HEDGE FUND FACTORS AND SURVIVAL ANALYSIS: EVIDENCE FROM ASIA PACIFIC

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Abstract: This paper investigates the issue of hedge fund attrition in the context of hedge funds domiciled in the Asia Pacific from January 1994 to June 2012. Using the parametric probit regression model and the less restrictive semi parametric Cox proportional hazard model, larger, better performing funds with lower redemption frequency have a higher likelihood of survival. Higher standard deviation is positively related to the survival of hedge funds domiciled in the Asia Pacific. This is because most of the defunct funds died before the global financial crisis began in 2007 and the remaining surviving funds have a higher standard deviation. Management fees, incentive fees and lock up provisions as part of the hedge fund incentive structure do not seem to impact on fund attrition. Lastly, the probit model shows that higher leverage is beneficial for fund survival.

Keywords: Survival, hedge funds, fund characteristics, institutional investors

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5.1 Introduction

Using the Eurekahedge, TASS and Morningstar databases, I analyse the survival of hedge funds domiciled in the Asia Pacific. The survival analysis is used to examine whether the hedge fund mortality can be predicted from certain hedge fund characteristics. The aim is to see whether the fund characteristics such as age, performance, standard deviation, size, leverage, lock up period and management fee impact on the survival time of individual hedge funds. I use a parametric probit regression method to examine the hedge fund survival status on several explanatory variables. To study the factors that influence the survival and mortality patterns of hedge funds, I use the less restrictive, semi parametric Cox proportional hazard model.

Institutional investors, such as endowments, foundations, and pension funds make up a larger portion of the hedge fund universe as time goes by. These investors have a preference for investing on a long-term basis due to the illiquidity nature of hedge funds. Since investors are constantly face with selection problem when trying to choose and invest in hedge funds, the issue of hedge fund survival and mortality patterns is relevant. If the probability of hedge fund death can be predicted based on some explanatory variables, then the selection of hedge funds based on these variables should increase future portfolio performance. Investor concerns regarding illiquidity face, when investing in hedge funds such as redemption and lock-up provisions, will be reduced when hedge fund with a higher chance of longevity is selected. Survival analysis allow for the identification of hedge funds with a higher probability of survival and a good long term outlook, hence reducing liquidation risk and the associated loss of capital.

As discussed, the research into the sources of hedge fund returns can be classified into macroeconomic and microeconomic factors. The macroeconomic factors are exposure to various asset classes on the performance of hedge funds. The microeconomic factors are firm specific characteristics like fund age, size, fees and lock up periods on the performance. So far I concentrate on the impact of macroeconomic factors and hedge fund performance. This paper I look at firm specific characteristics on the survival probability of hedge funds.

The reminder of this paper is structured as follows: Section 5.2 reviews the literature on the relationship between hedge fund performance and certain fund characteristics. Section 5.3 discusses the data and sections 5.4 the methodology used in this paper. Section 5.5 reports and discusses the results while Section 5.6 concludes.

5.2 Literature review

5.2.1 Fund size

There are lot of academic studies that investigate the relationship between hedge fund performance and hedge fund characteristics as fund size, age, management fees, and incentive fees and lock up periods. While the relationships between hedge fund size and its potential impact on fund performance is the most studied in the hedge fund studies, the conclusions and its impact of hedge fund size on performance are conflicting.

The link between the fund size and performance is important from the point view of the hedge fund manager as decision is made regarding the optimal size of the fund. From the investors' view point, the size of the hedge fund is one of the important characteristic to analyse before investing. Smaller funds face higher expenses and suffer diseconomies of scale. Some papers find that hedge funds beyond certain size will become inefficient to manage. When they execute trades, the ability of such funds to move the market arises and problems may occur in liquidating if the market is tough. The argument is smaller funds are more agile and more liquid and consequently perform better.

Using the TASS database from January 1994 to April 2005, Ammann and Moerth (2005) examine the impact of hedge fund size on fund performance. The impact of fund size relative to hedge fund returns, standard deviations, Sharpe ratios, and alphas derived from multi factor models is analysed. The authors find fund size is negatively related to returns when using the cross sectional regression. At the low end of the size spectrum or the very small funds, there is underperformance on average which the authors attribute to the higher total expenses ratios. Amenc et al. (2003) study various performance measurement models like standard CAPM, CAPM adjusted for stale prices, an implicit factor model derived from the principal component analysis to investigate the hedge fund characteristics on fund performance. The authors discover that the average alpha for large hedge funds is greater than the average alpha for small funds. These results are statistically significant, meaning that large hedge funds outperform small funds on average.

Boyson (2003a) examines how hedge fund managers' career concerns impact their decisions using various theories of reputation. The paper studies the link between fund size and performance after observing a manager's compensation is connected to both fund performance and size. She finds a positive relationship between fund size and fund survival and fund size and performance.

Using the TASS database from January 1994 until December 2002, Getmansky (2005) examine the relationship between industry and fund specific factors and the probability of hedge fund survival and performance. She discovers that hedge funds have hedge funds have an optimal size and exceeding that size has negative impacts on performance, in other words a positive, concave relationship between past fund asset size and current fund performance. For different hedge fund categories, the performance size relationship takes on different functional forms. Relatively more illiquid hedge fund strategies such as convertible arbitrage or emerging markets (when compared to liquid hedge fund strategies as equity long/short or dedicated short bias) are subject to limited opportunities and more likely to show a concave relationship between performance and fund size. The optimal size for these funds can be determined.

Edwards and Caglayan (2001) use the MAR database to examine the relationship between individual funds' excess returns and various fund characteristics from January 1990 to August 1998. Like Fama and French (1992 and 1990), excess returns are estimated using the multi factor model. The paper finds hedge fund performance rises at a declining rate as fund size increases.

Koh et al. (2003) examine the relationship between hedge fund size and performance in the Asian context. The authors regress monthly fund returns on stock characteristics in both the univariate and multivariate settings in the cross sectional Fama and MacBeth (1973) framework. Their findings show weak statistically insignificant relationship between fund size and fund returns. Malkiel and Saha (2005) use probit regression analysis to investigate the factors that cause the probability of a fund's demise. Their result shows a negative, highly significant coefficient for hedge fund size, smaller funds have a lower probability of dissolution than larger hedge funds.

5.2.2 Fund age

Assuming investors will not continue to retain and pay investment managers who underperform other managers and funds, according to Edwards and Caglayan (2001), the age or longevity of a hedge fund can illustrate the fund manager's skill.

Amenc et al. (2003) find the average alpha for newer funds is greater than the average alpha for older funds when different performance measurement models are used. Age is the length of time in operation prior to the beginning of their study. Most significant results are derived from the CAPM and explicit factor models while other varies. Using the cross sectional Fama and MacBeth (1973) framework, Koh et al. (2003) document no relationship between hedge fund age and performance. Edward and Caglayan (2001) on the hand find positive, statistically significant relationship for hedge fund strategies as global macro funds, global funds, and market neutral funds. Getmansky (2005) reveals that an increase in the hedge fund age is negatively related to fund flows. Brown et al. (2001) discover older hedge funds have a higher likelihood of survival. They use probit analysis to study hedge fund characteristics as absolute and relative performance, excess volatility, fund age and relate to fund termination. Using the same methodology, Liang (2000) finds younger funds have poor performance and smaller size funds have a higher chance of dissolution.

5.2.3 Performance fees

Edwards and Caglayan (2001) find that hedge fund performance is positively related to the performance fee charged. The authors argue that some of the positive excess returns generated by hedge funds can be explained by the fund managers' skill. This result challenges the mutual fund literature such as (Carhart, 1997b) that finds the negative relationship between high fees and fund performance. Amenc et al. (2003) also study the impact of incentive fees to fund performance. The funds are divided into two groups: one where the incentive fees are 20% or more and the other where the incentive fees are less than 20%. Various methodologies are used to study the relationship between incentive fees and fund performance. The findings show the average alpha for the second group is lower than the first group. Koh et al. (2003) find that hedge funds with lower performance fees show higher post fee return than funds with higher performance fees.

5.2.4 Other factors

Using a sample of 982 hedge funds in the TASS database, Boyson (2003) investigates the impact of manager's tenure on fund performance from the period January 1994 to December 2000. The underlying hypothesis is career concerns increase over time and as their career progresses, manager become more risk averse. Risk taking behaviour as measured in terms of manager tenure differs systematically among managers with different levels of experience. The results show that as managers' age, their risk taking behaviour increases. Compare to less experienced managers, they increase their volatility and herd less. More experienced managers tend to tolerate more risk resulting in higher returns for their funds. These results are consistent with theoretical evidence on agency costs and career concerns of hedge fund managers and also in line with the mutual fund industry.

Koh et al. (2003) investigate how the hedge funds' characteristics like redemption periods, size of holding companies and size of minimum investment affect fund performance.

In relation to performance, they find a statistically significant relationship to redemption period and holding company size. No significant relationship between fund performance and size of minimum investment is found. Schneeweis et al. (2002) find higher performance is associated with longer lock up periods for hedge funds adopting similar strategies than funds with shorter lock up periods. Redemption periods play a key role on fund performance.

5.2.5 Hedge fund survival and hedge fund characteristics

Various academic studies have linked the relationship between hedge fund characteristics to probability of hedge fund demise. Liang (2000) analyse the reasons for hedge fund resolutions using the TASS database and the probit regression. The probability of hedge fund demise is studied in relation to various hedge fund characteristics as average monthly returns, assets under management, managers' personal investments, incentive fees, management fees, fund age, and leverage ratios. The funds with smaller asset under management and younger funds with poor performance are more likely to dissolve. With the exception of management fees, the authors find statistically significant probability to fund characteristics. Brown et al. (2001) do a similar study with same database from the period 1994 to 1998. Industry benchmarks and poor hedge fund performance compare to the high water mark threshold increases the probability of fund dissolution. Hedge funds are more likely to shut down if the underperform the industry average. The authors reveal that risk and fund age have significant effects on hedge fund dissolution whereby relatively riskier and younger hedge funds are associated with higher probability of dissolution.

Malkiel and Saha (2005) also study the relationship between fund characteristics and the probability of fund demise through using the probit analysis and the TASS dataset. The hedge fund characteristics are slightly different namely: past performance, risk, past performance relative to the industry and fund size. In determining the probability of a fund's demise, the previous fund performance and risk are most important. Malkiel and Saha (2005) document that larger funds have a higher probability of dissolution which contradicts the finding of Liang (2000). Consistent with the previous literature, risker funds have a lower probability of survival.

Baquero et al. (2005) use the longitudinal probit method to study the liquidation process of hedge funds. Historical performance is an important factor to explain fund liquidation empirically while funds with high returns are much less likely to liquidate. They also find smaller funds are more likely to liquidate than larger funds and that fund age, investment style and magnitude of incentive fees are also related to hedge fund survival. Xu et al. (2010) use a probit analysis to the CISDM database to capture how hedge fund characteristics impact fund attrition. The period of study includes the financial crisis of 2007 to 2009. Older funds with better pre crisis performance and frequent audited funds have a higher probability of surviving the financial crisis and leveraged funds were more likely to close down. The fund characteristics tested include size, age, performance, risk, leverage and the regularity of an audit.

Brown et al. (2001) were the first to use the Cox model to study hedge fund mortality. They find younger hedge funds with low past return are more likely to fail consistent with the probit model. As well as, a strong relation between volatility and fund failure is documented.

This has implications for managers of hedge fund managers whose returns fall below the high water mark, as their incentives to increase volatility to improve future returns will be mitigated by the increased risk of fund failure arising from higher volatility.

Gregoriou (2002) applies survival analysis to the Zurich Capital Markets database from 1990 to 2001 to see if the explanatory variables explain the hedge fund failure. Various survival methods including the product limit estimate, the life table method, the accelerated failure time model and the semi parametric Cox (1972) proportional hazards model are used. While larger, low leveraged, better performing funds have a higher probability of survival, funds with a higher minimum investment requirement tend to die quicker.

Baba and Goko (2006) also use the survival analysis to study the individual hedge funds in the TASS database. Similarly various methodologies such as the non-parametric survival analysis, the Cox (1972) proportional hazards model with shared frailty and a logit analysis. They find large funds with higher returns, recent fund flows, lower volatilities, and higher skewness of returns and assets under management have a lower probability of failure. Funds with longer redemption notice period and a lower redemption frequency have a higher probability of survival. The authors did not find significant relationship between leverage and chance of fund survival.

Liang and Park (2010) compare the effectiveness of various downside risk measures to predict hedge fund failure. The result is funds with high historical performance and high water mark provisions are less likely to fail.

5.3 Data

I use the same databases: Eurekahedge, TASS and Morningstar like in previous two papers to investigate the relationship between the characteristics of hedge funds domiciled in the Asia Pacific and hedge fund survival. Following Xu et al. (2010) who argue that a set of 24 monthly returns guarantees adequate monthly observations for the estimation of performance and risk in the pre crises period, I select only those hedge funds that have complete monthly data.

The final dataset contains 3491 hedge funds domiciled in the Asia Pacific and includes information on such fund characteristics as fund size, inception date, fund location, management fee, performance fee, investment strategy, redemption frequency, notification period, lock up period, minimum investment and use of leverage. I record management fee, performance fee, lock up period, minimum investment and use of leverage as of January 2007 and assumed to be constant over the sample period. This assumption is unreasonable for the fund size characteristic as hedge fund size varies over time. Instead, I use the mean asset value of the fund in the pre-crisis period as a proxy for fund size.

In the hedge fund literature, the issue of survivorship bias is well documented. This bias is most visible in hedge funds returns prior to 1994. I gather both live and dissolved funds to reduce this bias. Reported returns can be affected as hedge funds operate in illiquid markets. To overcome this illiquidity bias, I use the desmoothed returns obtained from the Getmansky et al. (2004) procedure.

Since detailed information on defunct hedge funds is hard to retrieve, defining hedge fund dissolution is not that simple. The difference between failed and liquidated hedge funds is not clear in earlier studies. Fund liquidation does not necessarily imply fund failure as successful funds can be liquidated by hedge fund managers for a few reasons. Getmansky, Lo, and Mei (2004) differentiate the various reasons for fund exclusion from the database of live funds by using the status codes provided in the TASS database. Other than fund liquidation, fund exclusion can include: stop reporting, unable to contact, closed to new investments, merged into another fund, and dormant fund.

Three possible reasons for why successful hedge funds might liquidate without being considered as failures according to Liang and Park (2009). Firstly, hedge funds that successfully liquidate in anticipation of market crash should be treated as liquidated rather than failed funds. Secondly, after launching new funds, hedge fund managers could liquidate successful start-up funds. This is because the terms of the new funds can be defined in a more beneficial way by adding lock up periods or extending redemption frequency. Thirdly, some liquidated hedge funds should not be regarded as failed ad they have not failed terms of downside risk management.

5.4 Methodology

This section outlines the methods used to test the relationship between the probability of hedge fund mortality and fund characteristics. Given the widespread use of the probit model in the academic literature of hedge funds, I continue to use it and to check the robustness of my findings, I include the Cox semi parametric hazard rate regression.

5.4.1 Probit analysis

In the context of hedge fund mortality, a probit model can be used to explain how various fund characteristics or independent variables impact the dependent variable y_i. This y_i is binary in nature. It is constructed as dichotomous measure where the occurrence of the dissolution of the hedge fund during the crisis is coded 1, and the absence of the dissolution event is coded 0.

The easiest method of handling with dichotomous dependent variables is the linear probability model which is based on the assumption that the probability of an event occurring, P_i is linearly associated with a set of independent variables $x_{2i}, x_{3i}, \ldots. x_{4i.}$ The linear probability model is equivalent to the quantitative outcome dependent variables explained using linear regression analysis. The fitting of a binary dependent (y_i) to a set of explanatory variables using the linear regression framework is inappropriate as it will generate fitted values not restricted to lying between 0 and 1, required for the dependent variable. Using a function to overcome this limitation, a probit model transforms the regression model in a way that fitted values are bounded within the (0,1) interval. Under the assumption that the probability of y_i being equal to 1, the probit model is:

$$P(y_i = 1 \vdots x_i, \beta) = \emptyset(x_i'\beta)$$

The probability of y_i being equal to 0 is:

$$P(y_i = 0 \vdots x_i, \beta) = 1 - \emptyset(x_i'\beta)$$

Where $\emptyset(.)$ denotes the cumulative distribution function of the standard normal distribution. The probit analysis enables one to examine the probability of hedge fund demise as a function of some explanatory variables, $x_i' = (x_{1,i,\ldots\ldots,}x_{n,I})$. The probit model can then be rewritten as:

$$E(y_i \vdots x_i, \beta) = \emptyset = \emptyset(x_i'\beta)$$

The probit model can also be written in the form of the regression:

$$y_i = \emptyset(x_i'\beta) + \varepsilon_i$$

Where ε_i or the residual indicates the deviation of the y_i or the dichotomous variable from its conditional mean, x_i' are the variables that explain the probability of hedge fund death and β are the parameters to be estimated.

The methods to estimate the parameters involve nonlinear approaches such as maximum likelihood estimations procedures. Specifically, given the assumption of random exogenous sampling, the parameters of the probit model are estimated by maximizing the log likelihood function with respect to β:

$$\hat{\beta}=\sum_{i=1}^{N}(y_i\, ln\emptyset(x_i'\beta) + (1 - y_i)\ln(1 - \emptyset(x_i'\beta)))$$

The first order conditions for the likelihood equation, obtained by maximizing the log likelihood equation with respect of β are nonlinear. Hence, the parameter estimates are obtained by iterative solution. For statistical inference purposes, the asymptotic covariance matrix can then be estimated by using the inverse of the Hessian evaluated at the maximum likelihood estimates (Greene and Zhang, 2003).

There are several methods to test the goodness of fit of the probit model like in the linear regression framework. Even though the goodness of fit such as RSS or R^2 are easily calculable in linear regression framework, there is no meaning in the nonlinear probit model. Various other measures need to be computed to check the goodness of fit of the probit model. One of the measures is the percentage of y_i values correctly predicted by the model. According to Brooks (2008), this is the 100x number of observations correctly predicted divided by the total number of observations.

$$Percent\ correct\ prediction = 100/N \sum_{i=1}^{N} y_i I(\widehat{P_i}) + (1 - y_i)(1 - I_i(\widehat{P_i}))$$

Where $I(yi)$=1 if $\widehat{y_i} > \bar{y}$ and 0 otherwise. The higher the number, the better the fit of the model. Or, one can the pseudo R^2, a measure similar to R^2. This is defined as:

$$Pseudo - R^2 = 1 - \frac{LLF}{LLF_0}$$

Where LLF is the maximized value of the log likelihood function for the probit model and LLF_0 is the value of the log likelihood function for a restricted model in which all of the slope parameters are set to zero. Its value is always between 0 and 1. The pseudo R^2 is not good for comparing models with different sets of data even though it can compare difference specifications.

5.4.2. Cox semi parametric hazard rate regression approach

The Cox model is a regression based model to investigate the relationship between the multiple explanatory variables and the survival times in survival studies. The aim is to model time to event data whereby event is considered death and is operationalized through dichotomous variable. These analyses are longitudinal in nature and they enable for the effect of censoring and the dependency of survival times on explanatory variables. Essentially, survival analysis enables one to examine the probability of a hedge fund failure given some explanatory variables. Survival analysis estimate how is the duration of life time hedge funds domiciled in the Asia Pacific influenced by explanatory variables as funds' past monthly returns, volatility, age, size, management fees, use of leverage and lock up periods.

Traditional statistical models such as multiple linear regressions are not suitable as due to censoring and non-normality which are both characteristic of survival data. A standard normal distribution is symmetrical by nature as it includes both positive and negative values. Survival data (duration), only assumes positive values and thus violates the normality assumption. Timmermann et al. (1999) suggest the probit analysis is too restrictive. They encourage the use of the Cox hazard rate regression approach. The Cox method does not require the exact nature of the survival function. The problems with Cox are the restrictive assumption of proportional hazards for explanatory variable effects and the loss of the baseline hazard function.

Multiple regression methods do not account for censoring. The databases include censored funds because it includes both dead and live funds. Censored observations occur when the dependent variable exemplifies the time to the terminal event and the duration of the study is limited. Thus, the event of interest is very rarely observed in all subjects. If the period of observation expires or the subject is removed from the study prior to the event of interest occurs, it is known as right censoring. Censoring arises in the context of survival analysis of hedge funds. Some hedge funds die during the observed period which is immediately registered in the database together with the time of death, thus making the lifetimes of these hedge funds fully transparent. Funds that are still alive and operating at the end of the observation period are censored as the exact time of their death is unknown. Not including these censored funds in the analysis will generate a downward bias of the sample's survival time as the lifetimes of censored funds also provide important relevant information relating the overall hedge fund survival.

I define hedge fund's survival time or duration as a random variable denoted by T whereby T>0 from Gregoriou (2002). The entry date by hedge fund to the database is denoted as zero. Lastly, the survival function, denoted as S(t) shows the probability that the hedge fund will survive longer than time t:

$$S(t) = P(T > t)$$

Another important feature of the survival model is the hazard rate, represented as $\gamma_t = \lim_{\Delta t \to 0} \frac{P\{t \leq T < t + \Delta t : T \geq t)}{\Delta t} = \frac{f(t)}{S(t)}$

The hazard function is a derivative of the survival function. They converted to each other hence. In short, the survival study is to estimate hazard function $\gamma_i(t)$ using the semi-parametric Cox regression approach. Cox's method is similar to the multiple regression approach except the dependent variable is the hazard function:

$$\gamma(t) = \gamma_0(t)\exp(age\beta_1 + perf\beta_2 + stdev\beta_3 + size\beta_4 + lev\beta_5 + mnfee\beta_6 + perffee\beta_7 + hwm\beta_8 + redfreq\beta_9 + lockup\beta_{10} + mininv\beta_{11} + listed\beta_{12})$$

Where the quantity $\gamma_0(t)$ is the baseline hazard function and is equal to the probability of fund dissolution when all the covariates are zero. The value of the hazard function corresponds to the product of the baseline hazard and a covariate effect. The baseline hazard function is similar to the intercept in the ordinary multiple regression. The covariate effect is the same for all time points while the baseline hazard is dependent upon time. The ratio of their covariate effects is the ratio of the hazards of any two cases at any point in time. β_1 to β_7 show the proportional change that can be expected in the hazard relative to changes in the explanatory variables. The assumption for the Cox model to work is the constant relationship between the dependent variable and the explanatory variables.

The main aim of the Cox model is not to retrieve actual estimates of survival times. Instead, it is carried out to determine the relative influence of explanatory variables on survival. Hazard ratios help in the assessment. If it is greater than one, it means a decrease in survival. To test the strength of the relationship between the explanatory variable and the dependent variable, the magnitude, significance and direction of each beta are used.

5.4.3 Explanatory variables

The main aim of this paper is to investigate empirically the extent that certain hedge fund characteristics explain the survival of hedge funds. The explanatory variables used in this analysis are described and likewise the motivation for inclusion.

Previous academic literature when studying the attrition of hedge funds include the following characteristics as performance, risk, fund size, age, leverage, fees, high water marks, lock up provisions, minimum investment size and listing on an exchange. The decision to include performance and risk as independent variables of hedge fund survival is simple. According to Liang (2000), Brown et al. (2001) and Malkiel and Saha (2005), funds with lower risk and better performance are less likely to close down. While the risk is measured by the standard deviation of returns over the sample period, the performance of the hedge fund is estimated by average monthly returns during the period. In the academic literature, the influence of fund size on attrition of hedge fund is ambiguous. Since bigger hedge funds have a larger and more stable asset base, size can be beneficial for fund survival. Malkiel and Saha (2005) use AUM recorded in December 2005 to represent size and held this fixed over the period study. In contrast, they find smaller, nimbler hedge funds are more likely to survive.

In the studies of fund survival, leverage is another important hedge fund characteristic often discussed. Hedge funds that use leverage will be at a higher risk of liquidation that those funds that do not. The extensive use of leverage by hedge funds is widely perceived as volatile (Baba and Goko, 2006). The databases contain a binary variable of yes or no for leverage. Similarly, I treat leverage as a fixed binary variable with 0 meaning no use of leverage and 1 meaning the use of leverage. Survival analysis can also be linked to the age of hedge fund.

I use the independent variables as management fee, performance fee and high water mark to examine the effect of the incentive structure on the attrition probability of hedge funds. Performance fee is an idiosyncratic feature of the hedge fund industry while management fee is paid to all fund managers. As a result of the convexity in compensation it creates for fund managers, participants believe that high performance is associated with more risk (Panageas and Westerfield, 2009). In short, high performance fees increase the risk associated with hedge funds and hence increase the probability of liquidation.

Another feature to protect the investor is the high water mark. It laids out the potential payout of the performance fee when the share price is greater than its previous highest value. The manager is required to bring the value back above the previous level before he or she can receive the performance fees when the investment drops in value. The relationship between the liquidation probability of hedge funds and high water mark provisions is not clear. While high water mark provisions can provide fund managers an incentive to manage funds more prudently, they can increase the risk taking behaviour of managers, leading to an increased probability of liquidation. Panageas and Westerfield (2009) find that the managers' risk taking behaviour depends on the time horizon they have. If the time horizon is finite, their model predicts more risk taking behaviour.

I also link the impact of lock up period and redemption frequency with hedge fund survival. Investors are concerned as the presence of lock up period and a lower redemption frequency illustrate a lower liquidity for investment. In relating the impact of lock up periods and redemption frequencies to the survival of hedge funds, there are two opposing hypotheses. The first hypothesis argues that hedge funds with lock up provisions and longer redemption frequencies have more control over unforeseen outflows that could have destabilizing effect on fund survival. On the other hand, the second hypothesis state that lock up provisions and long redemption periods prevent fund managers from increasing their assets under management. Such liquidity constraints deter investors to invest in them.

The other factor I consider to impact on hedge fund dissolution is the minimum required investment. Hedge funds are more likely to experience larger outflows, therefore destabilizing funds' operations if they have a higher minimum investment. Alternatively, funds are more likely to have smaller outflows and more risk adverse investors if they have smaller minimum investment amounts.

I also examine the survival of hedge funds relative to being listed on an exchange. This status is beneficial for hedge fund managers. There is no risk of fund withdrawal at unfavourable times as the investor capital is tied up. Using the Barclay Hedge database, Gregoriou et al. (2009) discover that compare to the non-listed funds, the listed hedge funds tend to survive on average approximately two years longer. The period used is from 2000 to 2007. Similarly, I expect the dichotomous variable as to whether the fund is listed or not to have a positive effect on the hedge fund survival.

5.5 Results

The probit method models the chances of hedge fund dissolution as a function of specified idiosyncratic fund characteristics. The dependent variable is a binary, with the value of 1 if the fund is defunct and 0 if the fund is live. A negative coefficient for an explanatory variable shows that a higher value of that variable decreases the chances of fund dissolution. Using the maximum likelihood method, the coefficients for the probit model are estimated. The probit model is too restrictive in its strong distributional assumptions. Timmermann et al. (1999) prefer the use of Cox semi parametric hazard model. The following sections show the results derived from the probit regression and the Cox semi parametric proportional hazard model.

5.5.1. Probit regression analysis

Table 5.1 reports the results obtained through the probit regression analysis. I find older hedge funds domiciled in the Asia Pacific have a higher probability of survival with the coefficient estimate for age negative and statistically significant at 1%. Larger funds with better performance has a higher probability of survival as the coefficients for fund size and mean returns are negative and significant at 1%. Surprisingly, the coefficients for standard deviation and leverage are negative and statistically significant at the 5% level. These mean funds that use leverage and have highly volatile returns are more likely to survive. This is unexpected as many recent hedge fund failures have been associated with excessive use of leverage and volatility in returns. I discuss the effect of leverage and standard deviation in more detail later.

Funds with lower redemption frequency have a higher probability of survival as the coefficient for redemption frequency is positive and significant at the 5%. The listed hedge funds domiciled in the Asia Pacific have a lower probability of survival as the coefficient is positive and significant at the 1%. This finding is in contrast to Gregoriou et al. (2009) where they associate the lower probability of liquidation with listed hedge funds. The independent variables that make up the incentive structure aspect of hedge fund investing such as management fee, performance fee and high water mark are insignificant. Likewise, the lock up and minimum investment variables also gave insignificant coefficient estimates. Table 5.1 reports the parameter R^2 from the probit regression of hedge fund failures.

Table 5.1 Probit analysis

Variable	Coefficient	Std. Error	Z statistic	Prob.
Intercept	0.39	0.26	1.53	0.13
Age	-0.01	0	-5.42	0
Mean return	-0.39	0.06	-6.43	0
Standard deviation	-0.03	0.02	-2.05	0.04
AUM	0	0	-3.95	0
Leverage	-0.19	0.08	-2.22	0.03
Management fee	-0.15	0.1	-1.5	0.13
Performance fee	0.01	0.01	1.01	0.31
High water mark	0.11	0.16	0.72	0.47
Redemption frequency	0	0	2.74	0.01
Lock up	-0.2	0.14	-1.47	0.14
Minimum investment	0	0	-0.25	0.81
Listed	0.35	0.09	3.84	0
Pseudo R^2	17			

5.5.2 Cox regression analysis

Table 5.2 displays the results of testing the Cox semi parametric proportional hazard model to the hedge fund domiciled in the Asia Pacific. This model produces similar results to the probit regression model. The negative estimated coefficient for the explained variable in the Cox model or the hazard rate means the variable lowers the hazard rate. The mean returns are statistically significant predictor of the chances of fund failure at the 1% as the mean of fund returns is negative and highly significant. With the standard deviation, the estimated coefficient is consistent with the results from the probit model. It is negative and statistically significant meaning that a higher level of standard deviation leads to a lower chance of fund dissolution. This finding contradicts the pervious literature and reasons will be outline later.

Larger assets under management have a lower probability of failure since the size coefficient is negative and significant at the 1%. Funds with a higher redemption frequency face a higher probability of failure as the coefficient is positive and significant at the 5%. The estimated coefficient for leverage is negative but statistically insignificant. Likewise, the coefficients for management and performance fees, high water mark, lock up, minimum investment and the exchange listed variable are not statistically significant (refer to Table 5.2). Higher redemption frequency cause harm to the survival probability of hedge funds as the coefficient is positive and statistically significant.

In the Cox proportional hazard model, the hazard ratio enables the survival of different levels of explanatory variables to be compared. A hazard ratio higher than 1 implies that the independent variables have a negative effect on survival time or that a higher value of independent variable will lead to a shorter survival time. The opposite is true. A hazard ratio lower than 1 means positive effect on survival time – a higher value of an independent variable implies a longer survival time. While the hazard ratio for redemption frequency is greater than one, the hazard ratios for funds' mean returns, sizes, and standard deviations are all lower than one. The results are consistent with the literature except the hazard ratios for standard deviation which in the literature assumes a value higher than 1, meaning the higher volatility is harmful for fund survival.

Table 5.2 Cox proportional hazards regression analysis

Variables	Estimate of regression coefficient	Standard errors	Wald	Sig.	Hazard ratio
Mean return	-0.65	0.04	266.83	0	0.52
St. dev. Return	-0.14	0.02	46.68	0	0.87
AUM	-0.01	0	59.66	0	0.99
Leverage	-0.1	0.09	1.26	0.26	0.9
Management fee	0.18	0.12	2.12	0.15	1.19
Performance fee	0.02	0.01	2.73	0.1	1.02
High water mark	0.09	0.17	0.28	0.6	1.09
Redemption freq.	0	0	4.27	0.04	1
Lock-up	0.11	0.16	0.47	0.49	1.12
Minimum investment	0	0	0.88	0.35	1
Listed	0.04	0.1	0.19	0.66	1.05

5.5.3 Discussion

In this chapter, I confirm empirically the results found in most academic studies on hedge funds. The result is expected and intuitive as better performing funds are associated with lower probability of liquidation. The positive effects are not obvious when the likelihood of fund survival is tested on the fund volatility as measured by the standard deviation of returns. The higher volatility is often linked to higher probability of closure by the market participants. In contrary to most of the academic literature, using both the probit and Cox models, I find higher standard deviation enhance chances of fund survival. This may be explained by the nature of the databases. The group of surviving funds compare to the group of defunct funds has a higher standard deviation over the full sample period. This can be problematic as it leads to wrong conclusion that defunct hedge funds are less risky than surviving hedge funds.

I break the full sample period into two parts, with the breakpoint set as the start of the financial crisis in February 2007 to analyse the result further (Xu et al., 2010). I find the pre-crisis average standard deviation is lower than for surviving funds than for dead funds. Upon examining the databases, I noted most the dead funds in the databases do not have returns from 2007 to 2010, a period of highly volatile investment climate. The volatility for dead funds is lower than the surviving funds as most of the dead funds do not have returns during that period. The coefficient for standard deviation loses its statistical significance when the probit model is re run on the pre-crisis period from January 1994 to February 2007.

Funds that use leverage have a higher probability of survival based on the probit model as the coefficient is negatively significant. This is new as one would expect highly leveraged funds to have a higher chance of dissolution. The databases do not show the amount of leverage except whether the fund uses leverage. The leverage variable has no significant effect on liquidation hazard ratios according to the Cox model.

In my sample of hedge funds domiciled in the Asia Pacific, the incentive structure to explain the effect on the mortality rates using both models is zero. The coefficients for management fees, performance fees and high water mark policies are insignificant under the probit and Cox models. The variable to proxy for minimum investments is also insignificant in both models. I find that lower redemption frequency lowers the probability of hedge fund dissolution similar to Baba and Goko (2006). The lower liquidity relative to fund survival hypothesis is supported.

5.6 Conclusion

In recent years, institutional investors such as pension funds, governments have come to represent a significant proportion of hedge fund investors. The issue of hedge fund survival is crucial interest for them as it linked to their capital preservation/loss in the long term horizon. For these institutional investors it is important to choose hedge funds that will produce consistent returns.

While the previous chapter examines the issue of how to identify hedge funds that produce persistent returns, this chapter focuses on the likelihood of hedge fund survival and hedge fund selection. The period used is from January 1994 to June 2012. Various academic studies investigate the issue of hedge fund survival, but none examines in the context of hedge funds domiciled in the Asia Pacific.

To find the factors that influence the survival and mortality patterns of these hedge funds, I use both the parametric probit regression model and the less restrictive semi parametric Cox proportional hazard model. Firstly, the two models gave conflicting results on the impact of leverage on hedge fund survival. While the Cox model shows that leverage has no effect on hedge fund survival, the probit model displays that higher leverage is beneficial for fund survival. Secondly, the incentive structure of hedge funds (management fees, incentive fees, and lock up provisions) does not have an effect on fund survival. Thirdly, there is a positive relationship between standard deviation and survival of hedge funds. One of the possible reasons is that the defunct funds died before the global financial crisis began in 2007. Last but not the least, larger, better performing funds with lower redemption frequency is related to higher likelihood of survival in line with extant literature.

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