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The Effect of the GFC on Modelling and Predicting Financial Distress in Hedge Funds

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〈요 약〉

The aim of this study is to identify the effect that the recent Global Financial Crisis (GFC) has had on the financial distress in hedge funds, and the effect on the reliability of accepted models in Lee (2010) to predict financial distress across a time horizon that includes GFC. A mixed Cox proportional hazard (CPH) model used in Lee (2010) is used to identify the covariates that lose and gain importance in the prediction of failure for hedge funds because of the GFC. Based on model estimations over the period that includes the GFC and the period prior to the onset of the crisis, we can identify the factors that generated financial distress of hedge funds during the GFC. Additionally, to evaluate model robustness, we compare the predictive ability of the models for each period. An improvement in forecasting skill in the GFC-inclusive period highlights a benefit of the mixed CPH model.

주제어 : Hedge Funds, Financial Distress, Mixed Cox Proportional Hazards Model, Model Robustness, Global Financial Crisis

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Ⅰ. Introduction

The global financial crisis (GFC) that hit the world in 2008 is considered by many economists and financial analysts to have been the worst financial crisis since the Great Depression of the 1930s. Experts have assigned varying weights to the suggested possible causes for the GFC. Such causes include the collapse of large financial institutions such as Lehman Brothers, Merrill Lynch, and HBOS, the bailout of banks by national governments, and downturns in global stock markets. In 2008, hedge funds were exposed to a variety of risk factors as a result of the tumultuous financial event. It is assumed that many hedge funds suffered financial distress because of the effect of the global financial markets during this period. The influence of hedge funds on financial markets is well documented in previous studies in the academic literature and in practitioner and broadsheet publications (Boyson, Stahel, and Stulz, 2010). One unanswered question, however, is the effect that the GFC has had on the financial distress experienced by these important financial vehicles, along with the reliability of accepted models to predict financial distress across a time horizon that includes such a tumultuous financial event.

The current research extends Lee (2010) by focusing on the effect of the recent GFC on the modelling and predicting financial distress in hedge funds. A primary objective of this paper is to identify the effect that the GFC has had on the financial distress experienced by hedge funds, in addition, of paramount interest in this study is a robustness evaluation of the model adopted in Lee (2010) to predict the financial distress of hedge funds from January, 1990 to December, 2009. This period includes the period of the GFC that started to show its effects from the middle of 2007 and during 2008. The "robustness" of the model in this research refers to the extent to which predictive ability of the model is affected by including the GFC period in the sample. Our concern in this study is as to whether the model predictive ability is impervious to the tumultuous financial event. In this study, therefore, modeling and prediction are confined to the period from January 1990 to July 2007. It is assumed that this period was free of the underlying effects of the GFC. Further analysis that includes data for the period up until December 2009 makes it possible to evaluate model robustness and to identify significant predictors that hold across both periods rather than predictors that are only significant for one of these time periods. We can therefore identify the effects of GFC on modeling and predicting financial distress in hedge funds.

The current study utilizes a survival analysis approach to build a model to predict the financial distress of hedge funds. The survival analysis framework is chosen because it is primarily concerned with predicting the probability and timing of a particular event. The event of interest in this study is defined as the state when a fund changes from survival to failure. A number of existing academic studies focus on hedge fund failure and employ survival analysis. These studies include those by Brown, Goetzmann, and Park (2001), Bares, Gibson, and Gyger (2001), Boyson (2002), Gregoriou (2002), Rouah (2005), Grecu, Malkiel, and Saha (2007), Chapman, Stevenson, and Hutson (2008), Ng (2008), Baba and Goko (2009), Brown, Goetzmann, Liang, and Schwarz (2009) and Liang and Park (2010). All of these studies use the Cox proportional hazard (CPH) model to examine the factors that impact hedge funds and that contribute to their failure.

Two databases, one for "live funds" and one for "dead funds", which are provided by Hedge Fund Research Inc. (HFR), are used together with a mixed Cox proportional hazard (CPH) model, which utilizes time-varying covariates and fixed covariates. This mixed CPH model is analyzed using data for the period leading up to the GFC as well as for the period that includes it. Using model estimations for each of the two periods, we can identify the factors that led hedge funds to experience financial distress during the GFC. Additionally, the study compares the predictive ability of the models for each period to evaluate model robustness.

Our results indicate that the mixed CPH model offers a high level of predictive capability with respect to hedge fund failure for the GFC period and that the estimated model shows robustness over the GFC period as compared to the period leading up to the onset of the crisis. Although there are groups of covariates that remain important predictors for both periods, some covariates become apparent as significant predictors for the period that includes the GFC. These results provide insight into the role of certain covariates in determining financial distress in hedge funds during the GFC. Identifying the effect of the GFC on modelling and predicting financial distress in hedge funds provides significant benefits to investors and regulators in crisis-prone financial markets where the risks of investing in hedge funds are a significant concern.

Ⅱ. Background Literature

Financial distress and lifetime of the hedge funds have been interesting topics in the literature. Earlier work in this area used qualitative response models with dichotomous dependent variables such as probit or logit models. Since the study by Brown, Goetzmann, and Park (2001), many studies adopt survival analysis to research the lifetime of the hedge funds. Survival analysis estimates the probability of the time to default and allows the production of profiles of default probabilities of funds

Brown, Goetzmann, and Park (2001) examine the influence of performance and risk of fund termination using both the Cox (1972) proportional hazard and the probit regression models. Relative and absolute performance over multiple periods, volatility and seasonality of returns are employed as covariates in the regression models. They find that hedge funds with relatively poor performance or higher risk are more likely to terminate.

Boyson (2002) examines the effects of a manager's characteristics on hedge fund performance, volatility and survival. This study first examines the cross-sectional relationship between manager characteristics and hedge fund performance, controlling for fund characteristics and systematic market exposure and concludes that manager tenure and having an MBA is negatively related to performance. Additionally, Boyson (2002) investigates the relationship between manager characteristics and fund failure shows that the survival probability increases significantly with manager tenure and manager age, suggesting that older and longer-tenured managers take on less risk than their shorter tenured counterparts in order to survive, even at the cost of lower returns.

Gregoriou (2002) includes a range of covariates to explain a fund's survival lifetime and finds that fund size has an important impact on survival time with those funds above the median size being associated with longer survival times. Low leverage funds are found to be more likely to survive longer than high leverage funds, while funds with higher minimum purchases tend to fail faster. Notably, funds with annual redemptions are inclined to have longer survival times.

Rouah (2005) aims to reconcile important issues about the treatment of all funds that exit the database as failed funds. Rouah's study applies a competing risks model to account for the different reasons hedge funds cease reporting, rather than aggregating all the reasons into a single homogeneous group. The author argues that separately treating exit type, or the reason for discontinuing reporting, is essential in order to avoid blurring the effect of predictor variables on fund's survival. Another improvement in the analytical method offered by this study is incorporating time-varying covariates in the standard Cox (1972) proportional hazard model.

Further insight into the factors impacting on hedge fund liquidation is provided by Baba and Goko (2009). Baba and Goko (2009)'s analysis reveal the significant effects of return properties such as mean, variance and skewness, and AUM on the funds' survival probabilities. The effect of recent fund flows is found to be important to hedge fund survival. They show that higher survival probability of funds is associated with higher recent fund flows. Interestingly and contrary to previous studies, Baba and Goko (2009) do not find a significant effect of leverage on hedge fund survival.

Liang and Park (2010) compare downside risk measures which consider higher moments of funds' return with standard deviation in predicting hedge fund failure. Using the Cox (1972) proportional hazard model, the study examine the effects of historical risk patterns, prior performance, size, age, leverage, style, high water mark, personal investment and lockup provision on fund survival. The risk measures incorporated in the model to compare with the standard deviation include semi-deviation, nonparametric Value-at-Risk (VaR), Cornish-Fisher VaR, nonparametric expected shortfall, Cornish-Fisher expected shortfall, nonparametric tail risk and Cornish-Fisher tail risk. Liang and Park's study produce three major findings. Firstly, the downside risk measures such as expected shortfall and tail risk are superior to the standard deviation in terms of predicting hedge fund failure. Secondly, in line with previous research, liquidation do not necessarily mean failure in the hedge fund industry. Finally, the effects of performance, age, size, high water mark and lockup provision on hedge fund failure are clarified. Performance and high water mark are identified as significant determinants of fund failure irrespective of the failure definition, while the impact of age, size and the lockup provision change depending on the definition of failure.

Ⅲ. Data and Summary Statistics

It is difficult to identify a representative hedge fund database among a number of hedge fund databases. It is well known that hedge funds report their information only on a voluntary basis due to limited regulatory oversight. Since hedge funds are not permitted to advertise publicly, they report fund information voluntarily to a data collection agency in order to attract potential investors. As a result, conflicting results of studies based on different databases have been produced (Ackermann, McEnally, and Ravenscraft, 1999; Brown Goetzmann, and Ibbotson; 1999, Malkiel and Saha, 2005). This makes the comprehensive nature and integrity of hedge fund data questionable.

This paper utilizes the Hedge Fund Research Inc. (HFR) database that is commonly used by academics and practitioners.[1] HFR provides two separate databases : the dead fund database and the live fund database. The live fund database includes information concerning all hedge funds that currently report to HFR. The dead fund database provides corresponding information about those hedge funds that have discontinued reporting to HFR. From these two databases, the number of funds that change their status from live to dead can be determined.

1. Attrition Rate

The attrition rate is defined as the percentage of hedge funds that exit the database. The ratio is calculated by dividing the number of funds that exit during a given period by the number of funds at the beginning of the period. Grecu, Malkiel, and Saha (2007) demonstrate that most funds stop reporting because of poor performance, although some funds exit the database for other reasons, such as no new investment, a merger with another fund, or reorganization. <Table 1> presents the annual attrition estimates for hedge funds for the years 1997 to 2009. The new funds are funds that join HFR during the given period, and the dead funds are those that stop reporting to HFR during the given period.

1) The database used in this study does not include Korean hedge fund data.

<Table 1> Hedge Fund Attrition Rate, 1997 to 2009

This table shows the number of funds at the beginning and end of the year, the number of new funds and dead funds, and the attrition rate. The attrition rate is calculated as the number of funds exiting during a given year divided by the number of funds at the beginning of the year. The HFR estimates that there are 2,781 hedge funds at the end of 1996, and this figure is used as the number of funds at the beginning of 1997.

Year	Year Start	New Funds	Dead Funds	Year End	Attrition Rate
1997	2,781	396	207	2,970	7.44%
1998	2,970	400	354	3,016	11.92%
1999	3,016	267	232	3,051	7.69%
2000	3,051	358	359	3,050	11.77%
2001	3,050	427	278	3,199	9.11%
2002	3,199	801	277	3,723	8.66%
2003	3,723	966	342	4,347	9.19%
2004	4,347	1,418	430	5,335	9.89%
2005	5,335	1,813	628	6,520	11.77%
2006	6,520	1,665	841	7,344	12.90%
2007	7,344	1,765	1,058	8,051	14.41%
2008	8,051	1,224	1,964	7,311	24.39%
2009	7,311	1,508	1,056	7,763	14.44%

The last column in <Table 1> demonstrates that the yearly hedge fund attrition rates range from 7.44% to 14.44% except during the year 2008. More than 24% of hedge funds exited the HFR database in 2008, and it can be assumed that this significant attrition rate occurred because of the effect of the GFC. During the GFC, the number of dead funds (1,964) is notably greater than the number of new funds (1,224). This results in a substantial increase in the attrition rate from 14.41% in 2007 to 24.39% in 2008.

2. Pre-GFC Funds vs. GFC-Inclusive Funds

The dead and live fund databases used in this study cover two distinct periods. The first period is from January 1990 to July 2007 and is a period that is assumed to be essentially free of the GFC effects. This period will be referred to in this study as the pre-GFC period. The second period spans from January 1990 to December 2009 and is the period that contains the GFC and its aftermath. In this study, the second period is denoted as the GFC-inclusive period. During the pre-GFC period, the live fund database includes 2,503 funds, whereas the dead fund database contains 1,601 funds.

However, for the GFC-inclusive period, only 2,003 live funds remain, whereas the number of dead funds increases to 2,303.[2)]

The first step in the analysis is to filter the sample of funds from the raw HFR database. This initial filtering process includes restricting funds to those with a minimum of 36 months of data to guarantee a sufficient number of observations for the estimation process.[3)] This filtering also ensures that all funds in the sample are hedge funds that do not seek short term and high-risk objectives. To ensure data consistency, those funds that do not report returns net of all fees to HFR on a monthly basis or that have missing data are deleted. After filtering, the pre-GFC sample data include information for 1,590 live funds and 647 dead funds. In the GFC-inclusive sample, there are 1,484 live funds and 1,329 dead funds. There is a reduction of 106 live funds from the pre-GFC period to the GFC-inclusive period, and the adverse effect of the GFC on hedge funds is demonstrated by the more than two-fold increase in the number of dead funds. Simply based on the numbers, we can see that the GFC has a dramatic effect on the number of hedge funds that fail to continue to report to the data vendor. This study addresses the number of non-reporting funds that suffer financial distress in a later section.

A number of hedge fund characteristics are included in three information tables that are available from the HFR databases. The administrative table contains a variety of information with respect to each fund. Based on this information, hedge funds are categorized according to their type of investment strategy. The four possible types of investment strategy are equity hedge, event driven, macro, and relative value arbitrage. The other information in this table includes inception dates, minimum investment requirements, redemption policy, fee structure, leverage, and domicile. Several fund characteristics that are included in the administrative table are incorporated into the mixed CPH model as fixed covariates. They include minimum investment, leverage,

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2) The backfilled return and AUM data that covered the period before each fund's initial date of entry into the HFR are removed from the databases to avoid backfill bias. Additionally, two index funds and funds-of-hedge funds are deleted from the database to make hedge funds distinct from portfolio hedge funds.

3) Gregoriou (2002), Chapman, Stevenson, and Hutson (2008), Ng (2008), Baba and Goko (2009) and Liang and Park (2010) apply similar minimum observation requirements and report no resulting sample selection biases. The same analysis in this paper is conducted with funds with a minimum of 24 months of data to determine the sample selection bias, and no bias is found.

management fee, incentive fee, high water mark, hurdle rate, redemption period, notice period, lockup period, domicile[4], and strategy. The return and size of each fund are provided in a performance table and an asset table, respectively. The latter two time series represent the data incorporated as time-varying covariates in the mixed CPH model. <Table 2> compares the descriptive statistics of the covariates incorporated into the prediction models for the pre-GFC and GFC-inclusive periods.

<Table 2> Statistics for Fixed-Time and Time-Varying Covariates

The statistics for minimum investment, management fee, incentive fee, redemption period, notice period, and lockup period are average values for each fund group. The dollar value of the management fee obtained by a fund manager is calculated by multiplying the percentage by the average assets under management over the fund's entire life. The incentive fee is first calculated by multiplying the fund's average monthly return by the average monthly assets under management to evaluate the profit per month over the fund's lifetime. This figure is then multiplied by the percentage of the incentive fee to calculate the dollar value of the incentive fee obtained by a fund manager. The statistics for leverage, high water mark, hurdle rate and domiciled offshore are percentages of funds for each group. Average monthly return and average monthly assets under management (AUM) are time-varying covariates for each fund group.

	Pre-GFC (Jan 1990-Jul 2007)			GFC-Inclusive (Jan 1990-Dec 2009)		
	Live	Dead	Combined	Live	Dead	Combined
Number of Funds	1590	647	2237	1484	1329	2813
Minimum Investment (US$)	1,088,651	712,794	979,943	1,249,461	906,218	1,087,296
Leverage (%)	71.89	70.17	71.39	69.95	72.01	70.92
Management Fee (US$)	1,605,407	645,529	1,327,785	3,271,953	1,186,203	2,286,542
Incentive Fee (UD$)	235,000	98,555	195,537	368,513	103,424	243,272
High Water Mark (%)	92.20	90.26	91.64	91.51	89.01	90.33
Hurdle Rate (%)	15.28	17.62	15.96	13.95	15.53	14.61
Redemption Period (days)	75.46	79.51	76.63	71.46	71.60	71.53
Notice Period (days)	34.93	32.67	34.28	36.04	33.45	34.81
Lockup Period (days)	131.34	128.38	130.48	123.82	112.69	118.56
Domiciled Offshore (%)	53.14	51.16	52.57	55.66	51.32	53.61
Average Monthly Return (%)	1.11	0.94	1.06	0.68	0.50	0.59
Average Monthly AUM (MUS$)	156.37	82.34	134.96	222.53	88.18	159.06

The effect of the GFC on fund characteristics that are used as covariates in prediction models can be readily observed through changes in the statistics for the time-varying and fixed-time covariates from the pre-GFC period and the GFC-inclusive period. The covariate statistics in <Table 2> make it possible to analyze the differences between

4) The domicile indicates whether a fund is offshore (from the US).

live and dead hedge funds during a period of financial market stability (from December 1990 to July 2007) as well as during the period that includes the ramifications of the GFC (from December 1990 to December 2009). These differences are discussed below.

Minimum investment is the smallest dollar entry cost that is imposed by hedge funds on new investors seeking to join a fund. This amount increases markedly for both live and dead hedge funds during the GFC-inclusive period. A possible explanation for this increase is the increase in fund size as measured by monthly average assets under management (AUM) across the GFC-inclusive period. As the funds grow in size, so does the requirement for minimum investment.

The contribution of leverage to the financial distress of hedge funds is a debated topic in the literature after conflicting findings in a number of past studies. For example, Gregoriou (2002) finds that less leveraged funds are more likely to survive than their highly leveraged counterparts. The data in Gregoriou's study span January 1990 to December 2001, a period that is not considered to be influenced by the GFC. However, Baba and Goko (2009) challenge the findings of Gregoriou (2002) they find that leverage is not a significant factor in hedge fund financial distress. Their data period utilizes live and dead fund data from January 1994 to December 2005, a period that is also unaffected by the GFC. The HFR database provides information concerning funds' leverage usage and whether this leverage is limited with a maximum ratio. <Table 2> demonstrates that whereas leverage usage has dropped for live hedge funds over the GFC-inclusive period, there has been an increase in leverage usage with respect to dead hedge funds. It would appear that higher leverage is a factor that has affected the number of hedge funds that join the dead fund database as a consequence of the GFC.

Fee structure includes a management fee, incentive fee, high water mark and hurdle rate. The high water mark provisions allow managers to earn incentive fees only after they recoup all past losses, and the hurdle rate is the minimum rate (e.g., the Treasury rate or the LIBOR) that managers should achieve to earn an incentive fee. <Table 2> presents the percentages of funds with a high water mark or hurdle rate provision within each group, which decrease when the GFC is considered. This decrease in the fee structure for funds is to be expected because a severe downturn in an economy will eventually cause hurdle rates to be revised downward and will also generate a corresponding decrease in the number of funds with a hurdle rate or high water mark provision. The management and incentive fees are percentage rates that fund managers charge; both increase substantially throughout the period that includes the GFC. This process is repeated for both the live and dead categories. With the substantial increase in live funds (as measured using the AUM) during the period from July 2007 to December 2009, higher management fees are a logical inevitability. It follows that for a fund with a hurdle rate provision, the incentive fee can be charged based on the profit from investment above the hurdle rate. Accordingly, an increase in the incentive fee for hedge funds in the GFC-inclusive period could be explained by a combination of a decrease in the hurdle rate and (at the least) sustained profitability in the surviving and larger live hedge funds.

The effect of the GFC on redemption policy (or liquidity) is exhibited by differences in the redemption, lockup and notice periods. The lockup period is the length of time during which a new investor is prevented from redeeming assets, whereas the notice period is the number of days in advance that an investor is required to notify the fund before redeeming its assets. The redemption and lockup periods in days decrease during the period affected by the GFC, whereas notice period seems to be unaffected by the GFC.

The most notable differences in the statistics for the two periods are the differences in performance (return) and size (AUM). The drop in average monthly returns for live hedge funds for the GFC-inclusive period (39%) is lower than the corresponding decrease for the dead hedge funds (47%). Inversely, the increase in the size of the live hedge funds (42%) is greater than the increase in the size of the dead hedge funds (7%).

Ⅳ. Empirical Results and Discussions

1. Failed Funds Identification

The CPH model can be used to examine the risk of fund failure for funds that are in existence during the event of interest (financial distress) and for those that are not. However, it is necessary to first determine which funds are true failures to accurately define the time of failure. A failed fund is defined as a fund that has discontinued reporting to the Hedge Fund Research (HFR) database for reasons of financial distress. The remaining database funds are included in the risk set[5] at each time of failure. Estimating the model using genuinely failed hedge funds is critical to determining the predictive capability of the model.

Four criteria are used to distinguish failed funds in the dead fund database.[6] After failed funds have been distinguished from other closed funds in the dead fund database, the funds are classified into three categories : i) all funds included in the live fund database are assumed to be survivors, ii) funds that pass the failure filters but are included in the dead fund database are classified as likely survivors and iii) funds selected based on all of the failure criteria are classified as failures. To examine whether the criteria for selecting failures are appropriate, the average lifetime monthly return differentials for the survivor fund group and the likely survivor fund group, as well as the failed fund group and the likely survivor fund group, are tested using the nonparametric Wilcoxon test. The results demonstrate that the method of selecting failed funds effectively distinguishes between funds that have exited the database because of poor performance and those that have exited for other reasons.

The sample of GFC-inclusive dead hedge funds (1,329) is sorted into two groups, with 528 hedge funds classified as failures and 801 hedge funds classified as likely survivors. The failure rate for the hedge funds in the combined sample of GFC-inclusive funds is 18.77% (528/2,813). Of the dead funds that cease reporting in the same period, 39.73% (528/1,329) discontinued reporting because of poor performance rather than for any other reason. In comparison, for the pre-GFC period, the failure rate of hedge funds is 10.28% (230/2,237), whereas the failure rate within the dead fund category is 35.55% (230/647). Therefore, there is an overall increase in the failure rate as a result of the GFC. However, there is only a marginal increase in failure within the dead fund category during the same time period.

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5) The risk set refers to the set of all funds that are at risk at a given point in time.

6) They are : (i) funds must be represented in the dead fund database and must have (ii) decreasing AUM in the last 24 months, (iii) average monthly returns that are less than 0.25% in the last 12 months, and (iv) average monthly returns that are less than 0.25% in the last 24 months.

2. Mixed Cox Proportional Hazards Model

The Cox (1972) proportional hazards (CPH) model is a popular tool that is used by academics in survival literature. It is popular because it does not require an assumption with respect to the particular distribution used to represent survival time. In fact, the CPH model is parametric in that it is a regression model with a specific functional form and nonparametric in that it does not require the exact distribution of the underlying hazard function. Accordingly, it is classified as a semi-parametric method. Another advantage of the CPH model is its amenability to the relatively straightforward incorporation of time-varying covariates whose values may change over time.

To incorporate both fixed and time-varying covariates, the mixed CPH model is designed as follows :

$$h_i(t) = \lambda_0(t)\exp(\beta_{x1}x_{i1}(t) + \cdots + \beta_{xm}x_{im}(t) + \beta_{y1}y_{i1} + \cdots + \beta_{yn}y_{in}) \tag{1}$$

where $\lambda_0(t)$ is the baseline hazard, $x_{im}(t)$ is the value of the m^{th} time-varying covariate at time t in the i^{th} fund, and β_{mx} is the corresponding regression coefficient for $x_{im}(t)$. Additionally, y_{in} is the n^{th} fixed covariate value of the i^{th} fund, and β_{yn} is the corresponding regression coefficient for y_{in}. It is assumed that the number of time-varying covariates and the number of fixed covariates are m and n, respectively. Once the model is specified, the partial likelihood estimation method is used to estimate the coefficients of the model.[7]

A wide range of covariates that are anticipated to have an impact on hedge fund failure are considered and incorporated into the estimation of the mixed CPH model.[8] The fixed covariates are classified as minimum investment, leverage, fee structure,[9] liquidity,[10] domicile and strategy, whereas the time-varying covariates include monthly

7) For detailed explanation, see Lee (2010).

8) To examine multicollinearity, rank correlation coefficients are calculated for all covariates. Overall, significant multicollinearity problems are not found except for the fee variables. Although significant positive correlation between management fee and incentive fee are found, both covariates are incorporated into the model because they are considered to be important indicators of hedge fund failure.

9) The fee structure covariates include management fee, incentive fee, high water mark, and hurdle rate.

10) The liquidity covariates include redemption period, notice period and lockup period.

return and assets under management (AUM). The results for the period from January 1990 to July 2007 and the corresponding results for January 1990 to December 2009 are presented in <Table 3>. Estimating the CPH model provides coefficient estimates and associated statistics that indicate the direction and significance of a covariate's effect on the fund's hazard rate of failure. A positive coefficient estimate indicates that a covariate increases a fund's hazard rate of failure, whereas a negative value suggests that the covariate decreases a fund's hazard rate of failure, thus extending the lifetime of the fund.

<Table 3> The Mixed Cox Proportional Hazard Model : Pre-GFC and GFC-Inclusive Period

The table reports the results for the mixed CPH models in pre-GFC and GFC-inclusive periods. The chi-squared test statistics in the second column in each period model are calculated by squaring the ratio of each coefficient to its estimated standard error to test the null hypothesis that each coefficient is equal to zero. The last column, labeled "Hazard Ratio", is the value of e^{β} for each covariate. The figures reported are rounded up to four decimal places.

Variable	Pre-GFC (Jan 1990-Jul 2007)			Post-GFC (Jan 1990-Dec 2009)		
	Parameter Estimate	Chi-Square	Hazard Ratio	Parameter Estimate	Chi-Square	Hazard Ratio
Return	-0.0650***	59.0687	0.9370	-0.0581***	178.7287	0.9440
AUM	-0.0183***	65.1627	0.9820	-0.0067***	52.6221	0.9930
Minimum Investment	0.0000**	4.7687	1.0000	0.0000***	9.8757	1.0000
Leverage	0.1187	2.1589	1.1260	0.1169**	4.8596	1.1240
Management Fee	0.0000***	45.8659	1.0000	0.0000***	154.9664	1.0000
Incentive Fee	0.0000***	19.9019	1.0000	0.0000***	10.5913	1.0000
High Water Mark	0.0780	0.1139	1.0810	-0.2441	2.5058	0.7830
Hurdle Rate	-0.0111	0.0041	0.9890	0.1648	1.7351	1.1790
Redemption Period	0.0009	0.8956	1.0010	0.0004	0.2865	1.0000
Notice Period	0.0007	0.0381	1.0010	-0.0019	0.8422	0.9980
Lockup Period	-0.0006	1.9467	0.9990	0.0000	0.0128	1.0000
Domicile	0.5378***	13.2972	1.7120	0.1057	1.1172	1.1110
Event Driven	-0.3574	0.7753	0.7000	0.1822	1.5848	1.2000
Macro	-0.4464	1.4571	0.6400	-0.2590*	3.0672	0.7720
Relative Value Arbitrage	-0.2947	0.4501	0.7450	0.2207*	3.3381	1.2470

Note : The symbols *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The first column of results for the model in each period is the parameter estimate, and the second column reports its corresponding chi-squared test statistic. A high value of a chi-squared test statistic indicates that the coefficient is significantly different from zero and that the corresponding covariate has an impact on a fund's hazard rate of failure.

The last column, labeled “Hazard Ratio”, is the value of e^{β} for each covariate and is useful in interpreting the level of a covariate's influence on a fund's hazard rate of failure. For a binary indicator variable with a value of 1 or 0, the hazard ratio is calculated as the ratio of the estimated hazard for a variable value of 1 relative to the estimated hazard corresponding to a variable value of 0. The statistic is calculated by subtracting 1.0 from the hazard ratio and multiplying it by 100 and is interpreted as the incremental percentage change in the hazard for a variable value of 1. For a non-binary covariate, the hazard rate provides the estimated percentage change in the hazard for each single unit increase in the covariate. A hazard ratio that is greater than one implies a positive relationship between the covariate and the fund's hazard rate of failure, whereas a hazard ratio of less than one indicates a negative relationship (Allison, 1995).

For the GFC-inclusive period and the period that does not include GFC, <Table 3> demonstrates that there are a number of common covariates that are statistically significant at comparable significance levels and with expected signs. These covariates are returns, AUM, minimum investment, management and incentive fees. For the GFC-inclusive period, the most significant covariate with the highest chi-square value is return. The return covariate exhibits a strong negative effect on the hazard rate of failure, which indicates that funds with higher returns are more likely to survive for a longer period of time than funds with lower returns.

As with the fund performance covariate, the fund size covariate is found to have a strong negative effect on the hazard rate of failure during both periods, which indicates that an increase in the corresponding variable value leads to a reduction in the hazard function. These results show that irrespective of whether a financial crisis occurs, larger funds are less likely to fail than smaller funds. This outcome is expected and is consistent with previous findings (Gregoriou, 2002; Grecu, Malkiel, and Saha, 2007; Chapman, Stevenson, and Hutson, 2008; Ng, 2008; Liang and Park, 2010 among others).

Leverage is an important covariate that becomes significant in the GFC-inclusive period. Leverage has a positive coefficient indicating that increased leverage increases the hazard of financial distress. Certain previous studies find a negative effect of leverage on hedge fund performance and survival (Fung and Hsieh, 1997; Liang, 2000; Chan, Getmansky, Haas, and Lo, 2006; Gregoriou, 2002). In contrast, more recent studies including Rouah (2005), Chapman, Stevenson, and Hutson (2008), Ng (2008) and Baba and Goko (2009) do not find the relationship between leverage and hedge fund survival to be a significant indicator of hedge fund financial distress. Note that the data period in these studies is not influenced by the GFC. The results in <Table 3> indicate that as long as financial stability holds in the market, leverage is unimportant. However, in times of financial crisis, leverage is an important indicator of potential hedge fund failure and causes a significant increase in the number of defunct funds.

The minimum investment covariate, interestingly, has an opposite coefficient estimate in both periods, and the significance level of this covariate improves in the GFC-inclusive period (1% level) relative to the pre-GFC period (5% level). Funds with a higher minimum investment are more likely to survive for a longer period of time than are funds with a lower minimum investment in the pre-GFC period, whereas such funds are less likely to survive in a GFC-inclusive period. Funds with a lower minimum investment are likely to attract small-scale and more risk-averse investors who tend to prefer more stable funds with a longer survival period. In contrast, funds with a higher minimum investment are likely to attract larger institutional and high net-worth investors who have a tendency to demand higher returns from fund managers. This practice likely leads to a reduction in fund lifespan (Chapman, Stevenson, and Hutson, 2008). Therefore, a positive relationship between minimum investment and a fund's hazard rate of failure is expected, as is shown in the GFC-inclusive period. The negative relationship in the pre-GFC period can be explained by a counter-argument that funds with lower minimum investment are likely to have relatively limited assets, more volatile returns and, hence, shorter life spans. Consequently, minimum investment is a fund characteristic that changes the direction and significance of the effect on fund failure in the GFC-inclusive period.

Management and incentive fees are the only fee structure covariates that are found to be highly significant with little change in significance levels across the two periods – GFC and no GFC. The management and incentive fees are computed in dollars. Minimal variations in the fee as a percentage make it difficult to evaluate the impact of management and incentive fees on survival (Ackermann, McEnally, and Ravenscraft, 1999; Agarwal, Daniel, and Naik, 2009). Incentive fee contracts that compensate managers based on their performance create an option-like payoff for the assets under management. Such contracts can provide risk-taking incentives that can result in a higher likelihood of failure. On the contrary, managers who receive higher incentive fees may not want to miss these opportunities over the funds' lives and maintain a stable portfolio. Thus, a negative relationship may result between the incentive fee and a fund's hazard rate of failure, and the current study supports this hypothesis. Ironically, the funds with higher management fees tend to be more likely to fail. This finding challenges the underlying rationale for the higher fees charged by such hedge funds. A higher management fee should be associated with less risk because managers do not want to lose the management fees earned over the funds' lives if they continue to survive. Thus, there should be a negative relationship between management fees and a fund's hazard rate of failure. The counterintuitive results of the current study may be caused by the use of forward-looking dollar fees in the analysis. Regarding the high water mark and hurdle rate, we should note that positive relationships between these covariates and fund failure are predicted because fund managers are less risk averse because of incentive fee opportunities that exist when the fund return is negative. This hypothesis is supported by the results in the literature (Brown, Goetzmann, and Ibbotson, 1999; Liang, 2000; Brown, Goetzmann, and Park, 2001). In contrast, a negative relationship between the high water mark and fund liquidation is found in Chapman, Stevenson, and Hutson (2008) and Baba and Goko (2009). This result can be explained by the fact that the high water mark provision may have imposed additional pressure on fund managers to achieve high returns and maintain a stable portfolio. Nevertheless, the current study fails to show a significant effect of high water marks and hurdle rates on the funds' hazard rate of failure in both periods.

The effects of the liquidity covariates (redemption, notice and lockup periods) on the fund's survival are found to be insignificant in the model irrespective of whether the GFC is included in the data. These liquidity covariates can be considered as a disciplinary mechanism for fund managers such that shorter periods can pose a credible threat to capital withdrawal. This phenomenon would suggest that when these periods are shorter, fund failures are less likely to occur due to limits on risk-taking behavior. Therefore, positive relationships between these periods and fund failure rates are predicted.

However, the data used in the current study do not support this hypothesis for both periods.

A covariate that becomes an insignificant predictor in the GFC-inclusive period is domicile. Whereas domicile is an important indicator in the period leading up to the GFC, it loses significance when the GFC is considered. The hazard of failure increases when a hedge fund is located off-shore from the US in the period leading up to the GFC but is no longer important in the GFC-inclusive period.

The impact of particular strategies on the hazard rate of failure for hedge funds is interesting. Equity hedge is selected as the default strategy, and therefore, the hazard ratio of the other strategies represents an incremental percentage change in the hazard compared to that of funds using the equity hedge strategy. For example, in the GFC-inclusive period, the hazard ratio of relative value arbitrage is 1.2470, and that of the macro strategy is 0.772. In other words, the funds that employ relative value arbitrage have a 24.70% greater likelihood of failure than the funds using the equity hedge strategy and that those that employ macro have a 22.8% lower likelihood of failure. The macro and relative value arbitrage strategies are significant at the 10% level when the GFC is factored in. Both covariates are insignificant when the effects of the GFC are not considered.

3. Model Robustness Evaluation

The predictive ability of the model across the pre-GFC and GFC-inclusive periods is determined by calculating the statistics referring to the area under the relative operating characteristic (ROC) curve as a percentage (AUROC) at each time of failure. From the empirical survivor and failure distribution curves for a particular failure (event), the hit rates (H)[11] and the falsea larm rates(F)[12] are determined for the range of cut-off probabilities between 0 and 1. The F and H coordinates corresponding to each discrete

11) The hit rate (H) is the proportion of hedge funds that are correctly identified as experiencing financial distress.

12) The false alarm rate (F) is the proportion of surviving hedge funds that are incorrectly identified as experiencing financial distress.

cut-off probability are then mapped onto the x- and y-axis, respectively, to form the ROC curve (Lee, Stevenson, and Yao, 2012).

The average percentage and standard deviation of the AUROC statistics of the models at each failure time, during both the pre-GFC and GFC-inclusive periods, are shown in <Table 4> below.

<Table 4> Summary of AUROC Statistics

This table shows the average percentage and standard deviation of the AUROC statistics at every failure time based on the mixed CPH model in the pre-GFC and GFC-inclusive periods.

	Pre-GFC (Jan 1990-Jul 2007)	GFC-Inclusive (Jan 1990-Dec 2009)
Mean	73.51%	79.65%
Sandard Deviation	17.92%	18.61%

<Table 4> demonstrates that the mixed models offer a high level of forecasting ability in predicting financial distress in hedge funds in both periods. Consequently, we can find the robustness of the model over the GFC-inclusive period. Interestingly, there is a considerable increase in the predictive capability of the mixed model across the pre-GFC and GFC-inclusive periods. This improvement in predictive skill in the GFC-inclusive period highlights a benefit of the mixed model. Because the mixed model reflects return and AUM information that is measured contemporaneously and considers variations in the dynamic financial characteristics of a fund over time, the mixed CPH model is more realistic than the model that incorporates fixed covariates only.[13)]Accordingly, it can be argued that the mixed model should be able to indicate better warning signals to investors concerning possible fund failures because of the impact of a subset of the covariates measured in a contemporaneous manner at each failure time.

13) The time-varying covariates in the mixed model (return, AUM) are incorporated as fixed covariates in the fixed model by calculating their sample means for the monthly data over a fund's lifetime. Therefore, the fixed CPH model does not consider variations in the dynamic financial characteristics of a fund over time.

V. Conclusion

The results of this study indicate that the mixed CPH model offers a high level of forecasting skill in predicting the occurrence of hedge fund failure in both the pre-GFC and GFC-inclusive periods. The predictive capability of the model is markedly improved in the period that includes the GFC. There are groups of covariates that remain important predictors in both periods, whereas some covariates become significant or insignificant predictors in the GFC-inclusive period.

An important insight from the analysis concerns the impact of leverage as a covariate on financial distress in hedge funds. Prior to the GFC, leverage is not among the significant predictors in the mixed CPH model. However, in the GFC-inclusive period, leverage becomes a significant covariate in the model. One conclusion that can be drawn from this finding is that the high levels of indebtedness that are characteristic of most hedge funds affect the ability of many funds to make interest payments, or recalls on borrowing, in times of financial crisis and during associated credit tightening. Interestingly, minimum investment has the opposite impact on hedge fund failure in both periods, and the significance improves in the GFC-inclusive period. Additionally, covariates of particular strategies such as macro and relative value arbitrage become significant predictors when the GFC is included, whereas domicile loses its significance when the GFC is considered.

Periodic financial crises have continued to occur worldwide since the onset of the recent GFC. As the risks of investing in hedge funds are a significant concern in crisis-prone financial markets, identification of the effect of the GFC on modelling and predicting financial distress in hedge funds provides significant benefits to investors and regulators. Additionally, this study contributes to the debate regarding the reliability of accepted models to predict the financial distress of hedge funds during the period that includes the recent financial crisis. Utilizing covariates that are found to be important to the prediction of financial failure for hedge funds during the GFC-inclusive period, the mixed CPH model is able to predict failure with an improved, high level of accuracy. The remarkable improvement in the predictive accuracy of the mixed model from the pre-GFC period to the GFC-inclusive period is evidence of the importance of including time-varying covariates in this model and indicates the role that they play in providing early warning signals to investors of possible fund failure.

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