Three Studies on Hedge Fund Risk Taking and Herding

by

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Dissertation Submitted in Partial Fulfillment of the
Requirements for the Degree of
Doctor of Philosophy

in the
Ph.D Program
Beedie School of Business

SIMON FRASER UNIVERSITY

Spring 2017

Approval

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Degree: **Doctor of Philosophy (Finance)**

Title: ***Three Studies on Hedge Fund Risk Taking and Herding***

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Date Defended/Approved: October 5, 2016

Abstract

This dissertation consists of three studies on hedge fund risk taking and herding. The first paper documents the risk taking of hedge funds in the last three years prior to liquidation using the measures of return volatility. I find that the risk reduction is the greatest for the liquidated sample during the last two and three years as the fund performance drops. Moreover, the volatility-hazard regression shows that the risk taking of funds reduces during the last year prior to fund liquidation as the predicted hazard rates in the previous year increase. The evidence indicates that the liquidation is forced when the performance of the portfolios drops below the liquidation barrier.

The second paper investigates the risk taking choices of hedge funds following redemption requests. I find that hedge funds with longer restriction periods tend to take lower risk if there are no significant redemption requests. Second, hedge funds with short restriction periods tend to increase risks following redemption requests. The increase in risk is larger for large redemptions than for small redemptions. However, if there are large redemptions during market crisis, hedge funds tend to take higher post risk even when the restriction periods are longer.

The third paper examines hedge funds herding in response to macroeconomic uncertainty during periods of high volatility with extreme market returns. I find that hedge funds that follow directional strategies herd towards the consensus during periods of high macroeconomic uncertainty. The degree of herding towards the consensus becomes greater during periods of economic downturn. I also find that the degree of herding for live funds following directional strategies is greater during periods of high macroeconomic uncertainty in down markets. This suggests that the similar trading manners of the directional fund managers in times of macroeconomic uncertainty could be beneficial for fund survival.

Keywords: Hedge fund liquidation; redemption request; risk taking; herding; macroeconomic uncertainty

Acknowledgements

I would like to thank my senior supervisor Dr. Peter Klein for his insightful guidance and ongoing help during my Ph.D. study. His openness to ideas, interest in my research and encouragement for me to explore ideas deeper has inspired me to think openly, independently, and critically. I always find his advice invaluable.

I thank my committee members and examiners, Dr. Andrey Pavlov, Dr. Amir Rubin, Dr. Karel Hrazdil, and Dr. Blake Phillips for their time, interest, and unique advice on my research. Their helpful comments broadened the perspective of my thought.

I am also grateful for Dr. Avi Bick and Dr. Christina Atanasova for their enlightenment, warm encouragement and support. Moreover, I appreciate the finance faculty members and staffs at the Beedie School of Business at Simon Fraser University for their continuous support.

Finally, I would like to thank the SFU Library, the Beedie School of Business, Mr. Mark Bodnar, the library research team, collections and e-resources staff, and data librarian at Simon Fraser University for the funding of my data and data support.

I am also honoured to receive Beedie Family Graduate Scholarship from Mr. Ryan Beedie, Research Assistantships from the Centre for Studies in Global Asset and Wealth Management and Graduate Fellowship (PhD) Funding for my Ph.D. study. The funding is an important motivation for me to continue my enthusiasm in my study.

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Chapter 1. Hedge Fund Risk Taking Approaching Liquidation

1.1. Abstract

I study the risk taking choices of hedge fund managers approaching liquidation date using the measures of return volatility. I find that the reduction in risk is the greatest for the liquidated sample during the last two and three years as the fund performance drops. When I classify funds into sub-groups and sub-periods, the result shows that mediocre portfolios continue to reduce risks during the second-to-last year and last year as their performance falls. Moreover, the volatility-hazard regression shows that the risk taking of funds reduces during the final year prior to fund liquidation as the predicted hazard rates in the previous year increase. The evidence indicates that the results for the liquidated sample are more consistent with Goetzmann, Ingersoll, and Ross (2003). They argue that the managers would reduce risk when the fund values reduce if they are concerned about the potential management and performance fees in the future period. This is because increasing volatility may cause the fund values to hit the liquidation barriers sooner even though it may also help the fund values to reach the high water marks faster. Therefore, it is likely that the liquidation is forced when the performance of the portfolios drops below the liquidation barrier.

1.2. Introduction

The relationship between risk and incentive compensation features such as high water marks in the hedge fund contract is explored empirically and theoretically by a substantial literature (Aragon and Nanda, 2012; Buraschi et al., 2014; Carpenter, 2000; Clare and Motson, 2009; Kouwenberg and Ziemba, 2007; Panageas and Westerfield, 2009; Ray, 2012). The high water mark is a threshold that allows the fund managers to earn the incentive fees only after they generate a maximum post-fee cumulative return (Ray, 2012). In other words, performance fees to the managers are contingent upon the fund recovering previous losses, so the high water mark feature acts like option compensations in the corporate compensation schemes (Carpenter, 2000). Most empirical works exploring risk taking choices under different contract incentives consider the evaluation horizons to be relatively long. In other words, the effectiveness of the high water mark or incentive fees upon risk taking is often studied under the condition that the fund managers expect to operate the fund for many periods (Buraschi et al., 2014; Clare and Motson, 2009; Cukurova and Marin, 2011; Shelef, 2012). However, several authors have provided theoretical models of the risk taking choices of fund manager when there is incentive compensation such as high-water mark provision for the case when funds are approaching an end date; see, for example, Carpenter (2000), Goetzmann, Ingersoll, and Ross (2003), Kouwenberg and Ziemba (2007), and Hodder and Jackwerth (2007). One group of research shows that the funds will decrease risk as they approach liquidation date (Goetzmann, Ingersoll and Ross, 2003). However, the other group proposes that funds increase risks approaching liquidation (Carpenter, 2000; Hodder and Jackwerth, 2007; Kouwenberg and Ziemba, 2007; Panageas and Westerfield, 2009).

Many of the above theoretical models imply or assume that liquidation is forced when the portfolio performances are sufficiently low. However, Hodder and Jackwerth (2007) argue that there is an endogenous or voluntary shutdown choice where fund managers start to gamble prior to the closure decision. This is because the high attrition rate in the hedge fund industry indicates that a large percentage of hedge fund liquidation is the result of voluntary shutdown. In an attempt to understand whether the hedge fund risks increase or decrease prior to liquidation, I compute the measures of return volatility to study the risk taking choices of the funds classified as "liquidated". In particular, I am interested to know how the risks of these funds change as they approach liquidation date and whether I can draw inferences based on the risk change patterns to determine if the hedge fund shutdown choices are due to endogenous or exogenous decisions.

I compute the median standard deviation of return, excess volatility and excess returns for the liquidated sample during the last two or three years. I also examine the median percentage change in excess volatility to be clearer of the direction and magnitude of the change. The other non-reporting ("ONR") sample is included as a comparison. The reason to use the ONR sample as a comparison as opposed to a live sample is that live funds continue to exist after the end of sample period, so the end dates for the live funds cannot be identified. Second, hedge funds usually liquidate due to a suddenness of loss, in which case the potential incentive fees in the future for the managers would be impossible. On the other hand, funds that are closed but not liquidated usually suffer a prolonged period of underperformance prior to closure. In that case, managers would expect to work for a couple of more years with the opportunity to earn a bonus (Barry, 2002). As a result, the future potential incentive fees could still be earned for these managers, while it would be the opposite for the mangers in the liquidating funds. Therefore, it is possible that the reactions to closure for managers in funds to be closed and liquidated are different. For example, managers in the liquidated funds may increase the portfolio risk in an attempt to increase the portfolio return for a performance fee at the expense of the interest of investors if they realize the funds may be liquidated soon. Aragon and Nanda (2012) argue that the risk shifting may occur with asymmetric incentive contracts where hedge fund managers receives a performance fee when the fund does well but are protected from downside risk. This is because it may induce fund managers to increase portfolio risk which is detrimental to the interest of investors and may increase the systematic risk. Therefore, an analysis of both the evolution of hedge fund risk taking approaching liquidation and closure is also important for the understanding of the effect of asymmetric incentive contracts when there is an end date.

I find that the reduction in risk is the greatest for the liquidated sample during the last two and three years as the fund performance drops. When I classify funds into sub-groups and sub-periods, the result shows that mediocre portfolios continue to reduce risks during the second-to-last year and last year as their performance falls. Moreover, the below mediocre portfolio does not show increases in risk taking during the second-to-last year when the portfolio performance reduces. Although this is similar for the ONR sample, the below mediocre portfolio exhibits higher risk taking during the second-to-last year.

The evidence indicates that the results from the liquidated sample are more consistent with Goetzmann, Ingersoll, and Ross (2003). They argue that the managers should reduce more risks if the managers are concerned about the potential management and performance fees in the future period. This is because increasing volatility may cause the fund values to hit the liquidation barriers sooner even though it may also help the fund values to reach the high water marks faster (Goetzmann, Ingersoll, and Ross, 2003). Therefore, it is likely that the liquidation is forced as the portfolio values hit the liquidation barriers. For the ONR sample, there is some evidence that the below mediocre portfolio increases risk taking slightly during the second-to-last year when the portfolio performance drops. However, it does not support Hodder and Jackwerth (2007) since their model is based on liquidated funds.

To understand deeper of the hedge fund risk taking approaching liquidation, I conduct a regression of return volatility on predicted hazard rate (a volatility-hazard regression). The goal of this part is to understand the effect of hazard rate upon hedge funds volatility. Therefore, the first step is to analyze hedge fund liquidation, and then compute a predicted hazard rate in each month for each fund based on the model estimated in the first step. This will provide at each point in time each fund's predicted hazard rate which can be used to explain return volatility afterwards. In other words, in the final step I perform the regression of future return volatility on predicted hazard rate. Since the focus of my study is to distinguish among the theoretical explanations that model the risk of funds approaching an end date, I add a final year dummy variable that indicates only one year remaining for the liquidated fund's life. I find that that risk taking of funds increases as predicted hazard rate increases when the dependent variable is excess volatility. Although this is similar to precedent studies, I find the opposite result when I include in the regression the dummy variable indicating only one year remaining for the hedge fund's life. The implies that the risk taking of funds reduces prior to liquidation. This is consistent with my previous results using median excess volatility, EV, for the liquidated sample.

1.3. Literature Review

There are several theoretical models examining the risk taking behavior of fund manager approaching the termination date when there is incentive compensation (e.g., Carpenter, 2000; Goetzmann, Ingersoll, and Ross, 2003; Kouwenberg and Ziemba, 2007; Hodder and Jackwerth, 2007; Panageas and Westerfield, 2009). Carpenter (2000) solves the dynamic portfolio choice problem of a risk averse manager paid with call option incentive compensation and personal share of the fund value but cannot hedge his/her call option compensation. She argues that the risk averse mutual fund manager may change the risk taking behaviour under different conditions of moneyness. In her study, Carpenter (2000) considers a single evaluation period and the fund being liquidated when the fund value goes to zero because the asset portfolio is performing poorly. Giving more incentive options to the manager will lead him to reduce the portfolio volatility to a constant when his option is deep in the money approaching the evaluation date. The asset portfolio volatility may even be lower than the volatility that a manager would choose without inventive fees. This is because of his personal portfolio's exposure to the asset portfolio volatility. Therefore he desires to offset this leverage effect by reducing the asset portfolio volatility. However, when his option compensation is deep out of the money and the evaluation date is near, the manager desired to remain solvent increases the asset portfolio volatility. Therefore, the portfolio volatility will increase to infinity as total portfolio value goes to zero.

Goetzmann, Ingersoll, and Ross (2003) on the other hand incorporate a lower liquidation boundary where the funds liquidate when the fund value drops below that boundary in a continuous time framework. They show that as the asset value drops to near the liquidation barrier, the incentive and management fees to the managers will reduce to zero. The risk averse managers desired to earn these fees from the fund value will reduce the volatility so as to avoid liquidation. This means that the managers will decrease risk as the fund values reduce or approach liquidation barrier. Kouwenberg and Ziemba (2007) extend Carpenter (2000)'s model but apply the prospect theory with a loss averse manager. They argue that the loss averse managers who seek to avoid "loss" will be risk seeking as incentive fees increase. This is because negative consequences of loss will lead to fund outflows and loss of reputation for the managers. To avoid these negative consequences, loss averse managers will increase risks to reap more profit from the incentive fee contract with less emphasis on a potential decrease of fund value later. This indicates that managers will increase risks whether or not portfolio return increase or decrease as incentive fees increase. Therefore the manager's optimal reaction is to increase the risky portfolio holdings at the end of the evaluation period if there is an increase in the incentive fee level. Panageas and Westerfield (2009) assume a risk neutral manager compensated with incentive fees and high-water marks place no restrictions on risk taking choices but cannot trade on his own account. In their model, the fund has an infinite horizon but liquidates either at a random time or when its asset value drops to zero. They show that the risk neutral managers behave like a constant relative risk aversion investors and do not place unbounded weights on risky assets. This is because the manager who increases risk will increase the probability of lower payoffs in the next period while high-water mark remains unchanged. Therefore, the trade-off between current and future payoffs lead the managers to choose a constant risk taking behavior. However if there is a termination date, the hedge fund managers will be impatient and behaves as if he is risk averse as the termination time approaches. He or she will increase risk to infinity when the performance is below high-water mark. This is the same as the Carpenter (2000).

Finally, Hodder and Jackwerth (2007) use an American-style option framework where hedge fund managers make endogenous shutdown decisions based on fund value, time, and her outside employment opportunities. They propose that mangers start to gamble by taking more risks as the fund value drops to near the prespecified liquidation boundary as the number evaluation periods decrease. Specifically, managers will evaluate at each time point their compensation if they continue to manage the fund and their compensation if they choose to close the fund and seek other career opportunities. When the fund value approaches a region just above the prespecified liquidation level as periods of evaluation decrease, the managers will increase risk to avoid fund closure. Therefore, they will start to increase risks by a great deal starting from the second-to-last year and to last year. However, this behaviour of increasing risk near high water mark will be diminished when the manager anticipates staying with the firm for many years with many periods of evaluation.

The characteristics of hedge funds are closely related to the survival or the performance of hedge funds. For example, management fee, incentive fee, lockup period, payout period, redemption notice period, managerial investment, high water market (HWM), leverage, past performance, volatility, AUM, and investment styles affect the liquidation of hedge funds. (Gregoriou, 2002; Getmansky et al., 2004; Getmansky, 2004; Baba and Goko, 2006; Haghani, 2014). Ruckes and Sevostiyanova (2012) argue that high water mark provisions in the contracts increase probability of fund closing than contracts with only a performance fees. This is in contrast to Aragon and Qian (2010) who argue that high water mark provisions reduce the probability of fund closure as it reduces fund outflows following poor performance. In another study, Ray (2012) finds that when the fund values fall below the high water mark, the standard deviation of future return's increases, the performance or the Sharpe ratio decreases, and the rate of fund closure increases. Liang (2000) and Brown et al. (1999) show that a young fund with poor performance and small asset amount, is more likely to be dissolved. Grecu et al. (2007) find that hedges that cease to report have lower return. Since characteristics mentioned above affect the performance and survival of funds, I include them as explanatory variables in my survival analysis.

The literature has provided different theoretical models of the risk taking choices of fund managers approaching liquidation; however, empirical study on this topic is almost non-existent. Previous studies exploring risk taking choices under different contract incentives consider the evaluation horizons to be relatively long. In other words, the effectiveness of the high water mark or incentive fees upon risk taking is often studied under the condition that the fund managers expect to operate the fund for many periods (Buraschi et al., 2014; Clare and Motson, 2009; Cukurova and Marin, 2011; Shelef, 2012). For example, Buraschi et al. (2014) show that managers with incentive options increase leverage and risks when the distance to high water mark increases. Shelef (2012) finds that the managers will increase risk by 50% when the funds are below their high-water mark threshold. However hedge funds with the farthest distance below the threshold reduce risk compared to those closer to the threshold. Clare and Motson (2009) find that managers whose incentive options are in the money reduce risks while managers whose incentive options are out of the money do not increase risk. Aragon and Nanda (2012) show that risk shifting becomes more prevalent when performance drop and when the probability of liquidation is high. In general, past studies find that the risk taking of hedge fund increases as the performance and fund values reduce for the case of a relatively long evaluation horizon. In my paper, however, the focus is on the evolution of hedge fund risk taking approaching liquidation in an attempt to distinguish among the theoretical explanations. Therefore, I explore the risk taking choices of fund managers in the last two to three years prior to fund liquidation, and hedges funds closed but not liquidated (ONR) is used as a comparison.

1.4. Approach/Methods

1.4.1. Data

I use the Lipper TASS Academic Hedge Fund[1] database which provides "Live" and "Graveyard" funds. The Graveyard funds include several categories of funds based on different drop reasons: liquidated, no longer reporting to TASS, unable to contact, closed to new investment, merged into another entity, dormant and unknown. (Baba and Goko, 2006). In my study, the sample period spans from January 1994 to December 2012 following the literature that includes graveyard funds in their studies (Baba and Goko, 2006; Liang and Park, 2010; Haghani, 2014). Following the literature (Liang and Park, 2010, Cukurova and Marin, 2011, and Haghani, 2014), I only include hedge funds that report in U.S. dollars, report net returns, have at least two years of data for the calculation of the percentage change values, and exclude funds that report quarterly rate of return (ROR), or asset under management (AUM), gross RORs, missing monthly RORs, AUMs, management fees, incentive fees, minimum investment, management style. In my study, the focus is on the risk taking behaviour of hedge funds as they approach liquidation date,

[1] 2014, "Lipper Tass Academic Hedge Fund", http://hdl.handle.net.proxy.lib.sfu.ca/11272/10015 V6 [Version]

the date that the fund stops reporting performance to the database. Therefore, funds from liquidated classification is the main focus in my study, and I separate the "Liquidated" funds from the "Graveyard" category. Those non-reporting funds in the Graveyard category with other closure reasons are then grouped as "Other Non-reporting" or "ONR" category. This is to compare the "Liquidated" sample to "ONR" sample.[2]

1.4.2. Calculation of Variables and Methodology for Risk of Funds Approaching an End Date

Several authors have mentioned that the risk taking of funds toward the end of their lives should increase when the fund performances drop. To have a general idea of whether this argument holds, I look at the risk and performance measures for universe of liquidated and ONR samples for a window of two years and three years prior to closure. Two and three years are chosen since this is the period where most of the liquidated funds show continued dropping in performances. I define t_{liq} as the date that the funds exit the database, so t_{liq-1}, is the last month prior to funds exiting the database. I compute the standard deviations of returns (SD), the excess volatility (EV), and the excess return (ER) over the last 24 months and 36 months for all the funds. First, the SD of returns is calculated over the "Post" 24 months window of t_{liq-24} to t_{liq-1}, and over the "Post" 36

[2] Precedent papers that focus their analysis only on the behaviour of firms approaching bankruptcies include Baldwin and Mason (1983), Clark (1983) and Johnson (1989). However, Aharony, Jones, and Swary (1980) compare the characteristics of bankrupt and non-bankrupt firms by matching each bankrupt firm to one or two non-bankrupt firm. Based on criteria similar to their study (for example, for each liquidated fund choose a live fund at the same period based on same investment objective/strategy, close in net asset value (NAV), annualized return, annualized excess volatility and identical calendar period), I am able to match 26 liquidated funds to 27 live funds. The result is that the median excess returns continue to reduce (increase) for liquidated (live) funds in the third-to-last and second-to-last year. The median excess volatility in the last year prior to liquidation reduces (increases) for liquidated (live) funds. In my study, I focus on the analysis of liquidated and ONR funds only without matching funds to identical calendar period. Since live funds continue to exist after the end of the sample period, I do not include them in my study.

months window from t_{liq-36} to t_{liq-1}. The SD of 24-month returns and 36-month returns are computed as the standard deviation of monthly returns multiplied by the square root of 24 and 36, respectively. As a comparison, I also include the "Pre" 24- and 36-month windows of SD of returns. Because the funds may not liquidate at the same month, results may be biased if the time effects or style group risk at each point in time are not controlled by the mean style group SD level for each fund. So I compute the excess volatility (EV) which is the individual fund SD over the "Post" 24- and 36-month windows minus the mean SD of the style over the "Post" 24- and 36-month windows.[3] The excess returns (ER) are calculated as the cumulative returns of individual funds over the "Post" 24- and 36-month windows minus the mean style cumulative returns over the "Post" 24- and 36-month windows. For the volatility and performance measures, I include only the liquidated and ONR samples because live funds continue to exist after the end of the sample period. Authors such as Gregoriou (2002) and Liang and Park (2010) have looked at the standard deviation of returns as hedge funds in the graveyard (liquidated + ONR) category approach their last month. However, they did not control for this time effect or style group risk at each point in time, nor did they separately study the risk taking of liquidated funds in their analysis.

I also examine the median percentage change in SD and EV and the median difference in EV to be clearer of the direction and magnitude of the change. The percentage change in SD for each fund over the 24-month (or 36-month) window is calculated as the SD over the "Post" interval from t_{liq-24} to t_{liq-1} (or t_{liq-36} to t_{liq-1}) divided by SD over the "Pre" interval from t_{liq-48} to t_{liq-25} (or t_{liq-72} to t_{liq-37}) minus one. This is similarly done for the percentage change in EV. Finally, the difference in EV is calculated as the difference between the "Post" interval and "Pre" interval. However, since the results for median percentage change and difference values remain similar to the median levels, I only report the results for the median levels[4].

[3] Note that this approach is utilized as the database does not provide holdings for each hedge fund. Therefore this approach of controlling for the time effect or the style group risk assumes that the security holdings are consistent across funds of the same style when this may not be the case.

[4] The results for the median percentage change and difference in levels are available upon request.

Because authors such as Hodder and Jackwerth (2007) and Carpenter (2000) show situations when funds perform well approaching liquidation, I classify funds into sub-groups of winners and losers based on their relative performances at the time of ranking In particular, the funds are ranked at t_{liq-37} and t_{liq-25} for post-ranking windows of 24- and 36-months into six performance portfolios- three winner and three loser portfolios. Winners are the ones that have annual returns greater than the average annual return of the style that the funds belong to at t_{liq-37} and t_{liq-25}, where the annual returns of individual funds are based on their monthly returns. Losers are the ones that have annual returns less than the style average annual return. In particular, portfolio WWW (portfolio LLL) includes funds with their annual returns greater than two standard deviations above (below) the average annual return of the funds in the same style. Portfolio WW (portfolio LL) consists of funds with their annual returns between one and two standard deviations above (below) the average annual return of the funds in the same style. Portfolio W (portfolio L) includes funds with their annual returns between zero and one standard deviation above (below) the average style group return. This is done for both the liquidated and ONR samples.

Hodder and Jackwerth (2007) show that the risk taking during the third-to-last year and second-to-last year for loser funds (especially the most losing fund) should be higher than for the winner funds when managers have shutdown options. Those funds identified as the worst performing ones at the start of the three years before liquidation will exhibit reduced volatility during the second-to-last and last years. The funds identified as the best performing ones at the start of the three years before liquidation will have low risk taking at the start and reduce slightly over time. However, during the second-to-last year, there should be a big ramp-up in risk for the mediocre funds (including the below mediocre ones) than for the best and worst performing funds. If there is continued poor performance, they will continue to increase risk taking in the last year prior to the decision to closure. If however the performances improve, the mediocre and the below mediocre funds will reduce risk taking during this period. In order to verify whether this pattern shows up in the hedge fund groups, I further separate the post-ranking windows into sub-periods of 12 months. Specifically, I rank the portfolios at the point t_{liq-37} and calculate the volatility and performance measures during the third-to-last year, second-to-last year and last year. So the loser (winner) funds remain in the loser (winner) portfolios for the next three years. The standard deviations of returns (SD) is then calculated over the each of the next 12 months windows of t_{liq-36} to t_{liq-25}, t_{liq-24} to t_{liq-13} and t_{liq-12} to t_{liq-1}. This same procedure is done for EV and ER. When the ranking is at t_{liq-25}, I calculate the SD, EV, and ER over the 12 months window of t_{liq-24} to t_{liq-13} and t_{liq-12} to t_{liq-1}.

Next, I compute the percentage change in SD and EV for each fund in the each of the last three years when the ranking is at t_{liq-37} (or t_{liq-25}). For example, the percentage change in SD and EV in the third-to-last year (or second-to-last year) is calculated as the SD and EV over the "Post" interval from t_{liq-36} to t_{liq-25} (or t_{liq-24} to t_{liq-13}) divided by SD and EV over the "Pre" interval from t_{liq-48} to t_{liq-37} (or t_{liq-36} to t_{liq-25}) minus one. The reason to study the percentage change values is to understand deeper whether the mediocre portfolios (W and L) in the second-to-last year have a significant increase in risk relative to other portfolios. However, since the percentage change results remain similar to the level results, I do not report the median percentage change results. They are available upon request.

As a robustness, I check the direction of risk taking for each portfolio over time by examining the percentage change in EV when the denominator remains the same over the "Pre" window of t_{liq-48} to t_{liq-37} when the portfolios ranking is at t_{liq-37}. For example, the percentage change in EV from fourth-to-last year to second-to-last year, $\%CHEV_{4,2}$, (or from fourth-to-last year to last year, $\%CHEV_{4,1}$) is calculated as EV over the "Post" interval from t_{liq-24} to t_{liq-13} (or t_{liq-12} to t_{liq-1}) divided by EV over the "Pre" interval from t_{liq-48} to t_{liq-37} minus one. If the EV in the second-to-last year continues to increase from fourth-to-last year, then the $\%CHEV_{4,2}$ will be more positive than $\%CHEV_{4,3}$, which is the percentage change in EV over the third-to-last year. Goetzmann, Ingersoll, and Ross (2003) is the only paper proposing that the managers will decrease risk as the fund values reduce or approach liquidation. If this is true, then there should be a reduction in EV as the performance decreases over the last few years. For the above calculations, I do it separately for liquidated and ONR samples.

1.4.3. Calculation of Variables and Methodology for Volatility-Hazard Regression

The goal in this section is to understand the effect of hazard on hedge funds volatility. Therefore, the first step is to analyze hedge fund liquidation, and then compute a hazard function at each month for each fund based on the model estimated in the first step. This will provide at each point in time each fund's predicted hazard rate which can be used to explain return volatility after each point in time. Here, the survival analysis is employed to study the time until fund liquidation where the event of interest is the hedge fund liquidation. The funds that are still operating or closed but not liquidated are considered as censored observations. There are different approaches in survival analysis which include non-parametric analysis, the semi-parametric Cox proportional hazards (PH) model and parametric models (Nagler, 2015). The non-parametric and semi-parametric models evaluate funds at the time when liquidation actually occurs (Nagler, 2015). However, the parametric models provide information about each fund over the whole interval given the fund information at each point in time (Nagler, 2015). Therefore, I analyze the survival of funds using the parametric models and compute the hazard rates for each fund over the sample period from the model estimates in my study.

Denote *T*, a non-negative random variable (T > 0), as the survival time of a hedge fund and time zero as the date on which the fund enters the database which may start as early as in February 1977. (Gregorious, 2002; Baba and Goko, 2005). The hazard rate $h(t)$ is the instantaneous rate (or the conditional probability) of failure of fund *i* at time $T = t$ given the survival of the fund until time *t*, $S(t) = P(T > t)$ (Gregorious, 2002; Liang and Park, 2010). The unconditional probability of failure at time *t* (or the probability density function of the hedge fund lifetime), $f(t)$, is $f(t) = h(t)S(t)$ (Gregorious, 2002; Crowther, 2014). Parametric models assume that the underlying distribution of survival times follow some specific distribution; therefore, these models differ by the underlying assumption of the shape of the hazard function (Gregorious, 2002; Crowther, 2014). The parametric models used in my study include exponential, Weibull, and Gompertz distributions, and log-logistic and log-normal models. The exponential model assumes that the hazard function is constant over time, while Weibull and Gompertz distributions assume that hazard rates increase or decrease monotonically over time (Nagler, 2015). Finally, the log-logistic and log-normal models assume that the hazard rates are non-monotonically varying over time (Nagler, 2015).

The hazard function of the exponential model is $h(t) = \lambda$ where λ is parameterized as $e^{X'\beta}$ with X' denoting the transpose of the vector of covariates and *β* denoting a vector of regression coefficients (Jenkins, 2005; StataCorp., 2011). The hazard function of the Weibull distribution is specified as $h(t) = \lambda p t^{p-1}$ where p is a shape parameter (Jenkins, 2005; StataCorp., 2011). The hazard rate monotonically rises if $p > 1$, is constant if $p = 1$, and monotonically declines if $p < 1$ (Rodriguez, 2010). For $p = 1$, it is the special case known as the exponential model. The Gompertz hazard is $h(t) = \lambda e^{\gamma t}$ where γ indicates a shape parameter (StataCorp., 2011). If $\gamma > 1$, then the hazard increases monotonically with time. If the shape parameter $\gamma < 1$, then the hazard decreases monotonically with time. If $\gamma = 1$, then the hazard is flat and is the exponential model (Jenkins, 2005). The log-logistic hazard function is $h(t) = \frac{\psi^{\frac{1}{\gamma}} t^{\left[\frac{1}{\gamma} - 1\right]}}{\gamma\left[1+(\psi t)^{\frac{1}{\gamma}}\right]}$, where γ is a shape parameter and $\psi = e^{-(X'\beta)}$ as it is an accelerated failure-time model (Jenkins, 2005; StataCorp., 2011). For the log-logistic model, if $\gamma < 1$, then the conditional hazard increases first, and then decreases. However, if $\gamma \geq 1$, then the hazard decreases with time. Finally, the log-normal hazard is specified as $h(t) = \frac{\frac{1}{t\sigma\sqrt{2\pi}} exp\left[\frac{-1}{2\sigma^2}[ln(t)-\mu]^2\right]}{1-\Phi\left\{\frac{ln(t)-\mu}{\sigma}\right\}}$, where Φ is the standard normal cumulative distribution function, σ is the scale parameter and $\mu = X'\beta$ (Jenkins, 2005; StataCorp., 2011). The hazard rate for the log-normal model is similar to the hazard rate of the log-logistic model for the case when < 1 . So the hazard rate rises first and decreases later on (Jenkins, 2005).

In my study, the covariates in the parametric survival analysis include the *standard deviation* over previous 24-month period (*STD*), *style dummies* (*D*1–*D*12), average monthly rate of return during previous year (*Performance*)*, assets under management* (*AUM*), *average size* (*Avg Size*), *size volatility*, monthly *rate of return* (*ROR*), *management fee*, *incentive fee*, *lockup period*, *redemption notice period* (*Notice Period*), *payout period*, *minimum investment*, and dummy variables to indicate funds that has *HWM*, *personal investment* (*PI*), *and leverage*. These covariates are the main hedge fund characteristics used precedent papers in their empirical studies. For example, see Liang and Park (2010) who study the attrition of hedge funds using Cox proportional hazard analysis and Haghani (2014) who models the hedge fund life time using a competing risks model.

The *STD* is the fund's standard deviation of the 24 monthly returns multiplied by square root of 24. *Style dummies* are included to take into account of the investment style effect. *Performance* is calculated as the average net of fees 12 monthly rate of return during the previous year. *AUM* is the hedge fund's *AUM* in month *t* in million U.S. dollar. *Avg Size* is the average *AUM* during the previous year. *Size Volatility* is the standard deviation of a fund's *AUM* during the previous year. *ROR* is the hedge fund's net of fees rate of return in month *t* in percentage. *Management Fee* and *Incentive Fee* are the percentage fees charged by the hedge fund. *Lockup Period* (in months), *Redemption Notice Period* (in days), *Payout Period* (in days) are redemption restrictions hedge funds impose on investors. *Minimum Investment* is the minimum investment required from new investors in million U.S. dollar. *PI* is a dummy variable indicating 1 if the hedge fund manager has his/her personal capital invested in the fund, and 0 otherwise. *HWM* is a dummy variable indicating 1 if the hedge fund has a high water mark provision and 0 otherwise. Finally, *Leverage* is a dummy variable indicating 1 if the hedge fund uses leverage and 0 otherwise.

Next the hazard rate is estimated in each month according to the corresponding parametric hazard function for each fund based on the coefficient estimates from each the parametric model. Since my goal is to related this predicted hazard rate to volatility after that point in time, I conduct the regressions of hedge fund volatility on lagged predicted hazard rates. The time and fixed effects model with robust standard errors is used in my study (Petersen, 2009). The dependent variables are the annualized standard deviation of monthly returns and the annualized excess volatility. Specifically, they are:

$$ASD_{it+1,t+12} = b_0 + b_1\widehat{h_{it}} + \sum_{k=1}^{11} a_k T_k + \varepsilon_{it} \qquad (1)$$

$$AEV_{it+1,t+12} = b_0 + b_1\widehat{h_{it}} + \sum_{k=1}^{11} a_k T_k + \varepsilon_{it} \qquad (2)$$

where i indexes funds and t indexes months. $ASD_{it+1,t+12}$ ($AEV_{it+1,t+12}$) is the annualized standard deviation (excess volatility) of the 12 monthly returns following month *t*. The annualized excess volatility is calculated as the difference between individual fund standard deviation over a 12-month window and mean standard deviation of the style over the same window. $\widehat{h_{it}}$ is the predicted hazard rate for fund i at each month t. T_k is a set of monthly dummies k which gives the monthly fixed effects and the total number of k is 11, and ε_{it} are the residuals (Petersen, 2009). If b_1, the coefficient of $\widehat{h_{it}}$, is positive (negative), then this means that the lag period predicted hazard has a positive (negative) effect on the risk taking of hedge funds in the following year. So an increase in predicted hazard rate would increase (reduce) risk taking of hedge funds in the following year.

In order to study the effect of predicted hazard rate upon hedge fund risks as the evaluation period approaches to the point where there is one year left, I also run another regression that includes an additional dummy variable, $Last1yr_i$:

$$ASD_{it+1,t+12} = b_0 + b_1\widehat{h_{it}} + \ b_2Last1yr_i + \ b_3Last1yr_i\widehat{h_{it}} + \sum_{k=1}^{11} a_kT_k + \varepsilon_{it} \tag{3}$$

$$AEV_{it+1,t+12} = b_0 + b_1\widehat{h_{it}} + \ b_2Last1yr_i + \ b_3Last1yr_i\widehat{h_{it}} + \sum_{k=1}^{11} a_kT_k + \varepsilon_{it} \tag{4}$$

Specifically $Last1yr_i$ equals one for fund i if the observation occurs at t_{liq-13} prior to liquidation. This is to understand whether hedge fund risk changes over the subsequent year prior to liquidation. I expect that as the evaluation horizon decreases to only one year remaining, the predicted hazard rate whould affect the risks of the funds more significantly. Moreover, if an increase in predicted hazard rate reduces the hedge fund risk prior to liquidation, it would be consistent with the argument of Goetzmann, Ingersoll, and Ross (2003).

The variable of interest is the coefficient of the interaction term $Last1yr_i\widehat{h_{it}}.$ Note that the sum of b_1, the coefficients of $\hat{h}$, and b_3, the coefficient of the interaction variable $Last1yr_i\widehat{h_{it}}$, gives the effects of predicted hazard rate for two groups of hedge funds: $Last1yr$=1 group (naming it L_1 group) and $Last1yr$=0 group (naming it L_0 group). The L_1 group represents funds that are going to liquidate in 12 months and the L_0 group includes funds without such experience. This provides an examination of the risk for funds in L_1 group during the one-year period following an increase in predicted hazard rate by examining the sum of b_1 and b_3 and comparing it to the control group L_0 by examining b_1. If b_3, the coefficient of $Last1yr_i\widehat{h_{it}}$, is positive, then this means that the lag period predicted hazard rate has a positive effect on the risk of the L_1 group compared to the L_0 group. So the risk taking during the final year prior to liquidation would increase for funds in the L_1

group as the lagged period predicted hazard rate increases. However, a negative b_3 implies that there is a negative effect of the lagged predicted hazard rate on the risk for the L_1 group. So the risk taking during the final year prior to liquidation would reduce as the predicted hazard rate in the previous period increases. In this case, this would be consistent with Goetzmann, Ingersoll, and Ross (2003).

1.5. Results

1.5.1. Results for Risk of Funds Approaching an End Date

Table 1.1 shows the number of funds closed and liquidated each year over the sample period. The liquidation rates are highest in 2008 (7.3%), 2011 (7.6%), and 2012 (7.4%). For the average CBOE Volatility Index (VIX) in Table 1.2, the indices levels are similar in years 2008 and 2009. Moreover, the VIX levels in 2011 and 2012 are similar to the levels in other years, such as 1996 to 2003, 2007 and 2010 regardless of the liquidation rate. This is similar for the CBOE Russell 2000 Volatility Index (RVX). The RVX levels in 2011 and 2012 are similar to the levels in 2004, 2007, and 2010 even though the liquidation rates are high in 2011 and 2012. In addition, the proportion of funds that are liquidated out of all the funds that are closed each year (Table 1.1 last column) are similar over time regardless of level of risk in the market. For example, there is a low level of VIX (or RVX) in 2006 and 2007 compared to a high level in 2008, but the proportions (Liquidated/Closed) in the last column of Table 1.1 are quite similar in 2006 to 2008. So, it seems that funds liquidate without regard to market risk. Nevertheless, I calculate the excess volatility to control for the possible style group risk during the same period, and the results are shown in the following tables.

[Tables 1.1 and 1.2]

Table 1.3 shows the medians of SD, EV and ER over the 24- and 36-month windows for liquidated and ONR samples. First, there is a higher pre median SD level for liquidated sample (Table 1.3a) compared to the ONR sample (Table 1.3b). This result is similar to Barry (2003) who finds higher average standard deviation of returns for liquidated funds than other defunct funds from 1994 to 2001. In Panel A of Table 1.3b and

Panel B of Tables 1.3a and 1.3b, the median SD levels for both samples increase during the "Post" period. This suggests that the hedge fund risk taking increases approaching closure. However, when I control for the time effects and style group risks at each point in time, the median EV levels in Table 1.3c for the liquidated sample are lower in the "Post" periods (-2.30% to -3.00% and -2.47% to -3.14%), even though they are still higher for the ONR sample in Table 1.3d (-2.39% to -2.01% and -2.88% to -2.46%). For the performance, the median ER for both samples are lower in the "Post" periods in Tables 1.3e and 1.3f. This suggests that the hedge funds in the liquidated sample reduce risk taking approaching liquidation when their fund values end up lower. However, it seems that funds in the ONR sample increase risk taking approaching closure. This suggests that the liquidated funds reduce more risk approaching liquidation.

[Table 1.3]

Table 1.4 shows the median SD, EV and ER for liquidated and ONR samples when I separate the 36-month windows into sub-periods of 12 months. For the liquidated sample in Tables 1.4a, 1.4c, and 1.4e, the median SD are lower in the third-to-last and second-to-last years and that the median EV and ER are lower in each of the last three years. This shows that as the median ER in the previous year reduces, the median EV over the following year reduce. However, for the ONR sample the median SD and EV are lower in the second-to-last year but are higher in the last year. The median ER are lower in each of the last three years. This shows that there is no particular pattern for the risk taking of ONR funds when the previous year's performance drops. Therefore, the liquidated funds reduce risk taking approaching liquidation when the previous year's performance drops while this does not hold for ONR funds[5]. As a result, it seems that the evidence from the liquidated sample does not support the arguments from Carpenter (2000) and Panageas and Westerfield (2009) who propose increasing risk taking for funds approaching liquidation as performance drops.

[5] The results when the portfolio ranking is at t_{liq-25} remain similar and are available upon result.

[Table 1.4]

Hodder and Jackwerth (2007) argue that manager will increase risks when the fund value is approaching liquidation barrier if the managers have options to voluntarily close the fund due to potential outside opportunities. In an attempt to understand whether the risk taking choices of hedge funds follow the pattern that Hodder and Jackwerth (2007) propose, I examine the hedge fund samples in sub-groups and sub-periods. The median EV and ER results are shown in Tables 1.5 and 1.6 when the ranking of each performance portfolio is at t_{liq-37}.[6] Hodder and Jackwerth (2007) show that the risk taking during the third-to-last and second-to-last years for the loser and mediocre funds should be higher than that of the winner funds when managers have shutdown options. Here, Panel A of Table 1.5a exhibits the greatest median EV for the winner portfolio and smallest median EV for the mediocre portfolios during the third-to-last year. For example, the winner portfolio WWW has a median EV of 4.67% while loser portfolios LLL and LL have median EV of 1.60% and 1.17%, respectively. The mediocre portfolios W and L on the other hand have the lowest median EV with -2.65% and -2.20%. This result seems in contrary to Hodder and Jackwerth (2007). During the second-to-last year, the loser portfolios all have higher median EV than the corresponding winner portfolios (also 25th and 75th percentiles). For example, portfolio LLL (1.72%) exhibits higher median EV than portfolio WWW (-0.89%). This part is consistent with Hodder and Jackwerth (2007)'s argument that the loser portfolios (especially the worst performing funds) exhibit higher risk taking than the winner portfolios during the second-to-last year.

[Tables 1.5 to 1.6]

Since fund managers can take outside opportunities if the value of the manager's outside opportunity is high, they will increase risks when the fund value is approaching liquidation barrier. Therefore, Hodder and Jackwerth (2007) propose that during the

[6] Here, I only show the results with median EV. The results with median SD and percentage change values, and also those when portfolio ranking is at t_{liq-25} remain similar and are available upon request.

second-to-last year, there will be a big ramp-up in risk taking for the mediocre funds than for the best and worst performing funds. Moreover, if there is continued poor performance, then they will increase risk taking in the last year prior to the decision to closure. If however the performances improve, they will reduce risk taking during this period. Panel B of Table 1.5a shows that most of the portfolios (WWW, WW, L, LL) have reductions in median EV from the previous year. Moreover, the mediocre portfolios W and L have lower 25th and 75th percentile EV during the second-to-last year than during the previous year. For the ER in Panel A of Table 1.6a, the median excess returns are negative for nearly all the portfolios during the third-to-last year. This suggests that the risk taking of mediocre funds reduce as the performance drops. Therefore, this is inconsistent with Hodder and Jackwerth (2007). In the last year (Panel C of Table 1.5a), the mediocre portfolios in Panel C of Table 1.5a generally have low median EV. Moreover, portfolios LLL and WWW have higher median EV while the mediocre portfolios W and L continue to reduce median EV. Figure 1.1 shows the median EV over each of the last three years for the liquidate sample. It confirms that the mediocre portfolios L and W have the lowest median EV and do not exhibit a significant increase in median EV during the second-to-last year. However, for the performances of these portfolios, they show negative and continued reduction in median ER in each of the last three years (Figure 1.2). The results are in contrast to Hodder and Jackwerth (2007) argument since the mediocre portfolios continue to reduce risks as the performance drops further. Hodder and Jackwerth (2007) argue that the funds with the worst and best performance (portfolio LLL and WWW) during the start of the three years before liquidation will reduce volatility in the second-to-last and last years as portfolio values fall. However, the evidence indicates that portfolios WWW and LLL increase risks in the last year when the performance drops during the second-to-last year (also in Figures 1.1 and 1.2).

[Figures 1.1 and 1.2]

For the ONR sample in Table 1.5b, the portfolio WWW have less "Post" median EV than does the portfolio LLL during the third-to-last year. This is consistent with Hodder and Jackwerth (2007). Figure 1.3 shows the comparison between the ONR and liquidated samples during the third-to-last year. This shows that the ONR loser portfolios have higher median EV than for the liquidated loser portfolios. However for the ONR sample the mediocre portfolios have very low median EV compared to those of the winner portfolios. This is in contrary to the authors' argument during the third-to-last year. This is also shown in Figure 1.4 and in Panel B of Table 1.5b where the same pattern persists during the second-to-last years. The mediocre portfolios W and L have further reductions in median EV, but the above mediocre portfolio WW and the below mediocre portfolio LL have increases in median EV. During the third-to-last year (Panel A of Table 1.6b), the performances of the portfolios W, L, and LL continue to reduce while portfolios WWW and WW continue to increase. Therefore, only the below mediocre portfolio LL is consistent with Hodder and Jackwerth (2007) as they show increases in risk taking when performance during the previous year drops. In the last year (Panel C of Table 1.5b), most of the portfolios (WW, W, L, LL, LLL) have higher median EV than in the previous year while most of their median ER in Table 1.6b are lower during the second-to-last year. Figure 1.5 shows that portfolio performance continue to reduce in the last two years. Therefore, there is some evidence that the below mediocre portfolio increases risk when performance in the previous year reduces and that the best performing portfolio reduces risk taking over time. This is consistent with Hodder and Jackwerth (2007) with managerial shutdown option. However, this does not suggest I find support for Hodder and Jackwerth (2007) from the ONR sample since their model is based on liquidated funds. Moreover, the mediocre portfolios of the ONR sample do not increase risk by a great deal during the second-to-last and last years as the authors propose (Figure 1.4).

[Figures 1.4 and 1.5]

Goetzmann, Ingersoll, and Ross (2003) argue that if the managers are concerned about the potential management and performance fees in the later periods, they should reduce more risks to allow more asset base in the future to earn those fees. So, hedge funds will reduce risk taking as the fund performance and values drop to near liquidation barrier. However, they should take larger risk with higher asset values. The results for the liquidated sample (Figure 1.1) seem to be more consistent with their theory as these funds (especially the mediocre and loser portfolios) reduce risk taking in the last three years as the portfolio performance drops.

1.5.2. **Results for Robustness Test**

As a robustness check, I include the percentage change in EV based on the "Pre" interval window of t_{liq-48} to t_{liq-37} when the portfolios ranking is at t_{liq-37}. For example, $\%CHEV_{4,2}$, the percentage change in EV from fourth-to-last year or year of ranking to second-to-last year, is EV over the "Post" interval from t_{liq-24} to t_{liq-13} divided by EV over the "Pre" interval from t_{liq-48} to t_{liq-37} minus one. From Table 1.7a, all the portfolios show lower levels of EV in the second-to-last year from fourth-to-last year since the median $\%CHEV_{4,2}$ are more negative than $\%CHEV_{4,3}$ in the third-to-last year (Figure 1.6). Moreover, most of the portfolios have lower EV in the last year than those in the third-to-last year since the median $\%CHEV_{4,1}$ are more negative in the last year than median $\%CHEV_{4,3}$ in the third-to-last year. This means that the EV in the last year is lower than the EV in the fourth-to-last and third-to-last years as the performance drops. This is more consistent with Goetzmann, Ingersoll, and Ross (2003). For ONR sample in Table 1.7b Panel B, the median $\%CHEV_{4,2}$ is 8.60% which suggests that the risk taking increases for funds in the second-to-last year. Therefore, the risk taking is higher for portfolio LL in the last two years as the performance drops. As a result, I continue to find different results for the below mediocre in liquidated and ONR samples. This suggests that the liquidated sample shows no support for Hodder and Jackwerth (2007).

[Table 1.7 and Figure 1.6]

1.5.3. **Results for Volatility-Hazard Regression**

Summary Statistics

Table 1.8 shows the mean and standard deviation of these variables averaged over the hedge funds. Specifically, following Haghani (2014), the average mean of *ROR* is calculated as $\frac{1}{N}\sum_{i=1}^{N}\left[\frac{1}{T_i}\sum_{t=1}^{Ti} r_{it}\right]$ and the standard deviation of *ROR* as $\frac{1}{N}\sum_{i=1}^{N}\left[\sqrt{\frac{1}{T_i-1}\sum_{t=1}^{T_i}(r_{it}-\overline{r_i})^2}\right]$ where r_{it} is the monthly *ROR* for fund i in month t, $\overline{r_i}$ is the mean of the monthly *ROR*s for fund i, T_i is the number of monthly *ROR*s for hedge fund i, and *N* is the number of funds. The average of the mean monthly *AUMs*, *STD, Performance*, *Avg Size and Size Volatility* are calculated in the same way. The average mean of *ROR* is 0.36% per month and the average standard deviation is 4.39% per month. The average mean of *AUM* is $102.73 million per month and the average deviation is 63.93 million per month. In general, the values for other variables such as *Management Fee*, *Incentive Fee*, *Lockup Period*, *Notice Period*, *Payout Period, Minimum Investment*, *HWM*, *Leverage*, and *PI* are consistent with those reported by Haghani (2014).

[Table 1.8]

Regression Results

Table 1.9 shows the estimate β from each of the parametric models. Each of the model shows that larger *STD* has a negative impact on the hazard of the funds. Notice that the coefficients from the last two models have opposite signs as they are accelerated failure-time models, so a positive coefficient means that an unit increase in the covariate delays the time until failure (StataCorp., 2011). Overall, better performance over the previous year, having *HWM* provision, manager's personal investment, larger *AUM*, longer lockup period and notice period reduce the hazard of liquidation. This is consistent with the study by Liang and Park (2010) using Cox proportional hazard model. However, better most recent month *ROR*, higher management and incentive fees increase the hazard of hedge funds.

[Table 1.9]

Table 1.10 presents parameter estimates from fixed and time effects regression (1) with robust standard error (Petersen, 2009). The dependent variable is $ASD_{it+1,t+12}$, the annualized standard deviation of the 12 monthly returns during the year following month t. The coefficients b_1 of $\widehat{h_{it}}$ are insignificant in all the regressions. Table 1.11 shows the parameter estimates from the fixed and time effects regression (2) with the excess volatility, $AEV_{it+1,t+12}$, as the dependent variable. The coefficients b_1 are significantly positive, suggesting that predicted hazard has a positive impact upon the risk taking of funds over the following year. Overall this evidence is consistent with the previous studies that generally find larger risk taking of hedge fund as the distance below high water mark increases or the fund values and performance reduce given a relatively long evaluation horizon. Table 1.12 reports the parameter estimates in regression equation (3) with additional explanatory variables. Here, the dependent variable is $ASD_{it+1,t+12}$. The coefficients of the interaction term $Last1yr_i\widehat{h_{it}}$ are significantly negative. This suggests that as the evaluation period approaches to the point where there is only one year remaining before liquidation, the hedge fund managers take on lower risks as predicted hazard rate in the previous period increases. Table 1.13 reports the parameter estimates in regression equation (4) with excess volatility, $AEV_{it+1,t+12}$, as the dependent variable. The results are similar where the coefficients of the interaction term are significant negative. This is consistent with my findings for the liquidated sample using the median *EV* in the previous sections and suggests that the results are consistent with Goetzmann, Ingersoll, and Ross (2003).

[Table 1.10 to 1.13]

1.6. Conclusion

In this paper, I study the risk taking choices of hedge fund managers approaching closure date for liquidated and ONR samples. Specifically, I compute the median standard deviation of return, excess volatility and excess returns for the samples during the last two and three years. I find that the reduction risk is the greatest for the liquidated sample during the last two and three years as the fund performance drops. When I classify funds into sub-groups and sub-periods, the result shows that the mediocre portfolios continue to reduce risks during the second-to-last year and last year as their performance falls. Moreover, the below mediocre portfolios do not exhibit increases in risk taking during the second-to-last year when the portfolio performance reduces. Although this is similar for the ONR sample, the below mediocre portfolios exhibit higher risk taking during the second-to-last year.

Next, the volatility-hazard regression shows that the risk taking of funds increases as the predicted hazard rate increases. However, the risk taking of funds reduces as the funds are one year near the liquidation dates. This is evident by the negative coefficient of the interaction of the final year dummy with the predicted hazard rate. This indicates that as the predicted hazard rate increases, the risk of the fund reduces in the following year prior to liquidation which is consistent with the previous results using median excess volatility, EV, for liquidated sample.

The evidence indicates that the results for the liquidated sample are more consistent with Goetzmann, Ingersoll, and Ross (2003) who model the risk taking choices of the fund managers. Goetzmann, Ingersoll, and Ross (2003) point out that if the managers of these funds without managerial shutdown options are concerned about the potential management and performance fees in the future, they should reduce more risks to allow more asset base in the future to earn those fees. This is because increasing volatility may cause the funds to hit the liquidation barrier sooner even though it may also help the funds to reach the high water marks faster (Goetzmann, Ingersoll, and Ross, 2003). If the managers have options to voluntarily close the fund and take outside opportunities, the managers will increase risks of the fund when the fund value is approaching liquidation barrier (Hodder and Jackwerth, 2007). This is because they do not lose very much if the fund values hit the liquidation barriers. The results for the liquidated sample seem to be more consistent with Goetzmann, Ingersoll, and Ross (2003) since the managers with poorer performance portfolios reduce risk taking as performance drops. For the ONR sample, the below mediocre portfolio LL increases risk taking slightly during the second-to-last year when the portfolio performance drops. However, it does not support Hodder and Jackwerth (2007) with managerial shut down options since their model is based on liquidated funds. Therefore, it is likely that liquidation for many hedge funds is forced as the portfolio values hit the liquidation barriers.

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1.8. Tables and Figures

Table 1.1. Number of Closures and Liquidations Over the Sample Period

The table shows the number of funds closed and liquidated each year over sample period. The second column shows the number of funds at the beginning of the year, the third and fifth columns show the number of funds closed and liquidated during the year, respectively. The fourth and sixth columns show the percentage of funds that are closed and liquidated during the year, respectively. The last column shows the proportion of funds that are liquidated out of all funds that are closed each year.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Year	Number of funds	Closed	Attrition Rate	Liquidated	Liquidation Rate	Liquidated/Closed
1994	157	2	1.27%	2	1.27%	0
1995	228	5	2.19%	3	1.32%	0.60
1996	309	28	9.06%	15	4.85%	0.54
1997	391	18	4.60%	9	2.30%	0.50
1998	478	23	4.81%	14	2.93%	0.61
1999	567	30	5.29%	15	2.65%	0.50
2000	716	45	6.28%	22	3.07%	0.49
2001	854	55	6.44%	25	2.93%	0.45
2002	961	59	6.14%	34	3.54%	0.58
2003	1133	68	6.00%	46	4.06%	0.68
2004	1327	71	5.35%	37	2.79%	0.52
2005	1550	143	9.23%	73	4.71%	0.51
2006	1775	156	8.79%	57	3.21%	0.37
2007	1848	196	10.61%	49	2.65%	0.25
2008	1859	378	20.33%	136	7.32%	0.36
2009	1841	198	10.76%	106	5.76%	0.54
2010	1618	174	10.75%	70	4.33%	0.40
2011	1544	233	15.09%	118	7.64%	0.51
2012	1371	197	14.37%	102	7.44%	0.52

Table 1.2. Average Monthly CBOE Volatility Index (VIX) and Daily CBOE Russell 2000 Volatility Index (RVX) per Year

Year	Average VIX	Average RVX
1994	14.07	--
1995	12.40	--
1996	16.97	--
1997	23.26	--
1998	26.25	--
1999	24.54	--
2000	23.34	--
2001	25.49	--
2002	26.58	--
2003	21.81	--
2004	15.14	22.4
2005	12.93	19.1
2006	12.55	20.6
2007	17.73	23.5
2008	31.59	37.8
2009	31.79	38.7
2010	23.84	29.3
2011	23.61	31.3
2012	18.02	23.1

Source: Standard & Poor’s, CBOE.

Table 1.3. Medians of SD, EV and ER Over the 24- and 36-Month Windows for Liquidated and ONR Samples

The excess volatility (EV) is calculated as the difference between individual fund standard deviation of return (SD) and mean SD of the style. The excess return (ER) is the difference between the individual fund cumulative return and the mean style cumulative return over the 24-month window and 36-month window. The calculations are done for each fund in each of the liquidated and ONR samples. "Pre" represents the previous 24-month (or 36-month) window and "Post" represents the next 24-month (or 36-month) window. The numbers in the tables are the median, 25th and 75th percentile values over the 24-month window (Panel A) and 36-month window (Panel B). The N is the total number of funds in each sample. Since the time effect is not controlled, I include only the liquidated and ONR samples since live funds continue to exist after the end of the sample period.

		Panel A: 24-Month Window				N	Panel B: 36-Month Window				N
		Pre: %		Post: %			Pre: %		Post: %		
		Median	25th 75th	Median	25th 75th		Median	25th 75th	Median	25th 75th	
SD	1.3a: Liq	13.47	8.49 22.81	12.80	8.02 22.34	526	16.50	10.05 28.08	18.27	10.85 29.44	310
	1.3b: ONR	12.23	6.60 21.16	13.85	7.84 23.49	717	14.91	8.10 27.68	17.34	10.18 29.12	420
EV	1.3c: Liq	-2.30	-7.01 2.79	-3.00	-7.89 2.68	526	-2.47	-7.70 4.45	-3.14	-9.03 3.55	310
	1.3d: ONR	-2.39	-6.68 3.09	-2.01	-6.36 4.94	717	-2.88	-7.33 4.04	-2.46	-7.73 4.88	420
ER	1.3e: Liq	-5.41	-15.90 6.47	-15.15	-28.92 -5.57	526	-8.40	-21.15 8.27	-21.76	-36.84 -8.16	310
	1.3f: ONR	-3.18	-14.07 7.55	-10.55	-24.90 1.81	717	-6.16	-18.38 8.74	-14.85	-31.29 0.45	420

Table 1.4. Medians of SD, EV and ER Over Each of the Last Three Years for Liquidated and ONR Samples

The excess volatility (EV) is calculated as the difference between individual fund standard deviation of return (SD) and mean SD of the style. The excess return (ER) is the difference between the individual fund cumulative 12-month return and the mean style cumulative 12-month return. The calculations are done for each fund in each of the liquidated and ONR samples. "Pre" represents the previous 12-month window and "Post" represents the next 12-month window. The numbers in the tables are the median, 25th and 75th percentile values over the third-to-last year (Panel A), second-to-last year (Panel B) and last year (Panel C). The N is the total number of funds in each sample. Since the time effect is not controlled, I include only the liquidated and ONR samples as live funds continue to exist after the end of the sample period.

		Year of Ranking		**Panel A: Third-to-Last Year**		**Panel B: Second-to-Last Year**		**Panel C: Last Year**		N
		Pre: %		Post: %		Post: %		Post: %		
		Median	25th 75th	Median	25th 75th	Median	25th 75th	Median	25th 75th	
SD	1.4a: Liq	8.96	5.10 15.03	8.46	5.28 14.93	7.43	4.82 13.64	9.10	5.31 15.70	522
	1.4b: ONR	7.77	4.08 15.33	7.98	4.38 14.21	7.79	4.22 14.78	9.83	5.32 16.34	710
EV	1.4c: Liq	-1.53	-4.90 1.53	-1.83	-5.09 1.71	-2.19	-5.87 1.20	-2.54	-5.50 1.77	522
	1.4d: ONR	-1.61	-4.63 2.36	-1.95	-4.72 1.57	-1.95	-4.94 1.60	-1.55	-4.71 4.34	710
ER	1.4e: Liq	-1.84	-8.88 5.36	-3.87	-10.84 3.10	-5.40	-12.29 0.60	-7.92	-16.32 -1.19	522
	1.4f: ONR	-0.94	-7.37 5.17	-1.88	-8.87 5.05	-2.36	-9.62 3.10	-5.75	-15.84 1.36	710

Table 1.5. Medians of EV Over Each of the Last Three Years for Performance Portfolios in the Liquidated and ONR Samples

The excess volatility (EV) is calculated as the difference between individual fund SD and mean SD of the style. It is computed for each fund in each performance portfolio according to the portfolio ranking at t_{liq-37}. "Pre" represents the previous 12-month window and "Post" represents the next 12-month window. The numbers in the tables are the median, 25th and 75th percentile values over the third-to-last year (Panel A), second-to-last year (Panel B) and last year (Panel C). The N is the total number of funds in each portfolio. I include only the liquidated (Table 1.5a) and ONR (Table 1.5b) samples.

	Performance Portfolio	Year of Ranking		Panel A: Third-to-Last Year		Panel B: Second-to-Last Year		Panel C: Last Year		N
		Pre EV: %		Post EV: %		Post EV: %		Post EV: %		
		Median	25th 75th	Median	25th 75th	Median	25th 75th	Median	25th 75th	
1.5a: Liq	WWW	8.67	3.76 16.96	4.67	0.18 11.60	-0.89	-5.16 6.48	2.59	-3.26 20.18	12
	WW	0.13	-2.94 6.13	-2.14	-5.58 4.92	-2.41	-5.64 5.65	-2.17	-3.92 4.55	37
	W	-1.78	-6.34 0.36	-2.65	-6.00 1.31	-2.41	-6.14 0.81	-2.80	-5.66 0.93	171
	L	-2.18	-5.02 0.13	-2.20	-5.14 0.92	-2.28	-5.37 0.67	-2.55	-5.61 1.45	257
	LL	1.37	-2.91 11.25	1.17	-3.14 5.64	-0.94	-4.77 2.78	-0.93	-6.86 9.86	35
	LLL	7.62	3.03 14.16	1.60	-0.69 11.08	1.72	-8.92 6.72	2.23	-2.72 11.37	10
1.5b: ONR	WWW	13.74	9.13 28.92	8.32	-2.84 18.32	7.80	0.24 19.01	2.39	-3.93 10.95	27
	WW	2.05	-1.92 9.90	1.05	-3.73 7.37	1.78	-2.80 8.23	2.41	-2.21 11.93	52
	W	-1.74	-4.66 1.32	-2.13	-4.32 0.71	-2.36	-4.95 -0.33	-1.84	-4.71 2.04	249
	L	-2.40	-5.49 -0.45	-2.40	-5.94 0.24	-2.85	-5.71 -0.03	-2.29	-5.71 2.89	324
	LL	2.23	-2.50 8.80	-0.48	-2.54 8.90	1.34	-1.13 9.56	2.77	-2.92 11.24	46
	LLL	14.60	4.24 43.20	12.59	0.61 16.52	10.89	1.26 33.45	11.78	3.57 29.07	12

Table 1.6. Medians of ER Over Each of the Last Three Years for Performance Portfolios in the Liquidated and ONR Samples

The excess return (ER) is the difference between the individual fund annual return and the mean style annual return where the individual fund annual return is based on monthly returns. It is computed for each fund in each performance portfolio according to the portfolio ranking at t_{liq-37}. "Pre" represents the previous 12-month window and "Post" represents the next 12-month window. The numbers in the tables are the median, 25th and 75th percentile values over the third-to-last year (Panel A), second-to-last year (Panel B) and last year (Panel C). The N is the total number of funds in each portfolio. I include only the liquidated (Table 1.6a) and ONR (Table 1.6b) samples.

	Performance Portfolio	Year of Ranking			Panel A: Third-to-Last Year			Panel B: Second-to-Last Year			Panel C: Last Year			N
		Pre ER: %			Post ER: %			Post ER: %			Post ER: %			
		Median	25th	75th	Median	25th	75th	Median	25th	75th	Median	25th	75th	
1.6a: Liq	WWW	40.79	36.65	48.46	-6.99	-23.55	3.94	-10.70	-18.32	-1.48	-14.26	-33.38	-5.30	12
	WW	20.52	14.89	31.76	-2.87	-13.18	8.06	-8.32	-24.71	-1.98	-8.29	-15.63	-3.61	37
	W	4.82	2.36	11.87	-4.40	-12.65	3.35	-5.65	-12.51	0.25	-7.89	-15.92	-2.73	171
	L	-6.01	-10.27	-2.72	-3.88	-9.24	2.38	-5.00	-11.57	0.73	-7.02	-15.31	0.77	257
	LL	-16.78	-27.07	-12.15	-4.46	-11.37	3.79	-3.93	-10.19	1.23	-5.94	-20.50	0.30	35
	LLL	-22.80	-47.64	-17.67	6.02	1.68	40.94	-2.44	-12.22	5.23	-22.37	-37.29	-3.05	10
1.6b: ONR	WWW	51.76	27.31	95.88	10.42	1.69	37.35	-5.41	-11.20	5.65	-4.33	-10.75	14.24	27
	WW	21.52	11.61	27.94	1.96	-13.73	11.90	0.25	-5.99	11.42	-9.33	-20.06	5.99	52
	W	4.42	1.99	7.15	-2.00	-6.86	4.38	-2.34	-9.80	2.25	-6.35	-16.59	0.83	249
	L	-5.45	-9.90	-2.50	-3.01	-9.63	3.34	-2.54	-8.71	2.33	-5.31	-14.46	1.07	324
	LL	-22.94	-32.19	-15.20	-2.76	-11.21	4.28	-3.22	-10.61	1.77	-10.94	-17.75	1.65	46
	LLL	-35.61	-46.76	-24.95	14.86	-7.43	29.95	7.00	-15.95	53.82	-20.28	-45.15	1.92	12

Table 1.7. Medians of *%CHEV*$_{4,3}$, *%CHEV*$_{4,2}$, and *%CHEV*$_{4,1}$ Over Each of the Last Three Years for Performance Portfolios in the Liquidated and ONR Samples

The percentage change in excess volatility (EV) is calculated for each fund in each performance portfolio according to the portfolio ranking at t_{liq-37}. The numbers in the table are the median, 25th and 75th percentile percentage change in standard deviation for each portfolio over the third-to-last year (Panel A), second-to-last year (Panel B) and last year (Panel C). The N is the total number of funds in each portfolio. Note the percentage change values are winsorized at 5% by performance groups. I include only the results for liquidated (Table 1.7a) and ONR (Table 1.7b) samples.

	Performance Portfolio	Panel A: Third-to-Last Year			Panel B: Second-to-Last Year			Panel C: Last Year			N
		%CHEV$_{4,3}$:			*%CHEV*$_{4,3}$:			*%CHEV*$_{4,3}$:			
		Median	25th	75th	Median	25th	75th	Median	25th	75th	
1.7a: Liq	WWW	-78.98%	-102.24%	5.15%	-91.16%	-193.16%	-46.89%	-71.27%	-147.83%	81.93%	12
	WW	0.68%	-120.11%	80.54%	-28.16%	-158.23%	44.91%	-12.83%	-115.03%	48.39%	37
	W	-30.48%	-177.81%	41.56%	-27.30%	-208.07%	38.03%	-25.15%	-211.42%	42.76%	171
	L	-3.12%	-113.56%	53.76%	-14.40%	-161.73%	45.36%	-40.87%	-222.34%	46.89%	257
	LL	-36.34%	-103.60%	33.06%	-74.89%	-178.11%	53.36%	-56.36%	-242.77%	71.75%	35
	LLL	-79.76%	-108.70%	34.86%	-114.46%	-223.93%	-18.67%	-98.88%	-138.53%	-34.16%	10
1.7b: ONR	WWW	-39.75%	-115.02%	4.75%	-44.30%	-83.67%	20.39%	-80.99%	-127.49%	-10.89%	27
	WW	-23.88%	-84.42%	27.58%	-17.25%	-78.80%	43.83%	-3.37%	-94.17%	75.24%	52
	W	-15.64%	-104.44%	48.91%	-33.15%	-154.22%	35.81%	-9.16%	-194.78%	60.46%	249
	L	-4.75%	-103.07%	43.22%	-19.73%	-145.72%	31.45%	-29.91%	-217.76%	47.11%	324
	LL	-16.93%	-123.13%	28.19%	8.60%	-80.45%	61.72%	3.79%	-136.69%	117.21%	46
	LLL	-73.55%	-95.15%	4.34%	-51.56%	-85.33%	-28.70%	-45.72%	-108.22%	40.74%	12

Table 1.8. Summary Statistics of Explanatory Variables in Parametric Hazard Models

The table provides the mean and standard deviation of the explanatory variables of hedge funds for the period from inception of each fund to the date that the fund exist the database or December 2012. The variables include *standard deviation* (*STD*) over 24 months, average monthly *performance* during previous year (*Performance*), *assets under management* (*AUM*), *average size* (*Avg Size*), *size volatility*, monthly *rate of return* (*ROR*), *management fee*, *incentive fee*, *lockup period*, *redemption notice period* (*Notice Period*), *payout period*, *minimum investment*, and dummy variables to indicate funds that has *HWM*, *personal investment* (*PI*), and *leverage*.

Time-Varying Variables	Mean	Standard Deviation
ROR (%)	0.36	4.39
Performance (%)	0.47	1.20
STD (%)	19.14	5.25
AUM (Million US$)	102.73	63.93
Avg Size (Million US$)	107.61	57.19
Size Volatility (Million US$)	18.40	13.41
Incentive Fee (%)	17.40	6.51
Management Fee (%)	1.48	0.63
Minimum Investment (Million US$)	1.03	3.48
Lockup Period (in months)	4.07	6.95
Notice Period (in days)	39.83	31.33
Payout Period (in days)	18.75	26.77
Dummy Variables	**Mean**	**Standard Deviation**
HWM	0.73	0.44
PI	0.39	0.49
Leverage	0.75	0.43

Table 1.9. Parameter Estimate from Parametric Hazard Models

The table provides the parameter estimates β from the exponential, Weibull, and Gompertz distributions, and log-logistic and log-normal models. *z* statistics are in parentheses. *, **, and *** indicate that the parameter estimate is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1) Exponential	(2) Weibull	(3) Gompertz	(4) Log-logistic	(5) Lognormal
STD	-0.0161***	-0.0173***	-0.0167***	0.0101***	0.00845***
	(-6.58)	(-6.93)	(-6.74)	(6.52)	(6.04)
*D*1 (Convertible Arbitrage)	-0.130	-0.372	-0.245	0.231	0.152
	(-0.41)	(-1.17)	(-0.77)	(1.13)	(0.78)
*D*2 (Dedicated Short Bias)	0.439	0.400	0.435	-0.123	-0.0883
	(1.03)	(0.94)	(1.02)	(-0.45)	(-0.30)
*D*3 (Emerging Markets)	0.0636	-0.00310	0.0378	0.0662	0.0522
	(0.24)	(-0.01)	(0.14)	(0.40)	(0.33)
*D*4 (Equity Market Neutral)	0.365	0.333	0.348	-0.180	-0.196
	(1.37)	(1.25)	(1.31)	(-1.08)	(-1.19)
*D*5 (Event Driven)	-0.140	-0.329	-0.244	0.178	0.128
	(-0.51)	(-1.19)	(-0.88)	(1.03)	(0.78)
*D*6 (Fixed Income Arbitrage)	-0.284	-0.489	-0.382	0.305	0.238
	(-0.92)	(-1.58)	(-1.24)	(1.57)	(1.28)
*D*7 (Fund of Funds)	0.0625	-0.0226	0.0256	0.0271	-0.00928
	(0.25)	(-0.09)	(0.10)	(0.18)	(-0.06)
*D*8 (Global Macro)	0.228	0.236	0.241	-0.119	-0.174
	(0.81)	(0.84)	(0.86)	(-0.68)	(-1.02)
*D*9 (L/S Equity Hedge)	0.0474	-0.0818	-0.0177	0.0557	0.0407
	(0.20)	(-0.34)	(-0.07)	(0.38)	(0.29)
*D*10 (Managed Futures)	-0.329	-0.592**	-0.502*	0.335**	0.315*
	(-1.22)	(-2.18)	(-1.85)	(1.97)	(1.93)
*D*11 (Multi-Strategy)	-0.312	-0.364	-0.333	0.238	0.194
	(-1.03)	(-1.20)	(-1.10)	(1.29)	(1.12)
*D*12 (Options Strategy)	-14.05	-12.70	-12.87	6.915	4.307
	(-0.02)	(-0.04)	(-0.03)	(0.03)	(0.03)
Performance	-0.173***	-0.188***	-0.181***	0.116***	0.106***
	(-7.78)	(-8.40)	(-8.07)	(7.63)	(7.44)
Avg Size	0.000238	0.000164	0.000192	0.000368	0.000847***
	(0.59)	(0.40)	(0.47)	(0.60)	(3.38)
Size Volatility	-0.0000380	-0.0000660	-0.0000374	-0.000734	-0.00105***
	(-0.11)	(-0.20)	(-0.11)	(-0.67)	(-4.20)

Table 1.9. Continued. Parameter Estimate from Parametric Hazard Models

The table provides the parameter estimates *β* from the exponential, Weibull, and Gompertz distributions, and log-logistic and log-normal models. *z* statistics are in parentheses. *, **, and *** indicate that the parameter estimate is statistically significant at the 10%, 5%, and 1% levels, respectively.

	(1) Exponential	(2) Weibull	(3) Gompertz	(4) Log-logistic	(5) Lognormal
HWM	-0.306***	-0.322***	-0.311***	0.205***	0.199***
	(-3.52)	(-3.71)	(-3.59)	(3.59)	(3.46)
PI	-0.176**	-0.278***	-0.236***	0.173***	0.172***
	(-2.30)	(-3.61)	(-3.07)	(3.50)	(3.51)
Leverage	0.0758	0.113	0.0922	-0.0720	-0.0831
	(0.88)	(1.31)	(1.07)	(-1.30)	(-1.50)
ROR	0.00842	0.00910*	0.00873*	-0.00737**	-0.00748**
	(1.64)	(1.71)	(1.67)	(-2.18)	(-2.16)
AUM	-0.00309***	-0.00366***	-0.00344***	0.00159***	0.000138
	(-5.15)	(-5.80)	(-5.56)	(2.74)	(0.59)
Lockup Period	-0.00937	-0.0111*	-0.0100*	0.00860**	0.00791**
	(-1.56)	(-1.86)	(-1.67)	(2.36)	(2.13)
Payout Period	-0.000657	-0.0000834	-0.000237	0.000504	0.000251
	(-0.29)	(-0.04)	(-0.11)	(0.35)	(0.20)
Notice Period	-0.00316*	-0.00296*	-0.00301*	0.00149	0.00197**
	(-1.96)	(-1.81)	(-1.86)	(1.49)	(2.02)
Management Fee	0.0809	0.0637	0.0605	-0.0887**	-0.0785*
	(1.43)	(1.18)	(1.11)	(-2.14)	(-1.96)
Incentive Fee	0.0185***	0.0257***	0.0233***	-0.0152***	-0.0148***
	(2.69)	(3.74)	(3.38)	(-3.24)	(-3.14)
β_0	-5.143***	-7.782***	-5.421***	4.681***	4.801***
	(-17.50)	(-21.86)	(-18.41)	(25.04)	(26.51)
ln(*p*)		0.464***			
		(16.59)			
gamma			0.00532***		
			(8.06)		
ln(*gamma*)				-0.690***	
				(-23.74)	
ln(*sigma*)					-0.125***
					(-4.65)
N	2436	2436	2436	2436	2436
Likelihood ratio test (χ^2_{20})	281.6***	355.9***	318.0***	326.3***	258.8***

Table 1.10. Parameter Estimate from Fixed- and Time-Effect Model with Annualized Standard Deviation as Dependent Variable

The table provides the parameter estimates from fixed and time effects regression (1) with robust standard error: $ASD_{it+1,t+12} = b_0 + b_1\widehat{h_{it}} + \sum_{k=1}^{11} a_k T_k + \varepsilon_{it}$. $ASD_{it+1,t+12}$ is the annualized standard deviation of the 12 monthly returns following month t. $\widehat{h_{it}}$ is the predicted hazard rate for fund i at each month t. T_k is a set of monthly dummies k which gives the monthly fixed effects and the total number of k is 11, and ε_{it} is the residual.

	(1) **Exponential**	(2) **Weibull**	(3) **Gompertz**	(4) **Log-logistic**	(5) **Lognormal**
$\widehat{h_{it}}$	0.319	-0.555	-0.933	-0.432	-0.712
	(0.30)	(-0.87)	(-1.07)	(-0.67)	(-0.89)
b_0	0.127^{***}	0.130^{***}	0.131^{***}	0.129^{***}	0.131^{***}
	(30.50)	(40.83)	(36.02)	(38.05)	(32.16)
Monthly Dummy	Yes	Yes	Yes	Yes	Yes
N	118070	118070	118070	118070	118070
F-test	9.255^{***}	9.414^{***}	9.489^{***}	9.311^{***}	9.317^{***}

t statistics in parentheses
* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$

Table 1.11. Parameter Estimate from Fixed- and Time-Effect Model with Annualized Excess Volatility as Dependent Variable

The table provides the parameter estimates from fixed and time effects regression (2) with robust standard error: $AEV_{it+1,t+12} = b_0 + b_1\widehat{h_{it}} + \sum_{k=1}^{11} a_k T_k + \varepsilon_{it}$. $AEV_{it+1,t+12}$ is the annualized excess volatility of the 12 monthly returns following month t. The annualized excess volatility (*AEV*) is calculated as the difference between individual fund *SD* over a 12-month window and mean *SD* of the style over the same window. $\widehat{h_{it}}$ is the predicted hazard rate for fund i at each month t. T_k is a set of monthly dummies k which gives the monthly fixed effects and the total number of k is 11, and ε_{it} is the residual.

	(1)	(2)	(3)	(4)	(5)
	Exponential	**Weibull**	**Gompertz**	**Log-logistic**	**Lognormal**
$\widehat{h_{it}}$	1.547*	1.119**	1.365**	1.351**	1.606**
	(1.69)	(2.34)	(2.18)	(2.55)	(2.40)
b_0	-0.00558	-0.00508*	-0.00540*	-0.00635**	-0.00778**
	(-1.50)	(-1.91)	(-1.84)	(-2.12)	(-2.20)
Monthly Dummy	Yes	Yes	Yes	Yes	Yes
N	118070	118070	118070	118070	118070
F-test	1.676*	1.863**	1.813**	2.039**	2.032**

t statistics in parentheses

* $p < 0.10$;

** $p < 0.05$;

*** $p < 0.01$

Table 1.12. Parameter Estimate from Fixed-and Time-Effect Model with Annualized Standard Deviation as Dependent Variable

The table provides the parameter estimates from fixed and time effects regression (3) with robust standard error: $ASD_{it+1,t+12} = b_0 + b_1\widehat{h_{\iota t}} + b_2Last1yr_i + b_3Last1yr_i\widehat{h_{\iota t}} + \sum_{k=1}^{11} a_kT_k + \varepsilon_{it}$. $ASD_{it+1,t+12}$ is the annualized standard deviation of the 12 monthly returns following month t. $\widehat{h_{\iota t}}$ is the predicted hazard rate for fund i at each month t. $Last1yr_i$ equals one for fund i if the observation occurs at t_{liq-13} prior to liquidation. T_k is a set of monthly dummies k which gives the monthly fixed effects and the total number of k is 11, and ε_{it} is the residual.

	(1) Exponential	(2) Weibull	(3) Gompertz	(4) Log-logistic	(5) Lognormal
$\widehat{h_{\iota t}}$	0.349	-0.557	-0.929	-0.435	-0.718
	(0.33)	(-0.87)	(-1.07)	(-0.68)	(-0.90)
$Last1yr_i$	0.0415***	0.0234**	0.0286**	0.0308**	0.0388**
	(3.14)	(2.37)	(2.48)	(2.55)	(2.57)
$Last1yr_i\widehat{h_{\iota t}}$	-7.433***	-2.467*	-3.977*	-3.651**	-5.135**
	(-2.93)	(-1.66)	(-1.92)	(-2.03)	(-2.18)
b_0	0.127***	0.130***	0.131***	0.129***	0.131***
	(30.52)	(40.78)	(35.99)	(38.02)	(32.15)
Monthly Dummy	Yes	Yes	Yes	Yes	Yes
N	118070	118070	118070	118070	118070
F-test	9.291***	9.060***	9.132***	9.071***	9.111***

t statistics in parentheses

* $p < 0.10$;

** $p < 0.05$;

*** $p < 0.01$

Table 1.13. Parameter Estimate from Fixed-and Time-Effect Model with Annualized Excess Volatility as Dependent Variable

The table provides the parameter estimates from fixed and time effects regression (4) with robust standard error: $AEV_{it+1,t+12} = b_0 + b_1\widehat{h_{it}} + b_2 Last1yr_i + b_3 Last1yr_i\widehat{h_{it}} + \sum_{k=1}^{11} a_k T_k + \varepsilon_{it}$. $AEV_{it+1,t+12}$ is the annualized excess volatility of the 12 monthly returns following month t. The annualized excess volatility (*AEV*) is calculated as the difference between individual fund *SD* over a 12-month window and mean *SD* of the style over the same window. $\widehat{h_{it}}$ is the predicted hazard rate for fund i at each month t. $Last1yr_i$ equals one for fund i if the observation occurs at t_{liq-13} prior to liquidation. T_k is a set of monthly dummies k which gives the monthly fixed effects and the total number of k is 11, and ε_{it} is the residual.

	(1) Exponential	(2) Weibull	(3) Gompertz	(4) Log-logistic	(5) Lognormal
$\widehat{h_{it}}$	1.566*	1.126**	1.376**	1.356**	1.611**
	(1.72)	(2.35)	(2.19)	(2.55)	(2.40)
$Last1yr_i$	0.0275**	0.0196**	0.0234**	0.0229**	0.0303**
	(2.24)	(2.15)	(2.19)	(2.02)	(2.13)
$Last1yr_i\widehat{h_{it}}$	-4.896**	-2.685**	-3.826**	-3.167*	-4.548**
	(-2.09)	(-2.05)	(-2.08)	(-1.91)	(-2.05)
b_0	-0.00568	-0.00515*	-0.00548*	-0.00641**	-0.00784**
	(-1.53)	(-1.93)	(-1.87)	(-2.15)	(-2.22)
Monthly Dummy	Yes	Yes	Yes	Yes	Yes
N	118070	118070	118070	118070	118070
F-test	1.768**	1.814**	1.798**	1.987**	2.021**

t statistics in parentheses
* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$

Figure 1.1. Median Excess Volatilities (Post) for Liquidated Sample Over the Third-to-last, Second-to-last and Last Years

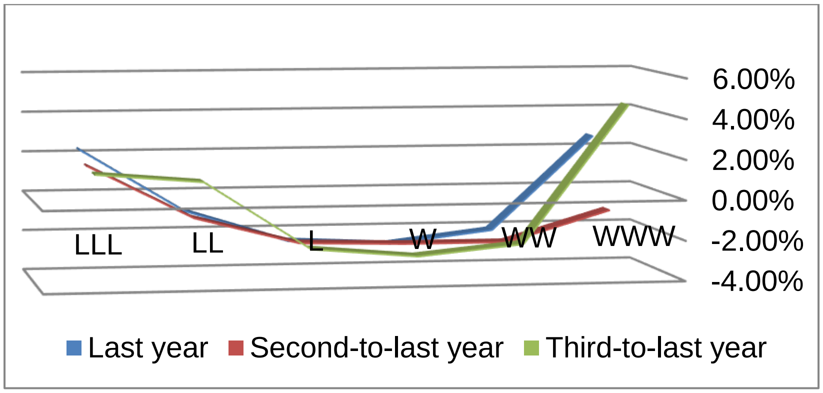


Figure 1.2. Median Excess Returns (Post) for Liquidated Sample Over the Third-to-last, Second-to-last and Last Years

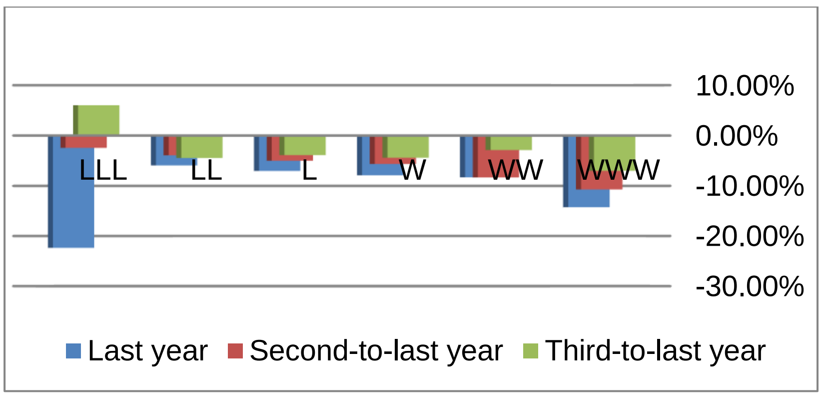


Figure 1.3. Median Excess Volatilities (Post) for Liquidated and ONR Sample in the Third-to-last Year

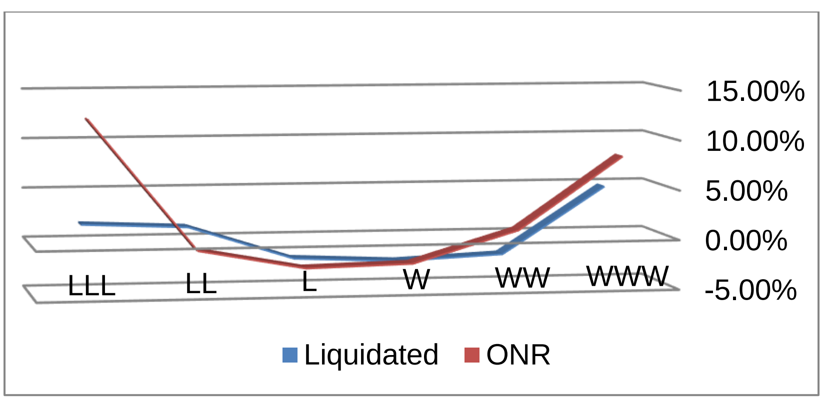


Figure 1.4. **Median Excess Volatilities (Post) for ONR Sample Over the Third-to-last, Second-to-last and Last Years**

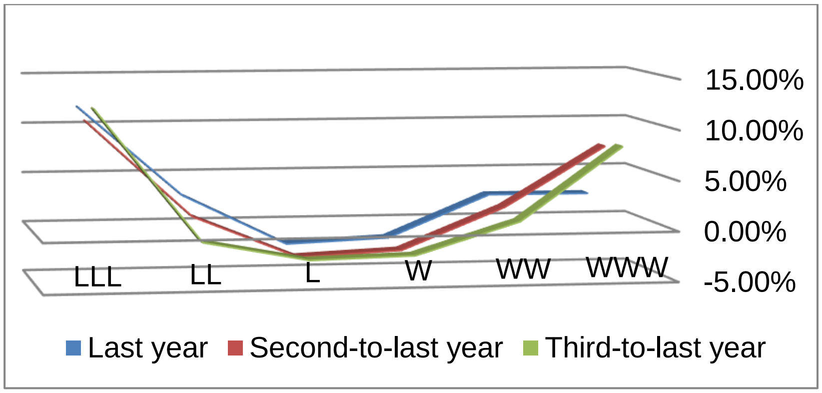


Figure 1.5. **Median Excess Returns (Post) for ONR Sample Over the Third-to-last, Second-to-last and Last Years**

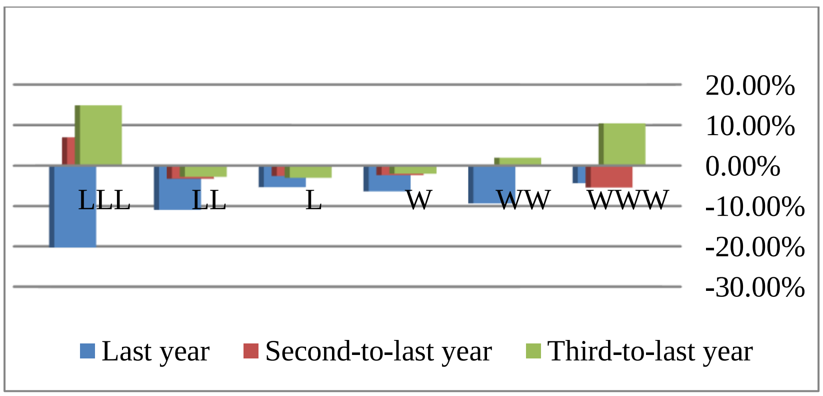
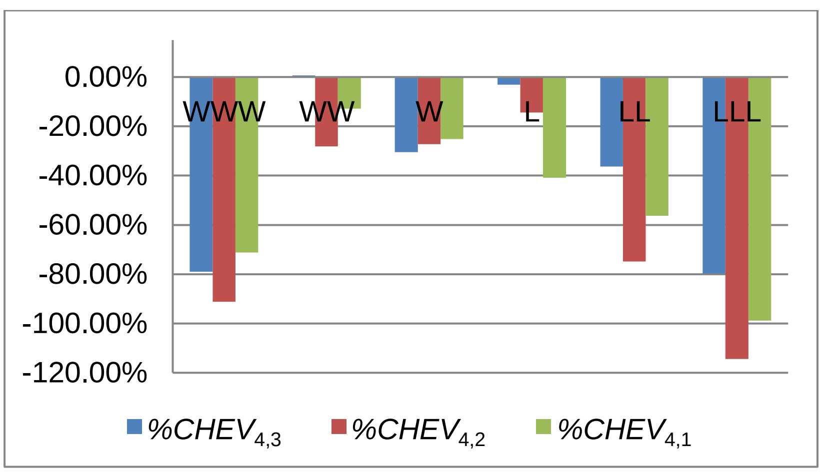


Figure 1.6. **Median** ***%CHEV*** $_{4,3}$**,** ***%CHEV*** $_{4,2}$ **and** ***%CHEV*** $_{4,1}$ **for Liquidated Sample**



1.9. Supplemental Information: Hedge Fund Institutional Background

Namvar and Phillips (2013) noted that mutual funds "are created by an investment contract which may contract an external management company". The investment company may terminate a mutual fund by way of liquidation or merger with another fund, with the latter being more common in reality.

Hedge fund industry however is different. Typically the management company sets up the fund and is not an independent party. So managers have the discretion to terminate the funds for different reasons. The reasons of closure normally include liquidation, fund no longer reporting, fund closed to new investment, losing contact with fund, and fund merger with another entity. Therefore, fund termination does not always result in merger. For instance, funds closed to new investment or stop reporting may still exit for a period of time, this means that there is no dismissal of the fund manager. This in contrast to termination of mutual funds which is related to fund liquidation or merger with other funds (Ter Horst and Verbeek, 2007). Either way of termination results in dismissal for the mutual fund manager. In the hedge fund literature, studies usually state that the decision to closure are at manager's discretion, for example, see Grecu et al. (2007), Liang (2000), Ruckes and Sevostiyanova (2012), and Hodder and Jackwerth (2007). Therefore, fund closure does not necessarily lead to a hedge fund manager dismissal. As a result, it is possible for the managers to continue earning the potential incentive fees.

Chapter 2. The Impact of Redemption Request on Hedge Fund Risk Taking

2.1. Abstract

In this study, I examine hedge fund risk taking choices with and without redemption requests. I find that hedge funds with longer restriction periods tend to take lower risk if there are no significant redemption requests. Second, hedge funds with short restriction periods tend to increase risks following redemption requests. The increase in risk is larger for large redemptions than for small redemptions. This may be due to the inability of fund managers to reduce the risks of funds when they have to close out their positions immediately at an unfavourable time to increase cash holding. However, if there are large redemptions during market crisis, hedge funds tend to take higher post risk even when the restriction periods are longer, suggesting that their ability to reduce risks during unfavourable market environment is diminished.

2.2. Introduction

Several studies have found that lockup, redemption notice, redemption and payout periods affect the risk and performance of hedge funds. Boyle, Li, and Zhu (2010) find that fund risk is significantly lower in general for hedge funds with longer notice and redemption periods. Joenväärä and Tolonen (2008) on the other hand find that the lengths of the notice period and the redemption period have no effects on the risk-taking behaviour of the hedge funds. Agarwal, Daniel and Naik (2009) find that longer lockup, notice, redemption period is related to greater performance of hedge funds. None of the studies examines whether redemption requests from investors affect the risk-taking choices of the hedge funds. Since hedge funds have to increase the cash positions to meet the redemption requests, redemption requests may affect the risk taking choices of hedge funds. Moreover, the risk-taking choices may depend on the amount of the aggregate investor redemption as a percent of the fund's assets and the length of restriction period defined as the sum of the length of notice and payout periods. Large redemptions may reduce the performance and survival probability of hedge funds (Klaus and Rzepowski, 2009a; Klaus and Rzepowski, 2009b), and longer restriction periods may allow hedge funds to invest in more illiquid assets (Agarwal, Daniel and Naik, 2009). Therefore it would be interesting to study how the risks of hedge funds change in response to different percentages of redemption and to different lengths of restriction period. This can help us understand how hedge funds respond to redemption demands in general as the amount of redemption requests together with redemption restriction periods could both affect the risk taking for funds.

Past studies have not considered the impact of redemption requests. Hedge funds need to increase cash positions over the restriction period following redemption requests. Therefore, it is important for investors and fund managers to understand the impact of the redemption requests on hedge fund risk taking. The reason is that large and frequent redemptions may increase the fund's risk taking. This could be harmful for both the remaining investors and managers. For example, if a fund receives more frequent and large redemption requests, this may cause an increase in fund volatility, which is unfavorable for the remaining investors and harmful for hedge funds if the remaining assets are illiquid. If the remaining assets are illiquid, it would affect hedge fund portfolio rebalancing as it would be hard to sell the asset to reduce the weight in the portfolio. For investors, if increases in hedge fund risk increases investors' overall portfolio risk than the targeted portfolio risk, this may trigger a rebalancing need for their personal portfolio. However, given that they are locked up over the restriction period, they can only adjust their equity and bond holdings. Even for those funds with longer restriction period, their risk taking may not necessarily reduce if the amount of redemption is large. Therefore it is important to study the effect of redemption requests upon risk taking for hedge funds.

This study uses the cross-sectional standard deviation as a measure of the pre-request and post-request period risks. This approach avoids the problem of calculating the volatilities over return periods less than five months for each fund. Moreover, this measure is able to capture the precise timing of spikes in risks common to the funds (Adrian, 2007). Therefore, this measure provides more representative results for risk changes based on groups of funds than the result based on the risk of individual funds. This is the first paper that uses the cross-sectional measure to determine the risk taking choices of hedge fund groups in the face of redemption requests. This is also the first paper that studies the effects of redemption requests and different redemption amounts as a percentage of fund's assets upon the risk taking of hedge funds.

I find that the lengths of the restriction and redemption notice periods as well as the redemption amounts affect the risk-taking choices of the hedge funds. First, hedge funds with longer restriction periods tend to take lower risk if there are no significant redemption requests. Second, hedge funds with short restriction and redemption notice periods tend to increase risks following redemption requests. The increase in risk is larger for large redemptions than for small redemptions. This may be due to the inability of fund managers to reduce the risks of funds when they have to close out their positions immediately at an unfavourable time to increase cash holding. For hedge funds with longer restriction periods, they tend to take lower risk following redemption requests for small and median redemptions as the managers are able to take advantage of the market conditions. However, if there are large redemptions during market crisis, hedge funds tend to take higher post risk even when the restriction periods are longer. Finally, for longer redemption notice periods, there is no change in risks following redemption requests for small and large redemptions. This implies that the hedge fund managers do not rush to close out the positions immediately following redemption requests prior to the end of the valuation dates.

2.3. Literature Review

Redemption restrictions allow managers to be more flexible in their investment strategies (Agarwal, Daniel, and Naik, 2009). Several studies find that redemption restrictions of hedge funds are associated with investment in illiquid assets. The investment in illiquid asset in the hedge fund portfolio allows the hedge funds to capture the illiquidity premium. For instance, Aragon (2007) finds that hedge funds invest in illiquid asset when there are redemption restrictions. These funds usually have higher returns, implying that investors are compensated by the holding illiquid fund shares. This finding is similar to Boyle, Li, and Zhu (2010) who find that a longer restriction period is associated with more illiquid assets investments. Some studies find that hedge funds tend to impose longer lockup and redemption notice periods when they invest in illiquid assets. For example, Joenväärä and Tolonen (2008) find that hedge funds impose longer notice period when the fund managers invest in illiquid asset and that a longer notice period provides a higher illiquidity premium. Liang and Park (2008) find that offshore funds impose share restrictions such as lockup, redemption and notice provisions due to illiquidity of assets in their portfolios. Investors who are aware of this require higher illiquidity premium for offshore hedge funds. Ang and Bollen (2010) find that investors' cost of illiquidity is large in presence of share restrictions. This cost can easily increase if the hedge fund managers are allowed to arbitrarily suspend withdrawals.

Some authors examine the effects of redemption restrictions conditioned on past performance and under different market conditions. Hombert and Thesmar (2009) develop a theoretical model to show that arbitrageurs with stable funding or guaranteed funding measured by redemption restrictions experience higher returns following poor performance. So investors should not redeem their shares for some funds since share restriction will outperform those without after bad performance in the past. On the other hand, Joenväärä et al. (2013) argue that redemption restrictions affect the persistence of return investors can earn from investing in hedge funds. This is because their portfolio performance becomes less persistent when investors need to take into account of the length of notice periods when rebalancing their portfolios. This argument is in line with De Roon et al. (2010) who point out that lockup period restricts the investor's ability to rebalance his portfolio and makes his portfolio become riskier. Finally, Aiken, Clifford and Ellis (2012) who study the effect of discretionary liquidity restrictions when facing substantial redemption requests during financial crisis find that these funds underperform in the following periods. Moreover, investors move cash away from those funds and their family funds. Finally, those funds tend to cut their fees in the later periods after crisis.

Since longer restriction periods provide managers with more flexibility in investment strategies, it can potentially affect the risk-taking choices and survival of funds. Joenväärä and Tolonen (2008) find that hedge fund managers take more risks when the funds have lockup provision since the managers invest in illiquid assets, but the investors are not compensated for that excess risk that arises when investing in illiquid asset. However, longer notice periods do not affect the risk taking of hedge funds but allow managers to be more effective in managing the illiquid assets in their portfolio. This is because they do not have to immediately close out their position in the face of redemption notice. Boyle, Li, and Zhu (2010) find that fund risk is significantly lower when a fund has a stricter redemption policy defined as longer notice and redemption periods. During normal periods, funds with more (or stricter) redemption restrictions exhibit higher return, lower standard deviation, and higher Sharpe ratio. But during crisis, funds with more redemption restrictions exhibit lower return, higher standard deviation, and lower Sharpe ratio. Moreover, investors tend to make withdrawals during market crisis. Therefore the market crisis constrains the ability of the fund managers to hold on to profitable opportunities. Finally, Baba and Goko (2006) find that longer redemption notice and payout periods reduce the liquidation probability and so they contribute to fund stability. Ding et al. (2009) find that live funds impose stricter share restrictions such as longer redemption and lockup periods compared to those of the defunct funds.

Large redemptions from investors affect fund performance and failure probability. Klaus and Rzepowski (2009a) document the three factors that can potentially affect hedge funds' funding risk. They find that financial distress of prime brokers, reliance on only one prime brokers and large investor redemption are associated with a significant decline in fund performance. Klaus and Rzepowski (2009b) find that large redemptions significantly contribute to the failure probability of the hedge funds. Redemptions from investors may force hedge funds to sell part of their assets or reduce leverage to meet the redemption demands and increase large cash position. This creates costs since their portfolios may include illiquid assets that may be difficult to sell. This may cause more withdrawal demands from remaining investors and increase the failure probability of the hedge funds. Therefore, not only do the length of restriction period affects the risks of hedge funds, the magnitude of redemptions can potentially affect the risks of hedge funds as well.

2.4. Hypotheses Development

First, Agarwal, Daniel and Naik (2009) point out that managers with longer restriction periods have freedom to pursue different investment strategies for meeting investor redemption needs. So, they can take advantage of arbitrage opportunities that require longer time to become profitable. They find that funds with longer restriction periods show superior returns. Other studies find that hedge funds are able to invest in illiquid assets when there are redemption restriction provision. Therefore, I expect that if there are no significant redemption requests, hedge funds with longer restriction periods will tend to take higher risk. Second, Klaus and Rzepowski (2009b) mention that redemption requests from investors may force hedge funds to sell part of their assets or reduce leverage to meet the redemption demands and increase cash position. Joenväärä and Tolonen (2008) argue that longer notice period allows managers to effectively manage illiquid assets since they do not have to close out their positions immediately at an unfavourable time. Baba and Goko (2006) find that longer redemption notice and payout periods reduce the liquidation probability and so contribute to fund stability. As a result, since longer restriction periods allow managers to effectively manage their assets to increase fund stability, I would expect a reduction in hedge fund risk over the period following redemption requests as the length of restriction (and redemption notice) period increases. This is because fund managers would be able to take advantage of market conditions to sell both liquid and illiquid assets. However, if hedge fund managers were only able to sell the liquid assets, then the assets remaining in the portfolios would be the riskier ones. This may occur under bad economic conditions for hedge funds that include many illiquid assets in the portfolios (Boyle, Li, and Zhu, 2010). Then it would be possible for the post-request period risk to increase for these funds even with longer restriction periods. Consequently, I would expect a reduction or an increase in hedge fund risk over the period following redemption requests as the length of restriction (and redemption notice) period increases. However, there should be an increase in risk over the post-request period for short restriction periods since the managers have to close out their positions to increase cash holdings at an unfavourable time. Moreover, this rate of increase in risk should be higher than the risk increases for funds with longer restriction periods. Finally, Klaus and Rzepowski (2009b) find that large redemptions significantly contribute to the failure probability of the hedge funds. Klaus and Rzepowski (2009a) argue that since hedge funds invest in illiquid assets, it takes more time to sell these assets when there is a redemption request. Therefore, since large redemptions may cause the funds to take more time to sell their assets and may increase the failure probability, I expect that hedge funds with large redemptions should experience higher risks compared to smaller redemptions.

Overall, the hypotheses are (H1) if there are no significant redemption requests, hedge funds with shorter restriction periods tend to take lower risk; (H2) the opposite is true once significant redemption requests occur; (H3) this second effect is clearer when the total amount of the redemption requests is large. This is shown in Figure 2.1.

[Figure 2.1]

2.5. Approach/Methods

2.5.1. **Data Description**

The Lipper TASS Academic Hedge Fund[7] database is used in this study. The database provides information about the net of fee monthly returns of hedge funds and

[7] 2014, "Lipper Tass Academic Hedge Fund", http://hdl.handle.net.proxy.lib.sfu.ca/11272/10015 V6 [Version]

information regarding redemption restrictions such as lockup, notice, redemption and payout periods for both "Live" and "Graveyard" funds. The Graveyard funds include several categories of funds based on different drop reasons: liquidated, no longer reporting to TASS, unable to contact, closed to new investment, merged into another entity, dormant and unknown. (Baba and Goko, 2006). The sample period spans from January 1994 to December 2013 following the literature that includes graveyard funds in their studies (Baba and Goko, 2006; Liang and Park, 2010). I only include live and graveyard hedge funds that report in U.S. dollars, report net returns and exclude funds that report only quarterly rate of return (ROR), or asset under management (AUM), gross RORs, missing monthly RORs, AUMs, management fees, incentive fees, minimum investment, management style. These criteria are consistent with most of the hedge fund studies in the literature, for example, Joenväärä and Tolonen (2008) and Baba and Goko (2006). I exclude those funds with both no payout and no redemption notice periods and funds with no redemption notice periods. Moreover, I include the funds with payout periods of 0, 30, 60, 90, 120, 150, ..., and 300 days. This is because the restriction period is based on the sum of the length of redemption notice and payout periods, and I would like to study the effect of redemption requests upon risk taking of hedge funds for different lengths of restriction and redemption notice periods. For robustness, I vary the lengths of the full restriction period by including only those funds with any length of payout periods not limited to 0, 30, 60, 90, ..., and 300 days. Another check is to include funds with both payout and redemption notice periods equal to 30, 60, 90, ..., or 300 days. My main results remain similar after varying the length of payout and redemption notice periods.

2.5.2. **Calculation of variables**

Following Boyle, Li, and Zhu (2010), I calculate the flow measure as $Flows_{i,t} = [AUM_{i,t} - AUM_{i,t-1}(1+Return_{i,t})]/AUM_{i,t-1}$ where $AUM_{i,t}$ is the assets under management for fund i in month t and $Return_{i,t}$ is the monthly net return for fund i in month t. If this flow measure is negative, I consider it as capital outflow from the fund. Similar to Klaus and Rzepowski (2009a), I identify the points of redemption requests by going back in the length of full restriction period[8] prior to each outflow point. I then construct a dummy variable, *Redreq*, that equals one if there is an outflow greater than or equal to 5% of the fund's assets. The indicates that investors make a redemption request to withdraw capital that is greater than or equal to 5% of the funds' assets at that time. Klaus and Rzepowski (2009a) classify large redemptions as those greater than 20% and small redemptions as those about 5%. Therefore I include only those redemptions that are greater than or equal to 5% in my study to understand the impact of the redemption requests. Next, to understand the impact of different redemption percentages upon hedge fund risks, I include studies of subgroups of redemption percentages. These are (i) outflows greater than or equal to 10%, (ii) outflows greater than or equal to 20%, (iii) outflows between 5% and 10% (greater than or equal to 5% and less than 10%) and (iv) outflows between 10% and 20% (greater than or equal to 10% and less than 20%). Outflows between 5% and 10% are classified as small redemptions, outflows between 10% and 20% are classified as median redemptions and outflows greater than or equal to 20% are classified as large redemptions.

The restriction period is the sum of the length of payout and redemption notice periods (Klaus and Rzepkowski, 2009a). The full restriction period is the restriction period rounded up to the next full number of months. For example, I set a restriction period of 1.6 to a full restriction period of 2 after truncating the decimal places and adding one to it. This is because a hedge fund with a restriction period of 1.6 months may receive withdrawals about one and a half months prior to the end of the outflow month (Klaus and Rzepkowski, 2009a). Therefore, for the capital outflow that occurs at the end of August, the hedge fund would receive the request by mid-July. If the fund manager immediately closes out any position or sells part of the fund's assets, the first impact would occur at end of July return.

[8] The restriction period is the sum of the length of payout and redemption notice periods (Klaus and Rzepkowski, 2009a). The restriction period rounded up to the next full number of months is referred to as a full restriction period. The concept of a full restriction period will be explained in the next paragraph.

I add one to the truncated restriction period to set the request occurring two months prior to the outflow, for example at the end of June. This is to capture the impact of their strategy upon fund return over the post period in July and August. However, if the restriction period is exactly one, two, three, four or five months, then the full restriction period is equal to the restriction period[9]. Table 2.1 shows the number of requests for each full restriction period. Approximately 94 percent of the funds have full restriction periods four months or less. Therefore, I include all the funds with any longer restriction period in the group of funds with four months restriction periods. Since redemption requests that occur consecutively may affect my results, I exclude those consecutive redemption requests that are greater than or equal to 5% according to the length of full restriction period. In other words, I include only those redemption requests without prior and after outflow requests greater than or equal to 5%. Therefore, for a redemption request of a fund with a full restriction period of four month, if there are other redemption requests occurring in any of the prior three months and of the following three months, I exclude all these requests in my sample. This is done so as to avoid the results being affected by consecutive redemption requests.

[Table 2.1]

In order to measure the risk-taking behavior, I first compute the cumulative monthly returns for individual funds where the cumulative returns correspond to each full restriction period. Then I express the cumulative returns on a monthly basis for each fund. For example, for a fund with a four-month full restriction period, I first calculate the cumulative return over a four-month period. Specifically, $t(req)$ is the month where *Redreq* equals one and $CR_{t(req)-3,t(req)}$ is the cumulative return over the four-month period prior to and including the month of redemption request. $CR_{t(req)+1,t(req)+4}$ is the cumulative return over the post four-month period after the month of request. The cumulative returns over the full restriction period pre and post redemption requests are then calculated for each fund according to their full restriction periods. Next, I express each cumulative return on a monthly basis by taking the power of 1 over the full restriction period. Finally, I compute the cross-sectional

[9] As mentioned for robustness, I separately examine the cases for funds with full restriction period exactly equal to the restriction period. The results remain similar and are available upon request.

standard deviation of returns (or cross-sectional SD), the standard deviation of returns across funds at each point in time according to the full restriction periods of the funds. For example, for all the funds with four-month full restriction periods and with requests occurring in month *t*, I calculate the cross-sectional standard deviation of their monthly returns (based on the cumulative four-month return) over the pre-request period ($t(req)-3, t(req)$) as well as over the post-request period ($t(req)+1, t(req)+4$). I ensure that in any particular month *t* at least five funds are included for calculating the cross-sectional standard deviation. The cross-sectional standard deviations over each of the pre-request and post-request periods are then calculated for other groups of funds with a full restriction period of four months at each point in time when there is a request. This process is repeated for different full restriction periods. The advantage of this cross-sectional standard deviation measure is that it captures the exact timing of the risks common to the funds (Adrian, 2007). However, since the cross-sectional standard deviations over the pre and post periods are calculated in each month *t*, I aggregate all the monthly cross-sectional standard deviations for a given full restriction period by calculating the pooled cross-sectional variances. The aggregation is based on a weighted average of the subgroup variances. For example, for a given full restriction period, there are two groups (i.e., pre and post groups) from *i*=1 to 2, the pooled cross-sectional variance is $\frac{(n_{i1}-1)SD_{i1}^2+(n_{i2}-1)SD_{i2}^2+\cdots+(n_{iK}-1)SD_{iK}^2}{(n_{i1}-1)+(n_{i2}-1)+\cdots+(n_{iK}-1)}$, where n_{iK} is the K^{th} subgroup sample size in the i^{th} group and SD_{iK}^2 is the K^{th} subgroup sample variances in the i^{th} group (Zientek and Yetkiner, 2010). Finally, I also include the aggregation of all the monthly cross-sectional standard deviations over the pre and post periods regardless of the lengths of full restriction periods. The *F*-test is then conducted for checking the equality of the variances between pre-request and post-request periods and between the pre-request periods for short and long full restriction periods. For my result, I report the pooled cross-sectional standard deviation.

For robustness, I calculate the cross-sectional standard deviations based on different return windows for each full restriction period. For example, for a four-month full restriction period, I compute the cross-sectional standard deviation of one month return during the month of redemption request and after the month of request. I also compute the cross-sectional standard deviation of monthly returns based on the cumulative two-month returns over the pre-request period ($t(req)-1,t(req)$) as well as over the post-request period ($t(req)+1,t(req)+2$). Finally, the cross-sectional standard deviations of monthly returns based on the cumulative three-month returns are also calculated for the pre-request period ($t(req)-2,t(req)$) and for the post-request period ($t(req)+1,t(req)+3$).

Since the end of the redemption notice period is a valuation date for hedge funds to calculate the amount to be redeemed to the investors, I also check the cross-sectional standard deviation of monthly returns based on the cumulative returns over each notice period. Recall that the full restriction period is obtained by rounding up the restriction period to the next full number of months. Since I have monthly return data, when calculating the cross-sectional standard deviation, I use one month return for funds with notice period between 1 and 30 days, cumulative two-month returns for funds with notice periods between 31 and 60 days, cumulative three-month returns for funds with notice periods between 61 and 90 days, and etc. Then I express the cumulative returns on a monthly basis for each fund. Table 2.2 shows that 96% of hedge funds have notice periods ranging from 0 days to 90 days, therefore, I include all the funds with longer notice periods in the group of funds with notice periods between 61 and 90 days. For robustness, I include calculations only for funds with payout and redemption notice periods of 30, 60, 90, ..., and 300 days and calculate the cross-sectional standard deviations based on different return windows of one month, two months and three months.

[Table 2.2]

2.6. Results

Table 2.3 shows the pooled cross-sectional standard deviations for redemptions greater than or equal to 5%. Since managers have freedom to pursue different investment strategies when the length of full restriction period increases, I would expect that hedge funds with shorter (longer) restriction periods tend to take lower (higher) risk when there are no requests. Table 2.3, however, shows that the pre pooled cross-sectional standard deviation decreases for hedge funds with longer restriction periods when there are no redemption requests. For example, when the full restriction period is one month, the pre pooled cross-sectional standard deviations are around 5.67%. When the full restriction period is four months, the pre pooled cross-sectional standard deviations are around 1.96%. This is the same for the redemption request sample since the pre pooled cross-sectional SD are 6.19% for the shortest restriction period and 2.38% for the longest restriction period. The differences reported in the last two rows are negative and significant. As a result, the longer the full restriction period, the lower the risks taken by the hedge funds. Moreover, this pattern holds in Tables 2.4 to 2.7 and is shown in Figures 2.2 to 2.6. Although the evidence does not support my first hypothesis that the pre-request period risk of funds increases with longer restriction period, the result is consistent with Boyle, Li and Zhu (2010) who find that fund risk is significantly lower for funds with longer notice and redemption periods.

[Table 2.3 and Figure 2.2]

For the second hypothesis, I expect an increase in risk following redemption requests for hedge funds with a shorter full restriction period. For the redemption request sample in the second row of Table 2.3, the post pooled cross-sectional standard deviation increases significantly when I aggregate all the monthly cross-sectional standard deviations regardless of the lengths of full restriction periods. However, the post pooled cross-sectional standard deviation in the first row does not change when there are no requests. For the full restriction period of one month the post pooled cross-sectional standard deviation increases significantly when there are redemption requests while there are no significant change for funds with no redemption requests. When the full restriction period is four months or higher, there is a significant decrease in risk with a larger magnitude for the redemption request sample in comparison with the no redemption request sample. This is also shown in Figure 2.2. Therefore the results for all restriction periods in the first two rows seem to be driven by the results of the shortest restriction period. Since the risks of funds increase (decrease) following redemption requests for shorter (longer) full restriction periods, this is consistent with the second hypothesis.

Table 2.4 and Figure 2.3 show the results for the redemptions greater than or equal to 10%. For all full restriction periods in the first row, there is a significant increase in risk following redemption requests. However, there is a small reduction in risk at 10% significance level for the no request sample over the same periods. This result may be driven by the result of the shortest restriction period. This is because when there are redemption requests, the post pooled cross-sectional standard deviation increases significantly for one-month full restriction period. For the no redemption request sample, however, the risk is significantly lower over the same period. For a three-month or higher full restriction period, there is no change in risk following redemption requests but a small reduction in risk over the same period for the no request sample. Since the risk increases following redemption requests for shortest full restriction period, there is some evidence in support of the second hypothesis.

[Table 2.4 and Figure 2.3]

Table 2.5 presents the results for redemptions greater than or equal to 20%. Similar to the first two rows of Table 2.4, there is an increase in risk following redemption requests but a reduction in risks over the same period for the no request sample. When the full restriction period is one month, the post pooled cross-sectional standard deviation increases significantly following redemption request. This may be due to the inability of fund managers to reduce the risks of funds when they have to close out their positions immediately at an unfavourable time to increase a large cash holding. When the full restriction period is two months, the post pooled cross-sectional standard deviation reduces significantly following redemption requests. (Figure 2.4). However, when the full restriction period is three months or higher, there is a significantly higher post pooled cross-sectional standard deviation following redemption requests. This may suggest that the hedge funds are only able to sell the liquid assets as they cannot take advantage of the market conditions. So, there are more illiquid assets remaining in the portfolios. Consequently, the hedge fund risk increases over the post period following redemption requests for longer restriction periods. Table 2.8 exhibits the number of requests classified by year and level of redemptions for full restriction period of three months or longer. It shows that for the redemptions greater than or equal to 20%, about one third of the redemption requests (33%) concentrate during market crisis in 2008 and 2009. Therefore these hedge funds experience more requests during market crisis. For the small redemptions between 5% and 10%, the redemption requests tend to occur during normal periods. Only 22% of the requests for small redemptions occur during market crisis in 2001 (technology bubble crisis), 2008 and 2009 (financial market crisis) (Boyle, Li, and Zhu, 2010). Therefore, I do not observe general increase in risk for hedge funds with small redemptions. For the median redemptions between 10% and 20%, the proportion of redemption requests during the market crisis periods is 28%. Therefore, the result for higher risks in the post period for longest full restriction period in Table 2.5 seems to be driven by more redemption requests during market crisis. This causes the hedge funds unable to take advantage of the market conditions to manage the illiquid assets in their portfolios. However, I cannot determine whether this increase in risk is at a slower rate compared to the increase in risk when the full restriction period is one month (or see green bars in Figure 2.7 when R=1 and 3). The unpaired two sample *t*-test show insignificant differences (not reported) between them.

[Tables 2.5 and 2.8]

[Figure 2.4]

For the small redemptions between 5% and 10% in Table 2.6, the post pooled cross-sectional standard deviation increases significantly when there are redemption requests for all full restriction periods in the second row. However, the post standard deviation does not change when there are no redemption requests in the first row. When the full restriction period is one month the post pooled cross-sectional standard deviation increases significantly for the redemption sample with a larger magnitude. However, it reduces when the full restriction period is four months (Figure 2.5). This is consistent with the second hypothesis. For the no redemption requests sample, the post pooled cross-sectional standard deviations are significantly higher with smaller magnitudes compared to the redemption samples for one- and four-month cases. Overall, the results for the small redemptions between 5% and 10% are consistent with the second hypothesis.

[Table 2.6 and Figure 2.5]

For the median redemptions between 10% and 20% in Table 2.7, there is an increase in risk following redemption requests but a reduction in risk over the same period when there are no requests for all full restriction periods. When the full restriction period is one month, there is an insignificant increase in post pooled cross-sectional standard deviation. However, the post period risk reduces significantly when the full restriction period is three months. This is also shown in Figure 2.6. Since the post period risk reduces significantly following redemption requests for the longest restriction period, I find some evidence in support of the second hypothesis for the long restriction period.

[Table 2.7 and Figure 2.6]

Joenväärä and Tolonen (2008) find that the lengths of the notice period and the redemption periods have no effects on risk taking by the hedge funds. Unlike their results, I find that the lengths of the full restriction period affect the risk-taking behaviour of hedge funds both with no redemption requests and with redemption requests. Hedge funds tend to have lower pre-request period risks as the lengths of restriction period increase. This is consistent with Boyle, Li, and Zhu (2010) who find that fund risk is significantly lower when a fund has longer notice and redemption periods. One possible reason is that funds with longer restriction periods smooth their reported returns. Another possible reason is that longer notice periods allow managers to be more effective in managing the illiquid assets in their portfolios (Joenväärä and Tolonen, 2008). So the risks are smaller for funds with longer restriction periods. When there are redemption requests, the post-request period risk tends to reduce by hedge funds with longer full restriction periods especially for small and median redemptions. This reflects that the hedge fund managers are able to manage their positions more effectively with longer restriction periods in the face of redemption requests. However, for large redemptions, post-request period risks tend to be higher for hedge funds with longer restriction periods. This may be due to more redemption requests during economic downturn. So there are more illiquid assets remaining in the hedge funds portfolios as managers are unable to take advantage of the market conditions to sell the illiquid assets in their portfolios.

The last hypothesis examines whether there is any difference between large and small redemptions upon hedge fund risks for a given full restriction period. There should be a larger increase in risk for larger redemptions given shorter restriction periods and smaller reduction or increase in risk for larger redemptions given longer restriction periods. Figure 2.7 shows the differences between the pre and post pooled cross-sectional standard deviations (post SD minus pre SD) for small redemptions between 5% and 10%, median redemptions between 10% and 20%, and large redemptions greater than or equal to 20% (the results from Tables 2.5, 2.6 and 2.7). When the full restriction period is one month, there is a tendency for funds with small and large redemptions to increase the post pooled cross-sectional standard deviations significantly, and the increases are higher the larger the redemptions. This is consistent with the third hypothesis for shorter restriction period since the managers have to close out their positions immediately at an unfavourable time, causing the risks to increase as the redemption percentages increase. For a two-month full restriction period, the post pooled cross-sectional standard deviations tend to reduce significantly for both funds with small and large redemptions. However, the reduction in post pooled cross-sectional standard deviation is larger for large redemptions. When the full restriction period is three months or longer, there is a significant reduction (increase) in post period risk taking for funds with median (large) redemptions, supporting the third hypothesis. For large redemptions, funds with longer restriction periods experience a small increases in risks. It is possible if hedge fund managers are only able to sell the liquid assets. So, illiquid assets continue to remain in their portfolios. However, there is no significant change in post period risk for funds with small redemptions; this does not support the third hypothesis with longer restriction periods. Overall, the third hypothesis is partially supported as hedge funds with large redemptions tend to experience higher risks compared to smaller redemptions.

[Figures 2.7 and 2.8]

Boyle, Li, and Zhu (2010) find that investment in longer term and illiquid asset provides larger fund risk during market crisis because the risks of the illiquid investments in their portfolios increase substantially during market crisis. Therefore funds with more redemption restrictions exhibit higher risks. Homert and Thesmar (2009) show that investors are more likely to withdraw their investments when the fund underperforms. Therefore, it may be possible that during crisis when funds underperform, there are large redemptions due to the combined redemption requests from investors. Table 2.8 shows that one third of the withdrawal requests for large redemptions concentrate during market crisis. Therefore for the funds with redemptions greater than or equal to 20%, it is possible that investors requesting withdrawals during market downturn explain for the higher post pooled cross-sectional standard deviations. When there are no redemption requests (Figure 2.8), the differences between the pooled cross-sectional standard deviations are approximately the same for different percentages of redemptions and different lengths of full restriction periods. Most of the differences are around zero. This shows that changes in pooled cross-sectional standard deviations tend to be larger when there are redemption requests.

[Table 2.8]

For the robustness test, I calculate the cross-sectional standard deviations corresponding to each redemption notice period instead of each full restriction period shown in Tables 2.9 and 2.10. The key results remain similar to those with full restriction periods except for the result of small redemptions between 5% and 10%. For example, in Tables 2.9 and 2.10, the pre-request pooled cross-sectional standard deviations decrease significantly as the lengths of restriction periods increase for both no redemption and redemption samples. This does not support the first hypothesis. In Table 2.9a and Figure 2.9 when there are redemption requests, the post pooled cross-sectional standard deviation increases significantly for a short notice period, but decreases significantly for a longer redemption notice period. This is consistent with the second hypothesis. In Table 2.9b and Figure 2.10 when there are redemption requests, the post pooled cross-sectional standard deviation increases (decreases) significantly for a shorter (longer) redemption notice period with greater magnitudes than for no request samples. This is consistent with the second hypothesis. In Table 2.9c and Figure 2.11 when there are redemption requests, the post pooled cross-sectional standard deviations increase significantly at 10% level for a short notice period but increase insignificantly for a longer notice period. This in part supports the second hypothesis.

When the redemptions are small between 5% and 10% in Table 2.10a and Figure 2.12, there is a significant reduction (at 10% level) in post pooled cross-sectional standard deviation for a shorter redemption notice period. Moreover, there are insignificant changes in post pooled cross-sectional standard deviations for longer redemption notice periods. This does not support the second hypothesis and shows that the hedge fund managers tend to avoid closing out their positions immediately following redemption requests prior to the end of the valuation dates. In Table 2.10b and Figure 2.13, there is a significant lower post pooled cross-sectional standard deviation for a longer redemption notice period when there are redemption requests. However, there is no significant change in risk when the notice period is shorter. This may be due to the reason that hedge fund managers avoid closing out their positions immediately following redemption requests prior to the end of the valuation dates. This is also confirmed by the second row in Table 2.10 (All notice periods) as there is no change in risks prior to the end of the valuation date for the redemption request sample. For the no request sample, most of them exhibit significant lower risks over the post periods.

[Tables 2.9 to 2.10]

[Figures 2.9 to 2.13]

Figures 2.14 shows a significant increase in post pooled cross-sectional standard deviation for large redemptions given a short redemption notice period less than or equal to 30 days similar to Figure 2.7. However there is a reduction in risk (at 10% significance) for small redemptions. Given a redemption notice period greater than 30 days, there is a significant reduction in risk for median redemptions only. Overall, half of the results are insignificant, suggesting that hedge funds tend not to change risks during the periods prior to the end of the valuation date when there are redemption requests. This implies that the hedge fund managers do not rush to close out the positions immediately following redemption requests prior to the end of the valuation dates. For the no redemption cases (Figure 2.15), nearly all of them exhibit significant lower risks but around zero over the post period. In general, the main results are consistent with those based on full restriction periods[10].

[Figures 2.14 and 2.15]

[10] For robustness check with cross-sectional standard deviation based on different return windows and with varying lengths of payout and redemption notice periods, I find that the main results in general do not change. The results are available upon request.

2.7. Conclusion

In this study, I examine hedge fund risk taking choices with and without redemption requests. Specifically, I study whether hedge funds change their risk-taking choices following redemption requests for different lengths of restriction and redemption notice periods and amount of redemptions as a percentage of fund's assets. First, hedge funds with longer restriction periods tend to take lower risk when there are no significant redemption requests. This may be due to smoothed return or more efficient management of illiquid asset by hedge funds with longer restriction periods. Second, hedge funds with short restriction and redemption notice periods tend to increase risks following redemption requests. The increase in risk is larger for large redemptions than for small redemptions. This may be due to the inability of fund managers to reduce the risks of funds when they have to close out their positions immediately at an unfavourable time to increase cash holding. For hedge funds with longer restriction periods, the managers do not have to immediately close out positions but take advantage of the market conditions to increase cash holding. Therefore hedge funds tend to exhibit lower risk taking following redemption requests. However, if there are large redemptions during market crisis, hedge funds tend to exhibit higher post risk taking even when the restriction periods are longer. Finally, for longer redemption notice periods, there is no change in risks following redemption requests for small and large redemptions. This implies that the hedge fund managers do not rush to close out the positions immediately following redemption requests prior to the end of the valuation dates.

2.8. References

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2.9. Tables and Figures

Table 2.1. Number of funds classified by restriction period

The sample period is from January 1994 to December 2013. Restriction period is the sum of the length of payout and redemption notice periods in months. Full restriction period is defined as the restriction period rounded up to the next full number of months. For the restriction period with no decimal places, the full restriction period is set equal to the restriction period. NF is the number of funds for each full restriction period.

Full restriction period (month)	NF	Full restriction period (month)	NF
1	483	6	33
2	662	7	6
3	566	8	2
4	252	9	5
5	69	11	2

Table 2.2. Number of funds classified by redemption notice period

The sample period is from January 1994 to December 2013. NF is the number of funds for each redemption notice period.

Redemption notice period (days)	NF	Redemption notice period (days)	NF
1	13	60	330
2	8	61	2
3	15	65	44
5	54	66	1
7	18	70	6
8	5	75	17
10	86	80	1
14	19	85	1
15	59	90	264
16	5	91	1
20	35	92	1
21	1	93	3
25	3	95	42
30	667	100	6
35	21	105	3
37	5	110	1
40	7	120	6
45	315	125	1
46	5	180	16
50	3	300	1

Table 2.3. Redemptions greater than or equal to 5%

The sample period is from January 1994 to December 2013. Full restriction period is defined as the sum of the notice and payout periods, rounded up to the next full number of months. *Redreq* is Redemption Request. It is "Yes" or "1" if there are requests for redemptions greater than or equal to 5% of the fund's assets. It is "No" or "0" if there are no requests for redemptions greater than or equal to 5% of the fund's assets during the corresponding month for the "Yes" group. "Pre" is the full restriction period prior to *Redreq*. "Post" is the full restriction period following *Redreq*. Pooled Cross-sectional SD is the square root of the pooled cross-sectional variance estimated as the weighted average of the subgroup variances for each of the pre and post periods. Difference is post pooled cross-sectional SD minus the pre pooled cross-sectional SD or the difference between pre pooled cross-sectional SD of the longest restriction period and of shortest restriction period. *K* is the number of months at least five funds had *Redreq* = Yes. *F*-statistic is the ratio between pre and post pooled cross-sectional variances from the *F* test of equality of variances.

Full Restriction Period (Month)	*Redreq*	Pre: Pooled Cross-Sectional SD	Post: Pooled Cross-Sectional SD	*K*	Difference	*F*-statistic	*p*-value
All	No (0)	4.16%	4.14%	228	-0.01%	1.007	0.147
	Yes (1)	4.38%	4.76%	228	0.38%	1.182***	0.000***
1	No (0)	5.67%	5.68%	206	0.01%	1.004	0.357
	Yes (1)	6.19%	7.10%	206	0.91%	1.314***	0.000***
2	No (0)	3.61%	3.67%	176	0.06%	1.031**	0.005**
	Yes (1)	4.09%	3.95%	176	-0.15%	1.076*	0.031*
3	No (0)	2.38%	2.30%	133	-0.07%	1.064***	0.000***
	Yes (1)	2.12%	2.29%	133	0.17%	1.167***	0.001***
≥ 4	No (0)	1.96%	1.83%	56	-0.13%	1.143***	0.000***
	Yes (1)	2.38%	2.01%	56	-0.37%	1.402***	0.001***
shortest vs. longest	No (0)	Pre: 5.67% vs. 1.96%			-3.71%	8.401***	0.000***
	Yes (1)	Pre: 6.19% vs. 2.38%			-3.81%	6.745***	0.000***

* indicates significance at 10% level;
** indicates significance at 5% level;
*** indicates significance at 1% level.

Table 2.4. Redemptions greater than or equal to 10%

The sample period is from January 1994 to December 2013. Full restriction period is defined as the sum of the notice and payout periods, rounded up to the next full number of months. *Redreq* is Redemption Request. It is "Yes" or "1" if there are requests for redemptions greater than or equal to 10% of the fund's assets. It is "No" or "0" if there are no requests for redemptions greater than or equal to 10% of the fund's assets during the corresponding month for the "Yes" group. "Pre" is the full restriction period prior to *Redreq*. "Post" is the full restriction period following *Redreq*. Pooled Cross-sectional SD is the square root of the pooled cross-sectional variance estimated as the weighted average of the subgroup variances for each of the pre and post periods. Difference is post pooled cross-sectional SD minus the pre pooled cross-sectional SD or the difference between pre pooled cross-sectional SD of the longest restriction period and of shortest restriction period. *K* is the number of months at least five funds had *Redreq* = Yes. *F*-statistic is the ratio between pre and post pooled cross-sectional variances from the *F* test of equality of variances.

Full Restriction Period (Month)	*Redreq*	Pre: Pooled Cross-Sectional SD	Post: Pooled Cross-Sectional SD	*K*	Difference	*F*-statistic	*p*-value
All	No (0)	4.15%	4.12%	208	-0.02%	1.012*	0.031*
	Yes (1)	4.48%	5.07%	208	0.59%	1.282***	0.000***
1	No (0)	6.11%	5.92%	117	-0.19%	1.065***	0.000***
	Yes (1)	6.63%	7.60%	117	0.98%	1.316***	0.000***
2	No (0)	3.59%	3.60%	125	0.01%	1.006	0.336
	Yes (1)	4.11%	3.58%	125	-0.53%	1.318***	0.000***
≥ 3	No (0)	2.21%	2.18%	112	-0.03%	1.028**	0.015**
	Yes (1)	2.29%	2.33%	112	0.04%	1.037	0.268
shortest vs. longest	No (0)	Pre: 6.11% vs. 2.21%			-3.90%	7.663***	0.000***
	Yes (1)	Pre: 6.63% vs. 2.29%			-4.34%	8.390***	0.000***

* indicates significance at 10% level;
** indicates significance at 5% level;
*** indicates significance at 1% level.

Table 2.5. Redemptions greater than or equal to 20%

The sample period is from January 1994 to December 2013. Full restriction period is defined as the sum of the notice and payout periods, rounded up to the next full number of months. *Redreq* is Redemption Request. It is "Yes" or "1" if there are requests for redemptions greater than or equal to 20% of the fund's assets. It is "No" or "0" if there are no requests for redemptions greater than or equal to 20% of the fund's assets during the corresponding month for the "Yes" group. "Pre" is the full restriction period prior to *Redreq*. "Post" is the full restriction period following *Redreq*. Pooled Cross-sectional SD is the square root of the pooled cross-sectional variance estimated as the weighted average of the subgroup variances for each of the pre and post periods. Difference is post pooled cross-sectional SD minus the pre pooled cross-sectional SD or the difference between pre pooled cross-sectional SD of the longest restriction period and of shortest restriction period. *K* is the number of months at least five funds had *Redreq* = Yes. *F*-statistic is the ratio between pre and post pooled cross-sectional variances from the *F* test of equality of variances.

Full Restriction Period (Month)	*Redreq*	Pre: Pooled Cross-Sectional SD	Post: Pooled Cross-Sectional SD	*K*	Difference	*F*-statistic	*p*-value
All	No (0)	4.05%	3.87%	167	-0.18%	1.094***	0.000***
	Yes (1)	4.60%	5.39%	167	0.79%	1.373***	0.000***
1	No (0)	7.16%	6.10%	34	-1.06%	1.376***	0.000***
	Yes (1)	7.31%	9.44%	34	2.13%	1.668***	0.000***
2	No (0)	3.65%	3.83%	58	0.18%	1.100***	0.000***
	Yes (1)	4.54%	3.42%	58	-1.11%	1.754***	0.000***
≥ 3	No (0)	2.16%	2.10%	50	-0.06%	1.059***	0.001***
	Yes (1)	2.10%	2.63%	50	0.53%	1.568***	0.000***
shortest vs. longest	No (0)	Pre: 7.16% vs. 2.16%			-4.99%	10.931***	0.000***
	Yes (1)	Pre: 7.31% vs. 2.10%			-5.21%	12.104***	0.000***

* indicates significance at 10% level;
** indicates significance at 5% level;
*** indicates significance at 1% level.

Table 2.6. Redemptions between 5% and 10%

The sample period is from January 1994 to December 2013. Full restriction period is defined as the sum of the notice and payout periods, rounded up to the next full number of months. *Redreq* is Redemption Request. It is "Yes" or "1" if there are requests for redemptions greater than or equal to 5% and less than 10% of the fund's assets. It is "No" or "0" if there are no requests for redemptions greater than or equal to 5% and less than 10% of the fund's assets during the corresponding month for the "Yes" group. "Pre" is the full restriction period prior to *Redreq*. "Post" is the full restriction period following *Redreq*. Pooled Cross-sectional SD is the square root of the pooled cross-sectional variance estimated as the weighted average of the subgroup variances for each of the pre and post periods. Difference is post pooled cross-sectional SD minus the pre pooled cross-sectional SD or the difference between pre pooled cross-sectional SD of the longest restriction period and of shortest restriction period. *K* is the number of months at least five funds had *Redreq* = Yes. *F*-statistic is the ratio between pre and post pooled cross-sectional variances from the *F* test of equality of variances.

Full Restriction Period (Month)	*Redreq*	Pre: Pooled Cross-Sectional SD	Post: Pooled Cross-Sectional SD	*K*	Difference	*F*-statistic	*p*-value
All	No (0)	4.16%	4.14%	213	-0.02%	1.009	0.090
	Yes (1)	4.22%	4.37%	213	0.15%	1.071**	0.020**
1	No (0)	5.82%	6.01%	107	0.19%	1.066***	0.000***
	Yes (1)	6.15%	6.85%	107	0.70%	1.239***	0.002***
2	No (0)	3.51%	3.62%	132	0.11%	1.066***	0.000***
	Yes (1)	3.82%	3.42%	132	-0.40%	1.249***	0.000***
3	No (0)	2.25%	2.19%	82	-0.06%	1.059***	0.001***
	Yes (1)	1.88%	1.98%	82	0.10%	1.105	0.101
≥ 4	No (0)	1.96%	2.10%	16	0.13%	1.141**	0.006**
	Yes (1)	2.54%	1.96%	16	-0.58%	1.681**	0.012**
shortest vs. longest	No (0)	Pre: 5.82% vs. 1.96%			-3.86%	8.791***	0.000***
	Yes (1)	Pre: 6.15% vs. 2.54%			-3.61%	5.872***	0.000***

* indicates significance at 10% level;
** indicates significance at 5% level;
*** indicates significance at 1% level.

Table 2.7. Redemptions between 10% and 20%

The sample period is from January 1994 to December 2013. Full restriction period is defined as the sum of the notice and payout periods, rounded up to the next full number of months. *Redreq* is Redemption Request. It is "Yes" or "1" if there are requests for redemptions greater than or equal to 10% and less than 20% of the fund's assets. It is "No" or "0" if there are no requests for redemptions greater than or equal to 10% and less than 20% of the fund's assets during the corresponding month for the "Yes" group. "Pre" is the full restriction period prior to *Redreq*. "Post" is the full restriction period following *Redreq*. Pooled Cross-sectional SD is the square root of the pooled cross-sectional variance estimated as the weighted average of the subgroup variances for each of the pre and post periods. Difference is post pooled cross-sectional SD minus the pre pooled cross-sectional SD or the difference between pre pooled cross-sectional SD of the longest restriction period and of shortest restriction period. *K* is the number of months at least five funds had *Redreq* = Yes. *F*-statistic is the ratio between pre and post pooled cross-sectional variances from the *F* test of equality of variances.

Full Restriction Period (Month)	*Redreq*	Pre: Pooled Cross-Sectional SD	Post: Pooled Cross-Sectional SD	*K*	Difference	*F*-statistic	*p*-value
All	No (0)	4.12%	4.09%	188	-0.03%	1.017**	0.006**
	Yes (1)	4.35%	4.56%	188	0.21%	1.099**	0.017**
1	No (0)	6.37%	6.35%	50	-0.02%	1.006	0.395
	Yes (1)	7.10%	7.73%	50	0.62%	1.183	0.084
2	No (0)	3.72%	3.63%	76	-0.09%	1.050***	0.003***
	Yes (1)	3.81%	3.73%	76	-0.08%	1.043	0.319
≥ 3	No (0)	2.17%	2.21%	66	0.04%	1.039**	0.011**
	Yes (1)	2.40%	2.16%	66	-0.24%	1.238**	0.009**
shortest vs. longest	No (0)	Pre: 6.37% vs. 2.17%			-4.20%	8.618***	0.000***
	Yes (1)	Pre: 7.10% vs. 2.40%			-4.70%	8.765***	0.000***

* indicates significance at 10% level;
** indicates significance at 5% level;
*** indicates significance at 1% level.

Table 2.8. Number of requests classified by year and level of redemptions for three months or longer restriction period

The sample period is from January 1994 to December 2013. Restriction period is the sum of the length of payout and redemption notice periods in months. Full restriction period is defined as the restriction period rounded up to the next full number of months. For the restriction period with no decimal places, the full restriction period is set equal to the restriction period. The numbers in the table are the number of redemption requests.

Full Restriction Period	≥ 3	≥ 3	≥ 3
Year	**Redemption requests between 5% and 10%**	**Redemption requests between 10% and 20%**	**Redemption requests greater than or equal to 20%**
1994	0	0	0
1995	0	0	0
1996	0	0	0
1997	0	0	0
1998	0	6	0
1999	20	0	0
2000	20	0	0
2001	12	0	0
2002	41	6	5
2003	33	21	5
2004	69	22	19
2005	100	71	71
2006	129	60	47
2007	109	59	28
2008	111	88	85
2009	124	70	40
2010	109	31	25
2011	114	59	35
2012	84	52	17
2013	69	13	5
Total	1,144	558	382

Table 2.9. Redemptions greater than or equal to 5%, 10% and 20% classified by redemption notice period

The sample period is from January 1994 to December 2013. NP is the redemption notice periods in days. *Redreq* is Redemption Request. It is "Yes" or "1" if there are requests for redemptions greater than or equal to 5%, 10%, or 20% of the fund's assets. It is "No" or "0" if there are no requests for redemptions greater than or equal to 5%, 10%, or 20% of the fund's assets during the corresponding month for the "Yes" group. "Pre" is the redemption notice period prior to *Redreq*. "Post" is the redemption notice period following *Redreq*. Pooled Cross-sectional SD is the square root of the pooled cross-sectional variance estimated as the weighted average of the subgroup variances for each of the pre and post periods. Difference is post pooled cross-sectional SD minus the pre pooled cross-sectional SD or the difference between pre pooled cross-sectional SD of the longest restriction period and of shortest restriction period. *K* is the number of months at least five funds had *Redreq* = Yes. *F*-statistic is the ratio between pre and post pooled cross-sectional variances from the *F* test of equality of variances.

Table 2.9a. Redemptions greater than or equal to 5%

Redemption Notice Period (days)	*Redreq*	Pre: Pooled Cross-Sectional SD	Post: Pooled Cross-Sectional SD	*K*	Difference	*F*-statistic	*p*-value
All	No (0)	4.52%	4.49%	228	-0.03%	1.013**	0.023**
	Yes (1)	4.99%	5.36%	228	0.37%	1.156***	0.000***
0 < NP ≤ 30	No (0)	5.45%	5.41%	224	-0.04%	1.015*	0.040*
	Yes (1)	6.00%	6.53%	224	0.53%	1.184***	0.000***
30 < NP ≤ 60	No (0)	3.19%	3.22%	169	0.02%	1.015	0.118
	Yes (1)	3.37%	3.32%	169	-0.04%	1.027	0.268
NP > 60	No (0)	2.10%	2.05%	101	-0.05%	1.047**	0.012**
	Yes (1)	2.05%	1.88%	101	-0.17%	1.193**	0.008**
shortest vs. longest	No (0)	Pre: 5.45% vs. 2.10%			-3.35%	6.738***	0.000***
	Yes (1)	Pre: 6.00% vs. 2.05%			-3.94%	8.518***	0.000***

Table 2.9b. Redemptions greater than or equal to 10%

Redemption Notice Period (days)	*Redreq*	Pre: Pooled Cross-Sectional SD	Post: Pooled Cross-Sectional SD	*K*	Difference	*F*-statistic	*p*-value
All	No (0)	4.51%	4.48%	208	-0.04%	1.017***	0.005***
	Yes (1)	5.16%	5.89%	208	0.73%	1.304***	0.000***
0 < NP ≤ 30	No (0)	5.41%	5.36%	191	-0.06%	1.021**	0.010**
	Yes (1)	6.26%	7.21%	191	0.95%	1.328***	0.000***
NP > 30	No (0)	2.73%	2.68%	141	-0.04%	1.033***	0.001***
	Yes (1)	3.12%	2.87%	141	-0.25%	1.183***	0.001***
shortest vs. longest	No (0)	Pre: 5.41% vs. 2.73%			-2.68%	3.935	0.000***
	Yes (1)	Pre: 6.26% vs. 3.12%			-3.13%	4.011	0.000***

* indicates significance at 10% level; ** indicates significance at 5% level;
*** indicates significance at 1% level.

Table 2.9. Continued.

Redemptions greater than or equal to 5%, 10% and 20% classified by redemption notice period

The sample period is from January 1994 to December 2013. NP is the redemption notice periods in days. *Redreq* is Redemption Request. It is "Yes" or "1" if there are requests for redemptions greater than or equal to 5%, 10%, or 20% of the fund's assets. It is "No" or "0" if there are no requests for redemptions greater than or equal to 5%, 10%, or 20% of the fund's assets during the corresponding month for the "Yes" group. "Pre" is the redemption notice period prior to *Redreq*. "Post" is the redemption notice period following *Redreq*. Pooled Cross-sectional SD is the square root of the pooled cross-sectional variance estimated as the weighted average of the subgroup variances for each of the pre and post periods. Difference is post pooled cross-sectional SD minus the pre pooled cross-sectional SD or the difference between pre pooled cross-sectional SD of the longest restriction period and of shortest restriction period. *K* is the number of months at least five funds had *Redreq* = Yes. *F*-statistic is the ratio between pre and post pooled cross-sectional variances from the *F* test of equality of variances.

Table 2.9c. Redemptions greater than or equal to 20%

Redemption Notice Period (days)	*Redreq*	Pre: Pooled Cross-Sectional SD	Post: Pooled Cross-Sectional SD	*K*	Difference	*F*-statistic	*p*-value
All	No (0)	4.43%	4.27%	167	-0.16%	1.078***	0.000***
	Yes (1)	5.17%	6.59%	167	1.41%	1.622***	0.000***
$0 < NP \leq 30$	No (0)	5.39%	5.20%	103	-0.19%	1.076***	0.000***
	Yes (1)	6.14%	6.61%	103	0.48%	1.162*	0.025*
$NP > 30$	No (0)	2.72%	2.68%	72	-0.04%	1.030**	0.022**
	Yes (1)	3.29%	3.39%	72	0.10%	1.061	0.262
shortest vs. longest	No (0)	Pre: 5.39% vs. 2.72%			-2.67%	3.933***	0.000***
	Yes (1)	Pre: 6.14% vs. 3.29%			-2.85%	3.483***	0.000***

* indicates significance at 10% level;
** indicates significance at 5% level;
*** indicates significance at 1% level.

Table 2.10. Redemptions between 5% and 10% and between 10% and 20% classified by redemption notice period

The sample period is from January 1994 to December 2013. NP is the redemption notice periods in days. *Redreq* is Redemption Request. It is "Yes" or "1" if there are requests for redemptions greater than or equal to 5% (or 10%) and less than 10% (or 20%) of the fund's assets. It is "No" or "0" if there are no requests for redemptions greater than or equal to 5% (or 10%) and less than 10% (or 20%) of the fund's assets during the corresponding month for the "Yes" group."Pre" is the redemption notice period prior to *Redreq*. "Post" is the redemption notice period following *Redreq*. Pooled Cross-sectional SD is the square root of the pooled cross-sectional variance estimated as the weighted average of the subgroup variances for each of the pre and post periods. Difference is post pooled cross-sectional SD minus the pre pooled cross-sectional SD or the difference between pre pooled cross-sectional SD of the longest restriction period and of shortest restriction period. *K* is the number of months at least five funds had *Redreq* = Yes. *F*-statistic is the ratio between pre and post pooled cross-sectional variances from the *F* test of equality of variances.

Table 2.10a. Redemptions between 5% and 10%

Redemption Notice Period (days)	*Redreq*	Pre: Pooled Cross-Sectional SD	Post: Pooled Cross-Sectional SD	*K*	Difference	*F*-statistic	*p*-value
All	No (0)	4.52%	4.49%	213	-0.03%	1.014**	0.015**
	Yes (1)	4.77%	4.69%	213	-0.08%	1.036	0.146
0 < NP ≤ 30	No (0)	5.41%	5.46%	195	0.06%	1.021**	0.011**
	Yes (1)	5.83%	5.61%	195	-0.22%	1.081*	0.044*
30 < NP ≤ 60	No (0)	3.00%	3.11%	108	0.11%	1.073***	0.000***
	Yes (1)	3.21%	3.29%	108	0.08%	1.051	0.247
NP > 60	No (0)	2.02%	2.10%	42	0.09%	1.090***	0.003***
	Yes (1)	1.78%	1.87%	42	0.09%	1.109	0.227
shortest vs. longest	No (0)	Pre: 5.41% vs. 2.02%			-3.39%	7.187***	0.000***
	Yes (1)	Pre: 5.83% vs. 1.78%			-4.05%	10.749***	0.000***

Table 2.10b. Redemptions greater than or equal to 10%

Redemption Notice Period (days)	*Redreq*	Pre: Pooled Cross-Sectional SD	Post: Pooled Cross-Sectional SD	*K*	Difference	*F*-statistic	*p*-value
All	No (0)	4.50%	4.46%	189	-0.05%	1.021***	0.001***
	Yes (1)	5.09%	5.08%	189	-0.01%	1.005	0.452
0 < NP ≤ 30	No (0)	5.43%	5.28%	131	-0.15%	1.057***	0.000***
	Yes (1)	5.83%	5.98%	131	0.14%	1.050	0.231
NP > 30	No (0)	2.58%	2.55%	90	-0.03%	1.025*	0.029*
	Yes (1)	2.74%	2.48%	90	-0.26%	1.219**	0.006**
shortest vs. longest	No (0)	Pre: 5.43% vs. 2.58%			-2.84%	4.411***	0.000***
	Yes (1)	Pre: 5.83% vs. 2.74%			-3.09%	4.535***	0.000***

* indicates significance at 10% level; ** indicates significance at 5% level;
*** indicates significance at 1% level.

Figure 2.1. Illustration of Hypotheses

The binomial tree illustrates the hypotheses in this study. The upper node represents the hypotheses for funds with short restriction period. The hypotheses are (H1) if there are no significant redemption requests, hedge funds with shorter restriction periods tend to take lower risk; (H2) the opposite is true once significant redemption requests occur; (H3) this second effect is clearer when the total amount of the redemption requests is large.

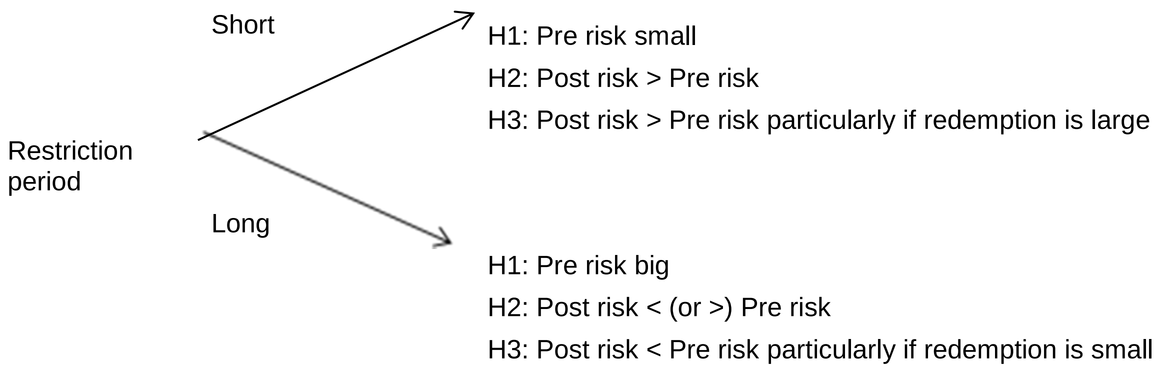


Figure 2.2. Pooled Pre and Post Cross-Sectional Standard Deviations for Redemptions Greater Than or Equal to 5% (R = Full Restriction Period)

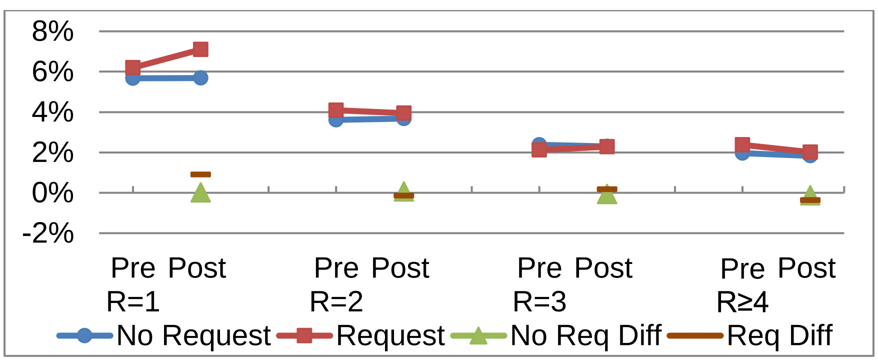


Figure 2.3. Pooled Pre and Post Cross-Sectional Standard Deviations for Redemptions Greater Than or Equal to 10% (R = Full Restriction Period)

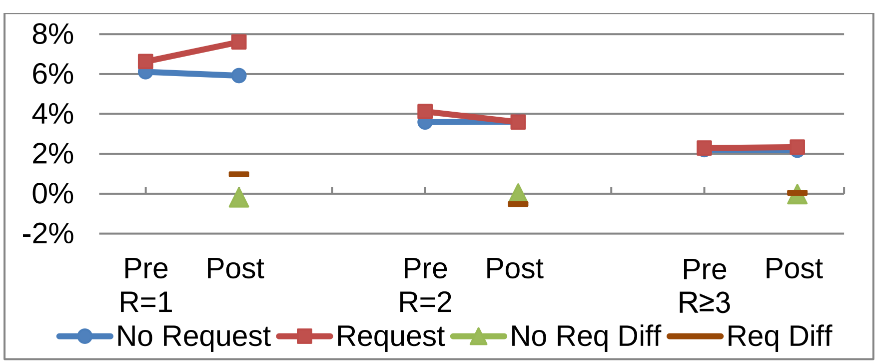


Figure 2.4. **Pooled Pre and Post Cross-Sectional Standard Deviations for Redemptions Greater Than or Equal to 20% (R = Full Restriction Period)**

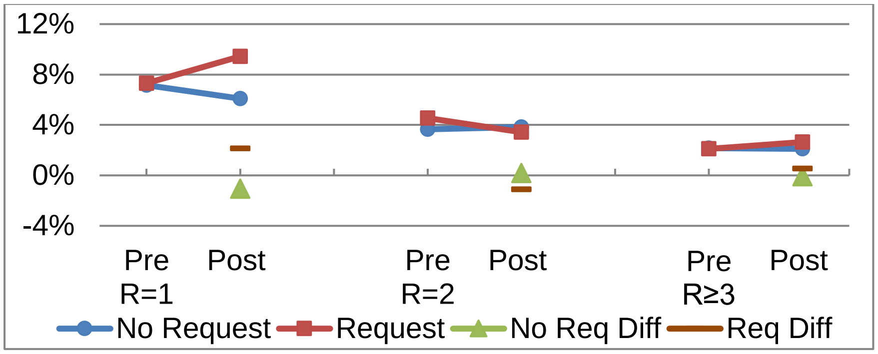


Figure 2.5. **Pooled Pre and Post Cross-Sectional Standard Deviations for Redemptions Between 5% and 10% (R = Full Restriction Period)**

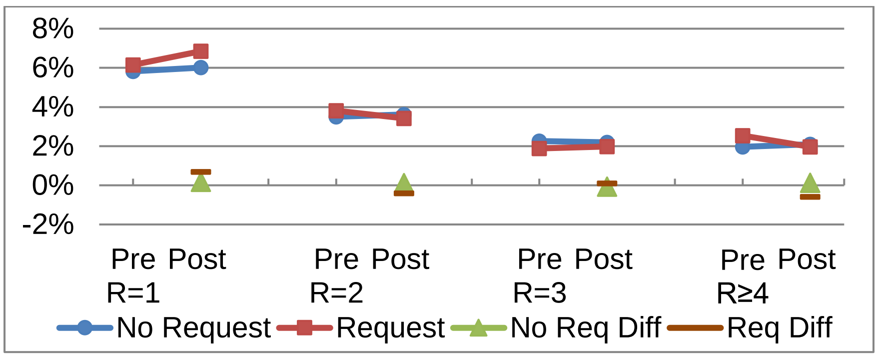


Figure 2.6. **Pooled Pre and Post Cross-Sectional Standard Deviations for Redemptions Between 10% and 20% (R = Full Restriction Period)**

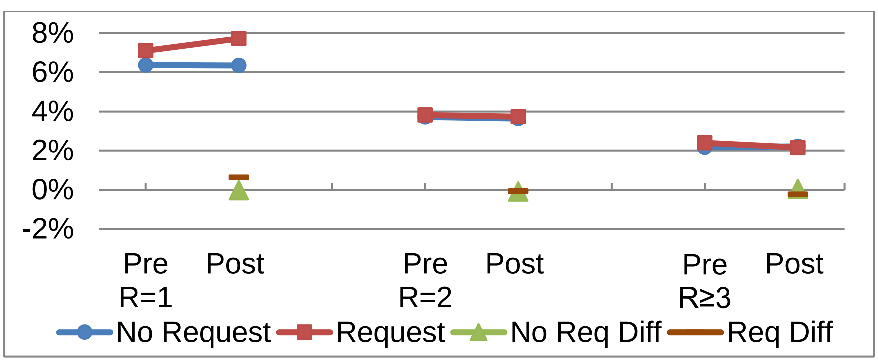


Figure 2.7. **Difference Between Pooled Pre and Post Cross-Sectional Standard Deviations When *Redreq* = Yes for Different Levels of Redemptions (R = Full Restriction Period)**

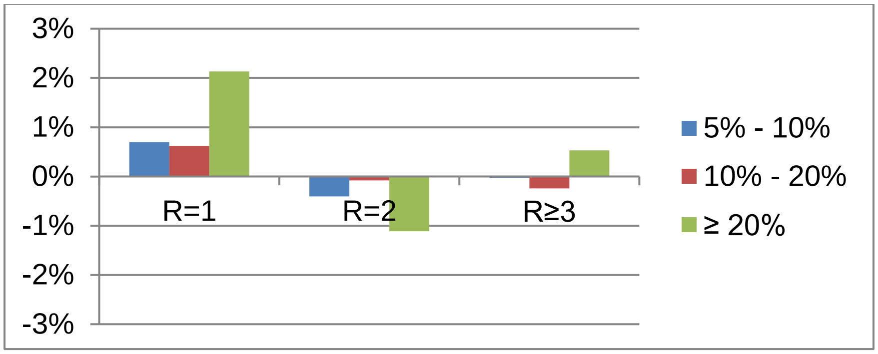


Figure 2.8. **Difference Between Pooled Pre and Post Cross-Sectional Standard Deviations When *Redreq* = No for Different Levels of Redemptions (R = Full Restriction Period)**

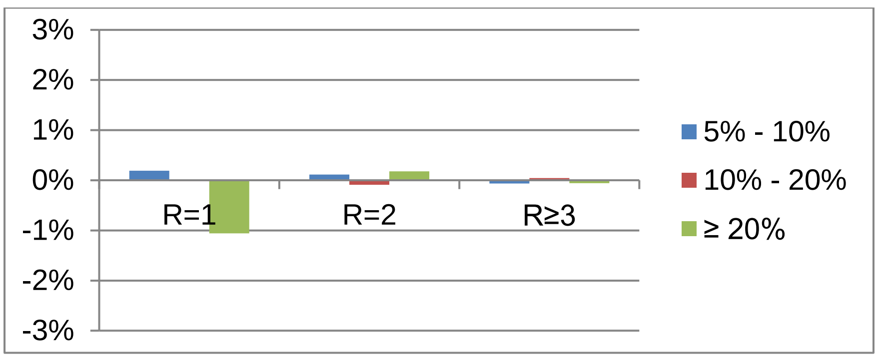


Figure 2.9. **Pooled Pre and Post Cross-Sectional Standard Deviations for Redemptions Greater Than or Equal to 5% (NP = Redemption Notice Period)**

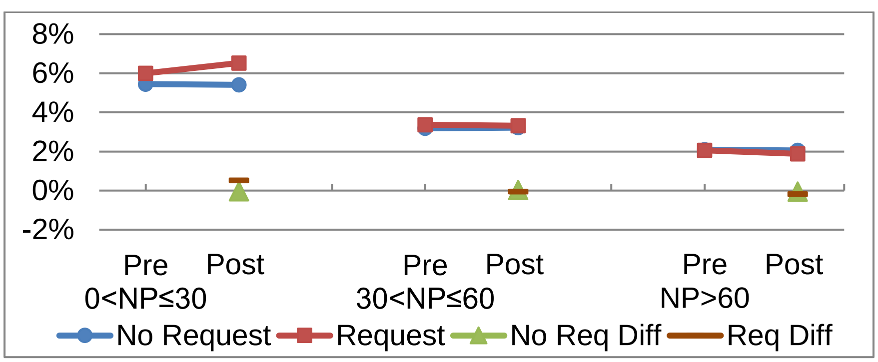


Figure 2.10. Pooled Pre and Post Cross-Sectional Standard Deviations for Redemptions Greater Than or Equal to 10% (NP = Redemption Notice Period)

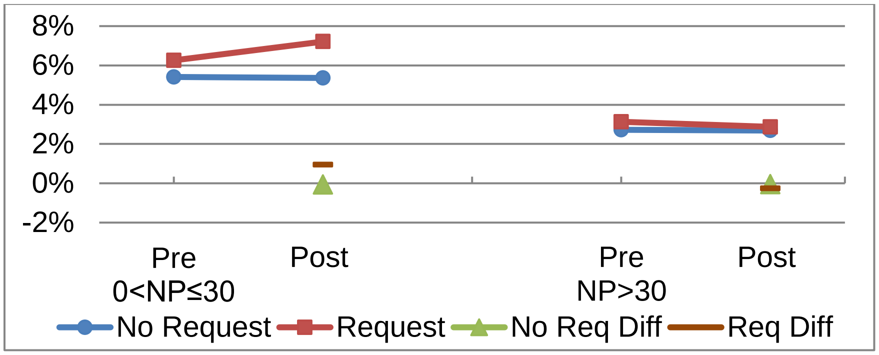


Figure 2.11. Pooled Pre and Post Cross-Sectional Standard Deviations for Redemptions Greater Than or Equal to 20% (NP = Redemption Notice Period)

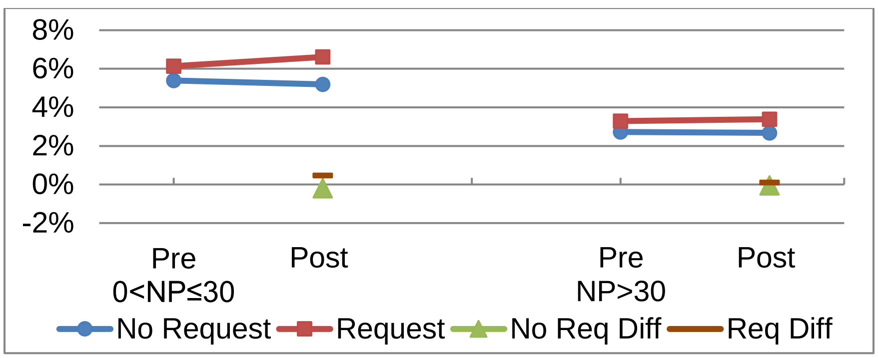


Figure 2.12. Pooled Pre and Post Cross-Sectional Standard Deviations for Redemptions Between 5% and 10% (NP = Redemption Notice Period)

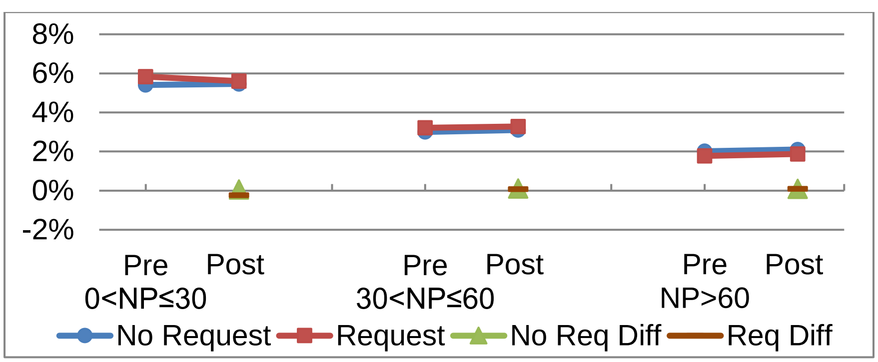


Figure 2.13. Pooled Pre and Post Cross-Sectional Standard Deviations for Redemptions Between 10% and 20% (NP = Redemption Notice Period)

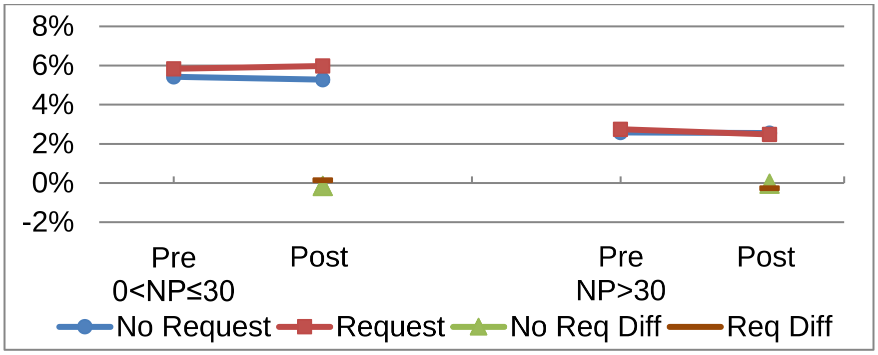


Figure 2.14. Difference Between Pooled Pre and Post Cross-Sectional Standard Deviations When *Redreq* = Yes for Different Levels of Redemptions (NP = Redemption Notice Period)

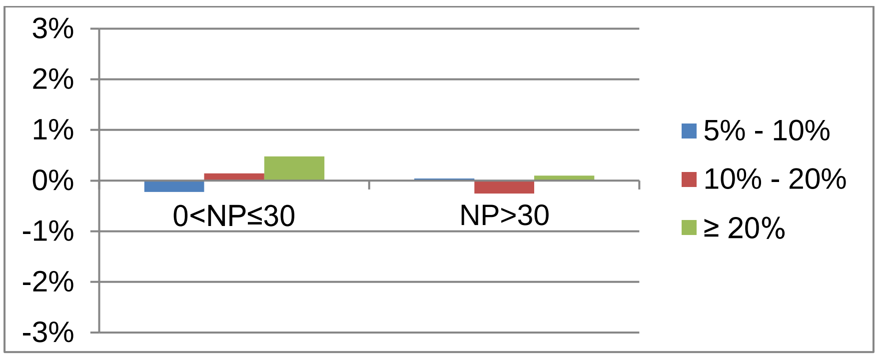
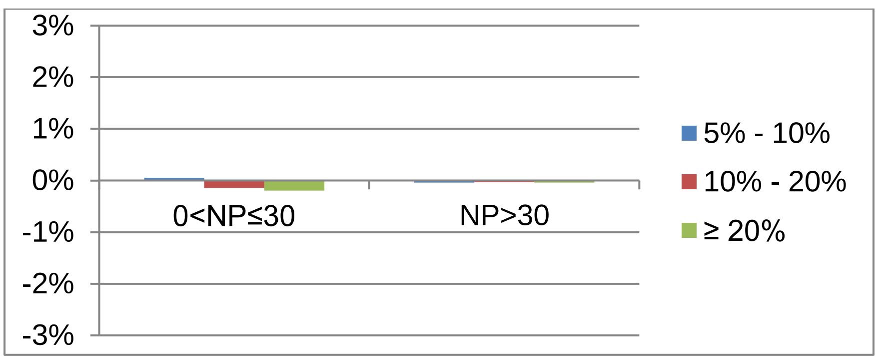


Figure 2.15. Difference Between Pooled Pre and Post Cross-Sectional Standard Deviations When *Redreq* = No for Different Levels of Redemptions (NP = Redemption Notice Period)



Chapter 3. Hedge Fund Herding During Uncertain Periods

3.1. Abstract

In this study, I examine whether hedge funds herd towards the market consensus in response to macroeconomic uncertainty during periods of high volatility with extreme market returns. I find that hedge funds that follow directional strategies herd towards the consensus during periods of high macroeconomic uncertainty. The degree of herding towards the consensus becomes greater during periods of economic downturn. This is because macroeconomic uncertainty usually increases in difficult and volatile times, and herding is more likely to occur during these periods when the market return becomes large in absolute terms. Moreover, directional strategy funds implement strategies based on the direction of market and may rely on aggregate stock market data for their trading decisions. Hence their security trading in the same way may be related to the uncertain macroeconomic and volatile market conditions. Finally, I find that the degree of herding for live funds following directional strategies is greater during periods of high macroeconomic uncertainty in down markets. This suggests that the similar trading manners of the directional fund managers in times of macroeconomic uncertainty could be beneficial for fund survival.

3.2. Introduction

Studies on institutional investor herding (buy or sell the same securities together) tend to concentrate on mutual funds or pension funds. There is only a small number of studies that examine hedge fund herding. Among the research that investigates hedge fund herding or commonality in hedge fund returns, they focus on herding behaviour relating to market conditions or fund characteristics. For example, Boyson (2010) finds that herding behaviour is related to reputation and increases fund survival. Bussière et al. (2015) find that the commonality in hedge fund returns increased during the period prior to financial crisis due to hedge funds' exposure to emerging market equities with a high downside and illiquidity risk. Boyson et al. (2010) find that hedge funds share a common exposure to large liquidity shocks and funding liquidity which lead to contagion among poor returns in hedge fund indices. However, none of the studies examines hedge fund herding in times of macroeconomic uncertainty.

The objective of this study is to examine whether hedge funds herd in response to macroeconomic uncertainty during periods of high volatility with extreme market returns. As Christie and Huang (1995) point out, herd behavior tends to form during periods of unusual market movements characterized by large swings in average prices. Chang et al. (2000) find that this is the case for Japan, South Korea and Taiwan during periods of extreme market movements. They argue that emerging markets suffer from the relative paucity of rapid and accurate firm-specific information. This influences the investors to focus more on the macroeconomic information especially during periods of extreme market movements. Therefore, investors tend to herd when the average market return becomes large in absolute terms. On the other hand, economic uncertainty is a source of macroeconomic risk and arises from unexpected changes in economic conditions such as changes in default spread, short-term interest rates, inflation rate, unemployment rate and growth rate of real GDP per capita (Bali et al., 2014). The unexpected changes in macroeconomic factors affect the investment decisions of hedge fund managers. This is because unexpected changes in economic conditions usually have impacts on prices of risky assets, affecting the investment opportunities for hedge funds. Bali et al. (2014) argue that hedge fund managers have the ability to predict and time unexpected changes and fluctuations of macroeconomic variables. By correctly adjusting their portfolio exposures to macroeconomic risk factors in a timely fashion, the hedge fund managers are able to generate superior returns when the unexpected changes in economic conditions increase. They find that this is the case for funds that pursue directional and semi-directional strategy investment objectives. These hedge funds increase their portfolio exposure to macroeconomic risk factors when the unexpected changes in economic conditions are predicted to be higher. Another study by Galariotis et al. (2015) shows evidence of herding towards the consensus in U.S. stock prices during days when important US macroeconomic information is released. Hence, it is possible that the security trading of certain hedge fund groups in the same direction during periods of macroeconomic uncertainty may be related to unexpected changes in macroeconomic information. Since herd behavior tends to form during periods of volatile market conditions, I study the combined effects of unexpected changes in economic conditions and extreme market movements. Specifically, I test whether uncertainty in economic conditions combined with extreme market returns is related to herding by directional or semi-directional hedge funds towards the market consensus.

When the state of the economy is bad with high unemployment and low output growth, the economic uncertainty usually increases (Bali et al., 2014). In particular, economic uncertainty becomes higher subsequent to large fluctuations in business conditions and recent financial crisis period (Bali et al., 2014). Moreover, periods of declining stock prices and high volatility provide active investors with better opportunities to identify high- and low-performing stocks (Gorman et al., 2010a; Gorman et al., 2010b). This is because stocks would yield more distinguishable returns in this case. As a result, hedge fund managers with similar investment objectives may be able to identify the same investment strategies at the same time during economic downturns. Therefore, I also study whether the tendency for hedge funds to herd is greater during periods of high volatility with large negative stock market returns as the uncertainty in economic conditions increases.

If hedge funds react similarly by correctly adjusting their portfolio exposures in response to uncertain economic conditions, then these funds should have a greater chance to survive and a greater herding degree. This implies that herding could be beneficial for fund survival. So, investing in hedge funds that herd due to selecting the right investment strategy could be beneficial for investors. Boyson (2010) finds that more experienced hedge fund managers who follow the herd are more likely to survive while those who deviate from the herd are more likely to be terminated. Therefore funds may increase their survival probability if they herd more. To understand whether there is a greater degree of herding for funds that survive, I separately study herding among live and liquidated funds. In particular, I examine whether the degree of herding tends to be greater for live funds during periods of high macroeconomic uncertainty with large negative market returns. In addition, if hedge fund managers are able to time the market uncertainty, then there should be a greater degree of herding for funds that follow directional strategy. Hence, I also separately examine herding for live and liquidated funds pursuing different investment objectives. To my knowledge this is the first paper that examines hedge fund herding during periods of high macroeconomic uncertainty with extreme market returns and this is also the first paper that separately studies herding for live and liquidated funds.

I find that hedge funds following directional strategies herd during periods of high macroeconomic uncertainty with extreme market returns. Moreover, the degree of herding towards the consensus becomes greater during periods of economic downturn. Finally, there is herding among live funds following directional strategies and semi-directional during economic downturns when there is high uncertainty. Although there is herding for liquidated funds following directional strategies, the herding degree is weaker. The results indicate that the macroeconomic uncertainty is an important factor affecting the portfolio construction process of the directional strategy hedge funds. Moreover, their similar trading manners can be attributed to uncertain macroeconomic and market conditions. Finally, the greater degree of directional hedge fund herding towards the market consensus in times of macroeconomic uncertainty could be beneficial for fund survival.

3.3. Literature Review

In general, the empirical studies on institutional investor herding have found that the institutional investors buy past winners and herd in small or growth stocks. Moreover, institutional investors follow other institutional investor's trading in the last period and their own past trading. For example, Grinblatt et al. (1995) find that mutual funds buy past winner but do not sell past losers. The most recent quarter's returns are more important for portfolio choice decisions than those returns in the distant past. Lakonishok, Shleifer and Vishny (1992) find that there is more herding and positive-feedback trading (buy past winner and sell past losers) by pension fund managers in small stocks than in large stocks. Wermers (1999) finds little herding overall, but there is strong herding in small or growth stocks especially for growth-oriented mutual funds. This is because it is usually more difficult to obtain precise information about small or growth firms, this leads the growth-oriented funds to follow the trades of each other. Sias (2004) finds that institutional investors follow other institutional investor's security trading in the last period and their own past security trading. Herding that results from inferring information from each other's trades into and out of the same securities and own past trades is consistent with information cascades. Choi and Sias (2009) find that mutual funds' demand for an “industry” in the current quarter follows their last quarter's demand for the “industry”. This means that institutional investors follow each other into and out of the same industries and is consistent with the informational cascades hypothesis. According to Bikhchandani and Sharma (2000), informational cascade is classified as "intentional" herding where investors intentionally copy other investors' actions. This is different from the "fundamental-spurious" herding which arises when investors who face similar decision problems and information sets take similar decisions. It may also occur when there is a sudden change in circumstances such as a sudden increase in interest rate. Investors reacting to this commonly known public information may reduce the percentage of stocks in their portfolio. This would create a fundamentals-driven spurious herding. Moreover even if their investment opportunity sets differ, spurious herding may occur due to changes in economic circumstances. Finally, for a spurious herding, investors do not reverse their investment in the subsequent period which is evident under "intentional" herding (Bikhchandani and Sharma, 2000).

A small number of studies which examine hedge fund herding provide evidence of hedge fund herding or contagion of hedge fund return. For example, Boyson (2010) finds that the herding behaviour increases with more experience and tenure. This is because more experienced senior managers increase the probability of failure and do not attract higher cash inflows if they deviate from the herd than the less-experienced young managers. Therefore, hedge fund herding behaviour is encouraged by career concerns of the managers. Since herding increases survival probability and cash inflows for more experienced senior managers as their careers progress, herding is related to reputation and does not lead to fund failure. Bussière et al. (2015) find that there is increased commonality in hedge fund returns during the period prior to financial crisis due to hedge funds' exposure to emerging market equities with a high downside and illiquidity risk. These funds exhibited negative returns during the subsequent financial crisis. Jiao and Ye (2014) find that hedge fund herding have a strong impact on mutual fund herding but not vice versa. Mutual fund herding leads to stock price reversal in the next quarter which destabilizes prices while hedge fund herding itself does not lead to price reversal. So hedge fund herding speeds the stock price adjustment process. Boyson et al. (2010) find that hedge funds share a common exposure to large liquidity shocks which lead to contagion among poor returns in hedge fund indices. This means that the given hedge fund style index is more likely to have a worst return when other hedge fund style indices also have worst returns. The contagion channels include credit spreads, the TED spread, prime broker and bank stock prices, stock market liquidity and hedge fund flows. So large negative shocks to these variables reduce asset liquidity and hedge fund funding liquidity which can explain the hedge fund return contagion. Hence the dependence among hedge fund indices increases with more poor returns generated when there is a large negative shock to asset and funding liquidity.

There is evidence that economic conditions, economic uncertainty, macroeconomic announcements, and macroeconomic risk factors affect investment decisions of investors and hedge fund managers. Gorman et al. (2010a) and Gorman et al. (2010b) demonstrate that periods of declining stock prices and high volatility provide active investors with better opportunities to identify high- and low-performing stocks. This is because stocks would yield more distinguishable returns. Verma (2015) finds that economic uncertainty significantly reduces the performance of market portfolios such as S&P 500 return and DJIA index return. Ben-David et al. (2012) who study the hedge fund trading in the U.S. stock market find that hedge funds increased their aggregate stock equity portfolio by about 6% per quarter following the financial crisis that occurred in 2007. Therefore, economic uncertainties and irrational pessimistic periods are favorable time for investment managers to buy securities. Nikkinen et al. (2006) find that several emerging regions in the world are not affected by U.S. macroeconomic news announcement even though U.S. economy has a leading role in the development of the world economy. Hence, diversification benefit can be obtained if international investors invest in those emerging regions. Bali et al. (2011) find that hedge funds are exposed significantly to macroeconomic risk factors such as default premium beta and inflation beta. Christie and Huang (1995) point out that herd behavior tends to form during periods of unusual market movements characterized by large swings in average prices. Chang et al. (2000) find that this is the case for Japan, South Korea and Taiwan as investors tend to focus more on the macroeconomic information during periods of extreme market movements causing them to herd towards the market consensus. Galariotis et al. (2015) investigate herding behavior in the US and the UK equity markets. They find that US investors tend to herd during days when important macroeconomic information announcement takes place. Savor and Wilson (2013) find that on the average U.S. stock market excess return is higher on prescheduled macroeconomic announcement dates as investors anticipate to be compensated for the risks that asset prices will respond to this macroeconomic news. In times of uncertainty, the risk premium is higher than in normal times, so the differential between returns on announcement and non-announcement days are greater during uncertain periods. Similarly, Bali et al. (2014) point out that investors should be rewarded for the macroeconomic risk exposures since macroeconomic risk affects their future consumption and investment decisions. So macroeconomic uncertainty is a relevant state variable proxy for consumption and investment opportunity in conditional ICAPM framework. They find that hedge fund managers actively vary their exposure to changes in macroeconomic conditions and that the macroeconomic uncertainty beta explains cross-sectional variation in hedge fund returns. Moreover, hedge funds following directional and semi-directional strategies time the macroeconomic changes by increasing portfolio exposure to macroeconomic risk factors when macroeconomic risk is high. Therefore in this study, I would like to understand whether certain hedge fund types such as directional strategy funds herd during periods of high economic uncertainty with extreme market returns.

3.4. Hypotheses Development

Prior literature has provided evidence that macroeconomic uncertainty and changes in economic conditions can affect an investment decision (Bali et al., 2014, Gorman et al., 2010a; Gorman et al., 2010b). In particular, unexpected changes in economic conditions have impacts on prices of risky assets and provide active investors with better opportunities to identify high- and low-performing stocks (Gorman et al., 2010a; Gorman et al., 2010b). Therefore, Nikkinen et al. (2006) and Verma (2015) suggest that institutional investors or fund managers can take advantage of the opportunities arising from changing economic conditions and economic uncertainty to generate superior returns. There is also evidence that hedge funds are able to predict unexpected changes in economic conditions (macroeconomic uncertainty) and actively adjust their portfolio exposures in a timely fashion (Bali et al., 2014). Moreover, hedge funds following directional and semi-directional strategies have superior macro-timing ability during periods when economic uncertainty increases.

On the other hand, periods of unusual market movements characterized by large swings in average prices also affect investment decisions (Christie and Huang, 1995 and Chang et al., 2000). Christie and Huang (1995) point out that investor herd behavior tends to form during periods of large market swings. Chang et al. (2000) find that this evidence for two emerging markets, Taiwan and South Korea, which indicates the presence of herd behavior during these periods of extreme market movements. This may be due to the relative paucity of rapid and accurate firm-specific information which influences the investors to focus more on the macroeconomic information especially during periods of extreme market movements. Therefore, investors tend to rely on aggregate market data and herd toward the market consensus when the average market return becomes large in absolute terms.

Bikhchandani and Sharma (2000) state that fundamental-spurious herding may occur if there is a sudden change in economic circumstances and if investors who face similar information sets take similar decisions. So herding is possible when investors react to this information. Galariotis et al. (2015) show evidence of herding towards the consensus in U.S. stock prices during days when important US macroeconomic information is released. Moreover, herding towards the market consensus is more likely to occur during periods of extreme market fluctuations as indicated by previous studies (Christie and Huang, 1995, Chang et al., 2000 and Galariotis et al., 2015). As a result, hedge funds following the same investment style may take similar investment decisions during periods of rising economic uncertainty and extreme market movements. Since directional strategy funds take direct market exposure and risk, it is more likely that they rely on aggregate stock market data for their investment decision. For funds with semi-directional strategies, it is also possible that they implement their trading based on aggregate stock market data. This suggests that:

Hypothesis 1: Directional or semi-directional hedge funds tend to herd towards the market consensus during periods of high macroeconomic uncertainty with extreme market returns due to their investment styles.

Secondly, economic uncertainty usually increases subsequent to large fluctuations in business conditions and bad state of the economy such as the recent financial crisis period (Bali et al., 2014). In times of economic uncertainties and economic downturn, active investors have better opportunities to identify high- and low-performing stocks and invest in securities as stocks yield more distinguishable returns (Gorman et al., 2010a; Gorman et al., 2010b). Verma (2015) finds that economic uncertainty significantly reduces the performance of market portfolios such as S&P 500 return and DJIA index return. So they suggest that economic uncertainties and irrational pessimistic periods are favorable time for investment managers to buy securities. Ben-David et al. (2012) who study the hedge fund trading in the U.S. stock market find that hedge funds increased their aggregate stock equity portfolio by about 6% per quarter following the financial crisis that occurred in 2007. There is also evidence that the commonality in hedge fund returns usually increases during economic downturn when there is large negative shocks to liquidity (Boyson et al., 2010 and Bussière et al., 2015). Therefore, if hedge fund managers following the same investment style take advantage of the opportunities arising from periods of economic uncertainty and declining stock prices, then they may be able to identify the same investment strategies using aggregate market data at the same time. Therefore, I would expect that the tendency for hedge funds to herd towards the market consensus is greater during periods of high volatility with large negative market returns when economic uncertainty increases. In particular:

Hypothesis 2: The herding degree should be stronger for directional or semi-directional strategy funds during economic downturns when macroeconomic uncertainty increases.

Finally, Bikhchandani and Sharma (2000) point out that a sudden change in circumstances may cause investors to react similarly in their investment strategy. Accordingly, since hedge funds' trading is based on public information relevant about the economy, they may implement the same trading strategy based on the changes in economic policies. Bali et al. (2014) find that hedge fund managers who are able to predict and time macroeconomic uncertainty generate superior returns during periods of economic uncertainty. If hedge funds have the ability to time macroeconomic uncertainty and react similarly in their investment strategy to generate superior returns, this will imply that these funds have a greater chance to survive. In this case, the degree of herding for live funds should be greater during periods of high macroeconomic uncertainty in down markets. This would suggest that the greater degree of herding is beneficial for fund survival and investors in the long-run. Boyson (2010) finds that hedge funds who follow the herd increases the chance of fund survival. As a result, I would expect that the degree of herding tends to be greater for live funds during periods of high macroeconomic uncertainty with large negative market returns. Therefore:

Hypothesis 3: The herding degree should be greater for live directional or semi-directional strategy funds during economic downturns when macroeconomic uncertainty increases.

In summary, my hypotheses are (1) there should be herding among hedge funds that follow directional or semi-directional strategies during periods of high macroeconomic uncertainty with extreme market returns and that (2) the degree of herding should be greater in down markets. Finally, (3) the degree of herding should be greater for live funds following directional strategies in down markets.

3.5. Approach/Methods

3.5.1. **Data**

I use the macroeconomic uncertainty factor developed by Bali et al. (2014) from Turan Bali's website[11]. The index is constructed by using Principal Component Analysis (PCA) to extract the common component of the eight macroeconomic risk factors as these risk factors are highly persistent and correlated with each other (Bali et al., 2014). The eight macroeconomic risk factors capture different dimensions of the aggregate economy, for example, uncertainty about default premium, aggregate dividend yield, real GDP per capita, the inflation rate, the equity market, short-term interest changes, term spread, and the unemployment rate (Bali et al., 2014). The sample period in this study is from January 1994 to December 2013 as the uncertainty factor is only provided until December 2013. The hedge fund data is obtained from Lipper TASS Academic Hedge Fund database[12], and I include both "Live" and "Graveyard" funds and separate the funds into three categories according to their investment styles. The first category of funds classified as "Directional Strategy" includes funds that take direct market exposure and risk (Bali et al., 2014). They bet on the direction of market, prices of currencies, commodities, equities, and bonds in the futures and cash market (Avramov et al., 2011). So, hedge funds with the investment style of managed futures, global macro, and emerging market funds are classified as taking directional strategy. The second category of funds classified as "Semi-directional Strategy" consists of fund-of-funds, long-short equity hedge, event-driven, and multi-strategy funds. These are funds that attempt to diversify market risk (Bali et al., 2014). So, they take long positions in underpriced securities and short positions in overpriced securities in equity markets or invest in a pool of hedge funds (Fund-of-funds)

[11] The economic uncertainty factor is provided by Turan Bali at http://faculty.msb.edu/tgb27/workingpapers.html. Several authors have used their data in their recent analysis of hedge funds and individual stocks, such as Agarwal, V., Green, T. C., and Ren, H. (2015), Agarwal, V., Ruenzi, S., and Weigert, F. (2015), Agarwal, V, Y. E. Arisoy, and N. Y. Naik (2015) and Bali, Turan, G., Stephen J. Brown, and Yi Tang (2015).

[12] 2014, "Lipper Tass Academic Hedge Fund", http://hdl.handle.net.proxy.lib.sfu.ca/11272/10015 V6 [Version]

(Avramov et al., 2011). Also, they may employ multiple strategies that take advantage of significant transactional events, such as mergers and acquisitions, bankruptcy reorganizations, recapitalizations, and share buybacks (Avramov et al., 2011). Finally, the "Non-directional Strategy" category includes the remaining funds with investment styles of equity market neutral, fixed income arbitrage, and convertible arbitrage funds. These are funds that try to minimize market risk altogether (Bali et al., 2014). Similar to Bali et al. (2014), I include hedge funds that report in U.S. dollars and report net returns. However, I exclude funds that report quarterly rate of return (ROR) or asset under management (AUM), gross RORs, missing monthly RORs, AUMs, management fees, incentive fees, minimum investment, management style. Since I would like to study the effect of high macroeconomic uncertainty upon herding among funds in live and liquidated samples, I also separate the "Liquidated" funds from the "Graveyard" category. Those non-reporting funds in the Graveyard category with other closure reasons are then grouped as "Other Non-reporting" or "ONR" category. Finally, I obtain data on equity market index, Standard & Poor's (S&P) 500 Index, from Lipper TASS Academic Hedge Fund database. It is used as I intend to study hedge fund herding towards the market consensus.

3.5.2. **Calculation of Variables and Methodology**

In this study, I examine herding towards the market consensus using aggregate market data based on previous studies that indicate that herding is more likely to form during economic uncertainties and periods of extreme market swings (Galariotis et al. 2015). In particular, studies by Chang et al. (2000) and Galariotis et al. (2015) have pointed out that investors tend to herd toward the market consensus when the average market return becomes large in absolute terms. In these studies, the authors analyze herding behavior in different equity markets in US, UK, Hong Kong, Japan, Korea, and Taiwan. Chang et al. (2000) argue that individual assets differ in their sensitivity to the market return, so return dispersions are an increasing linear function of the market return and will increase with an increase in market return. However, herding behaviour occurs when individuals tend to follow aggregate market behaviour during periods of large average price movements. In this case the security returns will not deviate too far from the overall market return. So the relation between the return dispersion and the aggregate market return should be non-linear when the absolute market return is large. In their study, Cross

Sectional Absolute Deviation (*CSAD*) is used as a measure of dispersion[13]. Chang et al. (2000) argue that the return dispersion will decrease with an increase in absolute market return if there is severe herding. For moderate herding, the return dispersion increases at a decreasing rate. Both Chang et al. (2000) and Galariotis et al. (2015) use a non-linear regression specification to determine the relationship between Cross Sectional Absolute Deviation (*CSAD*) and market return to detect herding based on daily equity returns. In addition Galariotis et al. (2015) include a dummy variable that indicates whether there is an important macroeconomic information announcement on a particular day. They find that herding tends to occur during days when important US macroeconomic information is released. I follow their approach and add a dummy variable of macroeconomic uncertainty, Dum_t^U, instead of macroeconomic announcement in Galariotis et al. (2015) to run a non-linear regression of

$$CSAD_t = \beta_0 + \beta_1 \left| R_{m,t} \right| + \beta_2 R_{m,t}^2 + \beta_3 Dum_t^U + \beta_4 Dum_t^U R_{m,t}^2 + e_t \quad (1)^{14}$$

where $CSAD_t = \frac{1}{N} \sum_{i=1}^{N} \left| R_{i,t} - R_{m,t} \right|$, $R_{i,t}$ is the monthly return of hedge fund *i*, $R_{m,t}$ is the monthly return of the market portfolio, and Dum_t^U equals 1 if the uncertainty index is higher than its time-series median uncertainty index and 0 otherwise. The interaction term is included because it is possible that the nature of hedge fund's herding behaviour vary during different time periods depending on the state of the world. Bali et al. (2014) find that uncertainty tend to increase following large fluctuation in business conditions which can affect investment decisions of hedge fund managers. Therefore taking into account of the interaction between the market return and macroeconomic uncertainty is important for

[13] Other studies that have used return dispersion measure or its variants include Christie and Huang (1995), Bessembinder et al. (1996), Gorman et al. (2010) and Galariotis et al. (2015). Christie and Huang (1995) and Galariotis et al. (2015) use cross sectional absolute deviation to detect herding. Bessembinder et al. (1996) use absolute deviations of individual firm returns from the market model expected returns to measure firm-specific information flows. Gorman et al. (2010a) and Gorman et al. (2010b) show that the cross sectional absolute deviation can serve as a signal for investors to decide when to increase the "activeness" of their long-only and long-short strategies.

[14] Galariotis et al. (2015) run the non-linear regression that includes independent variables of the absolute market return, the market return squared and the indictor variable with interaction term. The regression does not include the indictor variable as a base effect.

an understanding of the impact of the macroeconomic uncertainty on hedge fund herding. In addition, we should take this non-linearity into account (squared market return) since the relation between return dispersion and the aggregate market return becomes non-linear when the absolute market return is large (Chang et al., 2000). This non-linearity arrangement in the regression is similar to the study by Galariotis et al. (2015) who examine investor herding behaviour. Consequently, if there is herding during periods of high macroeconomic uncertainty with extreme market returns, then the coefficient β_4 should be negative and significant for directional and semi-directional funds.

To test whether the degree of herding during periods of high macroeconomic uncertainty is greater in down markets, I follow the approach of Chang et al. (2000) to separately run the following non-linear regression with periods of negative market returns

$$CSAD_t = \beta_0 + \beta_1 \left| R_{m,t}^{DN} \right| + \beta_2 \left(R_{m,t}^{DN} \right)^2 + \beta_3 Dum_t^U + \beta_4 Dum_t^U \left(R_{m,t}^{DN} \right)^2 + e_t \qquad (2)$$

where $R_{m,t}^{DN} = R_{m,t} < 0$. If the herding degree intensifies during periods of macroeconomic uncertainty with large and negative market returns, then the coefficient β_4 should be negative and significant for hedge funds that follow directional and semi-directional strategies.

Finally, I separately study the effect of macroeconomic uncertainty upon hedge fund herding for live and liquidated funds following different strategies in down markets. Specifically, I conduct the non-linear regression (2) separately for live and liquidated funds following different strategies. This is to understand whether herding tends to form for funds that survive. Boyson (2010) finds that hedge funds who follow the herd increases the chance of fund survival. Bali et al. (2014) find that there is superior macro-timing ability for directional and semi-directional hedge fund managers as they are able predict and time the macroeconomic changes. If hedge funds react similarly by correctly adjusting their portfolio exposures in response to uncertain economic conditions, then there should be a greater degree of herding for funds that survive. Therefore, I expect the coefficient β_4 to be negative and significant for live funds following directional strategies.

3.6. Results

Figure 3.1 shows the Standard & Poor's (S&P) 500 Index return (R_m), cross-sectional absolute deviation measure (*CSAD*) and economic uncertainty index (*EUI*) over time from January 1994 to December 2013. Several interesting observations can be seen from Figure 3.1. First, the cross-sectional absolute dispersion is the highest in October 2008 when the market return is the lowest, which means that the dispersion starts to increase when the stock market begins to slump. This is consistent with Gorman et al. (2010b) who find that the return dispersion increases during bear markets. The highest point of the economic uncertainty index is in February 2009 subsequent to a large market return movement. The lowest point for the cross-sectional dispersion occurs in November 2003 while the lowest point of the uncertainty index occurs in March 2007. The highest point of the market return over the sample period occurs in October 2011.

Second, there are several periods where the economic uncertainty index (*EUI*) increases following large movement in market return. For example, the *EUI* increases from October 1998 to December 1998 after a large market return movement in September 1998. It also increases between February 2000 and June 2000 following large market return swings between December 1999 and March 2000. This also occurs in January and February 2002 (in October and November 2002) following large market return swings between November and December 2001 (between September and October 2002). Finally, following big market return movements in June 2008, September 2008 and October 2011, the *EUI* increases in July 2008, between October 2008 and February 2009 and in November 2011, respectively. This is consistent with Bali et al. (2014) who finds that economic uncertainty usually increases subsequent to large fluctuations in business conditions and recent financial crisis period.

Third, the *CSAD* dispersion tends to reduce during periods when uncertainty in the economy increases following large market return swings[15]. For example, from October 1998 to December 1998, the *CSAD* reduces by 3.7% when the *EUI* increases from -1.3243 to -0.3075, subsequent to a large market swing in August and September of the same year. This pattern also occurs between March and June 2000 where the *CSAD* reduces while the *EUI* increases over the same period where there are large market return swings between March and April 2000. There is a significant negative correlation between the *EUI* and *CSAD* during this period (-0.985). Moreover, in July 2008, the *CSAD* reduces by 5.1% when the *EUI* increases over the same period following big market return movements in June 2008. In addition, from October 2008 to December 2008, the *CSAD* reduces by 10.3% when the *EUI* increases from 2.2364 to 7.4508. Finally, the *CSAD* reduces by 6.3% in November 2011 when the *EUI* increases subsequent to an 18% market return increase. This shows that hedge funds tend to herd towards the market consensus during periods of high economic uncertainty in volatile markets. This is consistent with Chang et al. (2000) who find the presence of herd behavior during periods of extreme market movements.

[Figure 3.1]

Table 3.1 shows the parameter estimates from regression (1) for all, directional, semi-directional and non-directional strategy portfolios. The coefficient on the macroeconomic uncertainty dummy variable, β_4, for all strategy portfolio in column (1) is significantly negative, suggesting that there is herding overall during periods of high macroeconomic uncertainty. β_4 is significantly negative for directional strategy portfolio in column (2). It supports the first hypothesis that hedge funds following directional strategy herd in times of high macroeconomic uncertainty with extreme market returns. However,

[15] There are also some instances of reduced dispersion during periods of large market return swings. For example, from August 1998 to September 1998, the *CSAD* reduces by 8.2% when there are large market swings (market return drops by 13.4% and then immediately increases by 20.9%) over the same period. Similarly, the market also has large swings in September 2002 and October 2002 (market return increases by 11.5% and 19.7%) with the *CSAD* reduced by 2.3% in October 2002 and 3.5% in November 2002. This also occurs in March 2009 where the market increases by 19.4% and the *CSAD* reduces by 2.6%.

β_4 is insignificant for semi-directional and non-directional strategy portfolios, suggesting that these hedge funds do not herd during periods of high macroeconomic uncertainty. Therefore, herding is primarily by hedge funds pursuing directional strategy investment objective; as a result, the first hypothesis is supported only for directional strategy funds.

[Table 3.1]

Regression (2) tests the degree of herding during periods of high economic uncertainty in down markets. Table 3.2 shows the parameter estimates from regression (2) for all, directional, semi-directional and non-directional strategy portfolios in down markets. The coefficient on the macroeconomic uncertainty dummy variable, β_4, for all strategy portfolio in column (1) is significantly negative, suggesting that hedge funds tend to herd during economic downturns with high macroeconomic uncertainty. β_4 is also significantly negative and with a larger magnitude for directional strategy portfolio in column (2). It supports the second hypothesis that hedge funds following directional strategy tend to herd during periods of high macroeconomic uncertainty in down markets. This also means that herding is primarily by hedge funds pursuing directional strategy investment objective. Moreover, the absolute value of the coefficient β_4 in Table 3.2 is greater than in Table 3.1, implying that the degree of herding is greater for directional hedge funds during economic downturns. However, β_4 is insignificant for semi-directional and significantly negative for non-directional strategy portfolios. This suggests that while hedge funds following semi-directional strategy do not herd during economic downturns with high macroeconomic uncertainty, there is herding for funds following non-directional strategy during down market periods with high economic uncertainty. However, as will be shown in Table 4, the non-directional strategy fund herding is primarily driven by liquidated hedge funds in down market periods. Overall, the second hypothesis is supported for directional strategy funds only.

[Table 3.2]

In an attempt to understand whether herding tends to occur for hedge funds that survive through periods of high macroeconomic uncertainty with large negative market returns, I separately study hedge fund herding for live and liquidated funds. Table 3.3 shows the parameter estimates from regression (2) for live funds and the three strategy portfolios in down markets. The coefficient on the macroeconomic uncertainty dummy variable β_4 for entire live portfolio in column (1) is significantly negative, suggesting that there is herding among live funds during periods of high macroeconomic uncertainty in down markets. The coefficient β_4 in column (2) is also significantly negative but with a larger magnitude for directional strategy portfolio. It supports the third hypothesis that the degree of herding for live funds following directional strategy is greater during periods of high macroeconomic uncertainty in down markets. Moreover, β_4 is becomes significantly negative for semi-directional strategy portfolio, supporting the third hypothesis. However, β_4 continues to be insignificant for non-directional strategy portfolio, suggesting that the live funds following non-directional strategy do not herd during economic downturns with high economic uncertainty. The third hypothesis is supported since the herding degree is greater for both live directional and semi-directional strategy funds during economic downturns when macroeconomic uncertainty increases.

[Table 3.3]

Table 3.4 shows the parameter estimates from regression (2) for entire liquidated funds and the strategy portfolios in down markets. The coefficient on the macroeconomic uncertainty dummy variable β_4 for entire liquidated portfolio in column (1) is significantly negative, suggesting that there is also herding among liquidated funds during periods of high macroeconomic uncertainty in down markets. However, when comparing the coefficient β_4 in Table 3.3 and Table 3.4 for live and liquidated funds, I find that the degree of herding is greater for live funds than for liquidated funds. β_4 in Table 3.4 column (2) is also significantly negative for directional strategy portfolio, but the coefficient β_4 for live directional funds has a greater absolute magnitude. This suggests that the average level of equity return dispersions is greater for liquidated funds than for live funds during economic downturns with high macroeconomic uncertainty. Finally, β_4 is insignificant for semi-directional portfolio and significantly negative for non-directional strategy portfolio, suggesting that hedge funds following semi-directional strategy in the liquidated category do not herd during periods of high macroeconomic uncertainty in down markets. However, there is herding by liquidated hedge funds pursuing non-directional strategy investment objective. This shows that non-directional hedge fund herding in economic downturns is primarily driven by liquidated hedge funds. Overall, the third hypothesis is supported since the degree of herding is greater for live directional strategy funds.

[Table 3.4]

Table 3.5 shows the parameter estimates from regression (2) for entire ONR funds and the strategy portfolios in down markets. The coefficient on the macroeconomic uncertainty dummy variable β_4 for entire ONR funds in column (1) is significantly negative, suggesting that there is herding among ONR funds during periods of high economic uncertainty. The coefficient β_4 is also significantly negative for directional strategy portfolio in column (2). However, when comparing the coefficient β_4 in Tables 3.3, 3.4 and 3.5 for live, and liquidated, and ONR directional funds, I find that the degree of herding is greater for live funds than for liquidated and ONR funds. On the other hand, the degree of herding is similar among liquidated and ONR funds. Finally, β_4 is insignificant for both semi-directional and non-directional strategy portfolios, suggesting that these hedge funds in the ONR category do not herd during periods of high macroeconomic uncertainty.

[Table 3.5]

3.7. Conclusion

In this study, I examine whether hedge funds herd towards the market consensus in response to macroeconomic uncertainty during periods of high volatility with extreme market returns. I find that hedge funds that follow directional strategies herd during periods of high macroeconomic uncertainty. The degree of herding towards the consensus becomes greater during periods of economic downturn. This is because economic uncertainty usually increases in difficult and volatile times (Bali et al., 2014), and herding is more likely to occur during these periods when the market return becomes large in absolute terms (Galariotis et al. 2015). Moreover, hedge funds classified as "Directional Strategy" are funds that take direct market exposure and risk by betting on the direction of market and that have the ability to time the macroeconomic uncertainty. Hence these hedge funds may trade assets in the same direction during uncertain economic and volatile market conditions, resulting in the convergence of their trading manner toward the consensus.

If hedge funds can correctly adjust their portfolio exposures in response to uncertain economic conditions during economic downturns, then these funds should have a greater chance to survive. In this case, there should be a greater degree of herding for live funds during periods of high macroeconomic uncertainty with large negative market returns. I find this evidence for live funds following directional and semi-directional strategies during down market periods. Although there is herding for liquidated funds following directional strategies, the degree of herding is weaker. Overall, the results indicate that the macroeconomic uncertainty is an important factor affecting the portfolio construction process of the directional strategy hedge funds. Moreover, their similar trading manners can be attributed to uncertain macroeconomic and market conditions. Finally, the greater degree of directional hedge fund herding towards the market consensus in times of macroeconomic uncertainty could be beneficial for fund survival.

3.8. References

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3.9. Tables and Figures

Table 3.1. Herding during periods of high macroeconomic uncertainty

The table presents the parameter estimates from $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \beta_3 Dum_t^U + \beta_4 Dum_t^U R_{m,t}^2 + e_t$, where *CSAD* is the Cross Sectional Absolute Deviation, $R_{m,t}$ is the monthly return of S&P 500, and Dum_t^U equals 1 if the uncertainty index is higher than its time-series median and 0 otherwise. Columns (1), (2), (3) and (4) present the results for all, directional, semi-directional, and non-directional strategy portfolios, respectively. Heteroskedastic and autocorrelation consistent t-statistics are reported in parentheses.

	(1) **All**	(2) **Directional**	(3) **Semi-directional**	(4) **Non-directional**
β_1	0.456***	0.277***	0.468***	0.748***
	(7.35)	(2.81)	(8.31)	(8.78)
β_2	2.576***	6.065***	1.263***	1.363**
	(6.13)	(8.02)	(3.19)	(2.10)
β_3	0.00523**	0.00598*	0.00527**	0.00510*
	(2.10)	(1.89)	(2.38)	(1.75)
β_4	-0.753**	-2.420***	0.177	-0.477
	(-2.13)	(-3.98)	(0.59)	(-0.96)
β_0	0.0178***	0.0308***	0.0144***	0.00634***
	(7.54)	(8.54)	(9.19)	(3.66)
N	240	240	240	240
adj. R^2	0.811	0.741	0.776	0.671

* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$

Table 3.2. Herding during periods of high macroeconomic uncertainty in down markets

The table presents the parameter estimates from $CSAD_t = \beta_0 + \beta_1 |R_{m,t}^{DN}| + \beta_2 (R_{m,t}^{DN})^2 + \beta_3 Dum_t^U + \beta_4 Dum_t^U (R_{m,t}^{DN})^2 + e_t$, where *CSAD* is the Cross Sectional Absolute Deviation, $R_{m,t}^{DN}$ is the negative monthly return of S&P 500, and Dum_t^U equals 1 if the uncertainty index is higher than its time-series median and 0 otherwise. Columns (1), (2), (3) and (4) present the results for all, directional, semi-directional, and non-directional strategy portfolios, respectively. Heteroskedastic and autocorrelation consistent t-statistics are reported in parentheses.

	(1) **All**	**(2)** **Directional**	**(3)** **Semi-directional**	**(4)** **Non-directional**
β_1	0.632***	0.544***	0.593***	1.086***
	(9.71)	(5.27)	(8.94)	(7.29)
β_2	1.519***	4.982***	0.362	-1.110
	(3.83)	(8.24)	(0.93)	(-1.27)
β_3	0.00565	0.00455	0.00696*	0.00570***
	(1.65)	(1.21)	(1.83)	(2.83)
β_4	-1.057***	-3.219***	-0.0283	-0.251**
	(-5.77)	(-14.83)	(-0.14)	(-2.29)
β_0	0.0181***	0.0295***	0.0154***	0.00488
	(6.72)	(7.80)	(6.91)	(1.62)
N	84	84	84	84
adj. R^2	0.878	0.877	0.803	0.814

* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$

Table 3.3. Herding among live funds during periods of high macroeconomic uncertainty in down markets

The table presents the parameter estimates from $CSAD_t = \beta_0 + \beta_1 |R_{m,t}^{DN}| + \beta_2 (R_{m,t}^{DN})^2 + \beta_3 Dum_t^U + \beta_4 Dum_t^U (R_{m,t}^{DN})^2 + e_t$, where *CSAD* is the Cross Sectional Absolute Deviation, $R_{m,t}^{DN}$ is the negative monthly return of S&P 500, and Dum_t^U equals 1 if the uncertainty index is higher than its time-series median and 0 otherwise. Columns (1), (2), (3) and (4) present the results for all live, directional, semi-directional, and non-directional strategy live fund portfolios, respectively. Heteroskedastic and autocorrelation consistent t-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)
	All	**Directional**	**Semi-directional**	**Non-directional**
β_1	0.666***	0.534***	0.687***	0.966***
	(9.45)	(3.74)	(10.45)	(9.29)
β_2	1.760***	6.275***	-0.0797	-1.273**
	(4.19)	(7.31)	(-0.21)	(-2.10)
β_3	0.00526*	0.00342	0.00641**	0.00441*
	(1.72)	(0.59)	(2.07)	(1.85)
β_4	-1.574***	-4.265***	-0.335**	0.386
	(-10.09)	(-15.61)	(-2.11)	(1.40)
β_0	0.0177***	0.0313***	0.0125***	0.0101***
	(6.67)	(5.96)	(5.91)	(3.93)
N	84	84	84	84
adj. R^2	0.880	0.820	0.814	0.874

* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$

Table 3.4. Herding among liquidated funds during periods of high macroeconomic uncertainty in down markets

The table presents the parameter estimates from $CSAD_t = \beta_0 + \beta_1 |R_{m,t}^{DN}| + \beta_2 (R_{m,t}^{DN})^2 + \beta_3 Dum_t^U + \beta_4 Dum_t^U (R_{m,t}^{DN})^2 + e_t$, where *CSAD* is the Cross Sectional Absolute Deviation, $R_{m,t}^{DN}$ is the negative monthly return of S&P 500, and Dum_t^U equals 1 if the uncertainty index is higher than its time-series median and 0 otherwise. Columns (1), (2), (3) and (4) present the results for all liquidated, directional, semi-directional, and non-directional strategy liquidated fund portfolios, respectively. Heteroskedastic and autocorrelation consistent t-statistics are reported in parentheses.

	(1) All	(2) Directional	(3) Semi-directional	(4) Non-directional
β_1	0.600***	0.631***	0.536***	0.831***
	(6.86)	(4.71)	(5.38)	(10.03)
β_2	1.921***	4.112***	0.746	0.614
	(3.49)	(4.91)	(1.28)	(1.26)
β_3	0.00761*	0.00638	0.00988**	0.00721***
	(1.76)	(1.22)	(2.37)	(2.67)
β_4	-1.325***	-3.226***	-0.00681	-0.521***
	(-4.92)	(-11.32)	(-0.02)	(-3.69)
β_0	0.0170***	0.0255***	0.0140***	0.00768***
	(4.90)	(4.92)	(5.01)	(3.27)
N	84	84	84	84
adj. R^2	0.836	0.831	0.734	0.934

* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$

Table 3.5. Herding among ONR funds during periods of high macroeconomic uncertainty in down markets

The table presents the parameter estimates from $CSAD_t = \beta_0 + \beta_1|R_{m,t}^{DN}| + \beta_2(R_{m,t}^{DN})^2 + \beta_3 Dum_t^U + \beta_4 Dum_t^U (R_{m,t}^{DN})^2 + e_t$, where *CSAD* is the Cross Sectional Absolute Deviation, $R_{m,t}^{DN}$ is the negative monthly return of S&P 500, and Dum_t^U equals 1 if the uncertainty index is higher than its time-series median and 0 otherwise. Columns (1), (2), (3) and (4) present the results for all liquidated, directional, semi-directional, and non-directional strategy liquidated fund portfolios, respectively. Heteroskedastic and autocorrelation consistent t-statistics are reported in parentheses.

	(1)	**(2)**	**(3)**	**(4)**
	All	**Directional**	**Semi-directional**	**Non-directional**
β_1	0.628***	0.483***	0.561***	1.398***
	(9.84)	(4.66)	(8.69)	(4.21)
β_2	1.265***	5.332***	0.497	-2.895
	(3.31)	(9.19)	(1.30)	(-1.49)
β_3	0.00545*	0.00455*	0.00619*	0.00685**
	(1.77)	(1.70)	(1.67)	(2.21)
β_4	-0.664***	-3.136***	0.173	-0.201
	(-3.98)	(-12.92)	(0.92)	(-1.60)
β_0	0.0186***	0.0304***	0.0176***	-0.00145
	(7.93)	(9.37)	(7.97)	(-0.23)
N	84	84	84	84
adj. R^2	0.879	0.887	0.819	0.419

* $p < 0.10$;
** $p < 0.05$;
*** $p < 0.01$

Figure 3.1. **Standard & Poor's (S&P) 500 Index (R_m), Cross-Sectional Absolute Deviation (*CSAD*) and Economic Uncertainty Index (*EUI*) From January 1994 to December 2013**