. If this perception is correct, then a positive coefficient is expected on the mean level of leverage. In addition, we try the difference between maximum historical leverage and mean leverage, which are denoted max-mean in this paper. The main motivation for the use of max-mean is that we try to test whether hedge funds with low performance try their luck by raising the leverage. If this effect is present, the coefficient on max-mean should be positive.[27]

Third, we use management fee, incentive fee, and a high water mark dummy to capture the effects of incentive structure on liquidation probability of hedge funds.[28] Among these

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[26] The use of winning ratio was motivated by our interviews with hedge fund managers and institutional investors who invest in hedge funds. They emphasize that struggle for survival soon becomes apparent in the hedge fund industry, and among the most commonly used indexes for this purpose is a winning ratio.

[27] Note, here, that some funds record the highest leverage at the birth of the fund. The number of such funds is much smaller than that of the funds that have raised leverage since its birth.

[28] Other variables of interest in this regard are "hurdle rates" and "the value of fund assets owned by key

variables, we pay particular attention to incentive fee and a high-water-mark dummy. The presence of an incentive fee is one of the most important and common features of the hedge fund industry. Sometimes, market participants comment that the presence of an incentive fee is associated with more risk-taking by fund managers since it creates the convexity of compensation to fund managers. If this hypothesis is correct, then the coefficient on the incentive fee should be positive. Another recent trend in the hedge fund industry is that incentive fees are frequently accompanied by a high water mark that conditions the payment of the incentive upon exceeding the maximum achieved share value. Broadly speaking, we can think of two competing hypotheses about the effects of high-water-mark provisions on liquidation probability. The first one is that it augments the risk-taking by fund managers, which leads to higher probability of liquidation. If this hypothesis is correct, then the coefficient on the high-water-mark dummy should be positive.[29] The second one is that high-water-mark provisions give fund managers an incentive to facilitate more stable fund management than otherwise.[30] This hypothesis makes sense particularly for fund managers who would like to maintain their funds on a relatively long-term horizon. Since the sign of the coefficient expected by this hypothesis is negative, total effects of a high-water-mark dummy should be judged empirically.

Fourth, we use four variables associated with cancellation policy of hedge funds, which are meant to capture liquidity constraints for hedge fund investors. These variables are redemption frequency, lockup period, payout period, and redemption notice period. The larger these variables,

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fund manager." W can find these questions in a survey form from the Lipper TASS to individual hedge fund managers. Unfortunately, however, in most of the cases, these items are unanswered.

[29] This line of prediction is suggested by Brown, Goetzmann and Ibbotson [1999], saying that the more the manager is "out of the money," the more he or she many increase volatility. Scholes [2004] also argues that once incurring a loss, fund managers subject to a high water mark are likely to lose the incentive to continue operating the fund, which may lead to liquidation.

[30] Quite recently, Panageas and Westerfield [2005] preset a theoretical model of a hedge fund manager faced with an incentive fee subject to a high water mark. The model predicts that whether the manager take on more risk, or not, depends on the time horizon he or she has. If he or she has an infinite or indefinite time horizon, then the model predicts less risk-taking. If he or she has a finite time horizon, on the other hand, then more risk-taking follows.

the longer a time period is needed for redemption and thus the liquidity is lower. We have two competing hypotheses regarding these variables. The first one is that lower liquidity contributes to more stable performance of hedge funds since fund managers can mitigate the possibility of abrupt outflows, which are likely to destabilize fund management. If this hypothesis is true, then negative coefficients are expected on these variables. The second one is that investors dislike lower liquidity, hence funds with an inflexible cancellation policy are unable to gather enough money from investors, which is likely to destabilize fund management. If this hypothesis is correct, then the coefficients should be positive. Total effects are judged empirically.

Fifth, we use a minimum investment for hedge fund investors. The first hypothesis about this variable is that funds with a larger minimum investment amount are likely to face a larger withdrawal, which may lead to fragility of fund management. The second hypothesis is that funds with a smaller minimum investment are likely to have small-scale and more risk-averse investors who have a tendency to favor safer and more conservative strategies and fund management.[31,32] Both of these hypotheses suggest a positive sign.

Next, Table 3 (ii) describes the variables used in the cross-sectional time-series analysis. Here, we have six categories of explanatory variables: (i) age, (ii) competitive pressure, (iii) return, (iv) AUM and fund flows, (v) drawdown, and (vi) yearly and monthly dummies.[33] The motivation and reasons for the use of these variables are straightforward except for competitive pressure. Funds with a worse recent performance in terms of both returns and fund size, and funds

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[31] The effects of a higher minimum investment on the riskiness of funds are not as straightforward as the effects of a lower minimum investment. Funds with a higher minimum investment tend to have institutional investors, as well as wealthier individual investors. Wealthy individual investors are likely to have a high degree of risk tolerance, but some institutional investors, typically, pension funds, take a very cautious stance toward risk-taking.

[32] Another possibility is that a minimum investment might be a proxy for fund size. This hypothesis is not likely to be the case, at least, in our analysis, since the correlation between mean AUM and minimum investment turns out to be less than 0.1.

[33] In each estimation, we control for the effects of the variables under the categories of leverage, fees, and liquidity, and minimum investment used in the cross-sectional Cox proportional hazard analysis.

experiencing an abrupt, large-scale drawdown are more likely to be liquidated. Regarding the age, we test non-liner quadratic effects of age, in the case of logit analysis. Specifically, by including squared age, we test whether the hazard ratio rises up to a certain level of age, beyond which it takes a downward turn. Flow variables are motivated by the "return-chasing" behavior of investors in that investors flock to funds with a good recent performance record, and leave funds with a poor recent performance.[34] On the other hand, the use of total number of funds, as a proxy for competitive pressure, needs more careful attention. Another possibility is that this variable may capture the manager quality of newly-born hedge funds. A rapid increase in the total number of funds causes concerns over the quality of fund managers, particularly, in recent years.[35] In either case, however, the direction of the effects is the same: an increase in the total number of funds leads to a higher liquidation probability.

Expected signs of coefficients are summarized as follows. The coefficients on age, total number of hedge funds, drawdown dummies should be positive, while the coefficients on squared age, current and lagged returns, lagged AUM, and current and lagged flows into and out of funds should be negative. This way, we aim to capture the dynamic aspects of fund liquidation.

Last, yearly and monthly dummies are meant to control for macro and institutional factors such as book-closing month. Another objective of yearly dummies is to detect possible disastrous impact of the collapse of LTCM in 1998, for instance. Specifically, we include yearly dummies from 1995 to 2005, and a December dummy to control for an industry practice that, typically, hedge funds close their books toward the year-end.[36]

Also, to facilitate comparisons across explanatory variables, as in Chan, Getmansky, Haas, and Lo [2005], we standardize explanatory variables other than dummy variables, and variables age,

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[34] For more details, see Chevalier and Ellison [1997] and Sirri and Tufano [1998], among others.
[35] We thank Toshiki Yotsuzuka for this perspective.
[36] In fact, we tried all the monthly dummies, and found that all the dummies other than a December dummy are insignificant.

in the logit analysis by subtracting their means and dividing by their standard deviations.

4.2 Empirical Results

4.2.1 Non-parametric Kaplan-Meier Analysis of Hedge Fund Survival

Let us look at the results of non-parametric analysis. Figure 1 shows non-parametric Kaplan-Meier survival and the corresponding smoothed Nelson-Aalen hazard curves.[37] First, Figure 1 (i) shows survival and hazard curves for Graveyard funds by Graveyard status. Here, we can observe that survival and hazard curves substantially differ by Graveyard status. To statistically test whether these survival curves differ, we conducted the log-rank test and the generalized Wilcoxon test.[38] Table 4 (i) reports that the null hypothesis of the equality of survivor functions across Graveyard statuses is rejected at the 5% significance level by the long-rank test and at the 1% level by the generalized Wilcoxon test. These results imply the importance of separately analyzing hedge fund hazards by Graveyard status, and thus, our focusing on liquidated funds is warranted in this regard.

Second, Figure 2 (ii) shows the survival and hazard curves for our sample funds: live and liquidated funds. We can see that the hazard curve shows a single-peaked pattern. Also, note that, since the sample number falls with an increasing rate particularly beyond 100 months of duration time, the 95% confidence interval greatly widens in that zone.

Third, Figure 1 (iii) shows the results for our sample funds by investment strategy. Survival and hazard curves appear to be different across investment strategies. This is statistically confirmed by the log-rank test and the generalized Wilcoxon test that are significant at the 1% level and 10% level, respectively, as shown in Table 4 (ii). This result is consistent with Getmansky, Lo,

[37] We smoothed the Nelson-Aalen hazard curves with an Epanechinikov kernel.
[38] In both tests, the contribution to the test statistic at each liquidation time is computed, as a weighted standardized sum of the difference between the observed and expected number of liquidation in each of the groups. The log-rank test uses 1 as the weight, and the generalized Wilcoxon test uses the number of funds at risk of liquidation at each distinctive time.

and Mei [2004], who argue that attrition rates significantly differ by investment strategy. Thus, in what follows, we control for the heterogeneity across investment strategies by shared frailty for the Cox proportional hazard model and by random effects for the logit model, and test of the significance of shared frailty components and random effects by the likelihood ratio test.

4.2.2 Cox Proportional Hazard Analysis

4.2.2.1 Cox Proportional Hazard Analysis using Cross-sectional Data

Table 5 reports the results of the Cox proportional hazard analysis using cross-sectional data. We tried four specifications. First, specification (i) is our baseline case. It includes only means and variances of returns and AUM. "Theta" in the bottom column of the table indicates the correlation within a group by investment strategy. The LR test for the null hypothesis of theta=0 is rejected at the 5% significance level, which shows that the shared frailty model is accepted. Looking at each estimate, the hazard ratios on the means of both returns and AUM are significantly below one, while the variances of both returns and AUM are significantly above one. Also, note that the effects of AUM are much larger than those of returns both for mean and variance. On the other hand, "Rho" in the table indicates a slope estimate of the Schoenfeld residual specific to each variable against time. The estimates of Rho show that the null hypothesis of Rho=0, proportional hazard assumption, is not rejected even at the 10% significance level, but the global Wald test reported in the bottom column shows that the proportional hazard assumption is rejected as a whole at the 1% significance level.

Second, specification (ii) adds skewness and kurtosis of returns and AUM as well as the winning ratio to specification (i). The null hypothesis of theta=0 is rejected by the LR test at the 10% significance level, thus we proceeded with shared frailty. The result shows that each skewness of return and AUM has the hazard ratio significantly below one at the 1% level. Also, the hazard ratio on winning ratio is found to be below one at the 1% significance level. The proportional hazard assumption is rejected by the global test at the 5% significance level, as in the case of specification (i).

Next, specifications (iii) and (iv) include almost all of the explanatory variables listed in Table 3 (i), and the only difference is that the former does not include AUM skewness. In specification (iv), the null hypothesis of theta=0 is not rejected even at the 10% level, thus we report the estimation result without shared frailty.[39] Also note that specification (iv) globally satisfies the proportional hazard assumption, although individually, some variables such as mean and variance of AUM, do not satisfy the assumption at the 5% level.

Now, let us look at the estimation results in detail. First, the hazard ratios on mean, variance, and skewness of both returns and AUM are significant with expected directions. Second, leverage variables are found to be insignificant in both specifications. Third, the management fee has the hazard ratio significantly below one in specification (iv). Also, we found the opposite effects between incentive fee and high water mark. Specifically, the hazard ratios on incentive fee are estimated to be above one at the 1% or 5% significance level. On the other hand, the hazard ratios on high water mark are found to be below one at the 1% level in both specifications. Fourth, regarding liquidity constraints in terms of cancellation policy, the notice period and payout period have hazard ratios significantly lower than one at the 1% and 10% level, respectively, in both specifications. Last, the hazard ratio on minimum investment is found to be significantly larger than one in both specifications.

[39] The result that the inclusion of AUM skewness removes the heterogeneous effects across investment strategies is quite interesting. One possible interpretation is that hedge funds within the same category of investment strategy are likely to be subject to a very similar pattern of (abrupt) fund outflows in times of stress or adverse market conditions. This tendency may be a major cause of heterogeneity in hazards across investment strategy.

4.2.2.2 Cox Proportional Hazard Analysis using Cross-sectional Time-series Data

Table 5 (ii) reports the results of the Cox proportional hazard analysis using cross-sectional time-series data. We tried three specifications. Specification (i) includes yearly dummies, but does not include drawdown dummies. Specification (ii) does not include both yearly and drawdown dummies. Specification (iii) includes drawdown dummies instead of current and lagged returns, but does not include yearly dummies. Before looking at estimated hazard ratios in detail, it is worth noting that in each specification, shared frailty across investment strategies is not rejected and the proportional hazard assumption is satisfied both globally and individually. Main findings about each variable are summarized as follows.

First, the total number of funds and all yearly dummies are estimated to be insignificant in specification (i).[40] The result of yearly dummies implies that macroeconomic or other common factors in a specific year are sufficiently captured by other variables. Also, the insignificance of 1998 dummy implies that our models can reasonably capture the turmoil, as a consequence of the collapse of LTCM in 1998. Second, the hazard ratios on all of the current and lagged returns are significantly below one, and both the magnitude and significance level of the estimated hazard ratios are larger for the most recent one. This is likely an indication of the short-term performance-driven nature of the hedge fund flows, as suggested by Chan, Getmansky, Haas, and Lo [2005].[41] Third, lagged AUM has a particularly large negative hazard ratio. Regarding the flows, as is the case with returns, the hazard ratios are all significantly below one, and both the magnitude and significance level are larger for the most recent one. Fourth, current drawdown dummies, except for 10% drawdown, significantly raise the hazard ratios. Fifth, leverage does not have any

[40] The estimated result of yearly dummies is totally different from Chan, Getmansky, Haas, and Lo [2005], who found that all of the yearly dummies are significant.

[41] Note that Chan, Getmansky, Haas, and Lo [2005] used yearly data instead of monthly data we used in this paper. Thus, the meaning of "short-term" of a short-term performance-driven nature is totally different between their analysis and ours.

significant effects on the hazard ratios, as is the case with the cross-sectional analysis. Sixth, funds with a higher management fee, a lower incentive fee and a high water mark have a significantly lower hazard ratio. Seventh, funds with a lower redemption frequency and a longer notice period have a significantly lower hazard ratio. Eighth, funds with a larger minimum investment have a significantly higher hazard ratio. Last, the December dummy always comes in significantly positive as expected.

4.2.2 Logit Analysis

Table 6 reports the results of logit analysis. We tried two versions of random effects specifications: across investment strategies, and individual funds.[42] First, the bottom columns of the table report the LR test for the null hypothesis rho=0, defined as the ratio of panel-level variance to total variance. The LR test results show that the null hypothesis is not rejected across investment strategies, but is rejected at the 1% significance level across individual funds. Thus, we report the pooled logit estimates in Table 6 (i) and estimates of random effects by fund in Table 6 (ii).[43]

We used three specifications that are the same as the Cox proportional hazard analysis, using cross-sectional time-series data, except for the inclusion of age variables. The estimation results are very similar to those of the Cox proportional hazard analysis. Thus, below we report only the difference in results between the Cox proportional hazard analysis and the logit analysis.

First, the coefficients on Age/Age^2 are significantly positive/negative at the 1% significance level, respectively, in each specification, which implies that the hazard ratio rises up to a certain age, beyond which it falls. This result is consistent with the shape of smoothed hazard

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[42] In fact, due to the relative computational inefficiency of the Cox proportional hazard model, we are not allowed to estimate frailty across individual funds. But, we were able to easily estimate random effects across individual funds using the logit model.

[43] Standard errors of the pooled logit models are adjusted for clustering on strategy categories by the Huber-White method.

curves displayed in Figure 1 (ii). An average of estimated threshold ages turns out to be 64.89 months. Second, the total number of funds is significantly positive in each specification. Third, funds with a longer payout period have a significantly lower hazard ratio. Fourth and last, the minimum investment does not have a significantly positive effect on the hazard ratio, except for one case, specification (iii) of the pooled logit model reported in Table 6 (i).

Figure 2 displays annualized liquidation probabilities estimated from our logit models. For comparison, we show two estimates (from specification (ii) in Table 6 (i) and Table 6 (ii)), as well as the empirical attrition rate for liquidation. Note that these three measures show a very close movement throughout the sample period. Interesting points here are as follows. First, we can observe a spike in 1998. This is likely to be caused by the turmoil triggered by the collapse of LTCM. Our models successfully trace such a stressful period without yearly dummies. Second, since around 2001, the liquidation probability is on a gradual uptrend and reaches the highest level in 2005. This is likely to stem from the effects of an increase in the total number of hedge funds.

4.3 Discussions

This subsection discusses implications from the above empirical results. In particular, we focus on return and AUM properties, leverage, fees, liquidity constraints, and minimum investment, since they have been frequently under discussion in literature, in terms of fund liquidation.

4.3.1 Return and AUM properties

As for return and AUM properties, our empirical results confirmed the results of almost all of the existing studies. First of all, the cross-sectional analysis shows that mean, variance, and skewness of returns and AUM matter for hedge fund survival in expected directions. The importance of skewness suggests the significance of the risk management to sudden changes in both returns and

AUM. Second, the cross-sectional time-series analysis shows that the short-term momentum effects of returns and fund flows are important to hedge fund survival. In particular, the most recent performance has the most decisive impact on hedge fund hazards.[44]

4.3.2 Leverage

In all the cases, leverage variables have no significant effect on liquidation hazard ratios. These results are rather surprising to us at first glance since hedge fund defaults including the aftermath of the LTCM debacle tend to be associated with the destabilizing effects of highly-leveraged hedge funds.[45]

To investigate the background behind these results, we conducted a Tobit analysis with mean leverage as a dependent variable.[46] It shows that funds with a larger mean leverage tend to have a larger AUM, a high water mark, and a longer notice period. From the analysis above, these three factors work as a stabilizer for fund management, in that they significantly lower the liquidation hazard ratios. Hence, one possible interpretation is that the funds with these attributes tend to have room for more risk-taking through high leverage.

Another possibility is that leverage measures reported in Lipper TASS database is not appropriate enough for us to detect the destabilizing effects of high leverage. Since hedge funds frequently use derivatives, we might need the data of margin rates.

4.3.3 Fees: Incentive Scheme

As for incentive scheme, our results are consistent across all of the empirical methodologies and

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[44] Some practitioners we interviewed commented that liquidation hazards are high for oversized hedge funds. As we mentioned in section 2, such oversized funds tend to stop reporting to the Lipper TASS data base, which makes difficult for us to test this hypothesis.

[45] Our result differs from Gregoriou [2002], who finds that leverage matters for liquidation probability.

[46] The detailed estimation results are available from the authors, upon request.

specifications: higher management fees and a high-water-mark provision lower the liquidation probability, while higher incentive fees raise the liquidation probability. These results are different from the existing studies, such as Baquero, Horst, and Verbeek [2005], who do not find any significant relationship between incentive fees and survival rates. The interpretation for management and incentive fees is straightforward. Higher incentive fees give fund managers an incentive to take more risk, due to the convexity of compensation schedule of fund managers, while higher management fees serve as a stabilizer for fund management since they are imposed as a constant rate of AUM in most cases, irrespective of market conditions.

The most interesting result here is that funds subject to a high water mark have significantly lower liquidation probabilities in all cases. In light of our hypotheses discussed in sub-section 4.1, we can conclude that a high-water-mark provision works toward facilitating more stable fund management rather than more risk-taking, possibly because fund managers, typically, have long-term horizons. Or, as suggested by market participants, having a high water mark itself may send a signal that the hedge funds have skills and philosophies sophisticated enough to keep stable performance in the future. On the flip side of the coin, hedge funds, subject to a high water mark, tend to attract highly-skilled, experienced managers.

4.3.4 Liquidity: Cancellation Policy

Our empirical results show that funds with longer notice periods tend to have a significantly lower liquidation probability in all cases. A lower redemption frequency and longer payout periods also lower the liquidation probability, although they are less robust than notice periods. These results imply the hypothesis that lower liquidity contributes to more stable fund management dominates the competing hypothesis that investors dislike hedge funds with lower liquidity.

4.3.5 Minimum Investment

Our empirical results show that funds with a smaller minimum investment tend to have lower liquidation probabilities, and this effect is estimated to be more significant in the Cox proportional hazard analysis. This is consistent with our hypotheses that funds with a smaller minimum investment are likely to face a smaller withdrawal, and have smaller and more risk-averse investors who have a tendency to accept less risky strategies.[47]

5. Concluding Remarks

This paper has applied a survival analysis to individual hedge fund data reported in the Lipper TASS database, which contains the relevant information about liquidated funds as well as live funds. We used several methodologies including the non-parametric survival analysis, the Semi-parametric Cox proportional hazard analysis, and the panel logit analysis to obtain robust effects of both fund-specific characteristics and the dynamic performance properties on survival probabilities of hedge funds. Also, we have tested the widest range of variables of all the existing studies, including various performance measures, leverage, incentive scheme, cancellation policy, minimum investment, and competitive pressure.

Estimation results are summarized as follows. (i) Funds with higher returns, assets under management (AUM), and recent fund flows, and funds with lower volatilities and higher skewness of returns and AUM have higher survival probabilities. (ii) Incentive scheme matters for survival probabilities, but the directions of the effects differ depending on the measures: funds with higher incentive fees have lower survival probabilities, while those with a high water mark have higher survival probabilities. (iii) Cancellation policies as proxies for liquidity constraints matter: funds with a longer redemption notice period and a lower redemption frequency have higher survival

[47] Not surprisingly, the hypothesis that a minimum investment is a proxy for fund size was not rejected.

probabilities. (iv) As the number of total hedge funds is becoming larger, the survival probability significantly falls. (v) On the other hand, leverage does not significantly influence survival probabilities.

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Table 1: Entries into and Exits out of the Lipper TASS Database

(i) All Funds

Year	Existing Funds	New Entries	New Exits		Attrition Rate (%)	
			All	Liquidated	Exits	Liquidated
1985	54	54	NA	NA	NA	NA
1986	77	23	NA	NA	NA	NA
1987	111	34	NA	NA	NA	NA
1988	144	34	NA	NA	NA	NA
1989	190	45	NA	NA	NA	NA
1990	307	117	NA	NA	NA	NA
1991	414	107	NA	NA	NA	NA
1992	573	159	NA	NA	NA	NA
1993	830	257	NA	NA	NA	NA
1994	1,102	272	32	17	2.90	1.54
1995	1,386	316	73	44	5.27	3.17
1996	1,668	355	138	66	8.27	3.96
1997	1,912	382	113	74	5.91	3.87
1998	2,179	380	179	122	8.21	5.60
1999	2,456	456	199	107	8.10	4.36
2000	2,723	466	247	98	9.07	3.60
2001	3,074	598	272	106	8.85	3.45
2002	3,434	632	261	135	7.60	3.93
2003	3,876	686	287	156	7.41	4.02
2004	4,337	703	348	183	8.02	4.22
2005	4,354	365	338	178	7.76	4.09

(ii) Sample Funds

Year	Existing Funds	New Entries	New Exits		Attrition Rate (%)	
			All	Liquidated	Exits	Liquidated
1985	6	6	NA	NA	NA	NA
1986	14	8	NA	NA	NA	NA
1987	18	4	NA	NA	NA	NA
1988	20	2	NA	NA	NA	NA
1989	24	4	NA	NA	NA	NA
1990	43	19	NA	NA	NA	NA
1991	64	21	NA	NA	NA	NA
1992	98	34	NA	NA	NA	NA
1993	147	49	NA	NA	NA	NA
1994	214	67	3	1	1.40	0.47
1995	287	76	4	3	1.39	1.05
1996	370	87	29	11	7.84	2.97
1997	439	98	17	8	3.87	1.82
1998	525	103	25	17	4.76	3.24
1999	667	167	28	14	4.20	2.10
2000	793	154	54	24	6.81	3.03
2001	909	170	55	30	6.05	3.30
2002	1,041	187	60	35	5.76	3.36
2003	1,158	177	68	39	5.87	3.37
2004	1,120	30	89	44	7.95	3.93
2005	1,031	NA	79	44	7.66	4.27

Notes:
1. The Lipper TASS database began to track fund exits from 1994; hence new exits and thus attrition rates are only available from 1994. All funds cover the entire Lipper TASS database, and sample funds are selected funds for our empirical analysis. New entries in 2004 and 2005 for sample funds are not available.,due to the sample selection rule.
2. Attrition rates are calculated as new exists (liquidated) divided by existing funds.

Table 2: Summary Statistics of Monthly Return and Assets under Management (AUM)

(i) Live Funds: January 1994-December 2005

Strategy	Sample Size	Monthly Return (%)				AUM (Million US$)			
		Mean	SD	Skew	Kurtosis	Mean	SD	Skew	Kurtosis
All Funds									
CA	117	0.946	2.056	-0.077	4.210	137.50	57.42	0.069	2.461
ED	355	1.069	2.528	0.183	5.265	131.06	80.26	0.230	2.650
EM	179	1.452	4.375	0.034	5.663	97.56	65.24	0.502	2.948
EMN	222	0.628	2.089	0.038	4.956	98.38	50.71	0.197	2.634
LSE	1,211	1.090	3.391	0.202	4.885	93.62	56.93	0.274	2.806
GM	179	0.742	2.965	0.240	4.510	119.52	72.02	0.327	2.705
FIA	186	0.898	1.877	-0.404	6.298	121.28	66.20	0.096	2.349
DSB	21	0.441	4.359	0.200	3.517	50.87	27.16	0.199	3.157
MF	241	0.954	4.153	0.170	5.183	82.62	53.59	0.304	2.870
FOF	1,160	0.708	1.866	-0.219	4.897	100.41	47.87	0.089	2.577
Others	145	0.985	2.397	0.026	6.247	182.30	96.97	0.229	2.795
All	4,016	0.925	2.733	0.019	5.050	105.49	58.72	0.211	2.694
Sample Funds									
CA	34	0.678	1.985	-0.100	4.604	90.14	51.87	-0.035	1.860
ED	89	1.088	2.513	0.147	5.180	117.14	92.16	0.217	2.420
EM	55	1.593	4.941	0.115	6.112	106.21	76.00	0.658	2.850
EMN	50	0.738	2.528	-0.021	8.100	99.36	61.24	0.295	2.710
LSE	305	1.184	3.874	0.360	5.445	100.19	75.37	0.381	2.598
GM	52	0.945	4.016	0.287	5.296	84.265	65.01	0.605	3.221
FIA	58	0.851	2.154	-0.605	9.607	146.24	98.89	0.262	2.320
DSB	5	0.743	4.273	-0.075	4.160	43.55	42.00	0.391	2.412
MF	68	0.983	4.802	0.026	5.400	100.50	78.20	0.554	3.187
FOF	202	0.757	2.075	-0.096	5.470	84.96	48.70	0.218	2.684
Others	34	1.011	2.197	-0.012	9.010	161.47	124.81	0.413	3.410
All	952	1.014	3.200	0.107	5.936	102.34	72.39	0.346	2.681

(ii) Graveyard Funds: January 1994-December 2005

Strategy	Sample Size	Monthly Return (%)				AUM (Million US$)			
		Mean	SD	Skew	Kurtosis	Mean	SD	Skew	Kurtosis
All Funds									
CA	84	0.641	2.097	-0.359	7.866	106.85	49.76	0.163	2.771
ED	167	0.736	3.099	-0.307	6.171	60.83	32.74	0.261	2.830
EM	158	0.237	7.607	-0.464	6.787	41.82	20.30	0.389	3.027
EMN	151	0.527	2.938	0.056	4.232	36.27	18.29	0.001	2.929
LSE	801	0.730	4.927	0.122	5.010	42.68	19.69	0.193	2.765
GM	159	0.210	2.965	0.187	4.980	118.49	47.23	0.034	2.840
FIA	105	0.414	2.524	-0.998	10.393	68.15	31.89	0.214	2.666
DSB	17	0.264	7.381	0.280	4.031	30.55	14.03	0.265	2.346
MF	371	0.142	5.607	0.094	4.655	10.97	5.08	0.342	3.136
FOF	398	0.197	3.195	-0.214	5.256	31.71	13.17	0.113	2.777
Others	76	0.389	3.686	-0.031	5.212	40.49	18.36	0.024	2.525
All	2,487	0.466	4.765	-0.069	5.461	36.30	16.60	0.179	2.320
Sample Funds									
CA	19	0.672	1.940	-0.781	6.594	45.15	29.17	0.482	2.965
ED	36	0.742	2.998	-0.442	5.937	20.56	10.88	0.105	2.456
EM	28	0.465	5.936	-0.302	7.079	35.96	20.91	0.204	2.400
EMN	33	0.553	2.538	0.128	4.594	48.86	25.55	-0.387	3.869
LSE	170	0.817	6.363	0.181	5.064	32.01	21.43	0.350	2.829
GM	31	0.388	4.387	0.448	5.553	208.76	101.94	0.177	3.434
FIA	23	0.443	2.417	-1.407	12.777	57.66	23.24	0.179	2.366
DSB	7	0.261	6.171	0.172	3.893	44.09	16.04	0.341	2.504
MF	81	0.491	6.872	0.122	4.708	15.13	8.70	0.563	4.035
FOF	70	0.436	3.264	-0.300	6.239	43.32	23.58	0.182	2.564
Others	13	0.441	2.556	-0.077	7.022	98.89	65.60	-0.194	2.617
All	511	0.606	4.952	-0.066	5.776	45.61	25.51	0.261	3.012

Notes: 1. All funds cover all of the funds that reported returns to the Lipper TASS database at least once, and sample funds are selected funds for our empirical analysis. AUM denominated in currencies other than US dollars are converted into US dollars, using the end-month exchange rates.

2. CA: Convertible Arbitrage; ED: Event Driven; EM: Emerging Markets; EMN: Equity Market Neutral; LSE: Long/Short Equity; GM: Global Macro; FIA: Fixed Income Arbitrage; DSB: Dedicated Short Bias; MF: Managed Futures; and, FOF: Fund of Hedge Funds.

(iii) Liquidated Funds: January 1994-December 2005

Strategy	Sample Size	Monthly Return (%) Mean	SD	Skew	Kurtosis	AUM (Million US$) Mean	SD	Skew	Kurtosis
All Funds									
CA	40	0.471	1.860	-0.756	8.597	91.01	45.83	-0.025	2.723
ED	72	0.468	2.827	-0.276	6.467	67.66	36.64	0.219	2.770
EM	85	0.160	7.089	-0.440	7.434	37.95	15.81	0.208	2.821
EMN	107	0.454	2.922	0.032	4.099	38.29	19.14	-0.121	3.046
LSE	384	0.430	5.091	0.063	4.830	28.83	15.62	0.148	2.708
GM	79	0.112	3.892	0.187	5.044	162.41	70.39	0.058	2.616
FIA	48	0.168	2.427	-0.830	7.812	69.03	34.41	0.147	2.498
DSB	9	0.165	5.825	0.345	4.572	22.34	13.94	0.692	2.335
MF	224	-0.034	5.587	0.038	4.622	9.79	5.25	0.334	3.290
FOF	187	0.209	3.489	-0.279	5.230	17.52	5.36	0.113	2.869
Others	51	0.398	3.196	-0.027	5.571	39.00	22.56	0.123	2.378
All	1,286	0.272	4.426	-0.098	5.324	39.16	18.96	0.150	2.845
Sample Funds									
CA	8	0.623	2.018	-1.322	9.531	50.36	20.54	0.223	2.936
ED	14	0.435	3.458	-0.608	6.044	19.04	10.34	0.250	2.299
EM	17	0.043	5.277	-0.243	7.233	22.44	11.37	-0.012	2.259
EMN	25	0.557	2.162	0.174	4.418	56.34	29.66	-0.588	4.433
LSE	87	0.713	5.702	0.212	5.010	37.66	24.68	0.326	2.897
GM	17	0.452	4.064	0.527	5.995	367.09	178.09	0.158	2.407
FIA	1	0.217	1.546	-0.445	4.626	71.30	27.71	0.118	2.295
DSB	7	-0.706	5.905	0.112	3.919	28.69	10.28	-0.387	1.930
MF	48	0.319	7.577	-0.053	4.892	18.56	11.18	0.671	4.732
FOF	39	0.536	3.870	-0.416	5.807	10.53	4.51	0.049	2.481
Others	6	0.638	1.109	-0.148	7.017	179.94	126.68	-0.191	2.901
All	270	0.513	4.863	-0.054	5.468	55.39	30.09	0.204	3.189

Notes: 1. All funds cover all of the funds that reported returns to the Lipper TASS database at least once, and sample funds are selected funds for our empirical analysis. AUM denominated in currencies other than US dollars are converted into US dollars using the end-month exchange rates.

2. CA: Convertible Arbitrage; ED: Event Driven; EM: Emerging Markets; EMN: Equity Market Neutral; LSE: Long/Short Equity; GM: Global Macro; FIA: Fixed Income Arbitrage; DSB: Dedicated Short Bias; MF: Managed Futures; and, FOF: Fund of Hedge Funds.

Table 3: Definitions of Explanatory Variables
(i) Cross-sectional Analysis

Return Property	
Mean	Sample mean of monthly return over the lifetime.
Variance	Sample variance of monthly return over the lifetime.
Skewness	Sample skewness of monthly return over the lifetime
Kurtosis	Sample kurtosis of monthly return over the lifetime
Winning ratio	Ratio of the number of months with positive returns to the total months.
Assets under Management (AUM)	
Mean	Sample mean of total assets under management (AUM) over the lifetime in U.S. dollars. AUM denominated in other currencies are converted by month-end exchange rates.
Variance	Sample variance of AUM over the lifetime.
Skewness	Sample skewness of AUM over the lifetime.
Kurtosis	Sample kurtosis of AUM over the lifetime
Leverage	
Mean	Sample mean of leverage defined as the ratio of portfolio to equity.
Max-Mean	Maximum historical leverage minus average leverage.
Fees: Incentive Scheme	
Management fee	Annual fixed percentage fee payable to the manager.
Incentive fee	Annual performance fee that typically allocates a proportion of the profits to the manager.
High water mark	Dummy variable for the option of incentive fees stating that the manager receives the incentive fee only if the net asset value (NAV) exceeds the highest point ever. It takes on 1 if the option is present, and zerootherwise.
Liquidity: Cancellation Policy	
Redemption frequency	Frequency at which investors can sell shares. It is denominated in days, so that a higher value of the index means a lower frequency.
Lockup period	Minimum holding period before investors can declare selling orders.
Notice period	Time period needed for processing of selling orders.
Payout period	Time period before investors receive cash back, after selling orders are processed.
Minimum Investment	Minimum subscription amount in US dollars. Minimum subscription amount denominated in other currencies are converted by month-end exchange rates.

Note: In estimation, each variable is normalized to mean zero and variance one, except a high-water-mark dummy.

(ii) Cross-sectional Time-series Analysis

Age (logit analysis, only)	
Age	Current age of the fund in months.
Age^2	Squared current age of the fund in months.
Competitive Pressure	
Total number of funds	Current total number of hedge funds included in the Lipper TASS database.
Return	
Return	Current monthly return.
Return(-1)	One-month lagged **Return**
Return(-2)	Two-month lagged **Return**
AUM and Fund Flows	
AUM(-1)	One-month lagged AUM in US dollars.
Flow	Current flow into or out of the fund in US dollars divided by previous month's assets under management. Flow is defined as $Flow_t \equiv AUM_t - AUM_{t-1}(1+R_t)$, where R_t denotes the fund's net return in month t.
Flow(-1)	One-month lagged **Flow**.
Flow(-2)	Two-month lagged **Flow**.
Drawdown	
Down5%	Dummy variable that takes on 1 if the fund's NAV falls by at least 5% of the maximum value over the lifetime and zero otherwise.
Down5%(-1)	One-month lagged **Down5%**.
Down10%	Dummy variable that takes on 1 if the fund's NAV falls by at least 10% of the maximum value over the lifetime and zero otherwise.
Down10%(-1)	One-month lagged **Down10%**.
Down15%	Dummy variable that takes on 1 if the fund's NAV falls by at least 15% of the maximum value over the lifetime and zero otherwise.
Down15%(-1)	One-month lagged **Down15%**.
Yearly and Monthly Dummy Variables	
1995～2005	Dummy variable that takes on 1 if the period is in the year, and zero otherwise.
Month12	Dummy variable that takes on 1 if the period is December, and zero otherwise.

Notes: 1. Drawdown dummies are set to zero in the first two years, after entry into the Lipper TASS database.
2. In estimation, each variable is normalized to mean zero and variance one except age and dummy variables.
3. In estimating logit models, we control for the effects of the variables under the categories of leverage, fees, and liquidity used in the Cox proportional hazard analysis.

Table 4: Equality Test of Survivor Functions

(i) Equality across Graveyard Statuses for Graveyard Funds

Strategy	Events observed	Events expected	Sum of ranks
Liquidated	270	238.36	10,531
No Longer Reporting	176	203.64	-9,507
Unable to Contact	20	20.64	-424
Closed to New Investment	4	6.86	-915
Merged into Another Entity	13	20.08	-2,093
Unknown	25	20.04	1,910
Blank Cell	3	1.36	493
Total	511	511.00	0.00
Log-rank Chi-squared		15.59**	
Wilcoxon Chi-squared		18.75***	

(ii) Equality across Investment Strategies for Live and Liquidated Funds

Strategy	Events observed	Events expected	Sum of ranks
Convertible Arbitrage	8	9.12	-1,287
Event Driven	14	21.41	-5,392
Emerging Markets	17	16.42	314
Equity Market Neutral	25	15.42	7,131
Long/Short Equity	87	83.61	2,863
Global Macro	17	15.27	2,985
Fixed Income Arbitrage	8	12.38	-2,734
Dedicated Short Bias	1	1.22	-36
Managed Futures	48	29.88	8,819
Fund of Hedge Funds	39	56.69	-11,434
Others	6	8.58	-1,229
Total	270	270.00	0.00
Log-rank Chi-squared		25.70***	
Wilcoxon Chi-squared		16.82*	

Note: Events observed indicates the number of failures observed and events expected indicates the number of events that would be expected, if all the groups shared the same survival function.

Table 5: Cox Proportional Hazard Analysis
(i) Cross-sectional Analysis

Number of Observations: 1,222 Sample Period: January 1985-December 2005

	Specification (i)		Specification (ii)		Specification (iii)		Specification (iv)	
Accepted method	Shared frailty		Shared frailty		Shared frailty		No shared frailty	
	Hazard	Rho	Hazard	Rho	Hazard	Rho	Hazard	Rho
Return Property								
Mean	0.574***	0.073	0.669***	0.030	0.726***	0.043	0.742***	0.052
Variance	1.222***	-0.019	1.177***	0.062	1.111***	-0.021	1.116***	-0.037
Skewness			0.777***	-0.093*	0.672***	0.045	0.862**	-0.011*
Kurtosis			0.858	0.024				
Winning ratio			0.568***	-0.034				
Assets under Management (AUM)								
Mean	0.226***	0.071	0.331***	0.085*	0.387***	0.087*	0.370***	0.089**
Variance	2.289***	-0.039	1.876***	-0.053	1.680***	-0.048	1.729***	-0.088**
Skewness			0.701***	0.067			0.716***	-0.025
Kutosis			0.885**	0.044				
Leverage								
Mean					0.904	0.038	0.881	0.023
Max-Mean					1.002	0.017	0.996	-0.044
Fees: Incentive Scheme								
Management fee					0.950	-0.030	0.879**	-0.027
Incentive fee					1.170**	0.026	1.231***	0.033
High water mark					0.540***	-0.029	0.584***	-0.038
Liquidity: Cancellation Policy								
Redemption frequency					1.007	-0.019	1.010	-0.045
Lockup period					0.943	-0.062	0.946	-0.047
Notice period					0.540***	-0.071	0.759***	-0.077
Payout period					0.836*	-0.025	0.854*	-0.008
Minimum Investment					1.135*	-0.057	1.159***	-0.067
Log Likelihood	-1,647		-1,604		-1,595		-1,573	
Theta	0.037 (0.030)		0.024 (0.025)		0.049 (0.046)		0.033 (0.018)	
LR test: theta=0	5.33**		2.09*		3.66**		0.04	
Global Ph Wald test	13.39***		17.56**		22.40*		18.43	

Notes: 1. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.
2. Figures in parentheses of theta are standard errors. Standard errors for without shared frailty are adjusted by Huber-White method. The LR test tests the null hypothesis of theta=0. The Global Ph test is a Wald statistic that tests whether all the variables jointly satisfy the proportional hazard assumptions. Rho is a slope estimate of Schoenfeld residuals specific to each variable against time.

(ii) Cross-sectional Time-series Analysis

Number of Observations: 78,002 Sample Period: January 1994-December 2005

		Specification (i)		Specification (ii)		Specification (iii)	
Accepted method		Shared frailty		Shared frailty		Shared frailty	
		Hazard	Rho	Hazard	Rho	Hazard	Rho
Competitiveness							
Total number of funds		3.028	0.008	1.070	-0.066	1.046	-0.080
Return							
Return		0.793***	-0.119	0.791***	-0.122		
Return(-1)		0.854***	0.016	0.848***	0.009		
Return(-2)		0.923*	0.048	0.914*	0.046		
AUM and Fund Flows							
AUM(-1)		0.031***	-0.024	0.030***	-0.024	0.047***	-0.015
Flow		0.768***	-0.035	0.767***	-0.035	0.798***	-0.026
Flow(-1)		0.876***	-0.073	0.877***	-0.056	0.874***	-0.055
Flow(-2)		0.929**	-0.066	0.929**	-0.042	0.928**	-0.049
Drawdown							
Down5%						1.706**	0.028
Down5%(-1)						0.582*	0.009
Down10%						1.626	-0.054
Down10%(-1)						1.065	0.059
Down15%						1.730*	-0.037
Down15%(-1)						0.758	0.034
Leverage							
Mean		0.951	0.016	0.947	0.015	0.925	0.015
Max-Mean		0.899	0.038	0.901	0.039	0.938	0.052
Fees: Incentive Scheme							
Management fee		0.831***	-0.060	0.826***	-0.053	0.802***	-0.071
Incentive fee		1.304***	-0.001	1.297***	-0.001	1.342***	-0.003
High water mark		0.586***	0.015	0.583***	0.013	0.579***	0.018
Liquidity: Cancellation Policy							
Redemption frequency		0.791**	-0.015	0.793**	-0.015	0.753***	-0.016
Lockup period		0.896	-0.082	0.894	-0.083	0.899	-0.076
Notice period		0.672***	-0.046	0.653***	-0.043	0.678***	-0.035
Payout period		0.887	-0.012	0.887	-0.015	0.891	-0.013
Minimum Investment		1.279***	0.026	1.281***	0.026	1.262***	0.021
Yearly Dummies	1995	1.543	0.019				
	1996	2.516	0.045				
	1997	1.061	0.014				
	1998	1.145	0.031				
	1999	0.652	0.032				
	2000	0.619	0.028				
	2001	0.466	0.007				
	2002	0.279	0.009				
	2003	0.185	0.013				
	2004	0.102	0.004				
	2005	0.073	0.006				
Month12		1.770***	-0.041	1.987***	-0.039	1.938***	-0.043
Log-Likelihood		-2,560		-2,565		-2,572	
Theta		0.158 (0.098)		0.155 (0.097)		0.199 (0.122)	
LR test for theta=0		16.85***		16.52***		18.81***	
Global Ph Wald test		26.39		19.09		18.72	

Notes: 1. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.
2. Figures in parentheses of theta are standard errors. The LR test tests the null hypothesis of theta=0. The Global Ph test is a Wald statistic that tests whether all the variables jointly satisfy the proportional hazard assumptions. Rho is a slope estimate of Schoenfeld residuals specific to each variable against time.

Table 6: Logit Analysis

(i) Random Effects Logit by Strategy Category vs. Pooled Logit

Number of Observations: 78,002 Sample Period: January 1994-December 2005

		Specification (i)		Specification (ii)		Specification (iii)	
Accepted method		Pooled Logit		Pooled Logit		Pooled Logit	
		Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
Age							
	Age	0.059***	0.009	0.059***	0.008	0.033***	0.009
	Age^2	-4.5E-4***	8.0E-5	-4.4E-4***	7.8E-5	-3.2E-4***	7.68E-5
Competitiveness							
	Total number of funds	1.481**	0.683	0.537**	0.065	0.617***	0.066
Return							
	Return	-0.244***	0.044	-0.242***	0.043		
	Return(-1)	-0.151***	0.052	-0.154***	0.050		
	Return(-2)	-0.089*	0.045	-0.090**	0.044		
AUM and Fund Flows							
	AUM(-1)	-3.107**	1.431	-3.145**	1.469	-2.203*	1.264
	Flow	-0.441**	0.177	-0.441**	0.178	-0.396**	0.167
	Flow(-1)	-0.162***	0.034	-0.162***	0.035	-0.172***	0.032
	Flow(-2)	-0.089***	0.019	-0.090***	0.018	-0.096***	0.017
Drawdown							
	Down5%					0.911***	0.285
	Down5%(-1)					-0.207	0.296
	Down10%					0.444	0.276
	Down10%(-1)					0.143	0.283
	Down15%					0.547**	0.237
	Down15%(-1)					-0.050	0.274
Leverage							
	Mean	-0.038	0.111	-0.036	0.111	-0.058	0.097
	Max-Mean	-0.046	0.102	-0.047	0.104	0.035	0.074
Fees: Incentive Scheme							
	Management fees	-0.123**	0.057	-0.129**	0.058	-0.131**	0.055
	Incentive fee	0.208***	0.061	0.202***	0.061	0.220***	0.063
	High water mark	-1.053***	0.139	-1.056***	0.140	-1.123***	0.142
Liquidity: Cancellation Policy							
	Redemption frequency	0.045	0.086	0.042	0.086	0.011	0.087
	Lockup period	-0.088	0.098	-0.088	0.098	-0.123	0.099
	Notice period	-0.461***	0.092	-0.453***	0.100	-0.366***	0.104
	Payout period	-0.259**	0.100	-0.261**	0.101	-0.243**	0.099
Minimum Investment		0.139	0.071	0.143	0.090	0.131**	0.063
Yearly Dummies	1995	0.471	1.223				
	1996	0.985	1.195				
	1997	0.207	1.296				
	1998	0.330	1.359				
	1999	-0.138	1.475				
	2000	-0.142	1.613				
	2001	-0.355	1.791				
	2002	-0.898	2.026				
	2003	-1.329	2.289				
	2004	-1.931	2.603				
	2005	-2.104	2.670				
Month12		0.607***	0.182	0.717***	0.174	0.713***	0.172
Constant		-6.661***	2.012	-7.553***	0.495	-7.016***	0.424
Log-Likelihood		-1,553		-1,558		-1,524	
rho		2.53E-7		2.53E-7		2.53E-7	
LR test for rho=0		0.00		0.00		0.00	

Notes: 1. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors for pooled logit models are adjusted by Huber-White method.

2. Rho is the ratio of panel-level variance to total variance. LR test for rho=0 tests whether rho is zeo or not. If the null hypothesis rho=0 is rejected, then the panel estimator is different from the pooled estimator.

(ii) Random Effects Logit by Fund vs. Pooled Logit

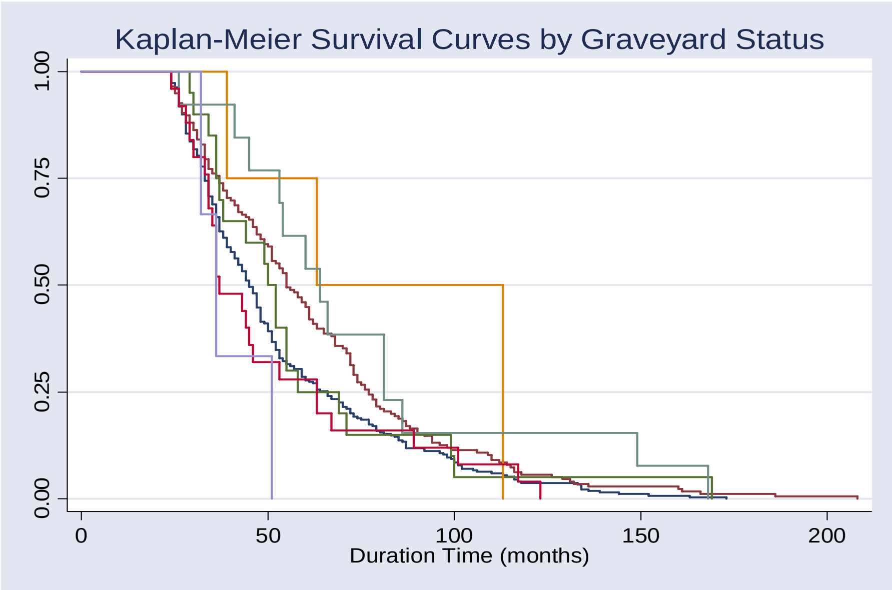
Number of Observations: 78,002 Sample Period: January 1994-December 2005

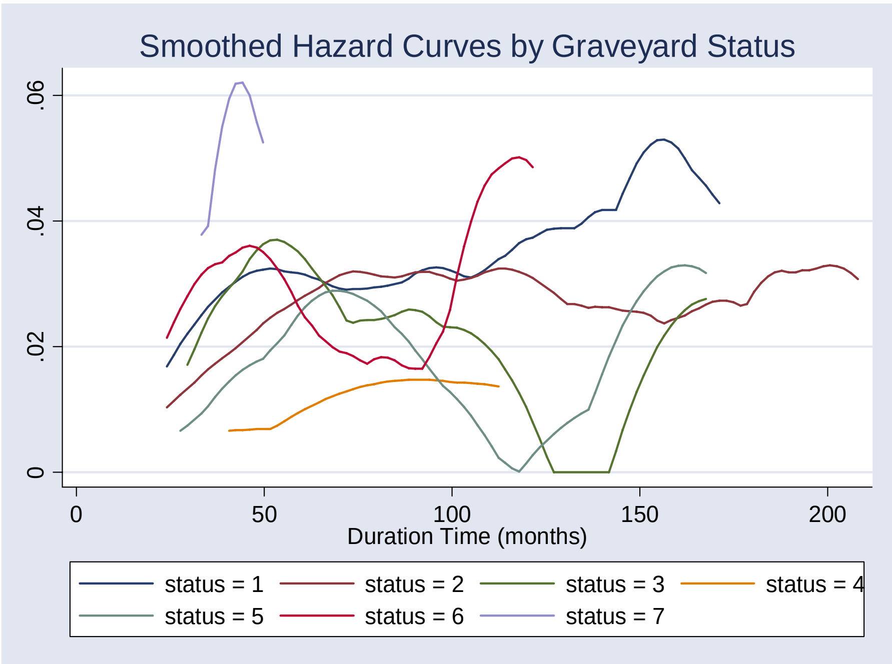
	Specification (i)		Specification (ii)		Specification (iii)	
Accepted method	Ramdom Effects		Random Effects		Random Effects	
	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
Age						
Age	0.073***	0.011	0.060***	0.008	0.060***	0.013
Age^2	-5.1E-4***	7.5E-5	-4.5E-4***	6.2E-5	-4.5E-4***	8.3E-5
Competitiveness						
Total number of funds	1.620**	0.729	0.556***	0.075	0.979***	0.154
Return						
Return	-0.262***	0.045	-0.246***	0.041		
Return(-1)	-0.156***	0.049	-0.155***	0.045		
Return(-2)	-0.091*	0.054	-0.091*	0.051		
AUM and Fund Flows						
AUM(-1)	-3.578***	0.603	-3.207***	0.517	-2.967***	0.617
Flow	-0.455***	0.102	-0.444***	0.090	-0.395***	0.118
Flow(-1)	-0.161***	0.056	-0.163***	0.048	-0.164***	0.068
Flow(-2)	-0.090**	0.041	-0.090**	0.036	-0.095*	0.056
Drawdown						
Down5%					0.945***	0.295
Down5%(-1)					-0.190	0.311
Down10%					0.530	0.327
Down10%(-1)					0.236	0.336
Down15%					0.617**	0.299
Down15%(-1)					0.154	0.295
Leverage						
Mean	-0.095	0.122	-0.043	0.134	-0.139	0.191
Max-Mean	-0.043	0.107	-0.047	0.128	0.004	0.153
Fees: Incentive Scheme						
Management fees	-0.162**	0.076	-0.137**	0.061	-0.224**	0.093
Incentive fee	0.267***	0.086	0.210***	0.066	0.322***	0.105
High water mark	-1.334***	0.232	-1.089***	0.156	-1.707***	0.291
Liquidity: Cancellation Policy						
Redemption frequency	0.080	0.110	0.046	0.090	0.055	0.129
Lockup period	-0.106	0.119	-0.090	0.105	-0.177	0.142
Notice period	-0.582***	0.131	-0.468***	0.100	-0.542***	0.150
Payout period	-0.312***	0.115	-0.267***	0.099	-0.353***	0.136
Minimum Investment	0.144	0.134	0.144	0.103	0.162	0.118
Yearly Dummies 1995	0.391	1.195				
1996	0.985	1.151				
1997	0.160	1.252				
1998	0.304	1.328				
1999	-0.155	1.459				
2000	-0.113	1.584				
2001	-0.256	1.763				
2002	-0.804	2.021				
2003	-1.235	2.300				
2004	-1.869	2.629				
2005	-2.028	2.721				
Month12	0.625***	0.192	0.720***	0.172	0.739***	0.176
Constant	-7.550***	2.032	-7.645***	0.290	-8.673***	0.668
Log-Likelihood	-1,555		-1,563		-1,514	
rho	0.25		0.03		0.43	
LR test for rho=0	5.83***		11.11***		18.41***	

Notes: 1. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Standard errors for pooled logit models are adjusted by Huber-White method for clustering on strategy categories.

2. Rho is the ratio of panel-level variance to total variance. LR test for rho=0 tests whether rho is zeo or not. If the null hypothesis rho=0 is rejected, then the panel estimator is different from the pooled estimator.

Figure 1: Non-Parametric Survival and Hazard Curves
(i) Graveyard Funds by Graveyard Status

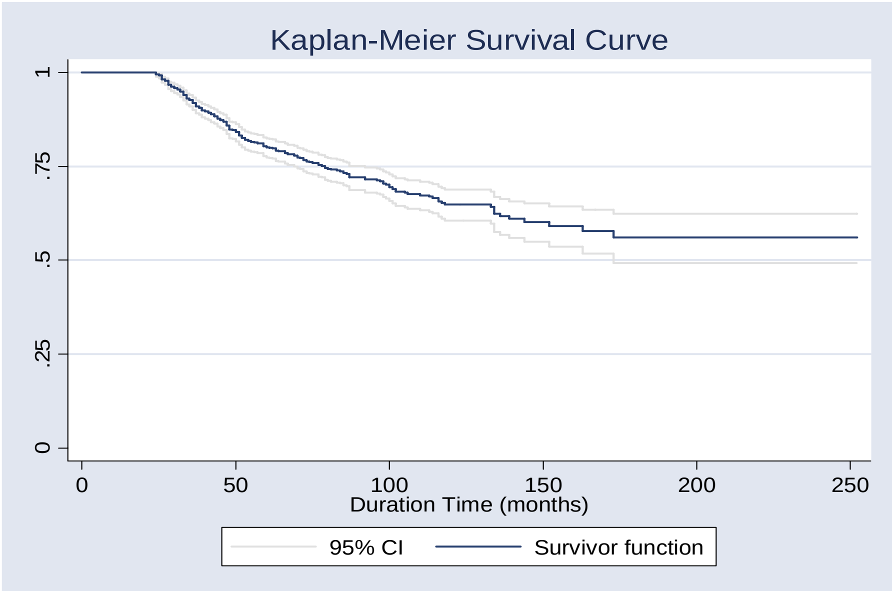


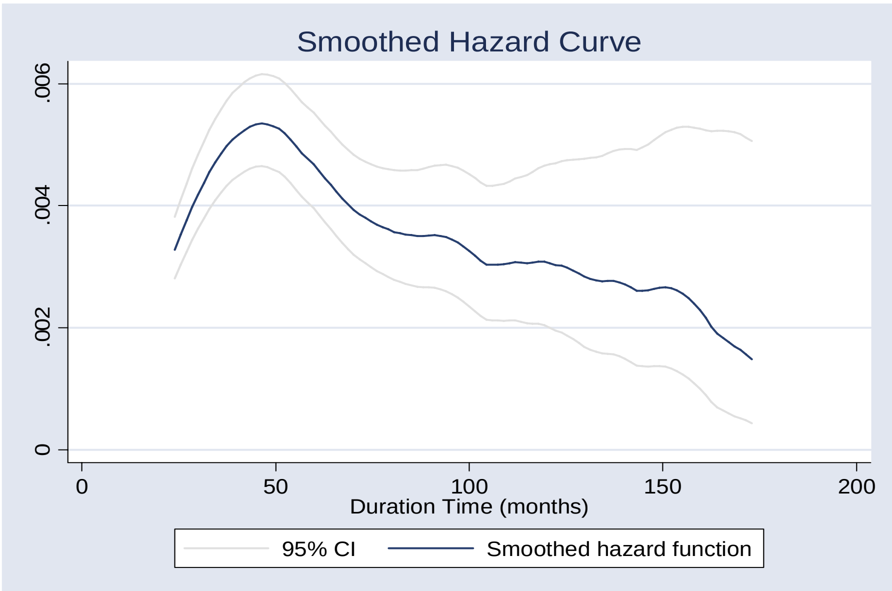


Notes:

1. Graveyard status codes are as follows: status 1: liquidated; status 2: no longer reporting; status 3: unable to contact; status 4: closed to new investment; status 5: merged into another entity; status 6: unknown; and, status 7: blank cell.
2. We estimate hazard curves by smoothing the Nelson-Aalen hazard estimates with a kernel smoother.

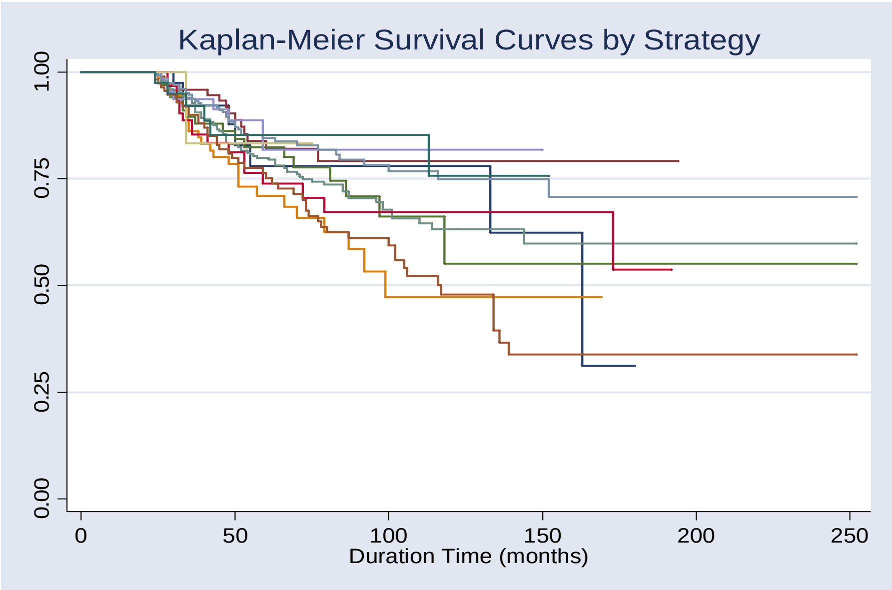
(ii) Live and Liquidated (Sample) Funds

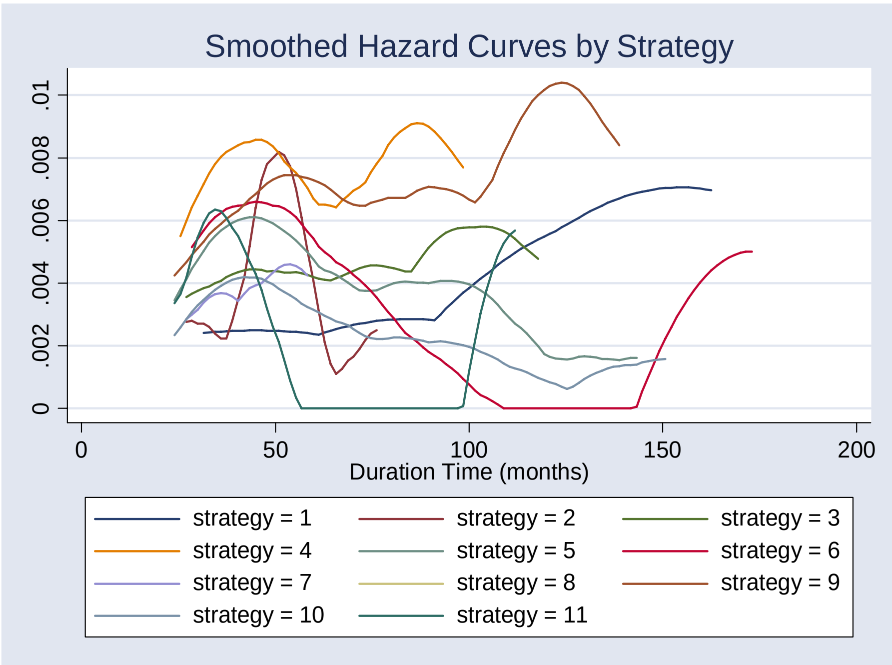




Note: The hazard curve is estimated by smoothing the Nelson-Aalen hazard estimates with a kernel smoother. 95% CI indicates a 95% confidence interval based on the variance calculation proposed by Aalen [1978].

(iii) Live and Liquidated (Sample) Funds by Investment Strategy

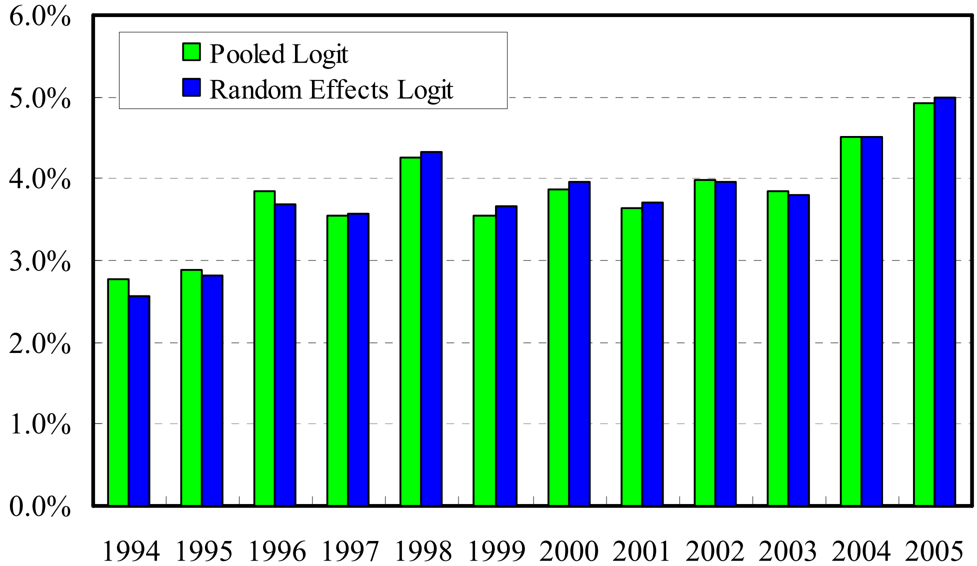




Notes:

1. Investment strategies are as follows: strategy 1: Convertible Arbitrage; strategy 2: Event Driven; strategy 3: Emerging Markets; strategy 4: Equity Market Neutral; strategy 5: Long/Short Equity; strategy 6: Global Macro; strategy 7: Fixed Income Arbitrage; strategy 8: Dedicated Short Bias; strategy 9: Managed Futures; strategy 10: Fund of Hedge Funds; and, strategy 11: Others.
2. We estimate hazard curves by smoothing the Nelson-Aalen hazard estimates with a kernel smoother.

Figure 2: Annualized Liquidation Probabilities Estimated from Logit Models



Note: Liquidation probabilities are the respective simple averages of liquidation probabilities for each hedge fund in each period estimated from the logit models. Specifications used here are specification (ii) in Table 6 (i) and (ii) for both pooled logit model and random effects logit model.