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Predicting Hedge Fund Failure: A Comparison of Risk Measures

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Abstract

This paper compares downside risk measures that incorporate higher return moments with traditional risk measures such as standard deviation in predicting hedge fund failure. When controlling for investment strategies, performance, fund age, size, lockup, high-water mark, and leverage, we find that funds with larger downside risk have a higher hazard rate. However, standard deviation loses the explanatory power once the other explanatory variables are included in the hazard model. Further, we find that liquidation does not necessarily mean failure in the hedge fund industry. By reexamining the attrition rate, we show that the real failure rate of 3.1% is lower than the attrition rate of 8.7% on an annual basis during the period of 1995–2004.

I. Introduction

The hedge fund industry has more than doubled in size and number in recent years to currently estimated assets under management (AUM) of $1.5 trillion (Adrian (2007)). Such a rapid growth in hedge funds has been accompanied by substantial growth in the number and severity of failures. Since the aftermath of Long-Term Capital Management (LTCM), investors recognize that hedge funds may provide high expected returns but many of them might be exposed to a huge downside risk that is not easily detected by traditional risk measures such as standard deviation.

Unique aspects of risk in hedge funds such as nonlinearity are well documented in literature (Lo (2001), Jorion (2000a)). Hedge funds can generate nonlinear and nonnormal payoffs for various reasons: they i) actively trade derivatives, ii) implement option-like dynamic trading strategies, iii) have investment styles that can experience severe losses during market downturns, or iv) charge an

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incentive fee that has the same effect to investors as shorting a call option on the value of the fund portfolio (Agarwal and Naik (2004), Mitchell and Pulvino (2001), Taleb (2004), and Goetzmann, Ingersoll, and Ross (2003)). Empirical research using hedge fund returns reports that hedge funds on average have negative skewness and excess kurtosis, and the rejection rate of the Jarque-Bera (JB) (1980) test for normality is 40.5%–85.9%, depending on the test periods and databases (Cremers, Kritzman, and Page (2005), Alexiev (2005), Bali, Gokcan, and Liang (2007), and Liang and Park (2007)).

This paper makes two major contributions to the hedge fund literature. The first is to employ downside risk measures incorporating higher return moments in predicting hedge fund failure. Using a survival analysis based on the Cox (1972) proportional hazard (PH) model, we compare semideviation (SEM), value-at-risk (VaR), expected shortfall (ES), and tail risk (TR) with standard deviation.[1] As a result, we extend the literature about hedge fund failure (see Liang (2000), Brown, Goetzmann, and Park (BGP) (2001), Gregoriou (2002), Baquero, Horst, and Verbeek (2005), and Rouah (2005)) by using the above downside risk measures instead of standard deviation and show that the downside measures are better than the traditional measures in predicting hedge fund failure.

To compare downside risk measures with standard deviation, we focus on the time-series variation in the risk profile of hedge funds, while Liang and Park (2007) use a cross-sectional approach. They find that downside risk measures such as ES and TR can explain the cross-sectional variation in hedge fund returns better than standard deviation. This finding is consistent with Agarwal and Naik (2004), who compare the mean-variance approach with the mean-ES framework and find that standard deviation significantly underestimates the left-tail risk in hedge funds.

The second contribution of this paper is to distinguish the "real failure rate" from the attrition rate of hedge funds. By clarifying the definition of hedge fund failure, despite the fact that the two concepts have been deemed one in most of the previous papers, we provide an estimate of the real failure rate.

Defining hedge fund failure is a challenge because it is difficult to obtain detailed information on defunct hedge funds. In addition, liquidation does not necessarily mean failure in the hedge fund universe, since successful hedge funds can be liquidated voluntarily due to the market expectation of the managers or other reasons.[2]

Unlike mutual funds, hedge funds are not required to make periodic reports to the Securities and Exchange Commission (SEC).[3] The available hedge fund databases are based on voluntary reporting. When a hedge fund does not report to

[1]ES is sometimes called conditional VaR (CVaR) (see Agarwal and Naik (2004), Alexander and Baptista (2004)). ES is also known as tail conditional expectation, conditional loss, or tail loss (see Jorion (2000b)). As we recognize that CVaR sometimes means VaR based on conditional moments, we use the term ES instead of CVaR. TR is introduced by Bali, Demirtas, and Levy (2009) to explain the time-series variation in market returns.

[2]In Section IV.D, we present three case studies that show that successful hedge funds can be liquidated.

[3]For more information on the difference in the reporting requirement between hedge funds and mutual funds, see the SEC Web site (http://www.sec.gov/answers/hedge.htm).

the database any longer, it is removed from the live fund database by the data vendor and placed in the defunct fund database, which is called "graveyard." Detailed information on why each fund is moved to the graveyard is usually not available.

Early studies on hedge funds regard moving to the defunct fund database as failure because such funds on average have poor performance (see Gregoriou (2002), Malkiel and Saha (2005)). The attrition rate of hedge funds estimated by previous research is based on such a classification, given that data vendors did not provide detailed reasons for failure.[4]

Recent studies use the classification prepared by data vendors and point out that "graveyard" may be a misnomer because it may contain funds that are still alive. For example, Getmansky, Lo, and Mei (2004) use the drop reason codes provided by TASS and indicate that liquidation is not the only reason why hedge funds drop out of the live fund database. Other reasons include stop reporting, unable to contact, closed to new investment, merged into another fund, and dormant funds. Later studies on hedge fund survival follow this classification and regard only liquidated hedge funds in the graveyard as failed funds (Baquero et al. (2005), Rouah (2005)).

However, this kind of classification based on the drop reasons themselves may still not be sufficient. For example, Feffer and Kundro (2003) argue that hedge fund failure should be distinguished from discretionary fund liquidation, which is much more frequent and is driven by the market expectations of fund managers. They define failed hedge funds as those that have been forced to cease investment operations for reasons outside management's control.

We argue that the liquidated fund category in TASS includes many of these discretionary fund closures. The remaining question is how to use available information to sort out those discretionarily liquidated funds as well as live funds from the graveyard. We find that simple criteria such as performance and change in fund size work better than the stated drop reasons. Thus we suggest new criteria for the "real failure" of hedge funds as follows: i) once listed in a database but stopped reporting, ii) negative average rate of return for the last 6 months, and iii) decreased AUM for the last 12 months. We realize that we are not the first to distinguish hedge fund attrition from real failure. In fact, BGP (2001) augment the TASS data by hand collecting missing data to address the issue of hedge fund failure.[5]

Our new criteria are based on the examination of all available information on defunct funds. We use the note section in TASS, obtain due diligence reports from a private source, and search information on the Internet.

Based on the new criteria, we calculate the real failure rate of hedge funds in order to compare it with the conventional attrition rate. We find that during the period 1995–2004, the average annual failure rate is 3.1% while the attrition rate is 8.7%. Malkiel and Saha (2005) compare the attrition rate of hedge funds with that of mutual funds and argue that hedge funds have a much higher attrition rate. However, a hedge fund is a more flexible investment vehicle and voluntarily

[4]For example, Fung and Hsieh (1997) find an upper bound of 8.5% for the attrition rate while Getmansky, Lo, and Mei (2004) report a similar attrition rate (8.8%) using a different sample.

[5]If a fund does not have a working phone number, then they classify that as a failed fund.

reports to a data vendor; attrition rates should be differentiated from failure rates in the hedge fund industry.

For example, Agarwal, Fung, Loon, and Naik (2009) report that during the recent bad years for the convertible arbitrage (CA) strategy, CA hedge fund investors withdrew subsequent to poor performance, whereas convertible bond (CB) mutual funds were unaffected. Sophisticated investors with a flexible investment vehicle can adjust their portfolio quickly in response to a sudden aggravation of the market environment for a specific strategy, which may appear as a high attrition rate of their investment vehicle. In other words, although hedge funds may have a higher attrition rate than mutual funds, they are not directly comparable.

To compare risk measures in terms of predicting hedge fund failure, we implement a survival analysis for each of the two definitions of failure: i) attrition, the traditional definition, and ii) real failure, the new definition. We find downside risk measures are superior to standard deviation in predicting both the attrition and the real failure of hedge funds. Using the TASS data from January 1995 to December 2004, we find that funds with a high ES have a high hazard rate when controlling for other factors such as the style effect, performance, fund age, size, lockup, high-water mark (HWM) provision, and leverage. Standard deviation, however, loses explanatory power when other explanatory variables are included.

The rest of this paper is organized as follows. Section II describes the data. Section III explains the methodology. Section IV presents the empirical results. Robustness checks are provided in Section V, and Section VI concludes.

II. Data

The data on individual hedge funds are from the Lipper TASS database (hereafter TASS). The major hedge fund databases used in the hedge fund literature are TASS, Hedge Fund Research (HFR), and Center for International Securities and Derivatives Markets (CISDM).[6] TASS consists of the live fund database and the defunct fund database (graveyard). Funds in the graveyard were once included in the live fund database.

TASS provides a variety of information such as investment style, monthly returns, management company, AUM, minimum investment, fee structure, HWM, leverage, and share restriction provisions such as lockup period, redemption notice period, and others.

The biases present in hedge fund databases are well documented in the literature, and we take measures to mitigate them (see Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), Liang (1999), and Fung and Hsieh (2000b)). Survivorship bias is reduced, as we include both live and defunct funds in the analysis. The test period starts in January 1995 and ends in December 2004 because the TASS graveyard database does not retain funds dropped out of the live fund database before 1994.

[6]TASS is used by Fung and Hsieh (1997), (2000a), (2000b), Liang (2000), Getmansky, Lo, and Makarov (2004), Bali et al. (2007), Fung, Hsieh, Naik, and Ramadorai (2008), and Liang and Park (2007). HFR is used by Ackermann, McEnally, and Ravenscraft (1999), Liang (2000), Bali et al. (2007), and Fung et al. (2008). CISDM is used by Ackermann et al. (1999), Cremers et al. (2005), and Fung et al. (2008).

As of the end of 2004, there are 2,590 live funds and 1,726 defunct funds in TASS. These numbers are obtained after we exclude those funds that report i) returns (not in U.S. dollars), ii) quarterly (not monthly) returns, or iii) gross returns (not net-of-fee returns) from the original TASS database. There are additional requirements for a fund to be included in the analysis. Funds with less than 24 months of return history are not included because we delete the first 2 years of return data to mitigate the instant history bias.

We analyze the failure of hedge funds with the following investment styles: CA, dedicated short bias, equity market neutral, event driven, fixed income arbitrage, global macro, long/short equity hedge, and multistrategies.[7] We exclude funds-of-funds to avoid double counting and managed futures to focus on hedge funds. Liang (2004) finds that managed futures differ from hedge funds and funds-of-funds in terms of trading strategies, attrition rates, and survivorship bias. Emerging market funds are not included in the analysis so that the highest risk group in each period is not dominated by a specific investment style.[8]

After applying these criteria, we have 2,134 funds (1,362 live and 772 defunct) in the sample. Table 1 presents the statistical summary of the data. The average monthly rate of return is 0.62%, and the funds have negative skewness (−0.04) and high kurtosis (5.57) on average. The left-skewed and leptokurtic

TABLE 1

Statistical Summary of Hedge Fund Returns

Table 1 shows the number of observations (N), mean and median values of the sample average, standard deviation, skewness, and kurtosis of individual hedge fund returns. The data is from the TASS database, and the sample period is from January 1995 to December 2004. This table also shows the percentage of hedge funds that reject the Jarque-Bera (JB) (1980) test of normality at the significance level of 1%: $\mathrm{JB} = n[(S^2/6) + (k-3)^2/24]$, where S is skewness, k is kurtosis, and n is number of observations. This is a joint test of $S = 0$ and $k = 3$. The JB statistic has a χ^2 distribution with 2 degrees of freedom. [a]Our sample period ends in December 2004, but the drop reason codes are available to us only up to August 2004.

Drop Reasons	No. of Funds	Average Return (%)		Standard Deviation (%)		Skewness		Kurtosis		Minimum Return (%)		Maximum Return (%)		% Rejection in JB Test for Normality
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	
Live funds	1,362	0.89	0.80	3.15	2.36	0.04	0.06	5.51	4.22	−6.98	−4.51	9.57	5.91	38.9
Defunct funds	772	0.13	0.44	4.83	3.74	−0.19	−0.06	5.69	4.13	−10.84	−7.39	11.03	7.16	32.6
Liquidation	327	−0.13	0.18	4.23	3.26	−0.28	−0.11	5.54	3.96	−9.30	−6.56	8.63	5.58	30.0
Not reporting	234	0.20	0.65	5.72	4.43	−0.17	−0.09	6.15	4.41	−13.40	−9.41	13.55	9.29	39.3
Unable to contact	80	0.44	0.70	6.32	4.79	−0.22	0.07	6.13	4.29	−14.52	−11.27	15.72	10.12	38.8
Closed	4	1.09	1.00	4.53	3.88	−0.65	−0.64	6.94	6.35	−13.28	−14.66	13.24	7.65	75.0
Merged	27	1.06	1.15	4.86	5.04	−0.16	−0.14	5.80	3.61	−10.44	−12.00	12.92	12.20	25.9
Dormant	1	−0.45	−0.45	6.00	6.00	−1.21	−1.21	6.44	6.44	−20.97	−20.97	11.04	11.04	100.0
Reason unavailable[a]	99	0.29	0.28	3.50	2.47	0.11	0.10	4.61	3.93	−6.83	−4.72	8.56	5.93	21.2
All funds	2,134	0.62	0.71	3.76	2.74	−0.04	0.02	5.57	4.19	−8.38	−5.42	10.10	6.30	36.6

[7]See the Credit Swiss First Boston/Tremont Hedge Index Web site (www.hedgeindex.com) for a detailed description of hedge fund investment styles.

[8]As a robustness check, we repeat the tests including emerging market funds and find that the main results do not change.

distribution of returns validates the use of higher moments in estimating the risk profile of hedge funds. We also present the result from the JB (1980) test of normality, which is a joint test of skewness and kurtosis. We find that 36.6% of the hedge funds reject the null hypothesis of normality at the 1% level, and the rejection rate is 43.4% at the 5% level.

Consistent with Liang (2000), we find that live funds outperform defunct funds and defunct funds are more volatile than live funds on average. Note that defunct funds have a higher maximum return as well as a lower minimum return than live funds on average, which implies higher risk taken by defunct funds.

Table 1 also shows that it might be misleading to regard all the funds in the graveyard as failed ones in survival analysis. Note that "closed" or "merged" funds in the defunct fund database outperform live funds as well as the other funds in the graveyard. Note also that the "unable to contact" group has the lowest minimum return and the highest maximum return as well as the highest standard deviation, while the "liquidated" group has the lowest average return if we ignore one "dormant" fund.

III. Methodology

A. Estimating the Risk Measures

We use 60-month returns to estimate the standard deviation, SEM, VaR, ES, and TR of all the funds in our sample. We implement the survival analysis annually because the proportion of censored observations already exceeds 90% even when we implement the analysis annually, not monthly.[9] We calculate risk measures of each fund as of the year-end using the previous 60-month returns to predict the survival of the fund next year. Where 60 months of data are not available, a minimum of 24 months is used.

For example, to predict a fund failure during the year 2001, we calculate standard deviation for each fund as of December 2000. The actual data used for estimation is from December 1996 to November 2000. We apply the same rule to estimate SEM, VaR, ES, and TR. To save space, we present a brief description of these risk measures. More information can be found in Liang and Park (2007).

SEM. In contrast to standard deviation, SEM considers deviation from the mean only when it is negative. Put more formally, it is defined as follows:

$$\text{SEM} \equiv \sqrt{\mathrm{E}\{\min[(R-\mu),0]^2\}}, \tag{1}$$

where μ is the average return. Previous research reports that SEM explains the cross section of stock returns in emerging markets and the cross section of Internet stocks returns (Harvey (2000), Estrada (2000), (2004)).

[9]"Censoring" is a term used in the statistical analysis of failure time data to describe the objects whose failure time is after the sample period. Note that our sample period ends before a live fund fails. That is, we cannot observe live funds to the end. In survival analysis, the data on these funds are said to be "censored." One important reason for specialized statistical methods for a survival analysis is the need to accommodate censoring in the data (see Kalbfleisch and Prentice (1980), (2002) for details).

VaR. To estimate VaR, we need to decide the confidence level ($1-\alpha$), the time horizon (τ), and the estimation model. We use the 95% confidence level ($\alpha = 0.05$) and the time horizon (τ) of 1 month, which is the frequency of the data.

Put more formally, let $R_{t+\tau}$ denote the portfolio return during the period between t and $t+\tau$. Let $F_{R,t}$ denote the cumulative distribution function (CDF) of $R_{t+\tau}$ conditional on the information available at time t. Then $F_{R,t}^{-1}$ denotes the inverse function of $F_{R,t}$, and the VaR of portfolio returns as of time t with a time horizon τ and the confidence level ($1-\alpha$) can be formulated as follows:

$$\text{(2)} \qquad \mathrm{VaR}_t(\alpha,\tau) = -F_{R,t}^{-1}(\alpha).$$

The Cornish-Fisher VaR (VaR_CF) extends the regular VaR by considering higher moments in the return distribution. In contrast to the traditional parametric method that makes a normality assumption, the Cornish and Fisher (1938) expansion incorporates skewness and kurtosis into the estimation and hence is more suitable for hedge fund research (see Liang and Park (2007)). It was first introduced by Zangari (1996) to estimate the VaR of option portfolios. The rationale behind this formula is that we can approximate any distribution with the known moments in terms of any other distribution (Johnson, Kotz, and Balakrishnan (1994), Mina and Ulmer (1999), and Jaschke (2002)).

Equation (3) shows the first 4 terms of the Cornish and Fisher (1938) expansion for the α percentile of $(R-\mu)/\sigma$, and equation (4) defines VaR_CF.

$$\begin{aligned} \text{(3)} \qquad \Omega(\alpha) &= z(\alpha) + \frac{1}{6}(z(\alpha)^2-1)S + \frac{1}{24}(z(\alpha)^3 - 3z(\alpha))K \\ &\quad - \frac{1}{36}(2z(\alpha)^3 - 5z(\alpha))S^2, \\ \text{(4)} \qquad \mathrm{VaR\_CF}(\alpha) &= -(\mu + \Omega(\alpha)\times\sigma), \end{aligned}$$

where μ is the average return, σ is the standard deviation, S is the skewness, K is the excess kurtosis of the past 24 to 60 (as available) monthly returns, $1-\alpha$ is the confidence level, and $z(\alpha)$ is the critical value from the standard normal distribution.[10]

ES. ES is the conditional expected loss greater or equal to the VaR. ES is also expressed in terms of a portfolio return instead of a dollar amount, and formulated as follows:

$$\begin{aligned} \text{(5)} \qquad \mathrm{ES}_t(\alpha,\tau) &= -\mathrm{E}_t[R_{t+\tau}\,|R_{t+\tau} \le -\mathrm{VaR}_t(\alpha,\tau)] \\ &= -\frac{\int_{v=-\infty}^{-\mathrm{VaR}_t(\alpha,t)} v f_{R,t}(v)dv}{F_{R,t}[-\mathrm{VaR}_t(\alpha,\tau)]} = -\frac{\int_{v=-\infty}^{-\mathrm{VaR}_t(\alpha,t)} v f_{R,t}(v)dv}{\alpha}, \end{aligned}$$

[10]Note that standard deviation and SEM are always positive, while the original VaR and ES are usually negative. To avoid confusion, the original VaR and ES numbers are multiplied by -1 in equations (4) and (5). Therefore, VaR and ES numbers presented in this paper are usually positive.

$R_{t+\tau}$ denotes the portfolio return during the period between t and $t+\tau$, and $f_{R,t}$ is the conditional probability density function (PDF) of $R_{t+\tau}$. Here $F_{R,t}$ denotes the conditional CDF of $R_{t+\tau}$ conditional on the information available at time t, $F_{R,t}^{-1}$ is the inverse function of $F_{R,t}$, and $1-\alpha$ is the confidence level.

Artzner, Delbaen, Eber, and Heath (1999) make a theoretical argument that ES is superior to VaR as a risk measure. They show that in contrast to VaR, ES has some mathematical properties such as subadditivity and continuity that are desirable as a coherent measure of risk. Liang and Park (2007) test this theoretical argument empirically under the traditional asset pricing framework and show that ES is indeed better than VaR in terms of explaining the cross-sectional variation in hedge fund returns.

To find the 95% ES_CF (the 95% ES using the Cornish-Fisher expansion), we first estimate the 95% VaR_CF using equations (3) and (4). Then we search through the 60-month estimation window and find the returns less than or equal to the 95% VaR_CF. We take the average of those returns, and use it as the 95% ES_CF of the fund for the window.

An alternative way to estimate ES_CF is to use the analytical solution suggested by Christoffersen and Goncalves (2005) and Giamouridis (2006). Their formula is based on the Gram-Charlier approximation, which is known to perform well only when skewness is between -1.2 and $+1.2$. We test the formula empirically and find that the formula is not applicable to our data. As many hedge funds in the data set have extreme skewness, the formula provides unreasonable estimates. Note that the Gram-Charlier series is not guaranteed to be positive and therefore is not a valid probability distribution in case of extreme skewness. Hence we do not use the formula to estimate ES_CF.

TR. While ES represents the mean of losses larger than VaR, TR measures the standard deviation of losses larger than VaR. Put more formally, TR is defined as follows:

$$\text{(6)} \qquad \mathrm{TR}_t(\alpha,\tau) = \sqrt{\mathrm{E}_t[(R_{t+\tau} - \mathrm{E}_t(R_{t+\tau}))^2 \,|R_{t+\tau} \leq -\,\mathrm{VaR}_t(\alpha,\tau)]}.$$

Note that among the downside risk measures used in this paper, TR is the best in terms of capturing the impact of an extremely low return observation because the deviations from the mean are squared before being averaged. As in VaR and ES, we use the parametric approach to estimate TR. TR_CF denotes the tail risk using VaR_CF as the cutoff criterion.[11]

[11]We also implement the survival analysis using the nonparametric approach to estimate VaR, ES, and TR. For example, if we draw 60 random samples from the true distribution of monthly rates of return of a fund, the fifth percentile of the 60 numbers is the nonparametric 95% VaR of the fund (VaR_NP). To estimate nonparametric ES (ES_NP), we use the left tail of the actual empirical distribution as in Agarwal and Naik (2004). That is, the average of the returns smaller than the 95% VaR_NP is the 95% ES_NP of a fund. We find that the results using a nonparametric approach are nearly identical to the ones reported. Hence we only include the results using parametric VaR, ES, and TR in the paper to save space. The results using the nonparametric approach are available from the authors.

B. Survival Analysis

The core of a survival study is modeling the hazard rate, $\lambda_i(t)$. Now $\lambda_i(t)$ specifies the instantaneous rate of failure of fund i at time $T = t$ conditional upon the fund's survival up to time t, while the numerator represents the conditional probability of failure during the time interval Δt. More formally, it is defined as follows:

$$\lambda_i(t) \quad = \quad \lim_{\Delta t \to 0^+} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}. \tag{7}$$

In the PH model of Cox (1972), a vector of fund characteristics is introduced to explain the hazard rate. The components of this vector z are called "covariates."

$$\lambda_i(t\,; z_i) \quad = \quad \lambda_0(t) e^{z_i^T \beta}, \tag{8}$$

where z^T denotes the transpose of the vector z. Here $\lambda_0(t)$ is an arbitrary, unspecified baseline hazard rate, which makes this model sufficiently flexible for many applications. The vector β is assumed to be the same for all funds. To estimate β, Cox (1972), (1975) introduced the partial likelihood function, which eliminates the unknown baseline hazard $\lambda_0(t)$ and accounts for censored survival times.[12]

BGP (2001) are the first to use the Cox (1972) model to analyze hedge fund failure. They find that performance, risk, and fund age play important roles in fund termination. They measure fund risk as the standard deviation of the fund returns over 12 months before termination. The higher the standard deviation, the higher the hazard rate of the fund. Gregoriou (2002) also uses this model and argues that performance, size, and leverage can be used to predict the survival of hedge funds.

An important generalization of the PH model is to allow the covariate vector z to depend on time.

$$\lambda_i(t\,; z_i) \quad = \quad \lambda_0(t) e^{z(t)_i^T \beta}, \tag{9}$$

where $z(t)^T$ is the transpose of the covariate vector z at time t. Rouah (2005) applies this model to allow time-varying covariates. He finds that i) performance, ii) risk (measured by standard deviation), iii) average and standard deviation of the fund size, and iv) HWM provision each has the explanatory power.

Allowing time variation in the explanatory variables is an important improvement in methodology. However, as in the previous research, Rouah (2005) makes a strong assumption on time homogeneity and considers only event time. That is, for all funds, time 0 means the first month when a fund starts reporting its monthly rate of return to the hedge fund database. For example, it can be August 1998 for Fund A and March 2000 for Fund B in Rouah (2005).

In contrast, we incorporate calendar time into the analysis by using the counting process style input (CPSI) of Anderson and Gill (1982). We compare the risk of Fund B measured as of March 2000 with the risk of Fund A measured as of

[12]See Kalbfleisch and Prentice (2002) for details.

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March 2000, not August 1998. Note that considering calendar time is important because the VaR, ES, and TR estimates are much higher with the return data in August 1998 (the Russian debt crisis), which we call "informative outliers" (see Liang and Park (2007)).

The next step is to select variables to explain the survival of hedge funds. Prior literature suggests that performance, risk, fund age, size, leverage, HWM, and lockup provision affect the attrition of hedge funds (see BGP (2001), Gregoriou (2002), and Rouah (2005) for a survival analysis; Liang (2000) and Malkiel and Saha (2005) for a probit analysis; and Chan, Getmansky, Haas, and Lo (2005) for the logistic regression of hedge fund attrition). The definitions of the covariates used in the analysis are as follows:

Risk Measures. The goal of this paper is to find the best risk measure in predicting the failure of hedge funds. The definition and estimation procedure of each risk measure is as described in Section III.

Style Effect. We use 7 dummy variables (D1–D7) to adjust for the investment style effect.

Performance (Avg_Return_1yr). The monthly average rate of return during the previous year is used to represent fund performance.

Average Size (Avg_Asset_1yr). Average AUM during the previous year is used to measure the size of a fund.

Size Volatility (Std_Asset_1yr). The standard deviation of a fund's AUM is used to measure the size volatility.

Age. It is the fund's age in months.

HWM, Personal Investment, Leverage, and Lockup Provision. We also include dummy variables to specify funds with HWM, personal capital, leverage, and a lockup provision.

IV. Empirical Results

A. Time Variation in the Risk Profile of Graveyard Funds

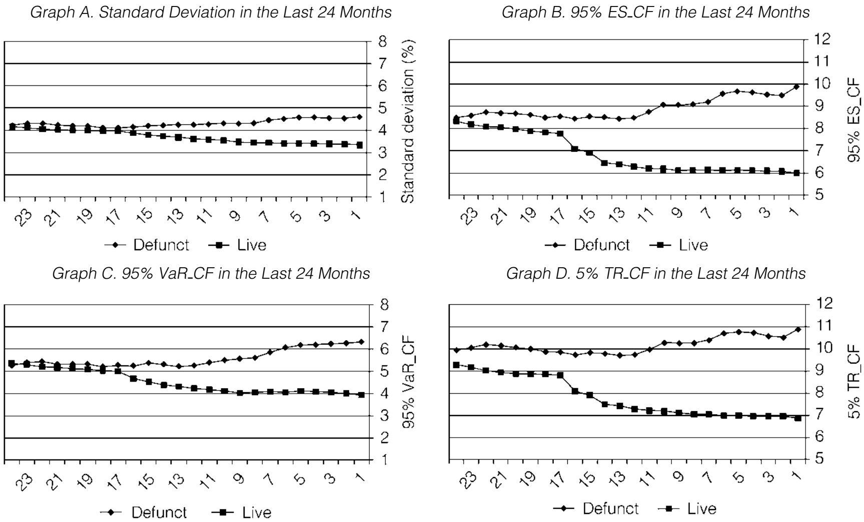
Before we present the result of survival analysis, we use simple plots to illustrate the superiority of downside risk measures to standard deviation in predicting hedge fund failure. In Figure 1, we plot the time variation in the average risk of defunct funds and live funds. The parallel axis in Figure 1 represents the event time. Time 1 stands for the last month when a defunct fund drops out of the live fund database and moves to the graveyard. Time 24 is 24 months before the exit.

In the case of live funds, we do not have the event (exit) time, so time 1 represents December 2004, which is the last month of the sample period. Note that the risk profile of live funds shows a sharp drop at time 16, which is the first month when the 60-month rolling estimation window does not include August 1998 (the Russian debt crisis). This pattern shows why we call the return data in August 1998 "informative outliers" and emphasize the use of calendar time in the survival analysis of hedge funds.

FIGURE 1

Time Variation in the Risk Profile of Hedge Funds

Figure 1 illustrates the change in the risk profile of hedge funds as they approach their last month (time 1 in the horizontal axis). For defunct funds, the last month is the event time when the funds exit the database. For live funds, the last month is December 2004 which is the last month of our sample period. Standard deviation, VaR, expected shortfall, and tail risk are used as risk measures, and rolling 24–60 months (as available) are used to estimate risk of each fund. We show the cross-sectional average risk for both live and defunct funds at each month.



Consistent with Bali et al. (2007), we find that the risk of defunct hedge funds increases as early as 12 months before they drop out of the live fund database. Note that the increasing pattern in the risk of defunct funds is most prominent when we use downside risk measures such as ES_CF or TR_CF, not standard deviation.

B. A Survival Analysis to Predict Attrition

For a more formal comparison of those risk measures, we perform a survival analysis as described in Section III. First, we follow the conventional classification and define "failure" as exit to the graveyard. As shown in Table 2, all 5 risk measures are significant at the 1% level when they are the only explanatory variables in the model. However, when the other variables such as performance, age, size, HWM, and lockup are included in the analysis, standard deviation loses the explanatory power while ES and TR are still significant at the 5% level. This means that downside risk measures can predict the survival of hedge funds while standard deviation does not. Note that the coefficient on the risk measure is always positive, which is intuitive because high risk means high hazard rate.

Regarding the impact of other explanatory variables, we find that performance, age, HWM, and lockup reduce the hazard rate of hedge funds. Note that the coefficients on performance (Avg_Return_1yr), age, HWM, and lockup are always negative and significant at the 1% level. This finding is consistent with

TABLE 2

A Survival Analysis to Predict Attrition of Hedge Funds (1995–2004)

Table 2 reports the parameter estimate β from the Cox (1972) proportional hazard analysis with time dependent predictor variables. All the risk measures are estimated using the parametric approach. Failure is defined as the exit from the live fund database. ***, **, and * denote that the parameter estimate is statistically significant at the 1%, 5%, and 10% levels, respectively.

Classification	Total	Event (Exit)	Censored	Percent Censored	
All exits	3,937	342	3,595	91.3	
Model	**STD**	**SEM**	**VaR**	**ES**	**TR**
Panel A. Univariate Model					
Risk measure	0.06***	0.11***	0.05***	0.03***	0.03***
Likelihood ratio test (χ^2_1)	14.0***	25.1***	23.9***	18.9***	19.1***
Panel B. Multivariate Model					
Risk measure	0.02	0.05*	0.02*	0.01**	0.01**
D1 (convertible arbitrage)	0.28	0.14	0.28	0.41	0.27
D2 (dedicated short bias)	0.56	0.49	0.52	0.61	0.58
D3 (equity market neutral)	0.29	0.24	0.30	0.50	0.43
D4 (event driven)	0.20	0.09	0.20	0.28	0.17
D5 (fixed income arbitrage)	0.75**	0.77**	0.75*	0.83**	0.85**
D6 (global macro)	0.66*	0.61*	0.66*	0.77**	0.73*
D7 (long/short equity hedge)	0.36	0.38	0.35	0.45	0.49
Avg_Return_1yr	–0.18***	–0.18***	–0.17***	–0.17***	–0.18***
Avg_Asset_1yr	–0.05*	–0.08**	–0.05*	–0.05*	–0.09**
Std_Asset_1yr	0.03	0.04	0.03	0.03	0.04
Age	–0.01***	–0.01***	–0.01***	–0.01***	–0.01***
HWM	–0.87***	–0.80***	–0.87***	–0.87***	–0.81***
Leverage	–0.05	–0.10	–0.05	–0.03	–0.08
Personal capital	0.04	0.04	0.04	0.06	0.05
Lockup	–0.56***	–0.52***	–0.56***	–0.55***	–0.51***
Likelihood ratio test (χ^2_{16})	176.4***	181.4***	177.7***	177.2***	180.4***

previous research that finds performance as an important factor in predicting hedge fund failure (Liang (2000), BGP (2001), Malkiel and Saha (2005), and Chan et al. (2005)).

The impact of age we find here is consistent with BGP (2001), who argue that the longer the fund has been in existence the more likely it is to survive. Regarding the impact of HWM, there are two reasons why funds with HWM are more likely to survive. The HWM provision requires that hedge fund managers recover past losses before they collect incentive fees, and thus the provision serves as a manager quality signal. Good managers are willing and eager to impose this provision, while bad managers may not afford to mimic. Hence HWM appears to reduce the hazard rate. Another explanation is provided by Aragon and Qian (2005), who argue that HWM lowers existing investors' marginal cost of staying with the fund following poor performance and hence allows fund managers to retain investors when liquidation is most costly.

Similarly, funds with a lockup provision can retain investors even after poor performance so long as the lockup period is not over, and thus these funds are more likely to survive. We also find that there are some style effects: Fixed income funds and global macro funds have high hazard rates. The explanatory power of size is weak; leverage and manager's personal investment do not explain the survival of hedge funds.

C. A Survival Analysis Based on the Drop Reasons

In the next step, we attempt to refine the graveyard database to sort out the funds that might not have actually failed. Recall that successful hedge funds can be moved to the graveyard and classified as defunct if they do not report to the database anymore because reporting to a hedge fund database is not mandatory.

TASS provides drop reason codes, which include liquidation, stop reporting, unable to contact, closed to new investment, merged into another fund, and dormant funds. Baquero et al. (2005) argue that only liquidated hedge funds in the graveyard should be regarded as failed ones. Rouah (2005) uses drop reasons provided by HFR and claims that only liquidated funds should be used in a survival analysis. He argues that the effect of covariates may become blurred when all the graveyard funds are regarded as failed funds.

As suggested by Rouah (2005), we use the drop reason codes provided by TASS and regard only liquidation as failure (see Model 2 (Liquidated) in Table 3).[13] The result for this model is not intuitive because the parameter estimates for the risk measures are negative, which means high-risk funds have a low hazard rate: In the case of ES, the negative coefficient is not significantly different from 0. However, when we use standard deviation as a risk measure, the negative coefficient is significant at the 5% level.[14]

We examine the graveyard funds as well as their drop reasons and find that the "unable to contact" group has high downside risk and poor performance. Therefore, we define failure as "unable to contact" (Model 3) or either "liquidated" or "unable to contact" (Model 4). Now the parameter estimates for ES are positive, but they are insignificant or only marginally significant. Standard deviation provides insignificant coefficients. That is, a survival analysis based on drop reasons does not provide intuitive results. Therefore, we search for alternative criteria that can be used to refine the constituents of the graveyard. First, in Section IV.D, we show why the drop reasons can be misleading in sorting out failed hedge funds, and then we suggest new criteria to define failure in Section IV.E.

D. Distinguishing "Liquidation" from "Failure"

Liquidation does not necessarily mean failure in the hedge fund universe. We present the following cases where some liquidated funds should not be regarded as failed ones. All the funds presented in these cases are included in our data set.

Case 1. Successful Liquidation before a Market Crash: Global Macro Funds

The dominant investment style in the hedge fund universe keeps changing according to the market condition. For example, global macro funds were managing more than one-third of the total hedge fund assets as of January 1994, and

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[13]In our analysis, we treat the defunct funds that are no longer viewed as failed funds as censored. That is, we cannot observe those funds until they fail because they disappear due to a reason other than failure. The Cox (1972) PH model has a mechanism to accommodate censoring, which is one of the advantages of this model over other failure prediction models such as the probit model (Kalbfleisch and Prentice (1980)).

[14]In Table 3 we present the results for standard deviation and ES, which is the best measure in predicting the survival of hedge funds. The results for the other risk measures are omitted to save space. They are available from the authors.

TABLE 3

Redefined Failure in the Survival Analysis of Hedge Funds (1995–2004)

Table 3 reports the parameter estimates from the Cox (1972) proportional hazard analysis where failure is defined based on the drop reason code or performance and size. ES is estimated using the parametric approach. ***, **, and * denote that the parameter estimate is statistically significant at the 1%, 5%, and 10% levels, respectively.

Classification	Total	Event (Exit)	Censored	Percent Censored
Drop Reason				
Liquidation (Model 2)	3,937	128	3,809	96.8
Unable to contact (Model 3)	3,937	39	3,898	99.0
Liquidation or unable to contact (Model 4)	3,937	167	3,770	95.8
Based on performance and size: "Real Failure" (Model 5)	3,937	155	3,782	96.1
Based on performance: "Loser" (Model 6)	3,937	189	3,748	95.2
All exits (Model 1)	3,937	342	3,595	91.3

		Based on Drop Reasons			Based on Size and Performance	
Model	Model 1 (All Exits)	Model 2 (Liquidated)	Model 3 (Unable to Contact)	Model 4 (Liquidation or Unable to Contact)	Model 5 (Real Failure)	Model 6 (Loser)
Panel A. Standard Deviation (STD)						
STD	0.02	–0.09**	0.04	–0.05	0.02	0.03
D1 (convertible arbitrage)	0.28	–1.09**	14.77	–0.78	1.75*	2.01*
D2 (dedicated short bias)	0.56	0.03	–0.55	–0.11	0.93	1.04
D3 (equity market neutral)	0.29	–0.38	–0.42	–0.31	2.18**	2.28**
D4 (event driven)	0.20	–0.88**	15.22	–0.47	1.54	1.87*
D5 (fixed income arbitrage)	0.75**	–0.41	14.31	–0.28	1.97*	2.33**
D6 (global macro)	0.66*	–0.15	15.54	0.17	2.23**	2.38**
D7 (long/short equity hedge)	0.36	–0.35	14.99	–0.14	1.67*	1.89*
Avg_Return_1yr	–0.18***	–0.34***	–0.15**	–0.28***	–0.26***	–0.21***
Avg_Asset_1yr	–0.05*	–0.03	–0.55	–0.06	–0.07	–0.07
Std_Asset_1yr	0.03	0.07	0.33	0.09	–0.07	–0.05
Age	–0.01***	–0.01***	0.00	–0.01	–0.004*	–0.01**
HWM	–0.87***	–0.88***	–1.18**	–0.94***	–1.08***	–1.13***
Leverage	–0.05	–0.02	0.20	0.04	0.01	0.04
Personal capital	0.04	–0.06	–0.26	–0.11	0.07	0.06
Lockup	–0.56***	–0.91***	–0.42	–0.82***	–0.35	–0.35
Likelihood ratio test (χ^2_{16})	176.4***	101.5***	46.7***	116.3***	141.3***	143.8***
Panel B. Expected Shortfall (ES)						
ES	0.01**	–0.02	0.03*	0.001	0.02**	0.02**
D1 (convertible arbitrage)	0.41	–0.89	14.75	–0.60	1.75*	2.00*
D2 (dedicated short bias)	0.61	–0.01	–0.61	–0.18	0.79	0.93
D3 (equity market neutral)	0.50	–0.13	–0.54	–0.06	2.28**	2.36**
D4 (event driven)	0.28	–0.74	15.20	–0.34	1.50	1.82*
D5 (fixed income arbitrage)	0.83**	–0.19	14.27	–0.11	1.91*	2.27**
D6 (global macro)	0.77**	–0.10	15.53	0.24	2.21**	2.36**
D7 (long/short equity hedge)	0.45	–0.37	14.90	–0.15	1.62	1.84*
Avg_Return_1yr	–0.17***	–0.30***	–0.13*	–0.24***	–0.24***	–0.20***
Avg_Asset_1yr	–0.05*	–0.03	–0.48	–0.05	–0.07	–0.08
Std_Asset_1yr	0.03	0.06	0.01	0.08	–0.09	–0.04
Age	–0.01***	–0.01***	0.002	–0.01**	–0.004*	–0.005**
HWM	–0.87***	–0.87***	–1.22**	–0.94***	–1.07***	–1.12***
Leverage	–0.03	–0.04	0.24	0.02	0.03	0.07
Personal capital	0.06	–0.01	–0.28	–0.08	0.08	0.09
Lockup	–0.55	–0.97***	–0.41	–0.86	–0.38	–0.37
Likelihood ratio test (χ^2_{16})	177.2***	94.5***	48.2***	111.6***	143.4***	145.9***

the average return on global macro funds based on the Hedge Fund Research Index (HFRI) during 1990–1999 was 26% per annum. However, the market moved downward and global macro funds experienced a market crash in 2000. As of January 2001, global macro funds are managing only 3% of the total hedge fund assets, and the return on the HFRI macro funds in 2000 is only 2%.

Funds S and L are two global macro funds. Both were liquidated during the market crash in 2000, but they took very different paths. The manager of

Fund S detected the downward movement in the market early, started to adjust the portfolio, and successfully liquidated the fund before the market crash. However, the manager of Fund L failed to take an appropriate measure, increased its position before the crash, experienced a huge loss, and then was liquidated. If one used the drop reason codes provided by the data vendor and regarded liquidation as the same as failure in a survival analysis, both Funds S and L would be regarded as failed funds. However, according to the new criteria we suggest in Sections I and IV.E, Fund L has failed but Fund S has not.

Case 2. Liquidation of a Successful Start-Up Fund after Launching New Funds

Another case is presented with three hedge funds that have exactly the same investment strategy, management company, and portfolio managers. Fund M was liquidated in March 2003 after building up an excellent track record. It never had a negative rate of return for 44 consecutive months before its liquidation. Its cumulative rate of return during its entire history (67 months) is 1,139%, and the last monthly rate of return reported to TASS is 116%.[15] It is not reasonable to consider Fund M as failed in a survival analysis just because it is liquidated.

Fund M had been closed to new investment for 30 months before it was liquidated because it had reached its capacity due to the surge of new money attracted by its outstanding performance. While Fund M was closed to new investment, the management company launched two new funds, T and F, to accept new money. Funds T and F have exactly the same investment strategy as Fund M, but their offering memoranda were more carefully prepared. Fund M did not have a well defined subscription and a redemption frequency, hence such decisions were at the manager's discretion. When investors of Fund M wanted to redeem their shares, they did not have to give notice in advance.

However, newly launched funds have all the terms well defined. In Funds T and F, the subscription frequency is 1 month and the redemption frequency is a quarter. Investors of Funds T and F have to give advance notice 90 days before they can redeem their shares. Fund M, the successful start-up fund, was liquidated after the new funds were well established. If we define failure the same as liquidation in a survival analysis, Fund M would be regarded as a failed fund. However, according to the new criteria defined in Sections I and IV.E, the liquidated Fund M has not failed.

We recognize that Fund M may not show the characteristics of an average liquidated fund, and many of the liquidated hedge funds were not very successful. However, we do note that 44.6% of liquidated hedge funds (146 out of 327 funds) have a positive average rate of return for the last 6 months before their liquidation.

[15]To make sure that this extraordinarily high performance is reliable, we searched for additional information on this fund and the management company. We could not find more information on Fund M itself, but we found the due diligence report of another fund that was launched by the same management company after the liquidation of Fund M. The new fund implements the same strategy and has the same manager as Fund M. According to the due diligence report of this new fund, the management company implements a very unique and successful strategy in the mortgage arbitrage market, its AUM keeps growing rapidly after the liquidation of Fund M, and the information provided by it is reliable.

Case 3. Liquidated Hedge Funds Have Not Failed in Downside Risk Management

There is another reason why we believe liquidation does not necessarily mean failure in the hedge fund universe. We examine the time variation in the risk profile of live and defunct hedge funds in each drop reason category and find that liquidated hedge funds on average have lower risk than the average hedge fund in the defunct fund database. The highest risk is observed for funds that are unable to be contacted by TASS. The managers of liquidated hedge funds on average may be more prudent than the manager of an average defunct fund, at least in terms of risk management. They might have liquidated their portfolios to avoid a catastrophic result under the changing environment of their investment strategy. Recall that in the example in Case 1, Fund S detected a downward movement in the market and hence successfully liquidated its portfolio before the market crash.

Table 4 compares hedge funds in each drop reason category in terms of risk, performance, age, and size. The "unable to contact" group looks like one of the worst categories in the graveyard. However, we find that 34 out of 80 funds in the "unable to contact" category have a positive average rate of return for the last 6 months. Out of those 34 funds, 31 have a positive cumulative rate of return, and 14 out of those 31 funds have increased in size for the last 12 months. Therefore, it is not surprising that we have insignificant results when we define hedge fund failure as "liquidation" and/or "unable to contact," then implement the survival analysis (see Models 2, 3, and 4 of Table 3).

TABLE 4

Performance, Risk, and Size of Hedge Funds in the Graveyard (January 1995–December 2004)

Table 4 presents the characteristics of graveyard funds by category. Reported numbers are the sample medians. Size is the AUM in US$ million as of the last month. ES is calculated based on the last 24–60 months (as available) return history using the parametric approach. Cum_A stands for the annualized cumulative rate of return. Av6_M is the monthly average rate of return for the last 6 months. Size_F, Size_6, and Size_12 mean the last month, 6-month prior, and 12-month prior size that is normalized by the fund's size as of the last month, respectively. Note that Size_F is always 100 by definition. If Size_6 is greater than 100, that means the fund has decreased in AUM for the last 6 months. If a fund's AUM has reduced for the last year, its Size_12 is greater than 100. "Loser" means all the funds in the graveyard for which Av6_M is negative. "Real Failure" is a subset of "Loser." It includes all the funds in the graveyard that have both negative Av6_M and Size_12 larger than 100.

Drop Reason	No. of Funds	Age	Size ($mm)	ES	Cum_A (%)	Av6_M (%)	Size_F	Size_6	Size_12
Panel A. Classification Based on the Drop Reasons									
Liquidation	327	47	10.5	7.12	1.25	–0.14	100	118	149
Not reporting	234	58	16.5	8.95	6.99	–0.06	100	105	114
Unable to contact	80	57	11.1	12.17	5.80	–0.47	100	108	122
Closed to new investment	4	87	60.8	11.73	12.72	0.42	100	111	104
Merged	27	80	17.0	10.62	13.13	0.29	100	103	118
Dormant	1	56	6.2	16.68	–6.67	–3.24	100	179	205
Drop reason unavailable	99	50	10.3	5.12	3.18	–0.33	100	117	132
Total	772	52	12.0	7.98	3.99	–0.14	100	112	129
Classification	**No. of Funds**	**Age**	**Size ($mm)**	**ES**	**Cum_A (%)**	**Av6_M (%)**	**Size_F**	**Size_6**	**Size_12**
Panel B. Classification Based on Performance and Size									
Loser	418	52	10.0	9.89	−1.53	−1.36	100	124	148
Not loser	354	53	15.6	6.28	9.67	0.96	100	100	106
Real failure	301	57	8.9	10.97	−1.99	−1.53	100	135	180
Loser but not real failure	117	44	16.8	9.21	0.85	−0.85	100	100	76

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E. A Survival Analysis to Predict "Real Failure"

As discussed above, we recognize that the stated drop reasons are not very informative in defining hedge fund failure. We find that simple criteria such as performance and change in size work better after we examine all the available information on defunct funds. Hence we suggest new criteria to define "real failure" of hedge funds as follows: i) once listed in a database but stopped reporting, ii) negative average rate of return for the last 6 months (Av6_M in Table 4 is less than 0), and iii) decreased AUM for the last 12 months (Size_12 in Table 4 is greater than 100). We define "real failure" if all 3 criteria are met.

Model 5 in Table 3 shows that ES_CF predicts the "real failure" at the 5% level, while the coefficient on standard deviation is not significant at any conventional level (p-value of 0.38). Note that there are some changes in the style effect under this new definition of failure. Equity market neutral funds have a high hazard rate in Models 5 and 6, while this pattern cannot be detected when we combine all the exit reasons and regard all graveyard funds as failed ones (Model 1).

Table 5 compares the five risk measures in terms of predicting the "real failure" of hedge funds. All the risk measures including standard deviation are significant at the 1% level when they are the only explanatory variable. However, under the presence of other important variables such as performance, HWM, and style dummy variables, only ES and TR maintain the explanatory power, while standard deviation, SEM, and VaR do not. This means that standard deviation is

TABLE 5

A Survival Analysis to Predict "Real Failure" of Hedge Funds (1995–2004)

Table 5 reports the parameter estimate β from the Cox (1972) proportional hazard analysis with time dependent predictor variables. All the risk measures are estimated using the parametric approach. "Real Failure" is defined based on the performance and the size criteria. ***, **, and * denote that the parameter estimate is statistically significant at the 1%, 5%, and 10% levels, respectively.

Classification	Total	Event (Real Failure)	Censored	Percent Censored	
All exits	3,937	155	3,782	96.1	

Model	STD	SEM	VaR	ES	TR
Panel A. Univariate Model					
Risk measure	0.08***	0.15***	0.07***	0.04***	0.03***
Likelihood ratio test (χ^2_1)	15.0***	23.6***	26.0***	20.2***	18.6***
Panel B. Multivariate Model					
Risk measure	0.02	0.05	0.02	0.02**	0.02*
D1 (convertible arbitrage)	1.75*	1.57	1.75*	1.75*	1.59
D2 (dedicated short bias)	0.93	0.82	0.89	0.79	0.73
D3 (equity market neutral)	2.18**	2.09**	2.19**	2.28**	2.18**
D4 (event driven)	1.54	1.37	1.54	1.50	1.33
D5 (fixed income arbitrage)	1.97*	1.99*	1.97*	1.91*	1.94*
D6 (global macro)	2.23**	2.14**	2.23**	2.21**	2.14**
D7 (long/short equity hedge)	1.67*	1.66*	1.65	1.62	1.64
Avg_Return_1yr	–0.26***	–0.26***	–0.24***	–0.24***	–0.26***
Avg_Asset_1yr	–0.07	–0.11	–0.07	–0.07	–0.10
Std_Asset_1yr	–0.07	–0.14	–0.08	–0.09	–0.17
Age	–0.004*	–0.004	–0.004*	–0.004*	–0.004
HWM	–1.08***	–0.93***	–1.08***	–1.07***	–0.93***
Leverage	0.01	–0.04	–0.01	0.03	–0.01
Personal capital	0.07	0.08	0.07	0.08	0.10
Lockup	–0.35	–0.36	–0.35	–0.38	–0.39
Likelihood ratio test (χ^2_{16})	141.3***	144.6***	142.1***	143.4***	145.7***

not a complete measure of total risk in hedge funds and considering downside risk is important. This finding is also consistent with the theoretical argument of Artzner et al. (1999) and the empirical finding of Liang and Park (2007) that ES is superior to VaR in capturing hedge fund risk. Note that ES is a coherent measure of risk but VaR is not.[16]

Regarding the impact of other explanatory variables, we find changes in the roles of lockup, age, size, and the style dummy variables. Note that in Table 2 (predicting attrition) the coefficient on lockup is negative and significant at the 1% level, but it is not significant at any conventional significance level in Table 5 (predicting failure). That is, the lockup provision reduces the attrition rate by prohibiting redemption for a predetermined period, but it does not reduce the "real failure" rate of hedge funds.

Tables 2 and 5 also show that the role of seasoned funds and large funds weakens when we redefine failure. That is, older hedge funds with large AUM will be more desirable only if staying in business is the only criterion to define failure. However, if we require staying in business with high performance and increased AUM, the impact of age and size disappears. Note also that the high hazard rate of equity market neutral funds and CA funds in Table 5 is not detectable when we define failure as attrition.

F. Attrition Rate versus Failure Rate

As we now have new criteria to define hedge fund failure, we calculate the failure rate to be compared with the conventional attrition rate. As shown in Table 6, the annual average attrition rate between 1995 and 2004 is 8.7%, which is consistent with Liang (2000) and Getmansky, Lo, and Mei (2004). The annual average failure rate we find is 3.1% during the same period.

TABLE 6

"Attrition Rate" versus "Failure Rate" of Hedge Funds (1995–2004)

Table 6 compares attrition rates with real failure rates of hedge funds. The time period is from January 1995 to December 2004. Attrition means exit from the live fund database to the defunct fund database. Real failure is defined using the 3 criteria of hedge funds: i) those that were once listed in the live fund database but stopped reporting, ii) those with negative average rate of return for the last 6 months, and iii) those that decreased in AUM for the last 12 months.

Year	Year Start	Entry	Exit	Real Failure	Year End	Attrition Rate	Failure Rate
1995	237	108	8	0	337	3.38%	0.00%
1996	337	110	33	5	414	9.79%	1.48%
1997	414	145	18	2	541	4.35%	0.48%
1998	541	191	38	15	694	7.02%	2.77%
1999	694	185	70	24	809	10.09%	3.46%
2000	809	196	101	43	904	12.48%	5.32%
2001	904	223	99	54	1,028	10.95%	5.97%
2002	1,028	211	113	53	1,126	10.99%	5.16%
2003	1,126	202	112	33	1,216	9.95%	2.93%
2004	1,216	94	99	40	1,211	8.14%	3.29%
Average						8.71%	3.09%

[16]See Artzner et al. (1999) for the details on coherent measure of risk.

Our failure rate is consistent with the practitioners' view presented in Derman (2006) and Feffer and Kundro (2003). Derman (2006) argues that the proportion of hedge funds that move to the graveyard each year due to poor performance is around 3%. He does not show what this 3% estimate is based on, but we do provide the basis of this failure rate. Feffer and Kundro (2003) argue that hedge fund failure should be distinguished from discretionary fund closures, which are much more frequent than failures and are often driven by business or market expectations of the fund managers.

There are some concerns about the high attrition rate of hedge funds compared to mutual funds. However, we should note that a hedge fund is a flexible investment vehicle that can adjust the portfolio quickly when the market environment moves in an undesirable direction, which may result in a high attrition rate. In addition to the case of global macro funds presented in Section IV.D, we can easily find another example. The CA hedge funds have been liquidating their portfolios quickly due to a recent downturn in the CB market, while CB mutual funds have remained in the market (Agarwal et al. (2009)). Recall that liquidated hedge funds on average have not failed in risk management. They might have liquidated their portfolios to avoid a catastrophic result under the changing environment of their investment strategy. Rapid liquidation and a high attrition rate can therefore be advantageous to investors under some circumstances. That is why we emphasize differentiating real failure rate from attrition rate.

V. Robustness Checks

This section addresses several issues related to the robustness of the main results. We show that downside risk measures are superior to standard deviation in predicting hedge fund failure regardless of the way we define failure or the statistical method we use.

A. "Losers" versus "Real Failures"

To see if modifying the criteria affects the main results, we define "losers" as the graveyard funds that have a negative average rate of return for the last 6 months. That is, we drop the size criterion here, so "real failure" is a subset of "losers." Again we find downside risk measures perform better than standard deviation in predicting the "losers." As shown in Model 6 of Table 3, high ES means high hazard rate, and this result is significant at the 5% level, while standard deviation provides an insignificant result.

B. Without the "Graveyard" Criterion

Here we remove the "graveyard" criterion to define failure. We recognize that the current live fund database may contain funds that are about to fail. Therefore, we apply the performance and size criteria to both live and defunct funds and regard all the funds that meet the criteria as failed funds. We have 128 live funds and 301 defunct funds that meet the performance and the size criteria. We find that downside risk measures are better than standard deviation in this case as well. The coefficients on ES and TR are significant at the 5% level, while the coefficient on standard deviation is only significant at the 10% level.[17]

C. Change in Risk as a Covariate

Another robustness check is provided by modifying the risk measure used as a covariate in the survival analysis. Recall that our survival analysis is inspired by the fact that the increasing risk pattern on average can be detected as early as 12 months before a hedge fund drops out of the live fund database. Bali et al. (2007) find that changing risk can be used to explain the cross-sectional variation in hedge fund returns.

Hence we use the change in risk during the last 12-month period as a covariate and repeat the survival analysis.[18] This change reduces the sample size because it requires an additional 12 months of return history for a fund to be included in the analysis, but we find that the main results remain the same. ES and TR provide significant results at the 5% level, while standard deviation does not. For example, when we regard all exit reasons together as failure, the coefficient on ES is significantly different from 0 at the 5% level, but the coefficient on standard deviation is not significant (p-value of 0.12).

D. The Probit Model and the Logit Model

The Cox (1972) model we used in this paper is not the only statistical method to analyze the failure of a hedge fund. We can also use regression models with dichotomous dependant variables such as the probit model and the logit model.[19] Liang (2000) and Malkiel and Saha (2005) use the probit model, while Chan et al. (2005) use the logit model. Gregoriou (2002) and Rouah (2005) adopt a survival analysis based on the Cox model, and BGP (2001) use both the probit model and the Cox model. Lunde, Timmermann, and Blake (1999) argue for the Cox model based on the fact that the probit model requires strong parametric as well as distributional assumptions, while the Cox model adopts a more flexible approach. In addition, the Cox model calibrates the effect of censoring for live funds, while the probit model does not.

We implement both the probit model and the logit model in addition to the Cox (1972) model. The results confirm that the findings are robust irrespective of the statistical method we use. Table 7 presents the parameter estimates from the logit model. Positive coefficients on the risk measures are intuitive, as higher risk means a higher probability of failure. As in the Cox model, both standard deviation and ES are significant in the univariate analysis, but the explanatory power of standard deviation becomes weaker when other explanatory variables are included. Note that ES is still significant at the 1% level in the multivariate model.

[17] To save space, we do not include detailed results for robustness checks in Sections V.B and V.C, but they are available from the authors.

[18] For example, we use the change in ES of a fund during the 12-month period between December 2002 and December 2003 to predict the failure of the fund during 2004. ESs at these 2 points are estimated using the prior 24–60 monthly returns, respectively.

[19] See Griffiths, Hill, and Judge (1993) for the details of the probit model, and see Chan et al. (2005) for the application of the logit model to the failure of hedge funds.

That is, downside risk measures are superior to standard deviation in predicting the failure of hedge funds.[20]

TABLE 7

The Logit Model to Predict Failure of Hedge Funds (1995–2004)

Table 7 reports the parameter estimates and pseudo-R^2 from the logistic regression of hedge fund failures. All the risk measures are estimated using the parametric approach. Failure is defined as either i) exit from the live fund database to the graveyard (attrition) or ii) "real failure" based on the performance and size criteria. ***, **, and * denote that the parameter estimate is statistically significant at the 1%, 5%, and 10% levels, respectively.

Classification	All Exits		Real Failure	
Sample size	3,937		3,937	
Number of failures	342		155	
Model	STD	ES	STD	ES
Panel A. Univariate Model				
Risk measure	0.07***	0.03***	0.10***	0.05***
Pseudo-R^2(%)	0.49	0.73	0.54	0.78
Panel B. Multivariate Model				
Risk measure	0.04**	0.02***	0.06*	0.03***
D1 (convertible arbitrage)	0.26	0.39	1.77*	1.76*
D2 (dedicated short bias)	0.59	0.63	0.74	0.59
D3 (equity market neutral)	0.31	0.55	2.29**	2.40**
D4 (event driven)	0.18	0.27	1.61	1.56
D5 (fixed income arbitrage)	0.81**	0.88**	2.00*	1.89*
D6 (global macro)	0.59	0.74*	2.12**	2.14**
D7 (long/short equity hedge)	0.29	0.41	1.56	1.56
Avg_Return_1yr	–0.22***	–0.21***	–0.33***	–0.30***
Avg_Asset_1yr	–0.07**	–0.07**	–0.08	–0.07
Std_Asset_1yr	0.07	0.07	–0.07	–0.11
Age	–0.01***	–0.01***	0.00	0.00
HWM	–0.89***	–0.90***	–1.01***	–1.01***
Leverage	–0.05	–0.02	0.02	0.06
Personal capital	0.07	0.08	0.12	0.13
Lockup	–0.58***	–0.57***	–0.34	–0.37
Pseudo-R^2 (%)	4.67	4.84	3.69	3.87

E. The 99% Value-at-Risk, Expected Shortfall, and Tail Risk

To examine whether the results are affected by the confidence level or not, we use the 99% VaR, ES, and TR instead of the 95% VaR, ES, and TR in predicting both attrition and real failure. We find that the results at the 99% confidence level are very similar to the results we have at the 95% level. The 99% VaR, ES, and TR have the explanatory power at the 5% level in predicting both hedge fund attrition and real failure when other explanatory variables are present, while standard deviation loses the explanatory power in the multivariate model.

VI. Conclusions

In this paper, we implement a survival analysis to examine the determinants of hedge fund failure. To the best of our knowledge, this is the first paper that

[20]Table 7 (the logit model) can be compared with the results from the Cox (1972) model presented in Table 3 (Models 1 and 5). As the results from the probit model are very similar to those from the logit model, they are not reported in tables, but they are available from the authors.

compares various downside risk measures to predict the failure of hedge funds. In addition, we have made progress in methodology. In contrast to previous research that makes a strong assumption on time homogeneity and considers only event time, we develop a methodology that can take calendar time into consideration.

We have three major findings that contribute to the literature regarding the risk profile and failure of hedge funds. First, we find that downside risk measures such as ES and TR are superior to standard deviation in terms of predicting hedge fund failure. This finding is consistent with Agarwal and Naik (2004) and Liang and Park (2007), who find that standard deviation significantly underestimates the left-tail risk in hedge funds.

Second, we show that liquidation does not necessarily mean failure in hedge funds. Liquidated hedge funds on average have lower downside risk than the average hedge fund in the graveyard. We claim that simple criteria such as performance and change in size work better than the drop reasons provided by the data vendor in defining fund failure. We reexamine the attrition rate of hedge funds based on this finding and show that the real failure rate (3.1%) is lower than the attrition rate (8.7%, annual average during 1995–2004).

Finally, we clarify the roles of performance, age, size, HWM, and lockup provision in predicting hedge fund failure. Performance and HWM are important determinants regardless of whether we use the new criteria or only attrition to define fund failure. Performance is always significant at the 1% level after we control for risk, age, size, style, leverage, personal capital, HWM, and the lockup provision. Funds with HWM provision are less likely to fail. However, the roles of age, size, and the lockup provision change depending on how we define failure. The lockup provision can prevent attrition by prohibiting redemption during a predetermined period, but it cannot prevent real failure of hedge funds. Similarly, the advantage of an old fund with large AUM disappears when we differentiate the real failure rate from the attrition rate of hedge funds.

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