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"EVALUATING AND PREDICTING THE FAILURE PROBABILITIES OF HEDGE FUNDS"

Hee Soo Lee
Yonsei University, Korea

Juan Yao
University of Sydney Business School

ABSTRACT

Hedge funds have the most sophisticated risk management practices; however, hedge funds also appear to have a short lifetime relative to other managed funds. In this study, we investigate the failure probabilities of hedge funds—particularly the failures due to financial distress. We forecast the failure probabilities of hedge funds using both a proportional hazard model and a logistic model. By utilizing a signal detection model and a relative operating characteristic curve as the prediction accuracy metrics, we found that both of the models have predictive power in the out-of-sample test. The proportional hazard model, in particular, has stronger predictive power, on average.

JEL Classification: G33, G14, G17

KEYWORDS: Hedge fund; failure probability prediction; proportional hazard model; logit model; signal detection model; relative operating characteristic curve

* Corresponding author, Discipline of Finance, School of Business, Yonsei University,
50 Yonsei-ro, Seodaemun-gu, Seoul 120-749, Korea, email: heesoo@yonsei.ac.kr
Tel:822-2123-6564, Fax:822-2123-8639

**Discipline of Finance, The University of Sydney Business School
The University of Sydney, NSW, 2006, Australia. Email: juan.yao@sydney.edu.au
Tel: 612-93517650, Fax: 612-93516461

1. INTRODUCTION

The hedge fund industry has reached a new peak, with $2.2 trillion in assets under management (AUM) in 2012 (Hedge Fund Research Year End Report, 2012). The phenomenal growth of these funds has been created in part by the failure of traditional investment strategies to satisfy the risk and return objectives of institutional investors. However, the role of hedge funds in financial markets has become a controversial issue in recent history because of large losses by high profile hedge funds prior to, and subsequent to, the Global Financial Crisis (GFC). The collapse of Long-Term Capital Management in 1998, the Soros Fund in 2000, and Amaranth in 2006 preceded the demise of the Bear Sterns funds in 2008 at the onset of the GFC, which, in turn, heralded the start of further collapses for investment banks and other hedge funds. While most contributors to the academic literature recognize that the hedge fund industry provides risk sharing and liquidity to the financial market, an opposing view considers the increased systemic risk of the financial system, along with the associated financial instability, to result from the nature of the risk exposure of hedge funds.

Owing to the private nature of hedge funds, hedge fund investors are challenged by large information asymmetries and high search costs. The entry into and exit from active management involve nontrivial costs (Brown *et al*., 2004; Liang, 1999; Malkiel and Saha, 2005). However, hedge funds can leverage limited investments to make very large bets, which are perceived to have the ability to move the direction of the market. Hedge funds also appear to be an important supplier of liquidity to the market (Aragon and Strahan, 2012). Among their many differences from traditional mutual funds, such as flexibility in investment strategy and voluntary reporting, one typical characteristic of hedge funds is their short lifetime. Although most funds impose conditions for the lock-up period and redemption frequency, the average life of a hedge fund is approximately 4 to 5 years (Amin and Kat, 2003; Gregorious, 2002). The most recent literature appears to depict a "fast aging" picture over a hedge fund's life. Hedge funds strategically list their best performing funds after their inception (Jorion and Schwarz, 2012). However, as funds grow older and larger, their performance deteriorates (Aggarwal and Jorion, 2010; Getmanski, 2004). As history depicts, the failure of a hedge fund not only causes a large loss to its investors but also has a negative impact on the entire industry as well as on other asset classes (Boyson *et al.*, 2010). Thus, the event of a hedge fund failure has become a major concern for the international investment community, and an earlier assessment mechanism for fund operation will be beneficial to both investors and market regulators.

To this end, we establish a prediction model for hedge fund failures and evaluate the predictive ability of the chosen model in an out-of-sample test. Though several researchers have studied the lifetime of hedge funds and the factors that contribute to fund failures,[1] to our best knowledge, no published work to date has evaluated a model's ability to predict financial distress for hedge funds. After generating the funds' failure probabilities, we present a method for quantifying the model's predictive ability.

Our established hazard prediction models are able to distinguish between failed and non-failed funds in the out-of-sample test. The evaluation metric based on a signal detection model (SDM) and the relative operating characteristic (ROC) curve show that the hazard model has satisfactory prediction ability, and the predictive power is stronger than that of the logit model that is commonly used in this type of study. The prediction framework presented here can be used by investors to evaluate the likelihood of failure for the funds that they are investing in or considering investing in, and for investors who have already committed to a fund, our prediction model is able to provide some warning signals about possible fund liquidation.[2]

This paper is structured as follows: In Section 2, a review of previous related studies on hedge funds is provided. The method used to estimate the failure probability of funds and the prediction evaluation metrics are discussed in Section 3. In Section 4, the details of the data and the filtering process that is adopted in this study are outlined. The results are presented in Section 5, and the conclusion is given in Section 6.

2. BACKGROUND LITERATURE

The topic of hedge fund lifetimes has been well researched. Earlier work in this area concentrates on the risk factors that drive hedge fund failure. Brown *et al*. (2001) find that hedge fund termination is a function of performance relative to the rest of the industry. Not surprisingly, they find that the degree of risk associated with a hedge fund plays an important role in hedge fund failure, in that the riskier funds are less likely to survive longer.

Getmansky (2004) examines the industry- and fund-specific factors that affect the survival probability of hedge funds. His study shows that performance and the fund flow decrease the probability that hedge funds are liquidated but that the top performing hedge funds chased by investors have an increased probability of being liquidated owing to a competition effect. The author claims that when competition increases, marginally performing funds are more likely to be liquidated.

Gregoriou (2002) finds that fund size has an important impact on survival time, with those funds above the median size corresponding to longer survival times. Funds with low leverage are found to be more likely to live longer than more highly leveraged funds, while funds with higher minimum purchases tend to fail faster. Notably, funds with annual redemptions are inclined to have longer survival times. More recent work by Gregoriou *et al*. (2009) shows that exchange-listed hedge funds are larger and more conservative than non-listed funds. Compared with non-listed funds, exchange-listed hedge funds perform more poorly but have lower volatility. Listed hedge funds appear to last approximately two years longer than non-listed funds.

Liang and Park (2010) compare downside risk measures that incorporate higher return moments with traditional risk measures, such as the standard deviation, to predict hedge fund failure. Controlling for investment strategies, performance, fund age, size, lock-up period, high-water mark, and leverage, they find that funds with larger downside risk have a higher hazard rate.

Other factors that affect the duration of funds include lock-up period, redemption frequency, and downside risk measures. Simon (2011) investigates the causal effect of fund lock-up period and fund duration and shows that the lock-up period variable should be treated endogenously. Using redemption frequency as the instrumental variable, the author claims that the lock-up period has protection power for funds in case of poor performance.

One controversy in hedge fund failure studies concerns the definition of fund failure. Hedge funds report to the database voluntarily, and in practice, they can stop reporting for various reasons. Though newer databases contain a specific data sample of funds that stopped reporting, the group in the “dead fund” database contains not only bankrupted funds but also other funds that closed because of restructuring or that were closed to investment, for example. Rouah (2006) finds that some funds have simply stopped reporting for no identified reason and report good returns and high AUM. Liang and Park (2010) further argue that liquidation does not automatically mean failure in the hedge fund industry, as profitable hedge funds can be liquidated voluntarily to return capital to investors.

Regarding hedge fund lifetime, a more recent work by Darolles *et al*. (2010) proposes two nonparametric duration models: a single risk model and a competing risks model. The authors find that there are various reasons that hedge funds exit the database and that the exit cannot be explained by low performance or low asset levels. Thus, the exact reason that funds exit the database is important information for analyzing a fund's survival. The results of some earlier works, including both Brown *et al*. (2001) and Gregoriou (2002), are therefore questionable because they classify funds for which reporting stopped as failed funds. If funds stopped reporting because of a restructuring or other unknown reasons, an analysis including those funds as failures will be misleading. Because the real concern for both investors and regulators is the financial distress suffered by funds and because this type of failure will realize losses to investors, the current study aims to concentrate on funds closed owing to financial distress. A predictive model of financial distress will be able to offer a warning signal to the investment community.

3. METHODOLOGY

3.1. Predicting the failure probability of hedge funds

The main aim of this study is to predict fund failure probabilities. Because we are examining the probability of failure conditional on the lifetime of funds, two types of models are useful. The logit model is a well-known qualitative response model that has been used to study the influence of various hedge fund characteristics on the likelihood of liquidation, such as in Chan *et al*. (2005). The logit model can be expressed in the following form with an unobserved continuous dependent variable Y^* and observed independent variables X:

$$Y_{it}^* = \boldsymbol{X}_{it}'\boldsymbol{\beta} + \epsilon_{it}$$

$\boldsymbol{X}'_{it}$ and $\boldsymbol{\beta}$ are vectors of covariates and unknown parameters, respectively, and ϵ_{it} is assumed to follow a logistic distribution. Although Y^* is unobserved, it is associated with an observable discrete random variable Y whose values are determined by Y^*. That is, a binary random variable Y can be modeled as an indicator variable that takes a value of zero, indicating the surviving funds, whenever $Y^*_{it} \leq 0$ and a value of one, indicating the failed funds, whenever $Y^*_{it} > 0$:

$$Y_{it} = 0 \quad if\ Y^*_{it} = \boldsymbol{X}'_{it}\boldsymbol{\beta} + \epsilon_{it} \leq 0$$

$$Y_{it} = 1 \quad if\ Y^*_{it} = \boldsymbol{X}'_{it}\boldsymbol{\beta} + \epsilon_{it} > 0$$

where $Y_{it} = 0$ corresponds to a surviving fund and $Y_{it} = 1$ corresponds to a failed fund. The probability of $Y_{it} = 1$ conditional on the covariates is given by

$$\Pr(Y_{it} = 1|X_{it}) = \Pr(Y^*_{it} > 0|X_{it}) = \Pr(\boldsymbol{X}'_{it}\boldsymbol{\beta} + \epsilon_{it} > 0) = F(\boldsymbol{X}'_{it}\boldsymbol{\beta})$$

where $F(\cdot)$ denotes the logistic cumulative distribution function and the unknown parameters $\boldsymbol{\beta}$ are estimated using the method of maximum likelihood. The logistic regression can reveal how the explanatory variable affects the outcome of an event. However, the logistic regression examines the outcome variable rather than the lifetime of funds and is not able to account for censoring of the data, which occurs when there are still funds yet to fail at the end of the study period. In consideration of these issues, the framework of survival analysis is a better choice to manage this type of problem, as it is primarily concerned with predicting the probability and timing of a particular event.[3] Survival analysis has been extensively used in different fields[4] but receives less attention in financial applications, except in studies of bankruptcies. Survival analysis establishes the relationship between an observation's characteristics and the timing of a particular event. An event is defined as a qualitative or a quantitative change that can be situated in time. One difficulty with a survival analysis of fund failure is that the exact form for the distribution of a fund's lifetime is unknown. To avoid the necessity of specifying or placing restrictions on the distributional form, a semi-parametric technique developed by Cox (1972), known as the Cox proportional hazards (CPH) model, is adopted.

The event of interest is defined as the state when a fund changes from survival to failure. The hazard function *h(t)* is defined as the instantaneous rate of change from a non-failed to a failed state at time t, given survival until time *t*. It is often referred to as the "instantaneous probability" of failure. The basic CPH model is usually written as

$$h_i(t) = \lambda_0(t)\exp(\beta_1 x_{i1} + \cdots + \beta_k x_{ik}) \qquad (1)$$

This equation incorporates two factors in the specification of the hazard function given by Eq. (1) for hedge fund *i* at time *t*: (i) a baseline or underlying hazard function, $\lambda_0(t)$, that is left unspecified, except that it cannot be negative,[5] and (ii) the exponential of a linear function of *k* fixed covariates, $x_{i1} \ldots x_{ik}$, and their coefficients, $\beta_1, \cdots, \beta_k$.

The hazard function given by Eq. (1) is called the proportional hazards model because the hazard for any hedge fund is a fixed proportion of the hazard for any other hedge fund. As shown by Eq. (2) below,

$$\frac{h_i(t)}{h_j(t)} = \frac{\lambda_0(t)\exp(\beta_1 x_{i1} + \cdots + \beta_k x_{ik})}{\lambda_0(t)\exp(\beta_1 x_{j1} + \cdots + \beta_k x_{jk})} = \exp\{\beta_1(x_{i1} - x_{j1}) + \cdots + \beta_1(x_{ik} - x_{jk})\} \qquad (2)$$

the baseline hazard function, $\lambda_0(t)$, cancels out, and thus, the ratio of the hazards for any two hedge funds is constant over time.[6] In this model, the baseline hazard function does not need to be specified. However, this model implicitly assumes that the effect of the covariates on the risk of fund failure should be constant over time and that the log hazard functions of any two individuals should be strictly parallel. This feature allows for the baseline hazard function, $\lambda_0(t)$, to be eventually backed out at each specific failure time. The coefficients of the proportional hazard model are estimated using the partial maximum likelihood method.

As revealed above, the proportional hazard model leaves the underlying hazard function unspecified, and the partial likelihood method discards some information about the hazard's dependence on time. Notwithstanding, nonparametric estimates can be calculated for the survivor function based on a fitted proportional hazard model. The Cox survival model including only fixed covariates can be derived as follows:

$$\begin{aligned} S_i(t) &= \exp\left[-\int_0^t h_i(u)\,du\right] = \exp\left[-\int_0^t \lambda_0(u)\exp(\beta_1 x_{i1} + \cdots + \beta_k x_{ik})\,du\right] \\ &= \exp\left[\left\{-\int_0^t \lambda_0(u)\,du\right\}\{\exp(\beta_1 x_{i1} + \cdots + \beta_k x_{ik})\}\right] \\ &= [S_0(t)]^{exp(\beta_1 x_{i1} + \cdots + \beta_k x_{ik})} \qquad (3) \end{aligned}$$

where $S_i(t)$ is the survival probability at time t for fund i with covariate values of $(x_{i1}, \cdots, x_{ik})$ and $S_0(t) = \exp\left[-\int_0^t \lambda_0(u)\,du\right]$ is the baseline survivor function, which represents the survivor function for a fund whose covariates all have values of zero. Once the coefficients $\beta_1, \cdots, \beta_k$ have been estimated using the partial likelihood method, the baseline survivor function $S_0(t)$ can be estimated using a nonparametric maximum likelihood method. Following the estimation of the baseline survivor function, the estimated survivor function for any set of covariate values can be generated by substitution in Eq. (3). When predictions are generated, the focus is conventionally on a single summary measure rather than the entire distribution. The median survival time can be easily acquired by finding the smallest value of t such that $S(t) \leq 0.5$.

A wide range of covariates that are anticipated to affect hedge fund failure are considered and incorporated in the estimation of the cross-sectional model. The choice of covariates follows previous literature on hedge fund failure, such as Baba and Goko (2009) and Liang and Park (2010). The covariates can be classified as follows: (i) performance measures, (ii) return risk measures, (iii) fund size measures, (iv) liquidity, (v) leverage, (vi) fee structure, (vii) strategy, and (viii) domicile. Table A.1 in Appendix A shows the list and description of covariates examined in this study

3.2. Assessing predictive accuracy

Given that this study focuses on predicting hedge fund failure, selecting an appropriate holdout sample on which to test the model's predictive accuracy is essential. The holdout sample consists of funds that are not used in the estimation process but that are representative of the mix of failed and non-failed funds in the estimation sample. To accurately test predictive ability, the same proportion of failed funds as seen in the estimation sample is selected for the holdout sample. A similar process is conducted for survivor funds and likely survivor funds.[7]

As the nature of probability prediction dictates, we are predicting an instantaneous probability of fund failure; however, we only observe the occurrence of fund failure and not a realized probability. Thus, the standard prediction error metrics are not applicable in this case. The predicted probabilities need to be contingently weighed against the occurrence of the failure. The process of testing for predictive accuracy involves fitting survival curves to each hedge fund from a holdout sample, selecting a point in time at which to evaluate the financial position of a fund, and then evaluating the models' ability to predict financial distress in an ex-post fashion. That is, the probabilities from the survival curves are converted into a state-based prediction according to a cut-off probability or a threshold. Above this threshold, probability funds are considered to be survivors and, otherwise, are failures. However, establishing an optimal threshold is by no means a trivial task.

While probability forecasting has only been of recent interest to fund managers, it has been well researched in the fields of psychophysics, neuroscience, and meteorology to assist in the decision-making process based on a probability forecast. The SDM introduced by Mason (1980, 1982, 1989) has been well established in verification practice for deterministic binary forecasts. The ROC curve, derived from the SDM, provides a quantitative estimate of the probability of the forecast outcome for any decision threshold.[8] The ROC curve has been adopted in financial fields for credit risk assessment and credit scoring, for example (Gool, *et al*, 2012; Irwin and Irwin, 2013).

The first step in assessing the predictive ability of the estimated models used is to examine the probability distributions at selected failure times across groups of failures and survivors from a holdout sample. By comparing the distributional characteristics of the two groups, the predictive skill of the model used in this study can be ascertained. In the SDM, the occurrence of an event (failure) is preceded by a "signal" in the data. A fund's estimated survival probability represents the signal. Depending on a chosen cut-off probability (s) for a given failure time t, a fund is predicted to fail when $S_i(t) \leq s$, where $S_i(t)$ is the survival probability at time t for fund i, and, otherwise, is predicted to survive.

Predictive ability is commonly evaluated using the hit rate (H). A hit occurs when the occurrence of the financial distress event is correctly predicted given a nominated probability threshold level. Alternatively, a false alarm is defined as the occurrence of survival when failure is predicted. The false alarm rate (F) is the proportion of surviving hedge funds that are incorrectly predicted to be funds subjected to financial distress. Once the probability distributions for failures and survivors have been determined, the ROC curve can be plotted. The ROC curve is a graph of the hit rate, H, against the false alarm rate, F, as the probability threshold value, *s*, varies. High values for threshold *s* often result in high H and F rates. This process provides a robust method from a statistical standpoint to confirm that the model is able to predict financial distress for hedge funds.

Additionally, the predictive ability of a model can be quantified by calculating the area under the ROC curve (AUROC). A perfect prediction model provides an AUROC value of 1, while a model that has accuracy equal to an even chance has an AUROC value of 0.5. The predictive ability of competing models can be evaluated by directly comparing their AUROCs. We compute both the ROC and the AUROC for predicted probabilities using CPH and logit models to compare the predictive performance of these two models.

4. DATA AND THE CLASSIFICATION OF FUND FAILURE

4.1. Data

This study adopts the Hedge Fund Research (HFR) database, which is a database commonly used by academics and practitioners. HFR provides two separate databases: a dead fund database and a live fund database. As indicated in the name, the live fund database includes information about all hedge funds that are currently reporting to HFR, while the dead fund database consists of information regarding all hedge funds that have discontinued reporting to HFR.

The literature acknowledges that hedge fund databases have several biases (Ackermann *et al*. 1999; Brown *et al*., 1999; Baquero *et al*., 2005; Malkiel and Saha, 2005, among others). The sample of HFR data adopted in this study includes dead funds as well as live funds to moderate survivorship bias. The dead and live fund databases that are used in this study cover the period from each fund's initial date of joining the HFR database up to December 2009. The backfilled return and AUM data, which cover the period before each fund's initial date of joining the HFR database, are removed from the databases to avoid backfill bias.[9]

The sample of funds from the raw database is filtered as the first step of the analysis. This initial filtering includes restricting the funds to those with a minimum of 36 months of data to guarantee a sufficient number of observations for the estimation process. In addition, this process ensures that all funds in the sample are hedge funds that do not seek short-term and high-risk objectives.[10] To ensure data consistency, those funds that do not report returns net of all fees to HFR on a monthly basis or that have missing data are deleted.

Hedge funds are categorized into four classes according to their investment strategies: equity hedge, event driven, macro, and relative value arbitrage. Two index funds and funds-of-hedge funds are deleted from the sample to distinguish hedge funds from a portfolio of hedge funds. After the removal of funds that do not meet the data requirements of this research, 1484 funds remain from the live fund database, while 1329 funds remain from the dead fund database.

A number of hedge fund characteristics are included in three information tables available from the HFR databases, namely, the administrative table, the performance table, and the asset table. Table 1 presents summary statistics for these fund characteristics provided in the sample in the live fund database, the dead fund database, and the combined fund database, which includes both the live and dead fund databases. Summary statistics for the administrative data are given in Panel A, and statistics for time series data (monthly returns and AUM) are reported in Panel B.

[Table 1]

The covariate statistics in Table 1 allow for an analysis of the differences between live and dead hedge funds. The proportion of hedge funds using leverage in the dead fund database (72.01%) is higher than that in the live fund database (69.95%). It is interesting that the management and incentive fees imposed by the dead funds are less than half of those charged by the live funds, perhaps because of the different realized returns and AUM between live and dead hedge funds. The proportion of live funds with a high water mark provision is higher than that of dead funds, whereas the ratio of dead funds applying a hurdle rate provision is greater than that of live funds.

Panel B of Table 1 presents the descriptive statistics for the return and size time series data that are sourced in this study from the live fund, the dead fund, and the combined fund databases. The duration indicates the average number of months over the lifetime of a class of funds. For the dead funds, it is measured as the difference between the fund's initial date of joining the HFR database and the last reporting date. For a live fund's duration, the calculation is the number of months from the fund's initial date of joining the HFR database to December 2009. The winning ratio is the ratio of the number of positive monthly returns divided by the total number of monthly returns.

As expected, the average duration and monthly return of the live funds are higher than those of the dead funds. The skewness statistics for returns indicate negative values across the live, dead, and combined funds. In addition, the average standard deviation of the live fund returns, while slightly greater than that of the dead fund returns, is a relatively large number compared with the average mean return. This result implies that the standard deviation may not be an appropriate risk measure for hedge funds (Liang and Park, 2010; Lee, 2011). The most distinct difference is found between the average monthly AUM of the live and dead funds. The average AUM of the live funds is more than double the average AUM of the dead funds, and funds that maintain reporting show a higher winning ratio than funds that stop reporting.

4.2. Classifying funds' failures

Estimating the model by using genuinely failed funds is of critical importance for the accurate predictive use of the model. The funds that are truly failures must be determined to accurately define failure times. A failed fund is defined as one that has discontinued reporting to the HFR database for reasons of financial distress. The remaining funds in the databases are included in the risk set at each failure time. HFR classifies each fund in the dead fund database on the basis of the following reasons for removal from the service: (i) closed to new investments, (ii) liquidated, or (iii) no longer reporting (no reason). The approach taken for the selection of failure times in this study seeks to appropriately distinguish between funds that have dropped out of the reporting mechanism owing to financial distress rather than for any other reason.

Various filters are applied to ensure that the funds selected have experienced financial distress. One filter is used to examine the return distributions of the sample portfolio of "liquidated" funds. If the "liquidated" funds, according to the HFR classification, show significant negative tails in their return distributions, while those whose classification is listed as "no reason" or "closed" do not, then this result would indicate that the "liquidated" funds are the funds closed owing to financial difficulties. If no distinction is found, then further filters are needed. These include the examination of the average returns and AUM for the life of each fund as well as for the last 12 and 24 months. By calibrating the returns in these filters, a clearer picture is formed as to the financial status of each fund, enabling the formation of a sample of genuine failures.

After consideration of methods adopted in the previous studies to define "failure" (Chapman *et al*., 2008; Liang and Park, 2010; Ng, 2008), the following four criteria are applied to distinguish the failed funds in the dead fund database:

i) funds represented in the dead fund database

ii) decreased AUM over the last 24 months,[11]

iii) average monthly returns that are less than 0.25% in the last 12 months, and

iv) average monthly returns that are less than 0.25% in the last 24 months.

After distinguishing failed funds from other closed funds in the dead fund database, the entire set of funds is classified into three categories: i) all funds included in the live fund database are assumed to be survivors; ii) funds that pass the failure filter but that are included in the dead fund database are classified as likely survivors; and iii) failed funds selected by all of the failure criteria are classified as failures.

As a consequence, the sample of dead hedge funds (1329) is successfully classified into two groups, with 528 funds and 801 funds classified as failures and likely survivors, respectively. The failure rate for the combined funds[12] is 18.77% (528/2813), while the failure rate for dead funds is 39.73% (528/1329). Table 2 below provides summary statistics for the classified fund groups (survivors, likely survivors, and failures). These summary statistics reveal the primary results related to the performance drivers.

[Table 2]

The performance variables, including lifetime return, return last 12 months, and return last 24 months show marginally different values between the survivor and the likely survivor groups. However, large differences are observed between these groups and the failed group. In contrast, the statistics for AUM last month and AUM depletion are markedly different between the three groups. The statistics for AUM last month show the highest value in the survivor group and the lowest value in the failed group, while the values for AUM depletion are highest in the likely survivor group and lowest in the failed group. As expected, the failed funds show the highest return volatility among the hedge funds, and the statistics for the winning ratio show the lowest values in the failed group.

In an effort to examine whether the criteria for selecting failures are appropriate, the average lifetime monthly return differentials between the survivor fund group and the likely survivor fund group, as well as between the failed and likely survivor fund groups, are tested using the nonparametric Wilcoxon test. The average lifetime monthly return between the survivor group and the likely survivor group is not significantly different (p-value = 0.1773), while the average lifetime monthly return of the likely survivor group is significantly different from that of the failed group at the 1% level (p-value < 0.0001). The results show that the method for selecting failed funds is effective for distinguishing between funds that have exited the database owing to poor performance and those that have dropped out for other reasons. This filtering process is clearly more informative than simply treating all funds that are classified as "liquidated" as failed funds.

5. EMPIRICAL RESULTS

5.1. Estimation of the CPH and logit models

As a preliminary analysis, we draw the dynamic changes in the average hazard rate of hedge funds in the sample, as shown in Figure 1. This figure is based on the CPH model.[13]

[Figure 1]

In Figure 1, the hazard rate increases to its first peak of 0.0063 at a lifetime of 40-60 months, which is consistent with the statistics in Table 2, indicating that the average duration of failed funds is close to 60 months. However, after the 60^{th} month, the hazard rate drops consistently until the 100-120 month interval, when it reaches 0.0018. This finding implies that funds that survive longer than 8-10 years have a lower probability of failure. Interestingly, the hazard rate peaks again in the 140-160 month interval and drops back in the 160-180 month interval. This result suggests that the funds that survive longer than 15 years are even less likely to fail. The hazard function in Figure 1 suggests that the most critical points for fund failure are when the funds are 5 years old or 12 years old. If funds survive beyond these hurdles, the possibility of failure drops significantly.

The results from the estimation of the CPH and logit models for hedge funds in the sample are presented below in Table 3. The left panel of Table 3 presents the estimated parameters and associated statistics from the CPH model, while the right panel presents the same set of results from the logit model.

[Table 3]

The estimated results from both models are generally consistent. A number of significant covariates are found to be relevant to the hedge funds' hazard rate of failure. Using the CPH model, the Cornish-Fisher expected shortfall risk measure is positively significant at the 5% level. The hazard ratio is 1.0179, which indicates that a one-unit increase in the expected shortfall risk increases the hazard rate of funds by 1.79%. The most significant covariates at the 1% level are the performance measures as represented by the mean return and the winning ratio. Their negative relationship with the hazard rate indicates that past performance is negatively related to the probability of failure. This result also implies that high return funds have lower hazard rates of failure. Moreover, the hazard ratio of the mean return covariate (0.4980) reveals that a 1% increase in the average monthly return of a fund over its entire lifetime decreases the hazard rate by 50.20%.

As with the fund performance covariate, the fund size covariate (represented by the natural log of the fund's AUM for the last month) shows a strong negative effect on the hazard rate of failure at a 1% significance level. That is, larger funds are likely to survive longer than small funds. This outcome is expected, and previous studies report similar results (Chapman *et al*., 2008; Grecu *et al*., 2007; Gregoriou, 2002; Liang and Park, 2010; Ng, 2008; among others).

In addition, the leverage covariate is positive and significant at the 1% level. The impact of leverage on hedge fund survival is an unresolved issue in the literature. A number of previous studies claim a negative effect of leverage on hedge fund performance and survival (Chan *et al*., 2006; Fung and Hsieh, 1997; Liang, 2000), while others report the opposite or no significant effect (Baba and Goko, 2009; Chapman *et al*., 2008; Rouah, 2006; Ng, 2008). Notwithstanding, the current study shows a strong positive effect of leverage on the hazard rate of hedge fund failures. This finding indicates that increased leverage heightens the hazard of financial distress in hedge funds.

Of all fee structure covariates, including management fees, incentive fees, high water marks, and hurdle rates, only two are found to be significant. Management fees and incentive fees are significant at the 1% level, while the high water mark and hurdle rates have an insignificant effect on the fund's hazard rate of failure. Like leverage, the finding of an effect of the fee structure covariates on the fund's hazard rate of failure contradicts results from previous studies (Ackermann et al., 1999; Chapman et al., 2008; Ng, 2008).

The minimum investment covariate and all liquidity covariates, including redemption frequency, notice period, and lock-up period, are found to be statistically insignificant. Further, the effect of the domicile covariate on the fund's survival is found to be significant at the 10% level. The positive coefficient estimates imply that offshore hedge funds that are not based in the United States are more likely to fail than those based in the United States.

The impact of the particular strategies on the fund's hazard rate of failure is of great interest.[14] As relative value arbitrage is selected as the default strategy, the hazard ratio of the other strategies represents the incremental change in the hazard compared with that of funds using the relative value arbitrage strategy. For example, the hazard ratio of equity hedge is 0.7010. This result indicates that funds adopting an equity hedge strategy have a 29.90% lower likelihood of failure than funds using the relative value arbitrage strategy. The results show that the strategies including equity hedge and macro are significant at the 1% level, while the event driven strategy is insignificant. This result indicates that the funds characterized by equity hedge and macro are more likely to fail relative to the funds implementing the relative value arbitrage strategy.

The results from the logit model are, in general, consistent with those from the CPH. The past performance, size, leverage, and strategy variables are all significant with the same sign as those from the CPH model. However, the risk measurement, Cornish-Fisher expected shortfall, and fees variables as well as the domicile variable are not significant in the logit model.

5.2. Testing the predictive accuracy

Finding significant variables that affect fund failure is straightforward. It is interesting to observe whether the CPH and logit models are able to provide out-of-sample forecasts and whether their predictive abilities are same because, in this case, the forecasted failure probabilities will be more valuable to investors. Because both the CPH and the logit models provide similar results, we also compare the predictive accuracy of both models to a naïve forecast that is simply based on the natural proportion of failed funds in the sample.

Using the survival probabilities estimated for each fund at a selected time (84 months), the probability densities for the survivors and failures in the holdout sample of hedge funds are produced. For the construction of the SDM, the two empirical probability distributions for survivors and failures are combined on the same graph, as shown in Figure 2 below.

[Figure 2]

As expected, the probability density function for failures, $f_1(S,t)$, lies somewhere to the left of the probability density function for survivors, $f_0(S,t)$, which suggests that the empirical probability distribution from both of the prediction models for hedge funds is capable of differentiating between survivors and failures, with higher probabilities for survivors than for failures in the holdout sample. This result suggests that both the CPH model and the logit model defined in Section 5.1 have some failure prediction skill for hedge funds.

The prediction of the occurrence or nonoccurrence of a fund's failure is determined on the basis of a cut-off probability (*s*) such that, for a given failure time *t*, a fund is predicted to fail when the estimated survival probability is below this cut-off probability and to survive when it is above the cut-off. The lines running perpendicular to the x-axis in the above figures are examples of possible cut-off probabilities for hedge fund failure. The area under the failure curve and to the left of the cut-off probability indicates the hit rate (H), while the area under the survivor curve and to the left of the cut-off probability represents the false alarm rate (F).

As shown in Figure 2, because there is substantial overlap between the probability density functions for survivors and failures, the selection of the cut-off probability entails a trade-off between the hit rate and the false alarm rate. The choice of cut-off probability is analogous to the problem of Type I and Type II errors in standard statistical inferences. Type I error occurs when a failed fund is predicted as a survivor, while Type II error occurs when a surviving fund is predicted as a failure. As the Type I error cost is higher than the Type II error cost, the cut-off probability that affords the minimum acceptable Type I error cost should be selected.[15] Once the probability distributions for failures and survivors have been determined, the ROC curve can be plotted. As shown in Figure 3 below, the ROC curve is a representation of the hit rate, H (y-axis), against the false alarm rate, F (x-axis), as the probability threshold value, *s*, varies.

[Figure 3]

Figure 3 presents the ROC curves derived from the predictions of the CPH and logit models as well as by naïve prediction (no skill). As shown in Figure 3, a low survival threshold, *s*, leads to a low F but also a small H, and high values of threshold, *s*, result in a high H and F. As the decision threshold, *s*, increases, H and F vary together according to the skill of the prediction model. The dotted line running through the center of the figure at the 45 degree line represents a prediction model with zero skill, that is, a naïve prediction. The naïve prediction is obtained by simply using the proportion of funds failed within the sample; the ROC curve from the zero skill model is linear where H = F. A curve running up the y-axis to the point (0, 1) and along the x-axis to the point (1, 1) is a model with 100% predictive accuracy. Both of the models with predictive value are expected to fall somewhere between these two boundaries. The ROC curve corresponding to the CPH model is constructed for a failure time of 84 months. As shown in the figure, for both of the ROC curves produced by the two models, the H is always above the F across the range of cut-off probabilities. This result implies that both models developed in this study offer a relatively high level of skill in predicting the occurrence of failures in hedge funds relative to the naïve prediction. The ROC curve from the CPH model is above the curve from that produced by logit model, which suggests that the CPH model has higher predictive accuracy than the logit model.

For a more formal evaluation of predictive ability, the statistics referring to the AUROC as a percentage are calculated for both models to compare their predictive power. In the current study, several evaluation times are selected to assess predictive accuracy, and the results for predictive ability are compared across the different evaluation times. The CPH model is evaluated at selected failure times of 36, 60, and 84 months. The average percentage AUROC statistics are 61.73%, 74.76%, and 82.45% at 36, 60, and 84 months, respectively. The AUROC statistics with an evaluation event time of 36 months are significantly lower than those with an evaluation time of 60 or 84 months, and the CPH model has the greatest AUROC value when evaluated at an event time of 84 months. For the logit model, the overall predictive power shows AUROC statistics of 76.64%.

The results from the AUROC statistics imply that the CPH model has better ability to explain a fund's failure than the logit model when the model predicts hedge fund failure at an event time of 84 months, while the logit model outperforms the CPH model when funds are evaluated at shorter failure times.

6. CONCLUSION

In this study, we evaluate and forecast the probabilities of hedge fund failure using both a hazard model and a logit model. By utilizing the lifetime information of funds, the predictive models that we establish are able to differentiate the funds that fail owing to financial distress from the surviving funds in the out-of-sample test. In particular, we establish a method for quantifying the model's predictive accuracy and evaluate the performance of the models using the SDM and ROC curves.

We found that both the CPH model and the logit model in this study offer a relatively high ability to predict the occurrence of hedge fund failures. Because the failed funds in this study are funds that failed because of financial troubles, the prediction of failure probabilities here provides warning signals against possible fund liquidation, which are valuable to both investors who are already committed and investors who have yet to allocate their capital.

Additionally, the CPH model can compute survival probability at every failure time, so we can evaluate the predictive power at every event time. We found that at a longer time horizon, the CPH model offers greater accuracy than the logit model, which is popularly used in this type of study. The analysis conducted in this study is useful for estimating the expected lifetime of a hedge fund or a fund-of-hedge funds. The results from this study would also be valuable to other stakeholders, such as regulators and creditors of hedge funds.

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Appendix A

Table A.1 Covariate list and description

Classification	Covariates	Description
1. Performance Measures	Mean Return	Sample mean of monthly returns
	Winning Ratio	Ratio of the number of positive monthly returns to the total number of monthly returns
2. Return Risk Meaasures*	Cornish-Fisher Expected Shortfall	Sample mean of monthly risk measures
3. Fund Size Measures	Asset Under Management	AUM in a fund's last reporting month
	Minimum Investment	Minimum initial investment required for a new investor
4. Liquidity	Lockup Period	Minimum holding period before redemption
	Redemption Frequency	Frequency at which investors can redeem assets
	Notice Period	Time period in days required for processing of redemption
5. Leverage	Leverage	0:No leverage, 1: Leverage capped at a maximum rate, 2: Open-ended leverage
6. Fee Structure	Management fee	Between one and two percentage of fund asset to cover administrative expense
	Incentive Fee	Imposed on the funds with good performance
	High Water Mark	Earn the incentive fee only after recouping all past losses
	Hurdle Rate	Minimum return to earn an incentive fee
7. Strategy	Relative Value Arbitrage	Default strategy
	Event Driven	
	Equity Hedge	
	Macro	
8. Domicile	Domicile	0:US-base fund, 1:Offshore fund

Note: * Liang and Park (2010) argue that standard deviation loses the explanatory power once the other explanatory variables are included in the hazard model. They suggest that downside risk measures such as the Expected Shortfall and Tail Risk are superior to standard deviation in terms of predicting hedge fund failure. Thus, the Cornish-Fisher expected shortfall is calculated as defined in Liang and Park (2010).

Table 1. Summary statistics for the sample

Panel A. Statistics for administrative data

	Live Funds	Dead Funds	Combined Funds
Number of Funds	1484	1329	2813
Minimum Investment (US$)	1,249,461	906,218	1,087,296
Leverage (%)	69.95	72.01	70.92
Management Fee (US$)	3,271,953	1,186,203	2,286,542
Incentive Fee (UD$)	368,513	103,424	243,272
High Water Mark (%)	91.51	89.01	90.33
Hurdle Rate (%)	13.95	15.53	14.61
Redemption Frequency (days)*	71.46	71.60	71.53
Notice Period (days)	36.04	33.45	34.81
Lockup Period (days)	123.82	112.69	118.56
Domiciled Offshore (%)	55.66	51.32	53.61

Note: The statistics for minimum investment, management fees, incentive fees, redemption frequency, notice period, and lock-up period are the average values for each fund group. The dollar value of the management fee obtained by a fund manager is calculated by multiplying the percentage by the average AUM for the fund's entire life. The incentive fee is first calculated by multiplying the fund's average monthly return by the average monthly AUM to evaluate the profit per month over the fund's lifetime. This figure is then multiplied by the percentage of incentive fees to calculate the dollar value of the incentive fee obtained by the fund manager. The statistics for leverage, high water mark, hurdle rate, and domiciled offshore are the percentage of funds within each group. *The redemption frequency is reported monthly, quarterly, semiannually, or yearly. For consistency with other liquidity variables, the frequency is converted to days so that a higher value indicates a lower redemption frequency.

Panel B. Statistics for return and size time series data

		Live Funds	Dead Funds	Combined Funds
Duration (months)		78	65	72
Return (%)	Mean	0.68	0.50	0.59
	Standard Deviation	4.32	4.28	4.30
	Skewness	-0.49	-0.34	-0.42
	Kurtosis	4.78	3.55	4.20
AUM (MUS$)	Mean	222.53	88.18	159.06
	Standard Deviation	124.36	45.99	87.34
	Skewness	0.35	0.32	0.33
	Kurtosis	-0.23	0.28	0.01
Winning Ratio		0.64	0.62	0.63

Note: The numbers reported are obtained on the basis of the average values for each fund included in each database. The duration indicates the average lifetime of the fund. The statistics of return and AUM are monthly averages. The winning ratio is the ratio of the number of positive monthly returns divided by the total number of monthly returns.

Table 2. Summary statistics for the classified fund group

	Survivor Funds	Likely Survivor Funds	Failed Funds
Number of Funds	1484	801	528
Duration (months)	78.28	65.52	63.75
Lifetime Return (%)	0.68	0.89	0.33
Return Last 24 Months (%)	0.06	0.72	-1.11
Return Last 12 Months (%)	1.52	0.56	-2.07
AUM Last Month ($)	250,747,014	83,913,044	43,639,050
AUM Depletion (%)	-11.48	-6.91	-53.67
Winning Ratio	0.64	0.64	0.58
Return Standard Deviation (%)	4.28	5.53	5.76

Note: The duration indicates the average lifetime of the fund. The lifetime return, the return last 24 months, and the return last 12 months denote the average monthly returns of the funds in each class during their entire lifetime, the last 24 months, and the last 12 months, respectively. The AUM last month represents the average AUM of the funds in the last month, while AUM depletion is the average percentage change in the fund's AUM within the last 24 months. The winning ratio and the return standard deviation indicate the average values for each class.

Table 3. The CPH model and logit model

	CPH Model					Logit Model				
Variable	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio	Parameter Estimate	Standard Error	Chi-Square	Pr > ChiSq	Hazard Ratio
Cornish-Fisher Expected Shortfall	0.0401**	0.0166	5.8378	0.0157	1.0179	0.0061	0.0069	0.7771	0.3780	1.0060
Mean Return	-0.6981***	0.0685	103.9622	<.0001	0.4980	-1.0318***	0.1191	75.0034	<.0001	0.3560
Winning Ratio	-1.9300***	0.5713	11.4130	0.0007	0.1450	-1.8630***	0.6746	7.6268	0.0058	0.1550
AUM	-0.15212***	0.0259	34.4344	<.0001	0.8590	-0.2235***	0.0353	40.0894	<.0001	0.8000
Minimum Investment	1.27E-08	1.3.E-08	0.9263	0.3358	1.0000	1.75E-08	1.2.E-08	2.1318	0.1443	1.0000
Leverage	0.1566***	0.0547	8.1957	0.0042	1.1690	0.1314**	0.0639	4.2289	0.0397	1.1400
Management Fee	3.47E-08***	1.2.E-08	7.9268	0.0049	1.0000	2.59E-08	1.7.E-08	2.3745	0.1233	1.0000
Incentive Fee	-1.84E-06***	4.2.E-07	19.2439	<.0001	1.0000	-5.48E-07	3.3.E-07	2.6882	0.1011	1.0000
High Water Mark	-0.1824	0.1544	1.3966	0.2373	0.8330	-0.2002	0.1870	1.1462	0.2843	0.8190
Hurdle Rate	0.04293	0.1250	0.1180	0.7312	1.0440	0.1072	0.1528	0.4923	0.4829	1.1130
Redemption Frequency	-0.0003	0.0007	0.1307	0.7177	1.0000	0.0004	0.0008	0.2866	0.5924	1.0000
Notice period	0.0006	0.0021	0.0769	0.7815	1.0010	-0.0006	0.0024	0.0715	0.7891	0.9990
Lockup Period	8.66E-05	0.0003	0.1119	0.7380	1.0000	-0.0001	0.0003	0.0430	0.8358	1.0000
Domicile	0.1919*	0.1016	3.5702	0.0588	1.2120	-0.0189	0.1201	0.0248	0.8748	0.9810
Event Driven	-0.1146	0.1662	0.4753	0.4906	0.8920	0.2382	0.1990	1.4331	0.2313	1.2690
Equity Hedge	-0.3560***	0.1380	6.6498	0.0099	0.7010	-0.2906*	0.1658	3.0726	0.0796	0.7480
Macro	-0.6355***	0.1901	11.1714	0.0008	0.5300	-0.8477***	0.2232	14.4189	0.0001	0.4280

Note: The table reports the estimation results for the CPH and logit models. The chi-squared test statistics in the third column are calculated by squaring the ratio of each coefficient to its estimated standard error to test the null hypothesis that each coefficient is equal to zero, with the corresponding p-values reported in the fourth column. The last column, labeled "Hazard Ratio," is the value of e^{β} for each covariate. The symbols ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

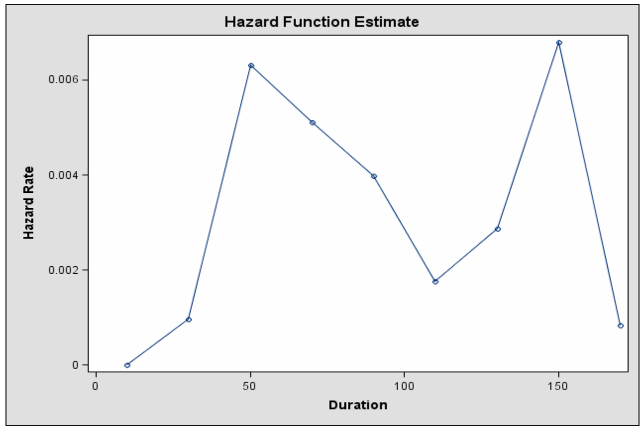

Figure 1. Hazard function of hedge funds

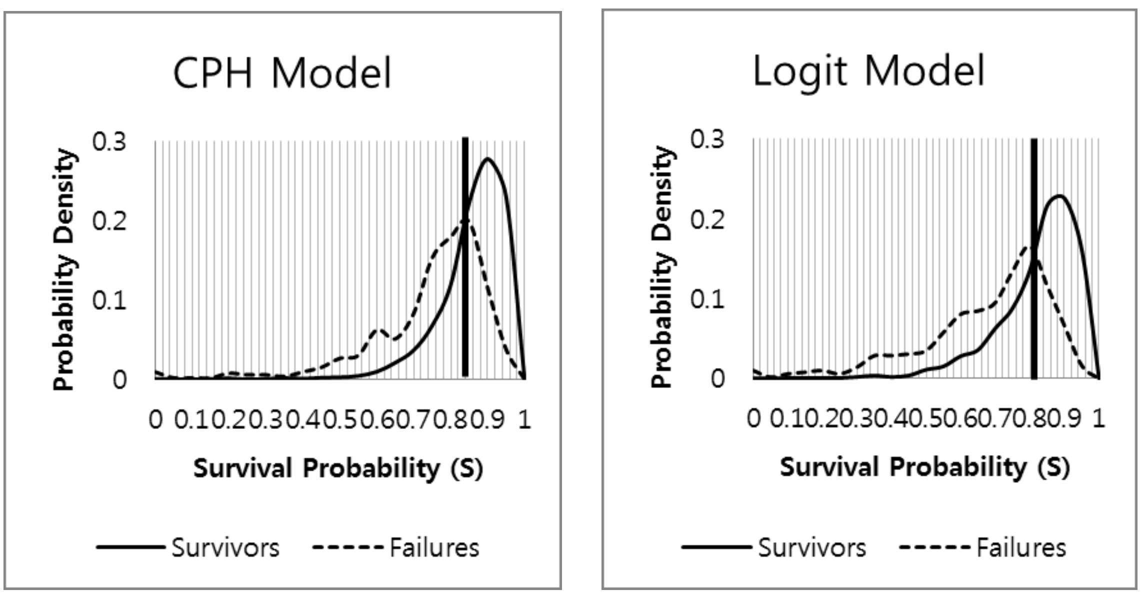

Figure 2. This figure shows the SDM for the CPH and logit models. The horizontal axis represents the probability of survival, while the vertical axis is the density of forecasts corresponding to each point on the horizontal axis. The hit rate (H) is calculated as the area under the failure curve and to the left of some nominated probability of survival, s. It is represented by a line that is vertical to the horizontal axis. The false alarm rate (F) is the area under the survivor curve and to the left of the same nominated probability of survival line. The SDM of the CPH model is constructed at an event time of 84 months. The figure includes the probability density function for survivors as well as failures.

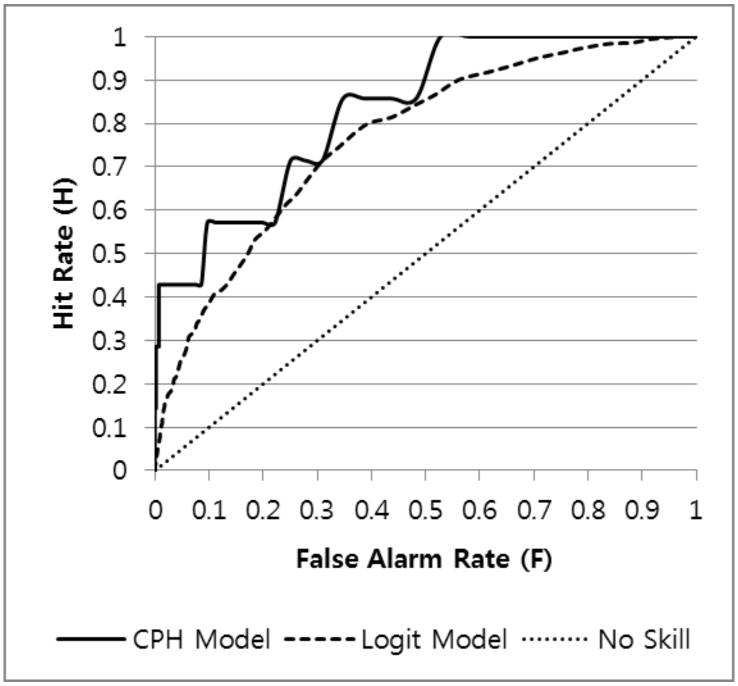

Figure 3. This figure presents the ROC curve for the CPH and logit models. As the decision survival threshold changes, the hit rates and false alarm rates vary together according to the skill of the prediction model. The CPH model is evaluated at event time 84 months with an AUROC percentage of 82.45%, while the AUROC percentage of the logit model is 76.64%.

NOTES

[1] See, for example, Rough (2006), Gregoriou (2002), Gregoriou *et al*. (2008), Baba and Goko (2009), Liang and Park (2010).

[2] Even investors might not be able to exit because of their contractual obligations; they could unwind their positions by hedging in other markets.

[3] For a detailed treatment of survival analysis, see Allison (1995).

[4] Survival analysis is also known by several different names across different fields: event history analysis (sociology), reliable analysis (engineering), failure time analysis (engineering), duration analysis (economics), and transition analysis (economics).

[5] This function represents the nonparametric specification of the CPH model.

[6] There is no theoretical guideline regarding the exact form for the hazard function. Because our focus here is to predict the failure probability, we maintain this assumption.

[7] We classify the funds into three categories—survivors, likely survivors, and failures—as explained in Section 4.2.

[8] For a more detailed discussion on the SDM and the ROC curve, see Mason (2003).

[9] The backfill bias is caused by including a hedge fund's previously unreported performance history as its first monthly report to data collectors.

[10] Gregoriou (2002), Chapman *et al*. (2008), Ng (2008), Baba and Goko (2009), and Liang and Park (2010) apply similar minimum observation requirements and report no resulting sample selection biases. In unreported work, we applied the same analysis that is used in this paper to funds with a minimum of 24 months of data and found no significant bias in our 36-month requirement.

[11] This criterion is defined as the percentage change in the fund's AUM within the last 24 months. That is, (AUM at the last report / AUM at 24 months prior to the last report) -1.

[12] The failure rate is calculated as follows: number of failed funds/total number of funds. Further, recall from Section 4.1 that the total of first-filtered combined hedge funds is 2813.

[13] Please note that the hazard rate by definition is the instantaneous probability of failing conditional on the lifetime of the fund.

[14]The dummy variable for relative value arbitrage is removed to avoid perfect multicollinearity in the estimation process.

[15] The costs for the two types of errors are obviously very different. However, a detailed examination of costs is beyond the scope of this paper. We thank Professor Terry Walter for pointing out this concern.