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Does Size Matter in Predicting Hedge Funds' Liquidation?

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Abstract

In this study, we propose a set of covariates that exploit information content of hedge funds' relative size, performance, growth, tail risk, and past liquidation rate, in predicting their liquidation. Empirical results show that our proposed covariates exhibit significant predictive power for up to two years even when we control for fund specific characteristics. Furthermore, we estimate separate liquidation prediction models for small, medium, and large funds. Our findings suggest that liquidation likelihood of hedge funds is inversely related to fund size, and statistical significance of factors affecting their liquidation vary across different size categories.

Keywords: hedge fund; liquidation; fund size; failure; default

JEL Classification Codes: G11; G17; G33

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1. Introduction

The hedge fund industry has experienced difficult times recently, with tense global macroeconomic conditions, high market volatility, enhanced regulatory vigilance, and underperformance relative to traditional asset classes. These factors may have contributed towards the closing down of funds at an increasing rate in recent years (see Table 1). Strikingly, some of the biggest names have also been affected by this phenomenon. In September 2016, after almost three decades of operation, Perry Capital announced the closure of its flagship fund, just as its predecessor Long Term Capital Management had done in 1998, and Amaranth Advisors had done in 2006. This subsequently raises concerns and scepticism regarding the role of Hedge Funds in financial markets. While the literature broadly agrees on the role of hedge funds in providing liquidity and risk sharing to financial markets, contrarians argue that the nature of their risk exposure increasingly contributes towards systematic risk and financial instability (e.g. Billio *et al.*, 2012).

Unlike mutual funds, hedge funds enjoy regulatory exemptions and greater flexibility in investment strategies, and are characterized by managing investment portfolios that promise high return but are coupled with high risk. Most of the empirical literature emphasises fund failure due to market risk (e.g. LTCM and Amaranth), however failure may also be attributed to sudden withdrawal of funds (e.g. Peloton) or high operational risk (e.g. Bayou). Another failure possibility may be persistent poor performance, which may motivate investors to withdraw funds over a period of time, eventually leading to smaller fund sizes which become difficult to manage profitably, and are hence closed down. Kim (2009) argues that if failure is triggered due to an external shock, then there is no reason why a fund should exhibit poor performance before the shock. However, if failure is triggered due to persistent past poor performance over a period of time, then we have strong motivation to believe that poor performance may lead to higher default probability. As hedge funds are often characterized by investment in high risk illiquid assets, such persistent poor performance may force fund managers to change the investment policy to meet any unforeseen redemption demands. They may therefore end up avoiding profitable trading options and investing in less profitable liquid assets to meet sudden redemption demands. In the worst cases, funds may need to dilute some illiquid positions, which may be costly and dampen performance. Redemption of funds by investors can also trigger a run among investors, leading to funds' failure. Agarwal *et al.* (2015) argue that there could be a liquidity mismatch between funds-of-hedge funds and their underlying hedge funds, and this mismatch can transmit outflows across the hedge fund industry. Due to certain characteristics of the hedge fund industry (e.g. lock-up periods, redemption notices), hedge fund investors and managers can be caught in strategic games in which it is optimal to withdraw funds, even if no external shock has occurred. Teo (2011) shows that a liquidity mismatch between the funding liquidity and the portfolio held by funds can lead to such failures. A theoretical framework for such runs is provided by Brunnermeier and Pedersen (2009). Recent literature also highlights the impact of past poor performance on hedge funds' failure (see among others Liang, 2000; Brown *et al*., 2002; Grecu *et al*., 2007), however examination of the effect of fund size on such failures is yet to be debated.

Is fund size a major driver of hedge funds' liquidation? How do other fund characteristics interplay with fund size in predicting the default likelihood of hedge funds? These are the primary questions we examine in this study. Although a handful of prior studies have examined the impact of size on hedge fund performance (e.g. Teo, 2009), its impact on funds' failure is yet to be empirically debated. Among the few studies that explore the relationship between fund size and performance, a consensus is yet to be reached. Aggarwal and Jorion (2009) show that young and small hedge funds outperform bigger, older ones. A similar relationship between performance and assets under management has also been reported in the mutual fund industry (e.g. Indro *et al.*, 1999; Chen *et al.*, 2004). Liang (1999) also reports a positive relationship between average hedge fund returns and funds' assets under management, and attributes this to the increasing benefits that arise through economies of scale. However, Getmansky (2012) argues that there is an optimum asset size that maximizes returns, as she finds positive and concave relationships between fund size and performance. Getmansky (2012) thus suggests that investors should be wary of hedge fund size before investing, and advises them to try investing in funds close to their optimum size. Perold and Salomon Jr (1991) also explain that there is an optimal size for investors: if a fund is too small, the fixed costs of running the fund are too high, and if a fund is too large, the liquidity issues and capacity constraints will reduce its performance. This is also confirmed by the findings of Yin (2016). He reports positive relationship between fund managers' compensation and fund asset growth, and finds that managers' allow fund size to grow beyond optimal size for performance to achieve a much larger fund size that maximizes their compensation. Gregoriou and Rouah (2002), on the contrary, report no relationship between fund size and performance. However, there appears to be reasonable evidence of an inverse relationship between hedge fund performance and size. Even if size provides more fund security, its negative impact on performance can counterbalance this effect and lead to a higher risk of failure. Small hedge funds generally outperform large ones, but they are comparatively riskier with a higher attrition rate (Aggarwal and Jorion, 2009). Furthermore, they are more fragile with respect to investors' outflows.

Our study contributes to this debate by adding the likelihood of liquidation to the fund managers' trade-off literature. If size has a strong impact on the probability of closing a fund, then managers can choose to let the fund grow even if it hurts the performance (and so decreases their performance fees), because they want to limit their failure risk. Indeed, Lan *et al.* (2013) explain that hedge fund managers trade off the benefits of taking more risks and improving performance against the cost of fund liquidation. As actualized future management fees account for the majority of managers' compensation, managers prefer to enhance funds' survival likelihood instead of increasing its performance. Furthermore, Kim (2016b) also reports the presence of size and value effects in equity hedge funds. We update the growing literature on hedge funds by developing comprehensive liquidation prediction models to assess the impact of funds' size on their default probability. In line with our prior discussion, we expect small funds to be more vulnerable to adverse changes in fund characteristics than their larger counterparts. If all else is equal, we consider fund size to have a significant impact on hedge funds' liquidation risk.

An additional contribution made by this study is that we propose several new covariates to explain hedge funds' liquidation. For the first time, we explore information content of funds' relative size (WRSIZE), growth in assets under management (GROWTH), total value of downside and upside returns (DRATIO), volatility of tail risk (TRISK), and past liquidation rate of hedge funds (INDRISK) in predicting liquidation likelihood of hedge funds. Some of these covariates are motivated from studies on corporate bankruptcy by Campbell *et al.* (2008) and Gupta *et al.* (2017), however they are suitably modified to fit the purposes of this study. Following the existing literature, we also investigate the discriminatory power of funds' own performance (RETURN) and their past 60 months winning ratio (WRATIO) in predicting hedge funds' liquidation. Section 2.3.2 provides further details on these covariates. We also employ a set of control variables to account for inherent variabilities in fund characteristics, such as high-water mark, leverage, age, investment style and personal capital. Section 2.3.3 presents the comprehensive list of control variables along with their respective definitions.

We perform our empirical analysis using the most comprehensive Lipper (TASS) hedge fund database, which contains information about live and defunct (graveyard) funds. Our study covers a sampling period between January 1995 and December 2016. A fund may exit the database for several reasons (see Section 2.3.1), however liquidation seems to be the most reasonable cause of funds' failure/exit (e.g. Baquero *et al.,* 2005). In this study we consider only *liquidated* funds to define our failure/exit definition, as liquidation is expected to have the highest adverse impact on stakeholders among all exit reasons, and thus the most costly form of fund exit. Additionally, to capture any non-linearity in the effects of covariates that may arise due to fund size, we use criteria based on funds' assets under management (AUM) to classify small, medium and large funds. We consider funds corresponding to the bottom 25 percentile of AUM as *small* funds, those in the top 25 percentile as *large* funds, and the rest *medium* funds.

Our empirical analysis begins by establishing the discriminatory power of our proposed covariates in identifying liquidated and non-liquidated funds for our entire sample of hedge funds. Using panel logistic regression techniques we estimate regression models for 6 months, 12 months, and 24 months lagged time periods. Test results prove that all our proposed covariates are strongly significant in explaining liquidation risk of hedge funds across all three lagged time periods. These results also remain unchanged when the models are re-estimated by supplementing control variables. This proves the complementary information content of our proposed covariates, and their statistical significance up to the 24 months lagged period establishes their intertemporal predictive ability.

We next turn our attention to assessing the impact of funds' size on their liquidation likelihood. An initial inspection of their hazard curves for different size categories reveals compelling evidence that there is significant influence of fund size on liquidation likelihood. As reported in Figure 1, small funds are most vulnerable to the risk of liquidation, followed by medium and then large funds. This is in line with the arguments of Aggarwal and Jorion (2009), who also raise similar concerns. The almost flat survival and hazard curves of large funds suggest that liquidation is a rare phenomenon for them, and they are not as vulnerable as small and medium firms to the risk of liquidation. This offers a very strong and clear indication that factors affecting hedge fund liquidation are expected to vary, in terms of their significance or magnitude of coefficients, across the size categories.

Based on our empirical analysis, we conclude that factors affecting liquidation risk of hedge funds vary across different size categories. While failure of small and medium funds is explained by a broad set of variables (WRSIZE, GROWTH, RETURN, WRATIO, DRATIO, TRISK and INDRISK), for large funds, only two variables (WRATO and DRATIO) show significant explanatory power. Broadly, magnitudes of respective regression coefficients for small and medium funds are marginally higher compared to estimates obtained for all funds. This suggests small and medium-sized funds are marginally more vulnerable to changes in factors or fund characteristics in comparison to estimates obtained for all funds. Insignificance of covariates in explaining liquidation of large funds, and their significance in explaining liquidation of small and medium funds, might imply that small and medium-sized funds have dominant influence on regression estimates, and estimates obtained by employing the entire sample of hedge funds are essentially biased. Thus, we present compelling evidence that respective coefficients of different significant predictors are not equal among different size groups of hedge funds, confirming non-linear relationships between predictors of liquidation and size. This is further reaffirmed when we include main effects and interaction effects of fund size and investment style into our regression model for all funds. A dummy variable for large funds, and interaction terms involving medium funds and investment style, enter significantly into our multivariate models. Thus, an appropriate modelling approach of fund liquidation should take into account the size of funds considered.

The remainder of this paper is structured in the following way. Section 2 presents discussion on our dataset and sample used in this study; Section 3 presents our empirical methods; Sections 4, 5 and 6 present and discuss our regression results; and Section 7 concludes this study.

2. Dataset, Sample and Covariates

The hedge fund data used in our empirical analysis comes from the Lipper (TASS) hedge fund database. Although a comprehensive fund-level database, it is not a true representation of the entire hedge funds universe. However, using a consolidation of the five largest commercial hedge fund databases, including Lipper (TASS), Joenväärä *et al.* (2016) find no difference in performance among different databases. Thus, we expect our analysis to be a true representation of the hedge funds universe. However, two popular known biases in hedge funds literature, survivorship bias and backfill bias, need to be mitigated before performing any empirical analysis. To account for survivorship bias, we restrict our sample range to January 1995 and December 2016, and include funds that exit the database during this time period. To mitigate the effect of backfill bias (Malkiel and Saha, 2005), we follow an approach similar to Yin (2016) and exclude data before the date when funds were added to the TASS database. If the date added to TASS information is not available, we exclude the first 18 months of observations from our analysis. Additionally, our analysis considers only those funds that report their return on a monthly basis (net of fees and trading costs) and excludes funds that report at any other frequencies.

Following Liang and Park (2010) we exclude emerging market funds to avoid any specific investment style from dominating the highest risk group in each time-spell. We also exclude funds that report financial information in currency other than United States Dollar (USD). Since our analysis is strictly focused on hedge funds, we exclude fund-of-funds (to avoid double counting) and managed futures (CTAs) from our analysis, as Liang (2004) reports that managed futures differ from hedge funds in several respects. We consider the following investment styles to analyse the hedge fund failure: equity market neutral, convertible arbitrage, event driven, fixed income arbitrage, dedicated short bias, long/short equity hedge, global macro, and multi-strategies.

2.1 Defining Small, Medium and Large Funds

In the absence of any formal definition, we use criteria based on funds' assets under management (AUM) to classify small, medium, and large funds. Specifically, we consider funds corresponding to the bottom 25 percentile of AUM as *small* funds, the top 25 percentile as *large* funds, and the rest *medium* funds. This gives us 49,109 fund-month observations for small funds, 101,144 fund-month observations for medium sized funds, and 51,425 fund-month observations for large funds. This subsequently leads to 1,923 small funds, 2,675 medium funds, and 1,229 large funds in our sample (see last row of Table 1). One should also consider that some funds may appear in more than one size category, but in different time periods. This is due to the changing AUM of funds. A fund may start small, but eventually move to the medium or large sized categories as its AUM increases, or vice versa.

2.2 Sample Description

Table 1 presents yearly liquidation rates of hedge funds from 1995 to 2016. To observe any differences between size categories, we also report the yearly liquidation rates of small, medium, and large funds. The average liquidation rate of our entire sample is 4.26%, this is about one-third of the overall attrition rate (around 12%) reported in recent literature (e.g. Haghani, 2014), and close to the liquidation rate (5.2%) reported by Baquero *et al.* (2005). The seminal study on hedge funds failure by Liang and Park (2010) does not report average of annual liquidation rates. However, their sample contains 15.32% of liquidated funds (327 liquidated out of 2134 funds for the sample period from January 1995 to December 2004), which is close to the percentage of liquidated funds in our sample (13.99%) for similar sampling period.

As expected, the average liquidation rate is highest for small funds (7.53%), followed by medium funds (2.77%), and lowest for large funds (1.02%). Further, we see in Table 1 that liquidation rate is inversely related to fund size. In any given year, the percentage of liquidated funds is highest for small funds and lowest for large funds. The liquidation rates of all funds experienced a significant rise around the financial crisis of 2007-08, but from 2012 onwards they gradually began to moderate. However, unlike small and medium sized funds, the liquidation rates of large funds did not rise dramatically during the crisis period. This may suggest that large funds have significantly higher shock absorbing capacity than their smaller counterparts, and that they are also better prepared for any forthcoming event that threatens their degree of solvency.

[Insert Table 1 Here]

2.3 Selection of Variables

In this section we discuss the rationale behind our choice of dependent variable, followed by relevant discussion on explanatory and control variables employed in this study.

2.3.1 Dependent Variable

The life of a hedge fund in the TASS database may be summarized as follows. First, the fund is started (inception date). Then, the fund may enter the database (date added) and start voluntary reporting of required information on a recurring basis. Subsequently, the fund may exit the database, and the date corresponding to the latest available information is equivalent to its exit/failure date. A fund may exit the database due to one of the following reasons: (1) liquidation; (2) no longer reporting to TASS; (3) TASS being unable to contact the manager for updated information; (4) closure to new investment; (5) merging into another entity; (6) becoming dormant; or (7) unknown. Among all of these exit reasons, liquidation seems to be the most reasonable cause of funds' failure/exit (e.g. Baquero *et al.*, 2005), however recent literature also argues that considering liquidation as the only cause of failure is inappropriate, and suggests that other defunct funds should also be included in the failure universe (Liang and Park, 2010).

There are two potential reasons why a fund may stop voluntary reporting. First, due to poor performance, managers may decide to evade voluntary reporting, which subsequently leads to selection bias and results in the superior performance of funds that voluntarily report their performance to commercial databases in comparison to non-reporting funds (Aiken *et al.*, 2013). Alternatively, the fund may be liquidated, merged, or closed due to poor performance. A fund manager may also evade voluntary reporting if the fund performs well, and they decide to close it to new investors. If the fund seeks new investors, it continues reporting and its performance information is made available to commercial databases. Thus, fund managers who choose to report until filing for liquidation may take an ethical stand to present their true performance in front of their investors, irrespective of the level of performance. Moreover, fund managers who choose to exit the database for reasons other than liquidation might make a strategic choice to hide poor performance. However, in this study we consider only *liquidated* funds to define our failure/exit definition, as liquidation is expected to have highest adverse impact on stakeholders and generally the costliest form of exit.

2.3.2 Main Explanatory Variables

An additional contribution of this paper is that we propose several new covariates (WRSIZE, GROWTH, DRATIO, TRISK and INDRISK) to explain hedge funds' liquidation. These covariates are novel to hedge funds' failure literature and exploit information content of funds' relative size, average growth, past performance, volatility of tail risk, and past liquidation rate, to predict hedge funds' liquidation for up to two years. Some of these covariates are adapted from previous studies on corporate bankruptcy by Gupta *et al.* (2017)

and Campbell *et al.* (2008), but are suitably modified to fit the scope of this study. Further details on all main covariates are as follows:

WRSIZE – Logarithm of past 12 months' weighted average of each fund's size relative to the total size of all funds for a given investment style in month *t*, calculated as:

$$WRSIZE_{t-1,t-12} = ln\left(\frac{1-\emptyset}{1-\emptyset^{12}}(RSIZE_{t-1} + \cdots + \emptyset^{11}RSIZE_{t-12})\right) \quad (1)$$

$$RSIZE_{i,t} = \left(\frac{AUM_{i,t}}{Total\ AUM\ of\ all\ funds_{investment\ style,t}}\right) \quad (2)$$

Here, $\emptyset = 2^{-\frac{1}{3}}$ (two raised to the power negative of one over three), implying that the weight is halved each month. AUM is assets under management in millions of USD.

A fund sufficiently close to liquidation is typically discounted by investors, and thus fund size is expected to bear a negative relationship to liquidation likelihood. This relationship might also be affected by a fund's relative market share. The likelihood that large funds would recover from their distressed state or may delay their liquidation filing is high, compared with small funds. Moreover, small funds might be more vulnerable to industry competition, and unfavourable political and policy changes. Thus, unlike previous studies, we use relative size of funds rather than their absolute values. It is also reasonable to assume that a long history of losses or sustained decline in funds' AUM would be a superior predictor of funds' liquidation than one large monthly/quarterly/annual loss or a sudden decline in AUM. Therefore, we impose geometrically declining weights on RSIZE as stated in Equation 1 and expect it to be inversely related to probability of funds' liquidation.

GROWTH – Weighted average of the past 12 months percentage change in AUM of a given fund *i*, calculated as:

$$GROWTH_{t-1,t-12} = \frac{1-\emptyset}{1-\emptyset^{12}}(\ln(AUM_{t-1}/AUM_{t-2}) + \cdots + \emptyset^{11}\ln(AUM_{t-12}/AUM_{t-13})) \quad (4)$$

Here too, $\emptyset = 2^{-\frac{1}{3}}$ (two raised to the power negative of one over three), implying that the weight is halved in each successive month. Weight is expected to bear an inverse relationship to funds' liquidation likelihood, as funds sufficiently close to liquidation might witness negative growth due to the withdrawal of funds and/or decline in inflow of new funds. Like WRSIZE, here too we assume that a long history of funds growth in AUM would be a superior predictor of funds' liquidation than a monthly/quarterly/annual growth rate. Thus, we calculate GROWTH as the weighted average of monthly growth rates of AUM over the past twelve months. Further, to give more importance to recent growth in AUM, we impose geometrically declining weights as stated in Equation 4.

RETURN – Geometric mean of the past 12 months rate of return.

WRATIO – Winning ratio over the past 60 months, calculated by dividing the number of months a fund reported positive returns in the past 60 months by 60. Although we expect it to have a negative relationship with funds' liquidation probability, funds might also choose to exit the database due to superior performance or persistent higher winning ratios. They might choose not to report to TASS when they perform poorly, or given insufficient reporting incentives above their superior performance. This in turn might lead to a positive relationship between winning ratio and liquidation likelihood. One might also need to consider that funds might continue to generate positive returns while simultaneously reducing their AUM. A few recent studies do not include winning ratios in their failure prediction models (Liang and Park, 2010; Haghani, 2014; Kim 2016a), while others report positive (e.g. Baba and Goko, 2009) and negative (e.g. Lee and Yao, 2015) relationships between winning ratio and failure likelihood of hedge funds. Irrespective of the sign of its coefficients, we find it highly significant in all our multivariate models and thus have included it in our study.

DRATIO – Natural logarithm of past 60 months *d-ratio*. Adapted from Bacon (2008, page 95), the *d-ratio* measures the ratio of the total value of downside returns (less than 0) compared with the total value of upside returns (greater than 0):

$$DRATIO = \ln(d\text{-}ratio) = ln\left(\frac{-n_d \times \sum_{i=1}^{i=n} \min(r_i, 0)}{n_u \times \sum_{i=1}^{i=n} \max(r_i, 0)}\right) \tag{5}$$

Here, n_d is the number of returns less than 0 and n_u is the number of returns greater than 0. The *d-ratio* will have values between zero and infinity, and can be used to rank the performance of hedge funds. The lower the value of *d-ratio* the better the performance; a value of zero indicates that there are no returns less than zero, and a value of infinity indicates that there are no returns greater than zero. Thus, fund managers with positively skewed returns will have lower *d-ratio* and face lower liquidation likelihood. Considering the extreme positive values that *d-ratio* might undertake, we use its natural logarithm (DRATIO) to offset any extreme biasness that might arise due to its extreme positive skewness.

One might expect DRATIO to be strongly correlated to WRATIO as both their constructs are centred on the idea of fund managers' ability to generate positive returns. However, the correlation between them is about -0.22 (see Table 3), signifying sufficient complementarity between these two measures. WRATIO just considers the count of positive returns, while DRATIO considers the value/magnitude of both positive and negative returns generated. If two funds report an exact number of positive returns in a given duration, they will have identical values of WRATIO. In this situation, an appropriate decision could be made by comparing their DRATIOs.

TRISK – Tail risk, measured as standard deviation of monthly Expected Shortfall estimated over the past 60 months.

Tail risk measures, namely Value-at-Risk (VaR) and Expected Shortfall (ES), are increasingly considered when predicting hedge funds' failure (e.g. Liang and Park, 2010; Lee and Yao 2015). Liang and Park (2010) are the first to explore the discriminatory power of downside risk measures (semideviation, VaR, ES and standard deviation of losses larger than VaR (TR)) in predicting hedge funds' failure, and conclude that these measures are superior to standard deviation as a risk measure. Among downside risk measures, they suggest that ES and TR are superior to VaR and semideviation. Theoretical superiority of ES to VaR as a risk measure is well documented in the literature as well (see Righi and Ceretta (2016) for additional discussion), however superiority of TR as a risk measure over ES is still an active area of scholarly debate (see Righi and Ceretta, 2016). ES represents the mean of losses larger than VaR, while TR measures the standard deviation of losses larger than VaR, and thus TR is better than ES in capturing tail risk (Liang and Park, 2010). However, our inspection of ES and TR reveals inconsistent results across lagged periods in univariate and multivariate regression models[1]. This inconsistency might be because these measures include only losses larger than VaR, and thus a low number of observations being used in computing ES and TR, as we employ monthly returns for computing these measures. Overall, we conclude that the statistical significance of VaR, ES, and TR show some inconsistency in predicting hedge funds' liquidation and thus might not be the most appropriate choice. However, the variable TRISK that we propose is highly significant in both univariate and

[1] Our inspection of Cornish-Fisher Value-at-Risk (VaR) in predicting hedge funds' liquidation revealed mixed results. In the univariate regression, VaR is a statistically significant predictor for up to two years, but witnesses sign reversal of its coefficient (from positive to negative) in the multivariate setup. Next we estimate univariate regressions using ES as an explanatory variable, and find it insignificant for 6 months lagged estimates, but significant for 12 and 24 months lagged estimates. It enters significantly in the multivariate models but witnesses sign reversal similar to VaR, and makes a couple of other variables insignificant. Additionally, Lee and Yao (2015) (estimates using panel logistic regression technique) and Liang and Park (2010) (see Panel B of Table 3) report ES as an insignificant predictor of hedge funds' failure/liquidation. Arguably TR is superior to ES, but our regression results do not support this claim. We find TR as a highly insignificant predictor across all lagged periods in both univariate and multivariate regression models. This might be strongly contrary to the findings of Liang and Park (2010), however they report weak significance of TR in their multivariate model reported in Table 5. Results for this analysis are not reported, but are available from the authors upon request.

multivariate regression models, and thus a consistent predictor of hedge funds' liquidation likelihood.

In this study, ES represents the mean of losses larger than Cornish-Fisher Value-at-Risk (see Liang and Park, 2010) and TRISK aims to capture the volatility of ES. A higher value of ES implies a higher likelihood of failure, but a higher value of its standard deviation might not imply the same. Hedge funds are known for undertaking risky investments, and thus fund managers generally have a predetermined loss expectation (or expected tolerance level). The deviation from the expected tolerance level shall be higher when the liquidation risk is low and the fund manager is optimistic about the future profitability. This shall lead to higher deviations from ES and thus higher standard deviation of ES when the fund is doing well or facing a lower threat of liquidation.

On the contrary, a fund manager facing the threat of liquidation in the near future is expected to turn conservative/risk-neutral, and avoid large deviations from the expected tolerance level or ES. This is in line with the findings of Kelly and Jiang (2014). They report that hedge funds earn a risk premium for being exposed to tail risk, and thus fund managers might try to minimize it while facing threats of liquidation. Moreover, a risk-neutral manager has incentives to preserve a fund's going-concern value so as to maintain fees income in the future (Lan *et al.* 2013). Thus, large deviations from ES might aggravate the liquidation risk and cause the fund's closure earlier than expected. This explanation is also in line with the theoretical explanation of hedge funds' endogenous risk-taking behaviour by Lan *et al.* (2013). They argue that, when hedge funds' failure is costly to its manager in reputational terms, it can be shown that most of their compensation comes from management fees. This implies that, in periods of stress, when the likelihood of failure is high, fund managers will reduce their exposure to risk in order to maximize their chances to earn future management fees.

Thus, funds facing liquidation risk are expected to have lower standard deviation of ES. In such situations, a *negative* relationship is expected between hedge funds' liquidation likelihood and TRISK. It is also noteworthy that our variable does not measure the global amount of tail risk but variability from the expected tail risk (ES).

INDRISK – To account for the impact macro-economic and industry specific conditions on funds' liquidation likelihood, we use log odds of the past 24 months' investment style specific liquidation rates (LRATE), computed as follows:

$$INDRISK_t = ln\left(\frac{LRATE_t}{1 - LRATE_t}\right), \tag{7}$$

$$LRATE_t = \frac{Number\ of\ funds\ liquidated_{Investment\ style,t-1,t-24}}{Total\ number\ of\ funds_{Investment\ style,t-1,t-24}}, \tag{8}$$

This serves as a useful proxy for controlling the volatile macro-economic conditions during the sampling period. We expect *INDRISK* to be positively related to a fund's liquidation risk.

Since all main covariates discussed above require rolling estimation over the past 12, 24 or 60 months, good numbers of missing values are generated in the variable generation process. To avoid losing observations, missing values of respective covariates are replaced with values computed using the available number of observations at time *t*. For instance, for missing values of WRSIZE, first we replace missing values with 11 months' average, then with 10 months' average, then with 9 months' average, and so on. However, for rolling estimations involving a 60 months period, we consider a minimum of 24 months of available information to replace missing values.

2.3.3 Control Variables

To establish the robustness of our proposed covariates, we also report our multivariate results, supplementing the following control variables:

AGE – Natural logarithm of a fund's annual age.

LUPD – Lock-up period dummy.

RNP – Redemption Notice Period in months.

OTP – Open to Public. This is a dummy variable which takes the value 1 if the fund is open for public subscription, and 0 otherwise.

LVG – Leverage. This is a dummy variable which takes the value 1 if the fund uses leverage, and 0 otherwise.

HWM – High Water Mark. This is a dummy variable with the value 1 for high HWM provision, and 0 otherwise.

PCAP – Personal Capital. This is a dummy variable which takes the value 1 if the fund manager has invested personal capital in the fund, and 0 otherwise.

MFEE – management fees charged by the hedge fund manager in percent.

IFEE – incentive fees charged by the hedge fund manager in percent.

Investment Style – As discussed earlier, the eight investment styles that we consider are: equity market neutral, CA, event driven, fixed income arbitrage, dedicated short bias, long/short equity hedge, global macro, and multi-strategies. Thus we use seven investment style dummy variables (D1 – D7) to control for the investment style effect. We exclude funds which do not report their investment style.

To gauge the discriminatory ability of respective control variables, first we run univariate regression for respective control variables. Only significant control variables are included in the multivariate models.

3. Empirical Methods and Descriptive Analysis

3.1 Logistic Regression

The vast majority of recent empirical studies employ time-constant or time-varying versions of the Cox proportional hazard (CPH) model to estimate the failure hazard of hedge funds (e.g. Baba and Goko, 2009; Liang and Park, 2010). However, the CPH model is primarily designed to model continuous-time data, while hedge funds provide monthly information which leads to a discrete-time data structure. The continuous-time survival model is an appropriate choice when exact censoring and survival times are recorded in relatively fine units of time (such as seconds, hours or days) with no *tied* survival time periods (Rabe-Hesketh and Skrondal, 2012). However, if the data shows relatively few censoring or survival times with *tied* survival time periods, and the event of interest takes place at any time within the defined time interval, then the discrete-time survival model is more appropriate where coarse times-scales are generally used (Rabe-Hesketh and Skrondal, 2012), for instance when expressing time to event in weeks, months, or years. Unlike in prior studies, which largely employ the Cox proportional hazard (CPH) model to estimate funds' failure hazard, we believe that the discrete-time duration-dependent hazard (DPH) rate modeling technique is more appropriate in this context. However, in line with the findings of Gupta *et al.* (2017), we use panel logistic regression with random effects to establish our empirical validation. They argue that the discrete-time hazard model with logit link is essentially a panel logistic model that controls for firms' age. Thus we assume that marginal probability of funds' liquidation likelihood over the next time period follows a logistic distribution that is estimated as follows:

$$P(Y_{it} = 1) = \frac{1}{1 + \exp(-\alpha - \beta X_{i,t-1})} \tag{7}$$

where Y_{it} is an indicator variable that equals one if the fund is liquidated in time t, and $X_{i,t-1}$ is a vector of explanatory variables known at the end of the previous (or any appropriate lagged) time period. To capture any duration dependency, we use the natural logarithm of funds' annual age (AGE) as a control variable in our multivariate models.

3.2 Analysis of Survival and Hazard Curves

Figure 1 presents a table of hazard and survival curves estimated using the Kaplan-Meier[2] estimator for our sample of hedge funds. H1 is the hazard curve of all funds and S1 is the survival curve for the same. As we see in H1, the risk of funds' liquidation witnesses a gradual increase up to an age of about 70 months, followed by a gradual decline up to an age of about 250 months, after which, surprisingly, it rises steeply. However, our primary interest lies in hazard and survival curves of funds across the different size categories. H2 shows hazard curves of small, medium, and large funds, and S2 shows survival curves for the same. It is absolutely clear from H2 and S2 that the liquidation risk varies across different size categories. Small funds are the most vulnerable to liquidation, followed by medium and then large funds. As we see in H2, the hazard risk of large funds is the lowest and is mostly invariant with their age. In S2, we see that the likelihood of survival of large funds is highest at any given age and lowest for the small funds. Unlike large funds, the survival rate of small and medium funds varies significantly with age as well. About 25% of small funds liquidate by the time they are about 50 months old, and about 50% liquidate before they reach the age of 100 months. The hazard risk faced by medium funds is about half of that faced by small funds. Age invariant (mostly) hazard and survival curves of large funds signal that they enjoy clear advantages over small and medium funds due to their size, and can manage/mitigate liquidation risk much more efficiently than their smaller counterparts. Furthermore, the shapes of hazard curves of all funds and of small funds are quite similar. This might imply

[2] See Kleinbaum and Klein (2012) for an understanding of the Kaplan-Meier estimator.

that small-sized funds dominate the sample, and thus the effect of medium and large funds is averaged out or marginalized. This may lead to heterogeneity within the sample and, subsequently, biased estimates. This gives us strong motivation to believe that the significance of factors affecting funds' liquidation risk might vary across the size categories, and respective covariates may also show varying degrees of sensitivity across the different size categories.

[Insert Figure 1 Here]

3.3 Summary Statistics and Correlation

Descriptive statistics for the explanatory variables are presented in Table 2. Column 1 presents the list of covariates along with five measures of descriptive statistics: mean, median, standard deviation, minimum and maximum. Columns 2 and 3 report measures for all funds in our sample respectively for liquidated and censored (when no default has been observed) funds. Subsequent columns present similar information for small, medium, and large funds respectively.

We expect the mean of covariates bearing a negative relationship with funds' liquidation likelihood to be lower for the liquidated group of observations than for its censored counterpart, and vice versa. For instance, GROWTH is expected to have a negative relationship with liquidation likelihood, and a look at its mean across all size categories shows that its value is lower for the liquidated group of observations than for its censored counterpart. This is also true for TRISK, as its mean is significantly lower for liquidated groups of funds across all size categories and for the full sample. This reinforces our explanation on the negative relationship between TRISK and liquidation likelihood. Our expectation is well supported by all covariates across respective size categories except WRATIO. The mean of WRATIOs for liquidated groups of funds is higher than for their non-liquidated counterparts. In an ideal situation, mean of liquidated group of funds is expected to be lower. In subsequent regression analysis, this might lead to a positive relationship between WRATIO and liquidation likelihood. Broadly, median values of respective covariates reported in Table 2 are also sufficiently close to their respective mean values, thus problems that could emerge due to significant skewness are not expected. Also, there is no unexpected variability in the values of standard deviation, minimum, and maximum descriptive statistics for respective covariates across all size categories.

A casual comparison of values of descriptive measures across the different size categories for respective covariates reveals reasonable differences in their values, particularly when comparison is made between small and large funds. We expect these differences to appear more prominently in our multivariate analysis. Furthermore, as reported in Table 3, there is no evidence of strong correlation among different covariates, thus multicollinearity is not expected to be an issue in the multivariate setup.

[Insert Table 2 Here]

[Insert Table 3 Here]

4. Regression Analysis for All Funds

This section and the next report the univariate and multivariate regression results of this study. Unlike the vast majority of previous studies, we do not predict funds' failure/exit probability over the next month or quarter. We believe that a failure prediction model should work as an early warning system, and the warning should give sufficient time to the decision maker/stakeholder to prepare for (or manage) the forthcoming crisis. It would be relatively easy for someone to predict cardiac arrest with very high likelihood after observing a person with severe chest pain. Thus we present our regression results for 6 months, 12 months and 24 months lagged time periods to allow for sufficient time between the liquidation warning and the actual event. This also helps us to gauge the intertemporal predictive ability of our proposed covariates.

4.1 Univariate Regression Analysis

4.1.1 Main Variables

Table 4 reports univariate regression results for our entire sample of hedge funds. All seven main covariates are statistically significant across all lagged time periods. This shows strong intertemporal predictive ability of our proposed covariates. As expected WRSIZE, GROWTH, RETURN and TRISK are inversely related to liquidation likelihood across all lagged time periods except WRATIO. It is positively related to liquidation risk, which we expect to be negative. This confirms our earlier concern that funds might also choose to exit the database due to superior performance or persistent higher winning ratios, thus leading to a positive relationship between winning ratio and liquidation likelihood. This is further reinforced if one compares the mean of WRATIO for liquidated (0.55) and non-liquidated (0.52) groups of funds. In an ideal situation, the mean of a liquidated group of funds is expected to be lower than their non-liquidated counterparts, but it is otherwise. Negative coefficients of TRISK across all lagged periods and their strong statistical significance reinforce our explanation on negative relationship between TRISK and liquidation risk. The lower the value of *d-ratio*, the better the performance and thus the lower the liquidation likelihood. This is confirmed by the positive coefficient of DRATIO across all lagged periods. Finally, as expected, INDRISK shows a significant positive relationship with liquidation likelihood, and establishes the impact macro-economic and industry specific conditions on hedge funds' liquidation likelihood.

[Insert Table 4 Here]

4.1.2 Control Variables

The standard error of a multivariate regression model increases with an increase in the number of covariates, and this subsequently adds to the numerical instability of the model (Hosmer Jr *et al.,* 2013; Gupta *et al.,* 2017). This also makes the model more dependent on the observed data (Hosmer Jr *et al.,* 2013). Thus, in order to keep the number of explanatory variables at a minimum and prevent insignificant control variables from entering the multivariate models, we perform univariate regression for all control variables discussed in Section 2.3.3. Our multivariate models exclude control variables that fail to be statistically significant at the 20% significance level in all three lagged time periods. Table 5 reports univariate regression results for control variables.

OTP is significant at the 20% significance level for 6 months and 12 months lagged periods, and is significant at the 10% level for 24 months lagged periods. Thus we decide to include it in our multivariate models. Variables LVG, MFEE, and IFEE are highly insignificant in discriminating between liquidated and non-liquidated hedge funds across all three lagged time periods. The case of leverage is extremely interesting. While the amount of leverage is often cited as a dangerous and potentially destabilizing characteristic of the hedge fund industry, it is statistically insignificant in explaining hedge funds' liquidation across all three lagged time periods. Insignificance of LVG is consistent with the results of Liang and Park (2010), where they also report that the presence of leverage has no statistically significant impact on funds' failure likelihood. Moreover, using the same database (TASS), Haghani (2014) reports that MFEE and IFEE are significant predictors of hedge funds' failure. The results of Kim (2016a) are contrary to her results as they also report that management fees and incentive fees are insignificant predictors of hedge funds' failure. Additionally, the seminal study by Liang and Park (2010) on hedge funds' failure does not include MFEE and IFEE as control variables in their multivariate models. Thus, considering our univariate regression results and recent literature, we exclude LVG, MFEE and IFEE from our subsequent multivariate models. The control variables that we consider for further multivariate empirical analysis are AGE, LUPD, RNP, OTP, HWM, PCAP and Investment Style. We do not report univariate regression results for Investment Style, as irrespective of their significance, we include all investment style specific dummies in our multivariate models.

[Insert Table 5 Here]

4.2 Multivariate Analysis

To assess the performance of proposed covariates in jointly predicting the probability of hedge funds' liquidation, we estimate two sets of multivariate regression models. The first set employs only main covariates, and estimation is done for all three lagged time periods. Columns 2, 3 and 4 of Table 6 show our estimation results, and illustrate that all covariates are strongly significant in the multivariate setup across all three lagged time periods. Coefficients of respective covariates bear signs similar to those we report in our univariate results. DRATIO enters significantly with positive coefficient, while coefficients of TRISK are negative. This conforms to our earlier explanation of the direction of their relationship with liquidation likelihood. Further, the statistical significance of our proposed covariates across all three lagged time periods establishes their predictive power across the longer time horizon, and in turn provides sufficient early warning.

The second set of regressions models are obtained by supplementing the first set with the control variables discussed in Section 2.3.3 and the findings in Section 4.1.2. This helps us to control for observable differences in individual hedge fund characteristics, and establish the stability and predictive power of proposed covariates after controlling for various fund characteristics. Columns 5, 6 and 7 of Table 6 present the results. As we see, all proposed covariates are strongly significant, even after introducing control variables into the multivariate setup with expected sign of respective coefficients.

Most of the control variables are statistically significant in predicting hedge funds' liquidation. AGE is statistically significant for all lagged estimations with negative coefficients. This implies that matured funds are less likely to enter liquidation. The fact that a fund has a lock-up period decreases its probability of default, thus LUPD is negative and statistically significant at the 1% level for the 6 months and 12 months lagged periods, and at the 5% level for 24 months. It is therefore in line with Brunnermeier and Pedersen (2009), who argue that when a fund has a lock-up period, it has more funding for liquidity, and thus it can recover from short term liquidity shocks, thereby increasing its chances of survival by lowering the risk of a “liquidity spiral” (Brunnermeier and Pedersen, 2009). Although RNP is negative, it turns insignificant for all lagged estimates. OTP is negative and weakly significant at the 10% level only for 6 months lagged estimates and at the 15% level for 12 and 24 months lagged estimates. Thus, open-ended funds have a marginally higher likelihood of survival than closed-ended funds. We can explain this phenomenon by the fact that open funds can get new inflows, while closed funds are restricted in their base capital, which increases the probability of investors running to the exit. On the other hand, a penalty on exit in the form of a high-water mark (HWM) is negatively correlated with funds' failure likelihood, and is statistically significant across all lagged periods. Finally, when a manager invests his/her own capital in a fund (and hence have “skin in the game”), the fund's default likelihood is reduced. This is weakly confirmed by the fact that PCAP is negative and statistically significant at the 15% level for 6 months, at the 10% level for 12 months, and insignificant for the 24 months lagged periods. Also, casual comparison of the magnitude of respective covariates' coefficients across both groups shows minor or very little variation. Thus predictive power of our proposed covariates is unaffected by the introduction of control variables. This in turn implies that our proposed covariates and the information content in control variables complement each other.

[Insert Table 6 Here]

5. Regression Analysis by Size Categories

5.1 Univariate Analysis

We perform univariate regression analysis of main covariates to verify their power to explain liquidation likelihood of small, medium, and large funds respectively. In particular we verify whether statistical significance of our main covariates vary across size categories or not. Table 7 presents univariate regression results across different sized categories of hedge funds. Regression results for small, medium and large funds, and for all funds, are presented for all three lagged time periods.

As reported in Table 7, all main covariates are highly significant in explaining liquidation likelihood of small funds for 6, 12 and 24 months lagged periods except RETURN (see columns 2, 6 and 10 in Table 7). It loses its significance beyond 12 months. These covariates also exhibit significant discriminatory power for 6 and 12 months' univariate regression estimates of medium sized funds, however GROWTH, RETURN and TRISK turns insignificant for 24 months lagged estimates (see columns 3, 7 and 11 in Table 7). Finally, the case of large funds is most interesting. All main covariates except WRATIO and DRATIO fail miserably in discriminating between liquidated and censored large funds across all lagged periods (see columns 4, 8 and 12 in Table 7). This reinforces our hypothesis and calls for an alternative mechanism to estimate liquidity risk of large funds. Comparison of coefficients of all funds and small/medium funds reveal observable differences in their magnitudes (and occasionally significance) across all three lagged time periods.

Interestingly, although significant, the coefficients of WRSIZE for small and medium funds experience a sign change across all lagged estimates. This implies that small/medium funds have a higher probability of default when they are bigger, which is contrary to the whole sample, implying that the likelihood of funds' liquidation is positively related to its size within a given size category, but negatively related to size in the absence of any size category. It indicates that size is not related to hedge fund failure in a linear fashion. Within a size class, size is a positive factor, whereas for the whole sample, belonging to a bigger size class reduces funds' probability of failure. This may imply that the significance of covariates for our sample of all funds might be driven by small and medium sized funds, and a detailed inspection must be undertaken to understand and identify the factors that threaten the survival of large funds.

Overall, all main covariates are highly significant in explaining liquidation likelihood of small and medium sized funds for up to one year, but are broadly insignificant in explaining liquidation of large funds. This can come from the fact that large hedge funds exhibit only a few defaults, and that these defaults are structurally different from the relatively numerous ones of small and medium hedge funds. Part of the inability of GROWTH can be explained by the already important size of big hedge funds: a big fund experiencing outflows still has large assets under management, decreasing its impact on the probability of failure. Statistical estimates that are unable to account for these size differences might results into biased estimates, with statistical significance of covariates/models being primarily driven by small and medium sized funds.

[Insert Table 7 Here]

5.2 Multivariate Analysis

In order to deepen our understanding of the differences observed in Section 5.1, we present here results obtained from multivariate regression analysis for our sample of hedge funds across different size categories and lagged time periods. Table 8 presents multivariate regression models obtained by employing only our proposed covariates. Further, to test the robustness of our proposed covariates, Table 9 presents multivariate regression results obtained using main and control variables.

[Insert Table 8 Here]

[Insert Table 9 Here]

5.2.1 Small Funds

As reported in Table 8 (columns 2, 6 and 10), for small funds, WRSIZE is significant across all lagged periods but the sign of its coefficient changes from negative (for all funds) to positive. Remaining covariates also exhibit significant discriminatory power across all lagged periods except GROWTH for 12 months lagged estimate. Thus, except the sign of WRSIZE, regression estimates for small funds are broadly in line with regression estimates obtained for the sample of all funds. However, there are noticeable differences in the magnitude of their respective coefficients when compared with coefficients of all funds. Globally, the results are similar to those obtained in the univariate section.

Next, we supplement the models estimated in Table 8 with control variables (see columns 2, 6 and 10 in Table 9). Statistical significance and sign of respective coefficients remains the same as the multivariate models estimated without control variables. This establishes the complementary information content of our main covariates.

5.2.2 Medium Funds

As reported in Table 8 (columns 3, 7 and 11), medium funds' regression estimates for the 6 months lagged period is almost similar to estimates of small funds. However, we see some difference in the 12 and 24 months lagged estimates. GROWTH is insignificant for 12 and 24 months lagged estimates, while WRATIO is insignificant only for the 24 months lagged estimate.

After introducing control variables, when we look at the results for medium funds, we see a different pattern compared to those for small funds with control variables. For the 6 months lagged estimations, all main variables are significant except WRSIZE. When we consider 12 months lagged estimates, GROWTH and RETURN (weakly significant) becomes insignificant. For the lagged period of 24 months, WRSIZE (weakly significant), GROWTH and RETURN are insignificant.

5.2.3 Large Funds

Finally, as reported in Tables 8 and 9, for large funds, empirical results are completely different compared to small and medium funds. For the 6 and 12 months lagged period, only WRATIO, DRATIO and TRISK are statistically significant. While for the 24 months lagged estimates, only WRATIO and DRATIO are significant. These results remain the same even in the presence of control variables. This indicates that large hedge funds have a different risk profile to small and medium funds, and it is inappropriate to explain their liquidation with traditional variables. This feature is interesting because it clearly shows that variables predicting hedge funds' liquidation do not affect funds equally across the different size categories.

An explanation of this fact can be that big hedge funds are structurally different from smaller ones. It might be that big hedge funds need to shrink before failing, so they change size category before failing. For example, a big hedge fund having continuously low returns can see its assets under management shrink but will not fail until it reaches the medium size category and effectively fail.

6. Interaction between Fund Size and Investment Style

Adding interaction between fund size and investment style to multivariate regression models reported in Table 6 would allow us to test the hypothesis that the impact of fund size on liquidation likelihood of hedge funds varies with investment style. Table 10 shows multivariate regression models with interaction terms for fund size and investment style. Results are presented without and with control variables and for the three lagged periods. Size category “Small Funds” and investment style “Convertible Arbitrage” are considered reference groups, and thus main and interaction effects are reported for medium funds, large funds and remaining investment styles.

First and foremost, when interactions between fund size and investment style are taken into account, the variable WRSIZE becomes positive, but remains statistically significant. This means that, once the fact that a fund belongs to a particular size group and investment style is accounted for, the bigger the fund the more likely it is to enter liquidation. This result can seem counterintuitive at first sight, but this can reflect the fact that within a particular category, bigger hedge funds are more exposed to specific risks. Edelman *et al.* (2013) show that the distribution of size is not uniformly distributed across the hedge fund industry. This may imply that a particular hedge fund being bigger relative to a particular size category is a risk, because it may induce bets to attract future inflows and change its size category. This effect of size on the risk of failure increases with the lagged time period in the observation of variables, and is robust to the inclusion of control variables. Variables RETURN, TRISK and GROWTH have negative and statistically significant impact on the probability of future hedge fund failure for all three lagged periods, without and with control variables. However, GROWTH is weakly significant for 12 and 24 months lagged estimates in the presence of interaction effects. Funds having higher WRATIO, DRATIO and INDRISK variables exhibit a higher probability of liquidation. This result is robust to the length of the lags and to the inclusion of control variables. A higher INDRISK means a greater macroeconomic or industry risk and thus a higher likelihood of liquidation. DRATIO measures the relative size of negative returns compared with positive ones. Therefore, a higher DRATIO implies a greater imbalance towards negative returns and hence is positively associated with future hedge fund failure. Broadly, statistical significance of all main variables is in line with the global patterns observed in previous univariate and multivariate regressions.

The main effect of medium sized funds (MF) is insignificant throughout, but the main effect of large funds (LF) is highly significant across all estimates. This reaffirms our earlier results and clearly supports our hypothesis that liquidation likelihood of hedge funds varies with size categories. The main effects of investment styles are mostly insignificant for all estimates, but are weakly significant for 'Equity Market Neutral' and 'Global Macro' for estimates without control variables. However, investment style bears some statistical relevance when interaction is considered between them and fund size. For interaction effects between fund size and investment styles, broadly we observe a significant relationship between the medium size category and investment styles for 6 and 12 months lagged estimates. However, 'MF×Dedicated Short Bias' and 'MF×Fixed Income Arbitrage' are insignificant throughout. No interaction terms are significant for 24 months lagged estimates. Concerning interaction terms between large funds and investment styles, the only statistically significant term is 'LF×Dedicated Short Bias', which is positive across all estimates. This implies that among big funds, following a dedicated short bias strategy will lead to a higher liquidation likelihood.

Broadly, the impact of fund size on liquidation likelihood of hedge funds varies with investment style and it might be appropriate to consider this while predicting hedge funds' liquidation. Other than sign reversal of WRSIZE and weak significance of GROWTH beyond 6 months lagged estimates, the rest of the proposed covariates are highly significant even in the presence of interaction terms. The weak significance of GROWTH might be due to the presence of a large number of insignificant control and interaction terms in the model. Also, comparisons of multivariate regression models in Table 6 with models in Table 10 reveal no drastic changes in respective coefficients of main covariates except WRSIZE. This shows the robustness and consistency of our proposed covariates.

[Insert Table 10 Here]

7. Conclusion

Liquidation of hedge funds can impose considerable costs to both the fund manager and its investors (Lan *et al.,* 2013). Furthermore, failures of very large funds can impose threats on the stability of the financial system as a whole, as seen with the spectacular failure of LTCM, and therefore understanding the causes of such failures is important for managers, investors, and related stakeholders such as prime brokers (who lend securities and money to hedge funds) and regulators. There is a sufficient volume of literature that explores factors affecting hedge funds failure, and different forms of fund failure. However, we contribute to the existing body of literature by acknowledging the differences in liquidation likelihood that might appear due to funds' size. We also propose several new covariates that explain hedge funds' liquidation. In particular we explore information content of funds' relative size (WRSIZE), growth in assets under management (GROWTH), total value of downside and upside returns (DRATIO), volatility of tail risk (TRISK), and past liquidation rate of hedge funds (INDRISK) in predicting liquidation likelihood of hedge funds. We also investigate the discriminatory power of funds' own performance (RETURN) and their past 60 months winning ratio (WRATIO) in predicting hedge funds liquidation.

Our empirical analysis, performed using a sample of hedge funds from the Lipper (TASS) database, shows compelling evidence that the liquidation likelihood is inversely related to fund size, and factors affecting hedge funds' liquidation vary in terms of their statistical significance across different size categories. While broad set of covariates explain failure of small and medium funds (WRSIZE, GROWTH, RETURN, WRATIO, DRATIO, TRISK and INDRISK), only two variables (WRATO and DRATIO) are show significant explanatory power in explaining liquidation of large. Magnitudes of respective regression coefficients for small and medium funds are also marginally higher compared to estimates obtained for all funds, suggesting that small and medium-sized funds are marginally more vulnerable to changes in factors or fund characteristics. The insignificance of our proposed covariates in explaining liquidation of large funds and their significance in explaining liquidation of small and medium funds might imply that small and medium sized funds have dominant influence on regression estimates, and estimates obtained by employing the entire sample of hedge funds might be biased. This is further supported when we include main effects and interaction effects of fund size and investment style into our regression model for all funds. Our results support the view that fund managers can choose to let the fund grow large even if it hurts the performance in order to limit their failure risk. Thus, an appropriate modelling approach of hedge funds' liquidation needs to account for the size of funds considered.

Our findings shall be of particular interest to safety-first investors, who may prefer to deal with large hedge funds to avoid losses that may arise due to the higher risk of liquidation faced by smaller funds. Hedge funds are often blamed for contributing towards increasingly systematic risk and financial instability, and in this context it is worth exploring if a particular size category of funds is primarily responsible for this. Exploring how other forms of fund exits vary across size categories may also be a worthy extension.

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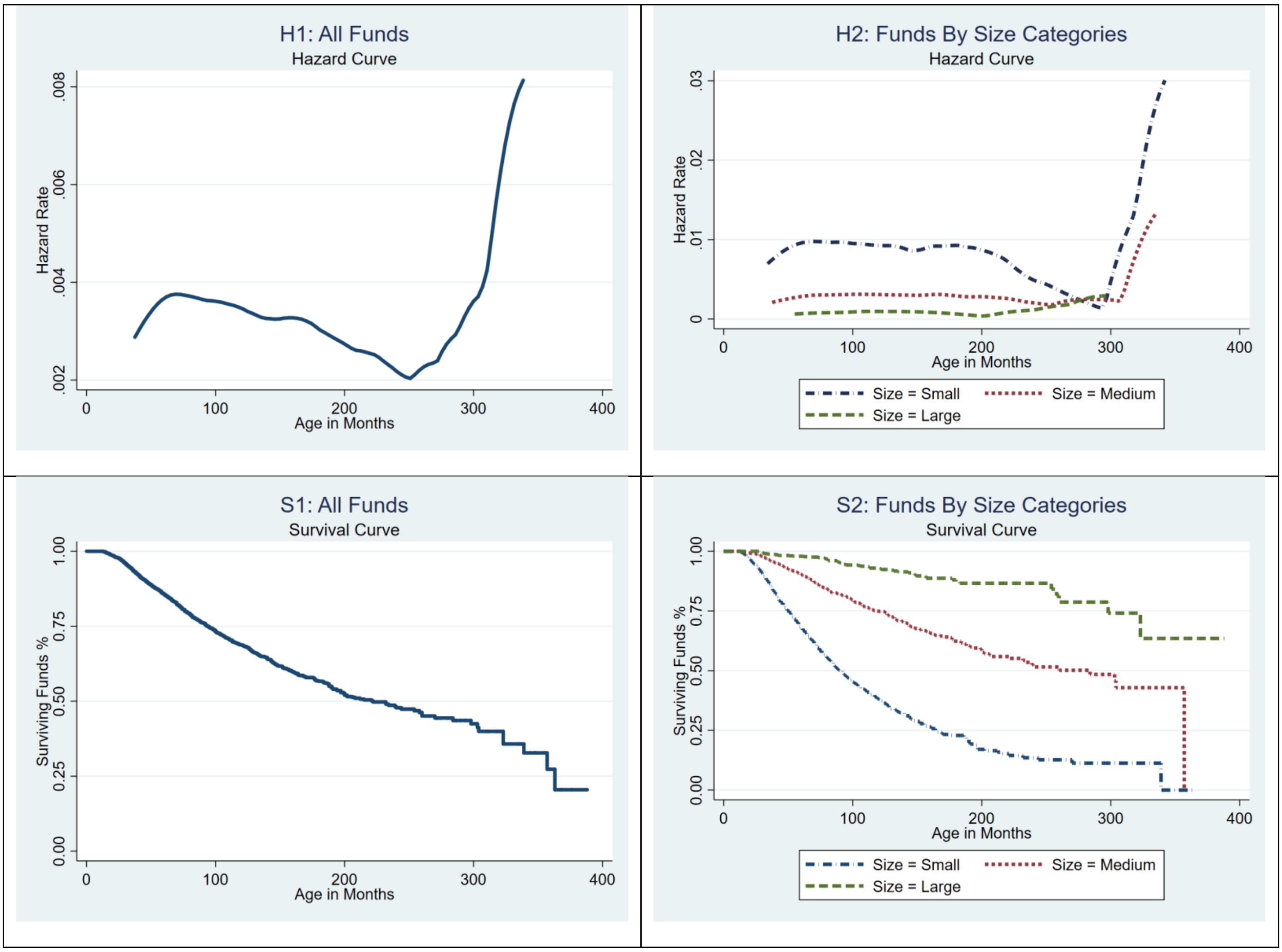
List of Figure and Tables

Figure 1: Table of Hazard and Survival Curves



Notes: This table presents hazard and survival curves of hedge funds estimated using the Kaplan-Meier Estimator (see, Kleinbaum and Klein, 2012). H1 is the hazard curve of all funds and S1 is the corresponding survival curve for the same. H2 presents hazard curves for small, medium and large funds, while S2 presents their survival curves.

Table 1: Liquidation Rate of Hedge Funds

Year	All Funds			Small Funds			Medium Funds			Large Funds		
	Liquidated	Total	%Liquidated	Liquidated	Total	%Liquidated	Liquidated	Total	%Liquidated	Liquidated	Total	%Liquidated
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1995	0	69	0.0000	0	32	0.0000	0	35	0.0000	0	9	0.0000
1996	4	166	2.4096	3	79	3.7975	1	86	1.1628	0	17	0.0000
1997	4	290	1.3793	3	132	2.2728	1	164	0.6097	0	36	0.0000
1998	21	443	4.7404	14	205	6.8293	5	237	2.1097	2	63	3.1746
1999	22	539	4.0816	20	233	8.5837	2	321	0.6230	0	79	0.0000
2000	29	587	4.9404	21	225	9.3333	6	358	1.6760	2	122	1.6393
2001	16	913	1.7525	10	278	3.5971	6	557	1.0772	0	208	0.0000
2002	36	1081	3.3302	19	355	5.3521	16	665	2.4060	1	234	0.4273
2003	51	1209	4.2184	28	402	6.9652	22	737	2.9851	1	295	0.3390
2004	62	1365	4.5421	40	413	9.6852	21	769	2.7308	1	372	0.2688
2005	82	1547	5.3006	40	462	5.6580	39	869	4.4879	3	447	0.6711
2006	52	1536	3.3854	34	423	8.0378	17	842	2.0190	1	484	0.2066
2007	45	1529	2.9431	23	377	6.1008	18	818	2.2005	4	555	0.7207
2008	103	1485	6.9360	49	454	10.7929	47	859	5.4715	7	500	1.4000
2009	72	1325	5.4340	44	452	9.7345	23	781	2.9449	5	340	1.4706
2010	77	1341	5.7420	43	411	10.4623	32	762	4.1995	2	330	0.6061
2011	79	1175	6.7234	35	351	9.9715	39	677	5.7607	5	303	1.6502
2012	76	1009	7.5322	39	296	13.1757	32	571	5.6042	5	275	1.8182
2013	20	856	2.3365	9	210	4.2857	10	480	2.0833	1	262	0.3817
2014	46	755	6.0927	20	182	10.9890	17	404	4.2079	9	244	3.6885
2015	41	627	6.5391	19	160	11.8750	18	327	5.5046	4	204	1.9608
2016	18	517	3.4816	11	134	8.2089	3	262	1.1450	4	185	2.1622
Average			4.2655			7.5321			2.7731			1.0266

Notes: This table presents yearly details of liquidated and censored hedge funds. Column 1 lists years followed by number of funds liquidated in that year (column 2), total number of funds in the database in that year (column 3), and percentage of funds liquidated (Liquidated/Total×100) in that year (column 4) for our entire sample of hedge funds. Subsequent columns show similar information for small, medium, and large sized funds. In the last row, 'Average' is mean of annual liquidation rates reported in columns 4, 7, 10 and 13 respectively.

Table 2: Descriptive Statistics of Main Variables

Variable	All Funds		Small Funds		Medium Funds		Large Funds	
	Liquidated	Censored	Liquidated	Censored	Liquidated	Censored	Liquidated	Censored
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
WRSIZE								
Mean	-7.7149	-6.6571	-8.8031	-8.9000	-6.6722	-6.6475	-4.5698	-4.5545
Median	-7.8013	-6.6603	-8.8990	-8.9294	-6.9300	-6.7889	-4.8671	-4.6971
SD	2.0010	2.0804	1.6930	1.6755	1.3038	1.3448	1.3150	1.2371
Minimum	-15.7514	-24.4254	-15.7514	-24.4245	-9.6197	-12.4805	-7.2946	-13.174
Maximum	-1.3552	0.0000	-2.2418	-0.0002	-1.3552	-0.0104	-1.3586	0.0000
GROWTH								
Mean	-0.0522	0.0036	-0.0701	-0.1324	-0.0336	0.0060	-0.0106	0.0073
Median	-0.0241	0.0041	-0.0346	-0.0002	-0.0195	0.0036	-0.0001	0.0109
SD	0.1044	0.0745	0.1235	0.1050	0.0712	0.6419	0.0493	0.0526
Minimum	-0.9723	-4.5291	-0.9723	-4.5290	-0.3941	-3.0555	-0.1399	-1.3812
Maximum	0.4405	3.1741	0.2986	3.1741	0.4405	1.3817	0.0946	1.5216
RETURN								
Mean	-0.0450	0.0053	-0.0059	0.0024	-0.0026	0.0057	-0.0034	0.0073
Median	-0.0007	0.0057	-0.0012	0.0037	-0.0001	0.0057	0.0046	0.0070
SD	0.0258	0.0208	0.0296	0.0268	0.0190	0.0196	0.0268	0.0155
Minimum	-0.2698	-1.1439	-0.2698	-1.1439	-0.1238	-0.1238	-0.1210	-0.1971
Maximum	0.2754	0.4230	0.2754	0.3861	0.0641	0.0641	0.0308	0.2897
WRATIO								
Mean	0.5469	0.5200	0.5266	0.4857	0.5683	0.5127	0.5939	0.5666
Median	0.5500	0.5500	0.5294	0.5000	0.5667	0.5500	0.6052	0.6000
SD	1.3193	0.2260	1.2822	0.2177	0.1277	0.2254	0.1586	0.2273
Minimum	0.0000	0.0000	0.0000	0.0000	0.0667	0.0000	0.0667	0.0000
Maximum	0.9661	1.0000	0.9661	1.0000	0.9592	1.0000	0.9355	1.0000
DRATIO								
Mean	-0.3211	-1.2199	-0.1108	-0.759	-0.4746	-1.2114	-1.2442	-1.6726
Median	-0.2355	-1.0213	-0.0569	-0.6327	-0.3883	-1.0235	-1.2643	-1.3989
SD	1.4478	1.4849	1.4049	1.3731	1.3887	1.4261	1.7298	1.5611
Minimum	-9.2522	-11.5364	-9.2522	-10.0747	-6.9077	-10.6139	-7.6145	-11.5364
Maximum	7.4838	7.4838	7.4838	7.4838	4.068	6.9591	2.2623	5.2307
TRISK								
Mean	0.0081	0.1138	0.0079	0.1121	0.0084	0.1150	0.0074	0.1130
Median	0.0012	0.0038	0.0004	0.0030	0.0018	0.0038	0.0023	0.0044
SD	0.0189	0.0215	0.0206	0.0236	0.0172	0.0222	0.0114	0.0179
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.3024	0.4155	0.3025	0.4155	0.1413	0.4145	0.05343	0.3063
INDRISK								
Mean	-2.2424	-2.8778	-2.2586	-2.9561	-2.2166	-2.8804	-2.2629	-2.7986
Median	-2.1907	-2.4805	-2.2311	-2.5427	-2.1517	-2.4737	-2.2676	-2.4474
SD	0.5884	1.3019	0.5971	1.3598	0.5724	1.3184	0.6159	1.2052
Minimum	-5.1705	-6.9067	-5.1705	-6.9067	-4.5326	-6.9067	-4.5493	-6.9067
Maximum	0.1823	0.1823	0.1283	-0.1823	-0.5596	0.1823	-0.5596	-0.5947

Notes: This table presents descriptive statistics of respective covariates for our entire sample of hedge funds, followed by measures across respective size categories. Funds corresponding to the bottom 25 percentile of assets under management (AUM) are considered as small funds, those in the top 25 percentile as large funds, and the rest medium funds. Funds are separated between liquidated and censored (for which the liquidation fate has not yet occurred) groups and descriptive measures are reported for both groups separately. If a fund fails in month *t*, the fund's failure indicator is '1' in that month *t* and '0' in other months. Column 1 lists main covariates along with names of descriptive measures that we report in subsequent columns. Columns 2 and 3 report descriptive measures for liquidated and non-liquidated groups respectively, while subsequent columns present similar information for respective size categories. WRSIZE is the weighted average of a fund's relative size; GROWTH is the percentage change in its assets under management; RETURN is the geometric mean of past 12 months' rate of return; WRATIO is winning ratio over the past 60 months; DRATIO is natural logarithm of the past 60 months d-ratio, which measures the ratio of the total value of downside returns over the total value of upside returns; TRISK is the volatility of tail risk; and INDRISK is the natural logarithm of the past 24 months' liquidation rates. See Section 2.3.2 for details.

Table 3: Correlation Matrix of Main Variables

	WRSIZE	GROWTH	RETURN	WRATIO	DRATIO	TRISK	INDRISK
WRSIZE	1.0000						
GROWTH	0.0448	1.0000					
RETURN	0.0490	0.3209	1.0000				
WRATIO	0.1147	0.0003	0.1148	1.0000			
DRATIO	-0.2580	-0.2006	-0.2392	-0.2249	1.0000		
TRISK	-0.0271	-0.0428	-0.0305	0.0826	0.0934	1.0000	
INDRISK	-0.0444	-0.1137	-0.0730	0.1071	0.1363	0.1613	1.0000

Notes: This table presents correlation among main covariates estimated over the sample period 1995-2016.

Table 4: Univariate Regression for All Funds: Main Variables

Variable	Lag Months		
	6 Months	12 Months	24 Months
	(1)	(2)	(3)
WRSIZE			
β	-0.1942[a]	-0.2001[a]	-0.1637[a]
SE	0.0159	0.0174	0.0210
R^2	0.0455	0.0426	0.0272
GROWTH			
β	-2.769[a]	-2.7739[a]	-2.7555[a]
SE	0.2810	0.3570	0.4414
R^2	0.0105	0.0086	0.0074
RETURN			
β	-10.5663[a]	-7.6738[a]	-6.3624[a]
SE	1.1021	1.2605	1.7965
R^2	0.0127	0.0059	0.0037
WRATIO			
β	1.0918[a]	1.6679[a]	2.2819[a]
SE	0.1507	0.1598	0.1887
R^2	0.0177	0.0369	0.0641
DRATIO			
β	0.5643[a]	0.6761[a]	0.7589[a]
SE	0.0253	0.0328	0.04758
R^2	0.1703	0.2060	0.2153
TRISK			
β	-14.7845[a]	-14.5488[a]	-5.4045[b]
SE	2.6175	2.9049	2.7693
R^2	0 .0298	0.0263	0.0033
INDRISK			
β	0.2115[a]	0.0604[b]	0.1263[a]
SE	0.0353	0.0311	0.0404
R^2	0.0193	0.0015	0.0061

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). This table presents univariate panel logistic regression results of main covariates estimated over a sampling period of 1995-2016. Regression estimates are reported for 6 months (column 1), 12 months (column 2), and 24 months (column 3) lagged time periods. If a fund fails in month *t*, the fund's failure indicator is '1' in that month *t* and '0' otherwise. A positive (negative) coefficient (β) suggests that the variable increases (decreases) the probability of funds' liquidation, SE is standard error of respective coefficients and R^2 is McKelvey & Zavoina's R^2. WRSIZE is the weighted average of a fund's relative size; GROWTH is the percentage change in its assets under management; RETURN is the geometric mean of past 12 months rate of return; WRATIO is winning ratio over the past 60 months; DRATIO is natural logarithm of the past 60 months d-ratio, which measures the ratio of the total value of downside returns over the total value of upside returns; TRISK is the volatility of tail risk; and INDRISK is the natural logarithm of the past 24 months' liquidation rates. See Section 2.3.2 for details.

Table 5: Univariate Regression for All Funds: Control Variables

Variable	Lag Months		
	6 Months	12 Months	24 Months
	(1)	(2)	(3)
AGE			
β	-0.1455[a]	-0.2834[a]	-0.3325[a]
SE	0.0381	0.0375	0.0435
R^2	0.0044	0.0166	0.0222
LUPD			
β	-0.4125[a]	-0.4465[a]	-0.4589[a]
SE	0.0771	0.0864	0.1022
R^2	0.0111	0.0113	0.0116
RNP			
β	-0.2878[a]	-0.3154[a]	-0.3219[a]
SE	0.0431	0.0480	0.0579
R^2	0.0221	0.0231	0.0231
OTP			
β	-0.1453[d]	-0.1580[d]	-0.2327[c]
SE	0.094	0.1067	0.1267
R^2	8.9e-04	9.2e-04	0.0020
HWM			
β	-0.3405[a]	-0.3876[a]	-0.4131[a]
SE	0.075	0.0855	0.1023
R^2	0.0061	0.0068	0.0074
PCAP			
β	-0.2361[a]	-0.2617[a]	-0.2088[b]
SE	0.0726	0.0819	0.0963
R^2	0.0038	0.0041	0.0025
LVG			
β	-0.1510	-0.0390	-0.0709
SE	0.0729	0.0823	0.0978
R^2	1.5e-05	8.4e-05	2.6e-04
MFEE			
β	0.0185	0.0197	-0.0084
SE	0.0703	0.0793	0.096
R^2	2.3e-05	2.2e-05	3.8e-06
IFEE			
β	-0.0052	-0.0097	-0.0005
SE	0.0072	0.008	0.0102
R^2	1.7e-04	4.8e-04	1.4e-06

Notes: a (b) [c] {d} significant at the 1 % (5 %) [10 %] {20%} level (two-sided test). This table presents univariate panel logistic regression results of control variables estimated over a sampling period of 1995-2016. Regression estimates are reported for 6 months (column 1), 12 months (column 2), and 24 months (column 3) lagged time periods. If a fund fails in month *t*, the fund's failure indicator is '1' in that month *t* and '0' otherwise. A positive (negative) coefficient (β) suggests that the variable increases (decreases) the probability of funds' liquidation, SE is standard error of respective coefficients and R^2 is McKelvey & Zavoina's R^2. AGE is natural logarithm of a fund's annual age; LUPD is Lock-up period dummy; RNP is Redemption Notice Period in months; OTP is Open to Public dummy which takes the value 1 if the fund is open for public subscription and 0 otherwise; LVG is Leverage dummy which takes the value 1 if the fund uses leverage and 0 otherwise; HWM is High Water Mark dummy variable with the value 1 for high HWM provision, and 0 otherwise; PCAP is Personal Capital dummy variable which takes the value 1 if the fund manager has invested personal capital in the fund, and 0 otherwise; MFEE is management fees charged by the hedge fund manager in percent; and IFEE is incentive fees charged by the hedge fund manager in percent.

Table 6: Multivariate Regression Model for All Funds

Variable	Without Control Variables				With Control Variables		
Lag Months	6 Months	12 Months	24 Months		6 Months	12 Months	24 Months
(1)	(2)	(3)	(4)		(5)	(6)	(7)
WRSIZE							
β	-0.1403^{a}	-0.1259^{a}	-0.0998^{a}		-0.1885^{a}	-0.1632^{a}	-0.1106^{a}
SE	0.0161	0.0163	0.0208		0.0180	0.0186	0.0225
GROWTH							
β	-1.6438^{a}	-1.7825^{a}	-1.7257^{a}		-1.5921^{a}	-1.6886^{a}	-1.8948^{a}
SE	0.2700	0.3813	0.4958		0.2607	0.3730	0.4365
RETURN							
β	-7.6823^{a}	-4.9115^{a}	-4.9075^{a}		-7.5856^{a}	-5.0110^{a}	-4.7534^{a}
SE	1.3138	1.4041	1.9572		1.3039	1.3903	1.8879
WRATIO							
β	2.9794^{a}	3.0641^{a}	3.4488^{a}		2.9564^{a}	3.0570^{a}	3.3999^{a}
SE	0.2025	0.1862	0.2201		0.2038	0.1876	0.2052
DRATIO							
β	0.6203^{a}	0.7028^{a}	0.8154^{a}		0.5886^{a}	0.6662^{a}	0.7269^{a}
SE	0.0296	0.0320	0.0471		0.0302	0.0329	0.0435
TRISK							
β	-25.5912^{a}	-26.0936^{a}	-23.4122^{a}		-20.6695^{a}	-19.8760^{a}	-15.1501^{a}
SE	2.8150	2.9178	3.2367		2.7966	2.8493	2.9192
INDRISK							
β	0.2579^{a}	0.0944^{a}	0.0972^{a}		0.2927^{a}	0.1540^{a}	0.2073^{a}
SE	0.0333	0.0285	0.2047		0.0363	0.0318	0.0390
AGE							
β					-0.1021^{b}	-0.1707^{a}	-0.4105^{a}
SE					0.0482	0.0470	0.0541
LUPD							
β					-0.2394^{a}	-0.2330^{a}	-0.2107^{b}
SE					0.0789	0.0807	0.0942
RNP							
β					-0.0546	-0.0531	-0.0382
SE					0.0429	0.0439	0.0507
OTP							
β					-0.1705^{c}	-0.1407	-0.1689
SE					0.0924	0.0940	0.1100
HWM							
β					-0.2507^{a}	-0.2437^{a}	-0.2533^{a}
SE					0.7546	0.0772	0.0904
PCAP							
β					-0.1118^{c}	-0.1287^{c}	-0.9071
SE					0.0712	0.0727	0.0835
Investment Style					Yes	Yes	Yes
Goodness of Fit Measures							
Wald Chi^2	830.9300^{a}	893.0900^{a}	568.0300^{a}		928.2600^{a}	987.8700^{a}	790.4400^{a}
Log Likelihood	-5,334.2057	-4,999.9527	-3,705.6916		-5,277.6453	-4942.7056	-3,639.2845
R^2	0.3367	0.3375	0.3570		0.3380	0.3389	0.3586
No. of "0"	176,035	154,854	119,436		175,814	154,673	119,316
No. of "1"	928	889	655		927	888	654

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). This table presents multivariate panel logistic regression results for 6 months, 12 months, and 24 months lagged periods, estimated over a sampling period of 1995-2016. Columns 2, 3 and 4 do not include control variables and the rest include control variables in the multivariate estimates. If a fund liquidates in month *t*, the fund's binary indicator is '1' in that month *t* and '0' otherwise. A positive coefficient (β) suggests a positive relationship with liquidation likelihood and vice-versa. SE is standard error of respective coefficients and R^2 is McKelvey & Zavoina's R^2. No. of "1" counts the number of failures in our sample, while No. of "0" counts the number of "non-failure" observations.

Table 7: Univariate Regression Analysis by Size Categories

Lag Months	6 Months Lag				12 Months Lag				24 Months Lag			
Variable	All Funds	Small Funds	Medium Funds	Large Funds	All Funds	Small Funds	Medium Funds	Large Funds	All Funds	Small Funds	Medium Funds	Large Funds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WRSIZE												
β	-0.1942[a]	0.1039[a]	0.0799[b]	0.08879	-2.0010[a]	0.0727[b]	0.1181[a]	0.0091	-0.1637[a]	0.1085[a]	0.1198[a]	0.0320
SE	-6.6407	0.0272	0.0361	0.1010	0.0175	0.0302	0.038	0.0998	0.0210	0.0361	0.0424	0.1116
R^2	0.0455	0.0123	0.0082	0.0102	0.0426	0.0050	0.0151	1.1e-04	0.0272	0.0101	0.0137	0.0013
GROWTH												
β	-2.7695[a]	-1.4446[a]	-3.1186[a]	-2.0885	-2.7739[a]	-1.1404[b]	-1.8324[a]	-1.6243	-2.7555[a]	-2.2198[a]	-0.997	-0.0608
SE	0.2811	0.3110	0.6244	2.6495	0.3570	0.4913	0.5761	2.5503	0.4414	0.6294	0.8221	2.7702
R^2	0.0105	0.0028	0.0138	0.0066	0.0086	0.0013	0.0039	0.0037	0.0074	0.0041	09.7e-04	4.8e-06
RETURN												
β	-10.5663[a]	-5.4966[a]	-11.8323[a]	-9.8612	-7.6738[a]	-2.9036[b]	-7.1146[a]	-8.9467	-6.3624[a]	-2.7930	-2.7247	-14.8823[c]
SE	1.1021	1.4415	1.9158	8.1605	1.2605	1.6641	2.6015	8.3095	1.7965	2.2985	3.1129	7.7605
R^2	0.0127	0.0032	0.0167	0.0117	0.0059	7.4e-04	0.0053	0.0097	0.0037	6.0e-04	06.7e-04	0.0256
WRATIO												
β	1.0918[a]	1.4077[a]	1.6691[a]	1.2299[b]	1.6679[a]	1.9752[a]	2.1731[a]	1.4613[b]	2.2819[a]	2.7094[a]	2.5850[a]	1.0236
SE	0.1507	0.2215	0.2419	0.6106	0.1598	0.2425	0.2545	0.6161	0.1887	0.2966	0.2859	0.6769
R^2	0.0177	0.0282	0.0425	0.0241	0.0369	0.0487	0.0639	0.0312	0.0641	0.0857	0.0813	0.0184
DRATIO												
β	0.5643[a]	0.4341[a]	0.4989[a]	0.3377[a]	0.6761[a]	0.5056[a]	0.5589[a]	0.5535[a]	0.7589[a]	0.5293[a]	0.6060[a]	0.5495[a]
SE	0.0253	0.0403	0.0451	0.1109	0.0328	0.0512	0.0528	0.1269	0.0476	0.0771	0.0720	0.1661
R^2	0.1703	0.1007	0.1367	0.0685	0.2060	0.1082	0.1498	0.1596	0.2153	0.0980	0.1451	0.1522
TRSIK												
β	-14.7545[a]	-11.8904[a]	-13.705[a]	-19.2209	-14.5488[a]	-12.5164[a]	-13.9339[a]	-20.3966	-5.4045[c]	-8.8157[b]	-5.2944	-6.0659
SE	2.6175	3.4572	4.0688	12.1855	2.9049	3.7617	4.3412	12.6351	2.7693	4.0785	4.0575	11.7049
R^2	0.0298	0.0182	0.0257	0.0493	0.0263	0.0171	0.0261	0.0557	0.0033	0.0075	0.0031	0.0051
INDRISK												
β	0.2116[a]	0.3382[a]	0.2024[a]	0.05457	0.0605[c]	0.1124[b]	0.1217[b]	-0.1164	0.1263[a]	0.1161[b]	0.1826[a]	0.1174
SE	0.0353	0.5590	0.0532	0.1128	0.0311	0.0468	0.0507	0.0880	0.0404	0.0569	0.0630	0.1371
R^2	0.0193	0.0416	0.0186	0.0016	0.0015	0.0045	0.0063	0.0074	0.0061	0.0045	0.0120	0.0077

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). This table presents univariate panel logistic regression results of respective covariates for 6 months (columns 1 to 4), 12 months (columns 5 to 8), and 24 months (columns 9 to 12) lagged time periods across different size categories. The sampling period is between 1995-2016. We consider funds corresponding to the bottom 25 percentile of AUM as small funds, those in the top 25 percentile as large funds, and the rest medium funds. If a fund liquidates in month *t*, the fund's failure indicator is '1' in that month *t* and '0' otherwise. A positive coefficient (β) suggests a positive relationship with liquidation likelihood and vice-versa. SE is standard error of respective coefficients and R^2 is McKelvey & Zavoina's R^2. No. of "1" counts the number of failures in our sample, while No. of "0" counts the number of "non-failure" observations.

Table 8: Multivariate Regression Models without Control Variables by Size Categories

Lag Months	6 Months Lag				12 Months Lag				24 Months Lag			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variable	All Funds	Small Funds	Medium Funds	Large Funds	All Funds	Small Funds	Medium Funds	Large Funds	All Funds	Small Funds	Medium Funds	Large Funds
WRSIZE												
β	-0.1403[a]	0.0930[a]	0.0990[a]	0.1305	-0.1259[a]	0.0770[a]	0.1303[a]	0.0468	-0.0998[a]	0.1064[a]	0.1169[a]	0.0632
SE	0.0161	0.0258	0.0374	0.1070	0.0163	0.0261	0.0365	0.1018	0.0208	0.0339	0.0415	0.1194
GROWTH												
β	-1.6438[a]	-0.7951[a]	-2.2350[a]	0.7964	-1.7825[a]	-0.6522	-0.6140	1.0250	-1.7257[a]	-1.6437[a]	0.7839	2.7710
SE	0.2700	0.3227	0.5685	2.7301	0.3813	0.4948	0.9839	2.5428	0.4958	0.6380	1.1442	2.0622
RETURN												
β	-7.6823[a]	-5.7913[a]	-9.7537[a]	-6.6804	-4.9115[a]	-4.3523[a]	-5.7245[a]	-5.5494	-4.9075[b]	-5.5385[b]	-4.9044	-13.7143
SE	1.3138	1.8661	2.5391	9.7828	1.4041	1.7542	3.1398	9.0895	1.9572	2.6323	3.5833	8.8308
WRATIO												
β	2.9794[a]	3.0568[a]	3.3736[a]	2.4474[a]	3.0641[a]	3.1490[a]	3.4446[a]	2.5910[a]	3.4488[a]	3.9094[a]	3.5644[a]	2.0547[a]
SE	0.2025	0.2981	0.3188	0.7470	0.1862	0.2773	0.3114	0.6812	0.2201	0.3652	0.3403	0.7973
DRATIO												
β	0.6203[a]	0.5561[a]	0.5952[a]	0.4576[a]	0.7028[a]	0.5847[a]	0.6710[a]	0.6474[a]	0.8154[a]	0.6449[a]	0.7415[a]	0.6342[a]
SE	0.0296	0.0459	0.0446	0.1146	0.0320	0.0507	0.0536	0.1237	0.0471	0.0764	0.0700	0.1730
TRISK												
β	-25.59125[a]	-20.6832[a]	26.0490[a]	-32.1740[b]	-26.0936[a]	-21.8708[a]	-26.0559[a]	-31.1651[b]	-23.4122[a]	-21.8907[a]	-22.3154[a]	-21.7145
SE	2.8150	3.6018	4.4266	13.7533	2.9178	3.8017	4.5614	13.9449	3.2367	4.4792	4.8834	14.9354
INDRISK												
β	0.25791[a]	0.2728[a]	0.2229[a]	0.0764	0.0944[a]	0.1058[a]	0.1422[a]	-0.0914	0.09725[b]	0.1228[b]	0.1432[a]	0.0149
SE	0.0333	0.0476	0.0487	0.7329	0.0285	0.0406	0.0465	0.0936	0.2047	0.0533	0.3495	0.1370
Goodness of Fit Measures												
Wald Chi^2	830.9300[a]	257.1900[a]	297.2400[a]	26.2500[a]	893.0900[a]	265.7200[a]	258.7600[a]	47.8100[a]	568.0300[a]	177.5100[a]	201.8900[a]	21.0800[a]
Log Likelihood	-5,334.2057	-2,565.0990	-2,210.4773	-411.6005	-4,999.9527	-2,395.5338	-2,068.6802	-391.5999	-3,705.6916	-1,665.259	-1,635.5298	-279.11423
R^2	0.3367	0.2738	0.3187	0.2308	0.3375	0.2544	0.3177	0.2738	0.3570	0.2819	0.3122	0.2317
No. of "0"	176,035	40,484	88,389	47,162	154,854	34,066	77,569	43,219	119,436	24,446	59,330	35,660

No. of "1"	928	507	366	55	889	487	348	54	655	341	277	37

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). This table presents multivariate panel logistic regression results without control variable for 6 months (columns 1 to 4), 12 months (columns 5 to 8), and 24 months (columns 9 to 12) lagged periods across different size categories. The sampling period runs between 1995-2016. We consider funds corresponding to the bottom 25 percentile of AUM as small funds, those in the top 25 percentile as large funds, and the rest medium funds. If a fund liquidates in month *t*, the fund's failure indicator is '1' in that month *t* and '0' otherwise. A positive coefficient (β) suggests a positive relationship with liquidation likelihood and vice-versa. SE is standard error of respective coefficients and R^2 is McKelvey & Zavoina's R^2. No. of "1" counts the number of failures in our sample, while No. of "0" counts the number of "non-failure" observations.

Table 9: Multivariate Regression Models with Control Variables by Size Categories

Lag Months	6 Months Lag				12 Months Lag				24 Months Lag			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variable	All Funds	Small Funds	Medium Funds	Large Funds	All Funds	Small Funds	Medium Funds	Large Funds	All Funds	Small Funds	Medium Funds	Large Funds
WRSIZE												
β	-0.1885^{a}	0.1148^{a}	0.0469	0.1042	-0.1632^{a}	0.0982^{a}	0.1164^{b}	0.0459	-0.1106^{a}	0.1492^{a}	0.0953^{c}	-0.0463
SE	0.0180	0.0341	0.0542	0.1295	0.0186	0.0324	0.0516	0.1227	0.0225	0.0389	0.0530	0.1470
GROWTH												
β	-1.5921^{a}	-0.7721^{b}	-2.1490^{a}	1.1107	-1.6886^{a}	-0.6989	-0.7544	1.3416	-1.8948^{a}	-1.7579^{a}	-0.1464	2.2651
SE	0.2607	0.3242	0.5878	2.7518	0.3730	0.4734	0.9379	2.3665	0.4365	0.5888	1.0624	1.9581
RETURN												
β	-7.5856^{a}	-5.8748^{a}	-10.1098^{a}	-7.3356	-5.0110^{a}	-4.4482^{a}	-5.8788^{c}	-7.7427	-4.7534^{a}	-5.2080^{b}	-3.9814	-13.6738
SE	1.3039	1.8615	2.5625	9.9175	1.3903	1.7256	3.1573	9.1010	1.8879	2.5053	3.5152	8.7349
WRATIO												
β	2.9564^{a}	3.0599^{a}	3.3589^{a}	2.6826^{a}	3.0570^{a}	3.1240^{a}	3.4259^{a}	2.8183^{a}	3.3999^{a}	3.6523^{a}	3.5217^{a}	2.1071^{b}
SE	0.2038	0.2965	0.3274	0.8028	0.1876	0.2680	0.3081	0.7156	0.2052	0.3429	0.3128	0.8543
DRATIO												
β	0.5886^{a}	0.5444^{a}	0.6038^{a}	0.4313^{a}	0.6662^{a}	0.5607^{a}	0.6731^{a}	0.6110^{a}	0.7269^{a}	0.5815^{a}	0.6844^{a}	0.5620^{a}
SE	0.0302	0.0451	0.0473	0.1243	0.0329	0.0477	0.0529	0.1290	0.0435	0.0721	0.0680	0.1844
TRISK												
β	-20.6694^{a}	-17.7186^{a}	-23.9185^{a}	-33.0417^{b}	-19.8760^{a}	-17.9085^{a}	-22.1927^{a}	-30.6602^{b}	-15.1501^{a}	-16.0579^{a}	-16.2325^{a}	-21.3327
SE	2.7966	3.6844	4.4538	14.7039	2.8493	3.7823	4.5090	14.6883	2.9192	4.1919	4.4425	16.1625
INDRISK												
β	0.2927^{a}	0.2937^{a}	0.2634^{a}	0.0765	0.1540^{a}	0.1129^{a}	0.2110^{a}	-0.1598	0.2073^{a}	0.1401^{a}	0.2772^{a}	0.0816
SE	0.0363	0.0507	0.0545	0.1392	0.0318	0.0426	0.0518	0.1167	0.0390	0.0551	0.0610	0.1671
AGE												

β	-0.1021[b]	-0.0895	-0.0651	0.2159	-0.1707[a]	-0.1354[b]	-0.1964[a]	0.1939	-0.4105[a]	-0.3076[a]	-0.4651[a]	0.0685
SE	0.0482	0.0661	0.0771	0.2234	0.0470	0.0644	0.0768	0.2119	0.0541	0.0859	0.0852	0.2648
LUPD												
β	-0.2394[a]	-0.1617	-0.2822[b]	-0.3020	-0.2330[a]	-0.1765	-0.2487[b]	-0.2995	-0.2107[b]	-0.1526	-0.2271[c]	-0.4839
SE	0.0789	0.1086	0.1235	0.3309	0.0807	0.1110	0.1266	0.3337	0.0942	0.1398	0.1426	0.4235
RNP												
β	-0.0546	-0.0093	-0.0624	0.1135	-0.0531	0.0236	-0.0605	0.1288	-0.0382	0.0881	-0.1283[c]	0.3579[b]
SE	0.0429	0.0638	0.0653	0.1406	0.0439	0.0654	0.0674	0.1403	0.0507	0.0828	0.0809	0.1600
OTP												
β	-0.1705[c]	0.0285	-0.2666[c]	-1.1630[b]	-0.1407	0.0360	-0.2460	-1.0638[b]	-0.1689	-0.0974	-0.1566	-0.8129
SE	0.0924	0.1194	0.1537	0.5261	0.0940	0.1222	0.1569	0.5266	0.1100	0.1589	0.1708	0.5442
HWM												
β	-0.2507[a]	-0.0919	-0.0909	-0.1797	-0.2437[a]	-0.0353	-0.0995	-0.2139	-0.2533[a]	0.0134	-0.1237	0.0072
SE	0.7546	0.1064	0.1226	0.3213	0.0772	0.1094	0.1262	0.3234	0.0904	0.1413	0.1421	0.4407
PCAP												
β	-0.1118[c]	-0.1474	-0.2346[b]	-0.2311	-0.1287[c]	-0.1679[c]	-0.2545[b]	-0.1934	-0.0907	-0.1020	-0.2146[c]	0.0594
SE	0.0712	0.0966	0.1161	0.3034	0.0727	0.0991	0.1187	0.3064	0.0835	0.1242	0.1307	0.3493
Investment Style	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Goodness of Fit Measures												
Wald Chi^2	928.2600[a]	287.4000[a]	315.2100[a]	48.2100[a]	987.8700[a]	310.5700[a]	323.9900[a]	69.4500[a]	790.4400[a]	242.5700[a]	294.1700[a]	52.5500[a]
Log Likelihood	-5,277.6453	-2,556.1298	-2,187.5128	-401.96548	-4942.7056	-2,384.7241	-2,042.4571	-382.44704	-3,639.2845	-1650.7299	-1,603.2006	-268.3466
R^2	0.338	0.2794	0.3399	0.3273	0.3389	0.2571	0.3360	0.3448	0.3586	0.2890	0.3351	0.3293
No. of "0"	175,814	40,453	88,356	47,005	154,673	34,045	77,542	43,086	119,316	24,444	59,316	35,556
No. of "1"	927	507	365	55	888	487	347	54	654	341	276	37

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). This table presents multivariate panel logistic regression results with control variable for 6 months (columns 1 to 4), 12 months (columns 5 to 8), and 24 months (columns 9 to 12) lagged periods across different size categories. The sampling period runs between 1995-2016. We consider funds corresponding to the bottom 25 percentile of AUM as small funds, those in the top 25 percentile as large funds, and the rest medium funds. If a fund liquidates in month *t*, the fund's failure indicator is '1' in that month *t* and '0' otherwise. A positive coefficient (β) suggests a positive relationship with liquidation likelihood and vice-versa. SE is standard error of respective coefficients and R^2 is McKelvey & Zavoina's R^2. No. of "1" counts the number of failures in our sample, while No. of "0" counts the number of "non-failure" observations.

Table 10: Multivariate Regression Models with interaction between Fund Size and Investment Style

Variable	Without Control Variables						With Control Variables					
Lag Months	6 Months		12 Months		24 Months		6 Months		12 Months		24 Months	
	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
WRSIZE	0.0995[a]	0.0272	0.0954[a]	0.0259	0.1117[a]	0.0305	0.0914[a]	0.0279	0.0962[a]	0.0268	0.1284[a]	0.0296
GROWTH	-1.0004[a]	0.2743	-0.6367[c]	0.4243	-0.9777[c]	0.5586	-0.9995[a]	0.2777	-0.6932[c]	0.4158	-1.2185[b]	0.5037
RETURN	-7.1919[a]	1.4218	-4.6792[a]	1.4683	-5.0422[b]	2.0438	-7.2195[a]	1.4131	-4.8215[a]	1.4580	-4.7379[b]	1.9515
WRATIO	3.1406[a]	0.2113	3.2261[a]	0.1956	3.6314[a]	0.2348	3.1486[a]	0.2115	3.2079[a]	0.1941	3.4812[a]	0.2098
DRATIO	0.5727[a]	0.0312	0.6232[a]	0.0339	0.6596[a]	0.0500	0.5634[a]	0.0315	0.6100[a]	0.0342	0.6158[a]	0.0452
TRISK	-22.7461[a]	2.7629	-23.2409[a]	2.8648	-20.666[a]	3.2359	-20.768[a]	2.8051	-19.9839[a]	2.8519	-15.9495[a]	2.9695
INDRISK	0.2425[a]	0.0319	0.0945[a]	0.0279	0.1110[a]	0.0384	0.2694[a]	0.0358	0.1378[a]	0.0316	0.1931[a]	0.0387
Medium Funds (MF)	-0.1512	0.3319	-0.1557	0.3342	-0.4857	0.4180	-0.1831	0.3326	-0.1697	0.3349	-0.3702	0.3892
Large Funds (LF)	-2.2117[a]	0.6461	-2.5554[a]	0.7638	-2.2992[a]	0.8041	-2.1559[a]	0.6471	-2.4989[a]	0.1647	-2.1568[a]	0.7778
Dedicated Short Bias	-0.1700	0.4629	-0.1005	0.4617	-0.1672	0.5911	-0.2444	0.4662	-0.1740	0.0464	-0.2949	0.5343
Equity Market Neutral	0.4804[c]	0.2994	0.6039[b]	0.3024	0.6579[c]	0.3829	0.3937	0.3011	0.4971	0.3041	0.4592	0.3479
Event Driven	0.3966	0.3069	0.2948	0.3118	0.1029	0.3947	0.3377	0.3077	0.2506	0.3124	0.1091	0.3585
Fixed Income Arbitrage	0.0049	0.3980	-0.0354	0.3991	-0.5821	0.5339	-0.0822	0.3992	-0.1069	0.4001	-0.5525	0.4905
Global Macro	0.5052[c]	0.3101	0.5391[c]	0.3135	0.5704	0.3956	0.3634	0.3132	0.4079	0.3167	0.4683	0.3631
Long/Short Equity Hedge	0.3566	0.2829	0.4155	0.2844	0.3431	0.3528	0.2990	0.2842	0.3726	0.2855	0.3563	0.3231
Multi-Strategy	0.3093	0.3173	0.4004	0.3184	0.1066	0.4094	0.2214	0.3193	0.3324	0.3206	0.1116	0.3735
MF × Dedicated Short Bias	-0.9724	0.6991	-0.9584	0.7009	-0.3423	0.8154	-0.9101	0.6999	-0.9117	0.7015	-0.2977	0.7598
MF × Equity Market Neutral	-0.9490[b]	0.3838	-0.9396[b]	0.3899	-0.7374	0.4903	-0.9159[b]	0.3842	-0.9359[b]	0.3905	-0.7289[c]	0.4538
MF × Event Driven	-1.3494[a]	0.3967	-1.3339[a]	0.4083	-0.9763[c]	0.5105	-1.2493[a]	0.3972	-1.2787[a]	0.4087	-0.8834[c]	0.4538
MF × Fixed Income Arbitrage	-0.2943	0.5069	-0.2099	0.5092	0.5642	0.6551	-0.2052	0.5077	-0.1606	0.5099	0.4475	0.6125
MF × Global Macro	-0.8870[b]	0.4049	-0.8405[b]	0.4110	-0.7517	0.5234	-0.8245[b]	0.4074	-0.8032[b]	0.4150	-0.7051	0.4896
MF × Long/Short Equity Hedge	-0.9893[a]	0.3425	-0.9830[a]	0.3458	-0.6491	0.4317	-0.9173[a]	0.3431	-0.9324[a]	0.3464	-0.6160	0.4025
MF × Multi-Strategy	-0.8513[b]	0.4050	-0.9106[b]	0.4102	-0.5305	0.5272	-0.8309[b]	0.4057	-0.9288[b]	0.4109	-0.5814	0.4934
LF × Dedicated Short Bias	4.4629[a]	1.2865	4.4011[a]	1.3600	6.3139[a]	1.6576	4.5065[a]	1.2881	4.5449[a]	1.3569	6.3981[a]	1.4729
LF × Equity Market Neutral	-1.5013	1.1937	-1.0603	1.2627	-1.3339	1.3006	-1.5765	1.1942	-1.1301	1.2629	-1.2421	1.2737
LF × Event Driven	-0.2909	0.7443	0.2109	0.8513	-0.7871	1.0091	-0.2438	0.7447	0.2453	0.8513	-0.6467	0.9821
LF × Fixed Income Arbitrage	-0.0459	0.9097	0.4415	0.9982	-0.3813	1.3505	-0.0176	0.9099	0.4438	0.9981	-0.3573	1.3209
LF × Global Macro	-0.1075	0.7279	0.2954	0.8367	-0.2722	0.9027	-0.0201	0.7286	0.3882	0.8369	-0.108 0	0.8698
LF × Long/Short Equity Hedge	-0.2499	0.6794	0.1641	0.7936	-0.3971	0.8459	-0.2737	0.6799	0.1314	0.7338	-0.3485	0.8204
LF × Multi-Strategy	0.0515	0.7386	0.405	0.8449	0.1881	0.9182	0.0786	0.7401	0.4326	0.8459	0.3519	0.8865
AGE							-0.0652	0.0486	-0.1459[a]	0.0478	-0.3933[a]	0.0549
LUPD							-0.2160[a]	0.0790	-0.2063[b]	0.0808	-0.1939[b]	0.0942
RNP							-0.0231	0.0427	-0.093 0	0.0436	0.0044	0.0501
OTP							-0.1349	0.0921	-0.1142	0.0939	-0.1645	0.0941

HWM							-0.0857	0.0777	-0.0648	0.0799	-0.0405	0.0941
PCAP							-0.1807[b]	0.0718	-0.1973[a]	0.0735	-0.1396[c]	0.0845
Goodness of Fit Measures												
Wald Chi^2	1,018.4500[a]		1,063.7600[a]		638.4000[a]		1,039.2800[a]		1,101.5900[a]		877.6200[a]	
Log Likelihood	-5,176.3722		-4,841.5364		-3,568.6022		-5,158.9262		-4,821.6450		-3,536.5679	
R^2	0.3917		0.3964		0.4309		0.3923		0.3917		0.4297	
No. of "0"	176,035		154,854		119,436		175,814		154,673		119,316	
No. of "1"	928		889		655		927		888		654	

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). This table presents multivariate panel logistic regression results with interaction terms (between fund size and the investment style) for 6 months, 12 months, and 24 months lagged periods. Size category "Small Funds" and investment style "Convertible Arbitrage" are considered reference groups, and thus main and interaction effects are reported for medium funds, large funds and remaining investment styles. Results are reported separately for multivariate models without control variables (columns 2 to 7) and with control variables (columns 8 to 13). The sampling period runs between 1995-2016. We consider funds corresponding to the bottom 25 percentile of AUM as small funds, those in the top 25 percentile as large funds, and the rest medium funds. If a fund liquidates in month *t*, the fund's failure indicator is '1' in that month *t* and '0' otherwise. β is the regression coefficient, SE is standard error of respective coefficients and R^2 is McKelvey & Zavoina's R^2. No. of "1" counts the number of failures in our sample, while No. of "0" counts the number of "non-failure" observations.