HEC MONTREAL

The Effect of the 2008 Financial Crisis on Hedge Fund Performance and Survival

by

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Résumé

Ma thèse étudie la relation entre les caractéristiques des fonds de couverture et leur performance et leur survie pendant la crise financière de 2008. Pour chaque caractéristique, j'implémente deux types de test: une test non paramétrique dans laquelle je compare les rendements moyens ou le taux de défaut de différents portefeuilles et groupes de fonds, et une test paramétrique où j'utilise des régressions linéaires lors de l'analyse de la performance des fonds et régressions de Cox à risques proportionnels lors de l'analyse de la survie des fonds. Je trouve que pendant la crise, l'exposition au risque de liquidité est négativement liée à la performance des fonds, bien que cette relation ne soit pas linéaire et ne soit présente que lorsque l'on compare les rendements des fonds les moins exposés à ceux les plus exposés. En outre, la commission d'incitation et la présence du capital personnel d'un gestionnaire dans un fonds se traduisent par une performance et une capacité de survie accrues pendant la crise.

Mots-clés: fonds de couverture, crise financière, crise de liquidité, performance des fonds, survie des fonds

Abstract

My thesis investigates the relationship between hedge fund characteristics and their performance and survival during the 2008 financial crisis. When analyzing each characteristic, I implement two types of approaches: a non-parametric approach in which I compare the average returns or the default rate of different portfolios and groups of funds, and a parametric approach where I use linear regressions when analyzing fund performance and Cox proportional-hazards regressions when analyzing fund survival. I find that during the crisis, exposure to liquidity risk is negatively related to fund performance, although this relationship is non-linear and is only present when comparing the returns of the funds with the lowest exposure to those with the highest exposure. Furthermore, the incentive fee and the presence of a manager’s personal capital in a fund lead to increased performance and survivability during the crisis.

Key words: Hedge fund, financial crisis, liquidity crisis, fund performance, fund survival

Table of Contents

INTRODUCTION-- 1
CHAPTER 1: LITERATURE REVIEW --- 6
1.1 Hedge Fund Investment Style-- 6
1.2 Fund Manager Skill -- 7
1.3 Hedge Fund Age-- 9
1.4 Hedge Fund Size-- 10
1.5 Hedge Fund Leverage -- 11
1.6 Hedge Fund Risk Exposures --- 13
1.7 Hedge Fund Managerial Incentives--- 14
1.8 Funding Restrictions-- 15
1.9 Hedge Funds During Crisis Periods --- 16
CHAPTER 2: DATA & FUND CHARACTERISTICS--- 19
2.1 Data Filters -- 20
2.1.1 Initial Filters -- 21
2.1.2 Filters for Poor Data Management and Duplicate Funds------------------------------------ 23
2.2 Overview of Data and Fund Characteristics --- 28
CHAPTER 3: RESULTS & ANALYSIS -- 34
3.1: Effect of the 2008 Financial Crisis on Hedge Fund Performance ------------------------------ 35
3.1.1 Hedge Fund Investment Style --- 35
3.1.2 Hedge Fund Alpha -- 41
3.1.3 Hedge Fund Age -- 45
3.1.4 Hedge Fund Size -- 49
3.1.5 Hedge Fund Historic Return -- 53
3.1.6 Hedge Fund Leverage -- 57
3.1.7 Hedge Fund Liquidity Risk Exposure -- 61
3.1.8 Hedge Fund Equity Market Exposure --- 65
3.1.9 Hedge Fund Managerial Incentives-- 69
3.1.10 Funding Restrictions -- 79
3.1.11 Investment Focus-- 89
3.1.12 Investment Approach Case Study -- 96

3.2: Effect of the 2008 Financial Crisis on Hedge Fund Survivability ---------------------------------100
3.2.1 Hedge Fund Investment Styles ---------------------------------100
3.2.2 Hedge Fund Alpha ---------------------------------104
3.2.3 Hedge Fund Age ---------------------------------109
3.2.4 Hedge Fund Size ---------------------------------113
3.2.5 Hedge Fund Historic Return ---------------------------------116
3.2.6 Hedge Fund Leverage ---------------------------------119
3.2.7 Hedge Fund Liquidity Exposure ---------------------------------120
3.2.8 Hedge Fund Equity Market Exposure ---------------------------------126
3.2.9 Hedge Fund Managerial Incentives ---------------------------------130
3.2.10 Funding Restrictions ---------------------------------133
3.2.11 Investment Focus ---------------------------------139
CHAPTER 4: CONCLUSION ---------------------------------144
4.1: Summary of Results ---------------------------------144
4.2: Future Research ---------------------------------148
BIBLIOGRAPHY ---------------------------------151

List of Tables

Table 2.1: Amount of funds dropped by each filter ... 27

Table 2.2: Monthly raw returns for each fund style... 31

Table 2.3: Summary statistics for various hedge fund characteristics ... 33

Table 3.1: Monthly returns of each hedge fund style ... 38

Table 3.2: Regression results of fund performance on fund investment style during the crisis .. 40

Table 3.3: Monthly returns of each portfolio of hedge funds, sorted from lowest to highest alpha ... 43

Table 3.4: Regression results of fund performance on fund alpha during the crisis ... 44

Table 3.5: Monthly returns of each portfolio of hedge funds, sorted from youngest to oldest... 47

Table 3.6: Regression results of fund performance on the age of hedge funds during the crisis 48

Table 3.7: Monthly returns of each portfolio of hedge funds, sorted from smallest to largest ... 51

Table 3.8: Regression results of fund performance on the size of hedge funds during the crisis 52

Table 3.9: Monthly returns of each portfolio of hedge funds, sorted from lowest historic returns to highest historic returns ... 55

Table 3.10: Regression results of fund performance on fund historic return during the crisis 56

Table 3.11: Monthly returns of non-leveraged hedge funds and leveraged hedge funds ... 59

Table 3.12: Regression results of fund performance on the presence of fund leverage during the crisis ... 60

Table 3.13: Monthly returns of each portfolio of hedge funds, sorted from lowest to highest exposure to liquidity risk ... 63

Table 3.14: Regression results of fund performance on fund exposure to liquidity risk during the crisis ... 64

Table 3.15: Monthly returns of each portfolio of hedge funds, sorted from lowest to highest exposure to equity market risk ... 67

Table 3.16: Regression results of fund performance on fund exposure to the equity market during the crisis ... 68

Table 3.17: Breakdown of Incentive Fee Portfolios ... 72

Table 3.18: Breakdown of Management Fee Portfolios... 73

Table 3.19: Monthly returns of funds with and without personal investment from the manager ... 74

Table 3.20: Monthly returns of each portfolio of hedge funds, sorted from lowest incentive fee to highest incentive fee ... 75

Table 3.21: Monthly returns of each portfolio of hedge funds, sorted from lowest management fee to highest management fee 76

Table 3.22: Monthly returns of funds with and without a high watermark 77

Table 3.23: Regression results of fund performance on managerial incentives during the crisis 78

Table 3.24: Breakdown of Redemption Frequency Portfolios 82

Table 3.25: Breakdown of Redemption Notice Period Portfolios 83

Table 3.26: Monthly returns of each portfolio of hedge funds, sorted from lowest to highest redemption frequency 84

Table 3.27: Monthly returns of each portfolio of hedge funds, sorted from lowest to highest redemption notice period 85

Table 3.28: Monthly returns of funds with and without a lockup period 86

Table 3.29: Regression results of fund performance on funding restrictions during the crisis 87

Table 3.30: Regression results of fund performance on funding restrictions before the crisis 88

Table 3.31: Monthly returns of funds that focus and that do not focus their investments in Mortgage-Backed Securities 91

Table 3.32: Monthly returns of funds that focus and that do not focus their investments in US Real Estate 92

Table 3.33: Monthly returns of funds that focus and that do not focus their investments in Distressed Markets 93

Table 3.34: Monthly returns of funds that focus and that do not focus their investments in Bankruptcies 94

Table 3.35: Regression results of fund performance on investment focuses during the crisis 95

Table 3.36: Performance comparison of hedge funds that engage in discretionary trading and systematic trading 98

Table 3.37: Characteristics of hedge funds from case study 99

Table 3.38: Cox Proportional-Hazards Regression results with respect to fund type 102

Table 3.39: Default percentage of funds for each Fund Type 103

Table 3.40: Cox Proportional-Hazards Regression results with respect to hedge fund alpha 106

Table 3.41: Default percentage of funds for each portfolio of hedge funds, sorted from lowest alpha to highest alpha 107

Table 3.42: Cox Proportional-Hazards Regression robustness check results, Fund Alpha 108

Table 3.43: Cox Proportional-Hazards Regression results with respect to hedge fund age 111

Table 3.44: Default percentage of funds for each portfolio of hedge funds sorted from youngest to oldest 111

Table 3.45: Cox Proportional-Hazards Regression results with respect to hedge fund size 114

Table 3.46: Default percentage of funds for each portfolio of hedge funds, sorted from smallest to largest fund size 115

Table 3.47: Cox Proportional-Hazards Regression results with respect to hedge fund average historic monthly raw returns 117

Table 3.48: Default percentage of funds for each portfolio of hedge funds, sorted from lowest to highest historic return 118

Table 3.49: Cox Proportional-Hazards Regression results with respect to the presence of leverage in a hedge fund 120

Table 3.50: Default percentage of leveraged funds versus non-leveraged funds 120

Table 3.51: Cox Proportional-Hazards Regression results with respect to hedge funds' exposure to liquidity risk 123

Table 3.52: Default percentage of funds for each portfolio of hedge funds, sorted from lowest to highest exposure to liquidity risk 124

Table 3.53: Cox Proportional-Hazards Regression robustness check results, Liquidity Risk Exposure 125

Table 3.54: Cox Proportional-Hazards Regression results with respect to hedge funds' exposure to the equity market........ 127

Table 3.55: Default percentage of funds for each portfolio of hedge funds, sorted from lowest to highest exposure to the equity market 128

Table 3.56: Cox Proportional-Hazards Regression robustness check results, Equity Market Exposure 129

Table 3.57: Cox Proportional-Hazards Regression results with respect to management incentives 132

Table 3.58: Default percentage of funds with respect to the management incentive 133

Table 3.59: Cox Proportional-Hazards Regression results with respect to funding restrictions (focus on crisis period) 136

Table 3.60: Default percentage of funds with respect to the management incentive 137

Table 3.61: Cox Proportional-Hazards Regression results with respect to funding restrictions (focus on pre-crisis period)........ 138

Table 3.62: Cox Proportional-Hazards Regression results with respect to a hedge fund's investment focus 141

Table 3.63: Default percentage of funds with respect to the investment focus 143

Table 4.1: Summary of Results 149

List of Figures

Figure 2.1: Monthly raw returns for each fund style 32
Figure 3.1: Share of funds that have defaulted, 5 portfolios 112
Figure 3.2: Share of funds that have defaulted, 10 portfolios 112

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INTRODUCTION

Can hedge funds protect investors during a financial crisis? Hedge funds are given great regulatory and trading freedom that enables them to pursue different investment strategies which can provide diversification benefits (Kooli, 2007). This diversification is meant to offer a degree of protection to investors, which is one of the reasons why hedge funds are an important component of the portfolios of high-net-worth individuals and large institutions. These individuals and institutions rely on the advanced strategies of hedge funds to earn high returns while also preserving their capital through diversification. However, the negative economic impact of a financial crisis may prove to be too strong for a hedge fund to fully diversify away the risks and protect the capital of its investors.

The 2008 Financial Crisis was a catastrophic event that shook global financial markets, particularly that of the United States. The excessively risky behaviour of U.S. banks and other financial institutions, combined with the burst of the U.S. housing bubble and the subprime mortgage crisis, created a domino effect that rippled throughout the entire economy, leading to the longest recession in the country since the Great Depression (Amadeo, 2020). During this crisis, the hedge fund industry suffered greatly, as the average annualized return of hedge funds was -8.41% (this number was computed using the dataset from this paper). However, this average performance masks a rich cross-section, where the top decile of funds delivered an average annualized return of +35% and the bottom decile delivered an average annualized return of -55%. This disparity in performance can be attributed to the various characteristics of hedge funds, such as the fund investment style, fund manager skill, or the type of performance incentives offered to the managers. My paper analyzes this large cross-section of returns and investigates if there are certain hedge fund characteristics that can predict superior performance or superior survivability in a crisis.

My paper relates to the following strands of the literature: the cross-sectional variation of hedge fund returns with respect to fund characteristics and the effect of financial crises on hedge fund returns. Liang (1999) was one of the first researchers to demonstrate that the cross-sectional variation of fund returns is strongly related to a number of fund characteristics. Subsequently, many studies have investigated the relationship between different characteristics and returns even further. For example, Howell (2001) and Aggarwal and Jorion (2010) find that younger funds outperform older funds, Brown and Goetzmann (2001) and Ding and Shawky (2007) show that fund performance varies greatly across investment styles, and Agarwal et al. (2009) find evidence that managerial incentives help improve fund performance. However, while previous papers study the relationship between fund characteristics and performance, these studies are quite limited and only offer a narrow range of characteristics. My paper is related to this branch of the literature as it also investigates the link between fund characteristics and performance, although with a much broader set of fund attributes. There are studies (Clare et al., 2015; Stoforos et al., 2017; Stafylas and Andrikopoulos, 2020) that examine fund performance during crisis and non-crisis periods, sometimes in relation to certain characteristics such as fund size or their investment style. These studies typically include multiple crises such as the LTCM crisis of 1998 or the burst of the dot com bubble in 2000, however, my paper focuses solely on the 2008 financial crisis. My thesis is also influenced by Fung and Hsieh's (2004) paper in which they proposed a 7-factor model that explains hedge fund returns. Much of the hedge fund literature uses this 7-factor model as it is shown to explain a significant part of the systemic risk present within hedge fund portfolios. This model is a vital component of my methodology since I use it (along with two other factors which will be discussed later) to estimate each fund's risk-adjusted returns and the fund alpha. The literature review section will provide further details on pertinent findings in hedge fund literature.

My work serves to fill several gaps within the literature. While the relationship between performance and certain characteristics such as investment style, size, or age has been studied extensively, the relationships with other characteristics such as past alpha, historic return, and investment focus have not. I select common characteristics which have been studied and uncommon characteristics which have not been covered adequately in the literature. Furthermore, these different characteristics are researched across a multitude of papers, which means that the methodologies and datasets vary. This is particularly important to note since many studies do not adequately clean up the raw datasets prior to analysis, which leads to results that do not accurately represent the hedge fund industry (further details will be given in Section 2). My paper uses the same dataset for all characteristics, and I use the same methodology for all my analyses, although there are minor variations where required. This brings about more reliable results since all findings are derived in a consistent manner. Additionally, I aim to fill the gap of how survivability during a crisis is related to fund characteristics. This area of hedge fund literature is severely underdeveloped as research typically tends to focus on returns during a crisis rather than survivability. My paper brings forth new results that would enhance researchers' understanding of what kind of hedge fund is more likely to default during a crisis.

The main contribution of my paper is to find support for previous findings in hedge fund literature and to provide new findings of how other, unexplored, characteristics relate to fund performance and survival during the 2008 financial crisis. My paper provides a comprehensive analysis using the following 12 hedge fund characteristics: the hedge fund's investment style, past alpha, age, size, historic return, presence of leverage, liquidity risk exposure, equity market exposure, managerial incentives, funding restrictions, investment focus, and investment approach. The managerial incentives are broken down into four subcategories: the presence of a manager's personal capital within the fund, the incentive fee, the management fee, and the presence of a high watermark. The funding restrictions are also broken down into subcategories: the redemption frequency, the redemption notice period, and the presence of a lockup period. I include four different investment focuses: mortgage-backed securities, US real estate, distressed markets, and bankruptcies. I perform my analysis for each characteristic through two approaches: a non-parametric approach in which I form portfolios (or groups) of funds and compare their average performance or default rate, and a parametric approach where I perform linear regressions when analyzing fund performance and Cox proportional-hazards regressions when analyzing fund survivability. My analysis is performed from January 1994 until June 2009, where I consider December 2007 and June 2009 to be the beginning and end of the financial crisis. The dates for the crisis are selected based on the peak and the trough of the US business cycle for that period, which is determined by the National Bureau of Economic Research (NBER, 2020).

My results show that while some characteristics do have a relationship with fund performance or survival during the crisis, others do not. The investment style of a fund has a relationship with both performance and survival, as different styles perform or survive better than others. A fund's past alpha is shown to have a negative relationship with performance but a positive relationship with survival. Fund age and fund size generally have a negative relationship with performance (although it is not linear) and a positive relationship with survival. I find in my paper that funds with good historical performance surprisingly exhibit inferior performance during the crisis, although they have superior survivability. Hedge funds with leverage are found to have both superior performance and survival during the crisis than hedge funds without leverage. The liquidity risk exposure of a fund has a negative relationship with performance, although it is non-linear: the two quintiles of funds with the lowest exposure outperform the two quintiles with the highest exposure. Furthermore, liquidity risk exposure also has a negative relationship with survivability. The results for liquidity risk exposure are important to point out since they show that investors were better off investing in funds with low exposure than high exposure, which may possibly also hold true for other future financial liquidity crises. The equity market exposure of a fund has a negative relationship with performance but no relationship with survival. The results for managerial incentives differ: personal capital and incentive fees have positive relationships to both performance and survival, however, the management fee and high watermark are not found to have a relationship with performance but may have a negative relationship with survivability. The incentive fee and personal capital are the only incentives that directly compensate managers for good performance. This allows us to understand why there is a positive relationship between these two incentives and fund performance and survival. Investors will realize greater returns if the hedge funds they are invested in directly reward managers for good performance. As for the funding restrictions, I do not find any evidence to support a relationship with either performance or survivability. For the investment focuses, I find that funds focusing on MBS and distressed markets have a negative relationship with both performance and survival. Funds focusing on US real estate do not have any relationship with performance or survivability. There is some evidence pointing to a negative relationship between the bankruptcy focus and fund performance, although a conclusion regarding the relationship with survival cannot be reached because of unclear results. As for the investment approach, I find that among large funds, discretionary funds have superior performance while among small funds, systematic funds have superior performance.

The remainder of this paper is split into four chapters. Chapter 1 provides a review of pertinent findings found in existing hedge fund literature. This includes how fund characteristics relate to fund performance and how this varies during financial crises. In Chapter 2, I discuss what datasets I use, how I clean them in order to obtain results that best reflect the behaviour of the hedge fund industry, and an introduction to each of the characteristics I use throughout my thesis. Chapter 3 presents the methodology, results, and analysis of results for each characteristic that I test. This chapter is split into two: the first half investigates the relationship of fund characteristics and returns, while the second half looks at the characteristics and their relation to fund survivability during the crisis. Chapter 4 offers a summary of the results found for each characteristic and suggests possible avenues for future hedge fund research.

CHAPTER 1: LITERATURE REVIEW

Hedge fund literature is a relatively young field of study. In the second half of the 20th century, hedge funds started emerging, but it was not until the 1990s in which they saw a large surge in their popularity. It was in this decade in which scholars increasingly started focusing on hedge fund research, as this industry was unique in that it included low regulation, high risk, and large returns. Studies have compared hedge funds to other types of investment funds, such as mutual funds: mutual fund managers are shown to employ more conservative strategies regarding the use of short selling, leverage, and derivatives (Ackermann et al., 1999), hedge fund managers more often receive better performance-based incentives (Ackermann et al., 1999; Elton et al., 2003; Kempf et al., 2009), hedge funds have stronger restrictions that make it tougher for investors to withdraw their capital (Agarwal et al., 2009), and hedge funds are not bound to the same level of information disclosure as mutual funds. These differences between the two types of investment funds can lead to superior performance for hedge funds (Ackermann et al., 1999; Liang, 1999; Stulz, 2007; Kapoor, 2010). The flexibility offered to hedge funds allows them to take on a vast range of different characteristics which have been shown to affect the fund's performance.

1.1 Hedge Fund Investment Style

Researchers have examined the impact that a hedge fund's style has on the fund. This includes the impact on performance, differing risk exposures, investor sentiment, and more. Hedge fund literature has shown that the different styles behave differently and thus, are a very important aspect to include when performing hedge fund research. Brown and Goetzmann (2001) measure the performance of different hedge fund styles from 1989 to 2000. Their findings show that 20% of the cross-sectional variability of returns can be attributed to the hedge fund style. They also find that the risk exposures of hedge funds differ depending on the fund style. Ding and Shawky (2007) compare the performance of different hedge fund styles and find that Distressed Securities and Event Driven styles exhibit superior performance than other fund styles. They find that the majority of

Emerging Markets, Equity Hedge, and Global Macro style funds perform below the average. They also find that the skewness and kurtosis of fund styles differ.

Kazemi and Li (2009) compare the market timing ability of Systematic CTAs to Discretionary CTAs (two similar hedge fund styles). Their results show that the two styles behave differently, and that Systematic CTAs have better market-timing skills while Discretionary CTAs have better risk-adjusted performance. Horst and Salganik (2014) show that investors are influenced by a hedge fund's style, which may either attract or deter investors. Their findings show that better-performing styles receive higher capital inflows from investors in subsequent periods. Within each style, the capital is allocated more towards the better-performing funds. Luo et al. (2017) study the hedge funds' liquidity timing in the largest financial market in the world: the foreign exchange market. They conclude that fund style has explanatory power in the liquidity timing abilities of hedge funds. Getmansky (2005) finds that investors in hedge funds that follow a directional/trend strategy (such as Global Macro or Dedicated Short Bias) are more responsive to past returns than investors of other hedge fund styles in which the current market conditions or new events are more important (such as Event Driven funds). The paper also concludes that as a fund style performs better, more investors decide to invest in hedge funds of that style, therefore increasing competition within the style and also increasing the default probability of individual funds of that style.

1.2 Fund Manager Skill

Studies regarding the presence of manager skill in hedge funds have reached different conclusions. While many papers show that managers of funds have skill, some papers find that they do not have skill but rather are just lucky. This may be as a result of different types of approaches used when measuring skill, which greatly differs across hedge fund literature. Fung and Hsieh's (2004) paper influenced how a large portion of hedge fund literature studies manager skill by suggesting the use of an asset-based multifactor approach. Fung and Hsieh proposed seven factors upon which fund returns would be regressed on: the Bond Trend-Following Factor, the Currency Trend-Following Factor, the

Commodity Trend-Following Factor, the Equity Market Factor, the Size Spread Factor, the Bond Market Factor, and the Credit Spread Factor. These factors are meant to capture the systematic portion of returns, which would then leave behind the constant (known as alpha or manager skill) and the residuals. Many researchers subsequently used this approach in their own studies, either by using the same set of factors or slight variations. Gu and Zhang (2015) use four performance-measuring models, one of them being Fund & Hsieh's eight-factor model, and find that that throughout 2004-2015, hedge funds deliver positive alpha, thereby confirming the presence of skill.

Other papers have opted for less traditional approaches, in which they estimate manager skill by using a wide variety of techniques. Berk and Binsbergen (2015) examine the presence of manager skill in the mutual fund industry. They argue that the skill of a manager is equal to the value the fund extracts from financial markets: the fund's gross excess return over its benchmark multiplied by the assets under management (AUM). They conclude that mutual fund managers do indeed have skill. Kooli and Stetsyuk (2020) implement this same approach but rather than studying mutual funds, they study hedge funds. They also apply bootstrapping to control for luck and use various benchmark indices in order to obtain robust results. The authors conclude that manager skill is the cause for added value, not luck. Furthermore, the value added was relatively high prior to the 2008 financial crisis, however, this decreased in the post-crisis period.

Kacperczyk et al. (2013) define manager skill as the ability to select the right stocks and the ability to time the market well. They find evidence that some managers have significant stock-picking and market-timing abilities. These funds are found to have superior performance to other funds and to benchmarks, which supports the theory that managers have skill. Kosowski et al. (2007) use the bootstrap approach in order to test whether managers are skillful or simply just lucky. Their approach consists of comparing the performance of real top-performing funds to the performance of artificially-generated top-performing funds where the variation in returns is due to randomness or "luck". They conclude that the performance of top hedge funds is indeed attributed to manager skill rather than luck. Some studies, however, do not find evidence for hedge fund manager skill. Malladi (2020) uses the False Discovery Rate method (used to identify false positives) to split managers into three groups: skilled, unskilled, and neutral. His results show that only 2.68% of managers are skilled while 33.20% are unskilled.

1.3 Hedge Fund Age

Studies of hedge fund age and its relation to performance have been plentiful. Most of these studies also include the relationship of size and performance since the age and the size of a hedge fund are commonly thought to go hand-in-hand. The consensus among hedge fund researchers is that older funds typically have lower returns than younger funds. This is largely due to diseconomies of scale, which means that as a fund gets larger, their performance worsens.

Howell (2001) studies the performance of old funds versus young funds. He finds that younger funds outperform larger funds and that the youngest decile of funds outperforms the oldest decile of funds by a difference of nearly 10% annualized return. However, he notes that the failure rate of funds peaks at the fund age of 28 months, which suggests that younger funds also have a tougher time surviving than older funds. Aggarwal and Jorion (2010) analyze the performance of emerging hedge funds. They find that younger funds outperform older funds, and that performance persists for up to five years before it starts decreasing. Frumkin and Vandegrift (2009) measure the effect of fund age on fund excess returns above the S&P 500 Index. They indeed find a negative relationship between the two and claim that the reason for this is “style drift”. This means that as funds get older, they deviate from their usual investment strategies and pursue investments in areas that they are not as familiar with, therefore leading to reduced returns. Boyson (2008) tests whether the persistence of hedge fund performance changes with respect to fund age. Boyson claims that as funds get older, they become more passively managed, which reduces the likelihood that the performance persists.

Gao et al. (2018) examine the performance across the life cycle of hedge funds. They find that as funds grow old, their performance worsens as a result of diseconomies of scale. Smaller funds provide superior returns at every stage of the hedge fund life cycle. They claim that one of the reasons for the performance decline as funds get older is the presence of management fees, which may disincentivize managers to chase returns as the fund gets larger. Jones (2007) studies the impact of hedge fund age and size on performance. Her findings show that young and small funds outperformed old and large funds. However, she also concludes that larger and older funds are better at preserving investor's capital. Although younger funds have superior returns, they also have more volatile performance which can result in larger losses for investors. In sum, although studies have shown that fund performance deteriorates with age, it is not the age itself that causes this, but rather other factors that come along with age.

1.4 Hedge Fund Size

The relationship between the size of a hedge fund and its performance and survivability has been the focus of many studies. One commonly-thought reason for this is the presence of capacity constraints and diseconomies of scale. Teo (2009) finds that large hedge funds do indeed struggle with diseconomies of scale and that smaller funds tend to outperform larger funds. He also finds that this effect is stronger among funds investing in smaller and more illiquid securities. Naik et al. (2007) find evidence for the presence of capacity constraints within the hedge fund industry. They find that the inflow of capital is statistically linked to future negative movements in the alpha for half of the hedge fund strategies they studied. Ding et al. (2009) examine the relative performance of large versus small hedge funds for different hedge fund strategies. Their findings show that smaller funds have superior performance in terms of absolute returns, however, larger funds have superior performance in terms of risk-adjusted returns. Ammann and Moerth (2005) find a positive relationship between fund size and performance. They hypothesize that this is due to the larger total expense ratio for smaller funds. They also find that larger funds have lower volatilities and higher Sharpe Ratios.

Chen et al. (2004) examine whether mutual fund returns are related to fund size. They find "strong evidence that fund size erodes performance" and that this effect is strongest among funds that tend to invest in small illiquid stocks. These findings may suggest that hedge funds suffer from this effect as well since their investments are more illiquid than that of mutual funds. Phillips et al. (2017) claim that the relationship between mutual fund size and performance is endogenous, and therefore, they opt to use a set of instrumental variables that affect size but are unrelated to performance. These instrumental variables include the "Holding Period Returns" of funds. They conclude that overall, fund size does not affect fund performance.

Chakravarty and Deb (2013) examine the propensity of hedge fund families to open new funds based on their capacity constraints. They find that an increase in excess fund size of the largest fund in a family leads to an increase in the family's propensity to open a new fund. The authors hypothesize that new funds are opened because the large funds face diseconomies of scale and the top investment strategies used by these funds are not scalable. Gupta et al. (2017) study the relationship between hedge fund size and liquidation. Their results show that the likelihood of liquidation is inversely related to fund size, meaning that larger funds are less likely to fail than small funds. They also find that the factors affecting liquidity likelihood are not the same across all funds, but rather they vary as the size of the fund varies. Furthermore, the liquidation likelihood of small and medium-sized funds is more sensitive to changes in fund characteristics than that of larger funds. While some papers within hedge fund literature may not support each other regarding the impact of fund size on performance, the general consensus is that funds face diminishing returns to scale, meaning that fund size is negatively related to fund performance.

1.5 Hedge Fund Leverage

While there exist many studies on the determinants of hedge fund leverage, literature regarding the relationship between leverage and fund performance is sparse. Choi (2016) studies the impact leverage has on hedge fund performance. They use three measures of risk-adjusted performance upon which the leverage of a fund is regressed on: Fung-Hsieh 7 and 8 factor models, a strategy-adjusted return, and a style-adjusted return. When using the strategy-adjusted returns, leverage is found to negatively impact fund performance, while no relationship is observed when using the other performance measures. The author also mentions that they observed the phenomenon of diseconomies of scale, where leveraged mid-sized funds outperformed leveraged large-sized funds.

Liang and Qiu (2018) study the determinants of hedge fund leverage and the impact that leverage has on fund performance. They find that better fund performance and lower return volatility lead to future increases in leverage. The authors implement the Fung-Hsieh 8-factor model in order to estimate the cumulative average abnormal returns (CAAR) one year prior and one year after a change in a fund's leverage level. They find that funds who increased their leverage had much higher CAARs than funds who decreased their leverage. However, this difference only persists for a short time after the change in leverage. Regarding the impact of leverage on performance, the authors find that an increase in fund leverage leads to inferior performance and more volatile returns in the six subsequent months. A decrease in leverage does not seem to change the performance of a fund, however, it does decrease the volatility. Furthermore, levered funds are shown to exhibit longer survival times and lower liquidation probability.

Bertelli (2007) tests how leverage affects performance across fund strategies. He claims that the use of leverage brings about lower risk-adjusted performance. Furthermore, he finds that the volatility of a strategy (without the use of leverage) is negatively related to the maximum amount of leverage that can be sustained. Schneeweis et al. (2005) also examine leverage and its effects on different fund styles. They find that across fund styles, the leverage differs, however, within each style, the degree of leverage is not related to superior or inferior risk-adjusted returns. Liang (1999) studies how various characteristics may affect hedge fund performance. He finds that leverage increases the volatility of funds and also increases the spread between the two extreme returns of a fund. Additionally, leverage is found to benefit certain fund styles while harming others. Overall, literature regarding the impact of leverage on fund performance has mixed conclusions, although the majority of papers tend to agree that leverage either reduces a fund's returns or does not have any impact at all.

1.6 Hedge Fund Risk Exposures

Hedge funds have exposures to a variety of different risks. Some of the most common ones include exposure to liquidity risk and systematic risk. Researchers have attempted to explain how these risk exposures vary and how they are related to fund returns. Huang et al. (2017) have shown that funds with good performance often have different risk exposures than funds with poor performance. They also find that funds' exposure to systematic factors varies dynamically across time. Billio et al. (2012) also study the dynamics of risk exposures of hedge funds. Their results show that hedge funds adjust their exposures depending on the state of the equity market. Hwang et al. (2017) take a look at the relationship between the systemic risk of hedge funds and their returns. They use marginal expected shortfall (MES) to measure the amount of systemic risk that each individual hedge fund contributes to the overall system's risk. Their findings show a positive and significant relationship between systemic risk and fund returns. These results hold when controlling for various fund characteristics and are not caused by autocorrelation in fund returns. The authors conclude that systemic risk is an important factor in explaining the cross-sectional variation of hedge fund returns.

Sadka (2010) studies how exposure to liquidity risk affects the cross-section of fund returns. The paper mainly uses the Sadka liquidity factor when measuring a hedge fund's loading on liquidity risk. The results show that during the 1994-2008 period, funds with higher exposure also have greater performance. However, funds that are more exposed to liquidity risk during crises are shown to perform worse than funds with lower exposure. Teo (2011) finds that among funds with relatively liquid capital (funds with low funding restrictions), there is a large cross-sectional variation in exposure to liquidity risk. This finding is interesting since we would expect managers to match the liquidity of investments to the liquidity of the fund's capital. He finds that funds with higher exposure to liquidity risk outperform funds with low exposure. Amihud (2002) examines the cross-sectional and time-series impact that market illiquidity has on stock returns. The findings show a positive relationship for both the cross-section and time-series perspectives. These effects are found to be particularly strong among stocks of small firms. Amihud's study gives an insight into how illiquidity might affect the whole market and not just hedge funds. In general, we observe that funds are rewarded with a premium when they are exposed to more liquidity risk.

1.7 Hedge Fund Managerial Incentives

Managerial incentives have been a focal point in hedge fund research. Managers are sometimes offered incentives in hopes that they will put more effort into choosing the best investments, therefore increasing the returns of the fund. Researchers have studied this topic extensively in order to determine whether these incentives actually help a fund perform better. There have been mixed conclusions, however, most researchers tend to agree that they do help increase fund performance.

Agarwal et al. (2009) study how managerial incentives affect a fund's performance. In their study, the following measures are used as incentives: higher total delta, higher option deltas, managerial ownership of the fund, and the presence of a high watermark. They conclude that funds with greater incentives exhibit better performance. Liang (1999) compares hedge funds to mutual funds and shows how the use of managerial incentives in hedge funds affect performance. He argues that incentives help align the manager's interests with those of the investors. The results in his study show that the incentive fee and high watermark have a positive relationship with performance while the management fee has no impact. Agarwal and Ray (2011) investigate why managerial incentives change and what their subsequent effect is on fund performance. Funds with good performance are shown to increase their incentive fee, although this comes with the addition of a high watermark. Following poor performance, funds decrease the incentive fee. An increase in fees is shown to worsen future fund performance, while a decrease in fees has no effect. The results of the paper also show that large funds tend to decrease the management fee. Correspondingly, a decrease in the management fee leads to an increase in future capital inflows.

Kouwenberg and Ziemba (2007) examine how a hedge fund manager's risk changes in relation to the incentives given and their personal investment in the fund. Relatively risk-averse managers are found to increase risk in response to higher incentive fees. However, once a manager has at least 30% of their personal wealth invested in the fund, their risk decreases. When looking at the cross-section of hedge funds however, incentive fees are shown to have a negative impact on returns and no impact on volatility. Li et al. (2019) take a look at how funds adjust their risk after a period of good performance or bad performance. This study is tied to managerial incentives since after good performance, managers are rewarded but after poor performance, they do not lose their compensation. As shown in the study, this asymmetric incentive scheme gives rise to "risk shifting", in which managers tend to increase risk after a period of poor performance. This effect is particularly strong among hedge fund managers whose incentives are "out of the money". However, this effect is only present in the short term; if funds exhibit poor performance for a long time, the managers are not found to increase risk. Ray (2011) finds further evidence of "risk shifting" when analyzing fund performance and behaviour in relation to the high watermark. The results of his paper show that when a fund is below the high watermark, the fund's return risk increases and the Sharpe ratio decreases. Additionally, there is a greater likelihood of fund liquidation in the subsequent periods.

1.8 Funding Restrictions

Like managerial incentives, funding restrictions are mechanisms used to increase a hedge fund's performance. Aragon (2007) investigates the relationship between funding restrictions and fund performance. The paper reports that lockup periods are positively related to excess returns; funds with lockup periods outperform funds with no lockup periods by approximately 4-7% annually. He additionally demonstrates that funding restrictions are negatively related to the liquidity of a fund's portfolio, which means that the funding restrictions help hedge funds match the liquidity of their investments to their capital. Agarwal et al. (2009) take a look at how manager discretion affects a hedge fund's performance. They use the lockup period, notice period, and redemption periods as measures of manager discretion since they give managers more freedom when pursuing certain strategies. The results in their paper show that with greater manager discretion comes greater fund performance. On his paper regarding the effects of different characteristics on hedge fund performance, Liang (1999) shows that a longer lockup period is related to better fund performance. Deemed as a “stylized fact”, Joenvaara et al. (2012) test if funding restrictions have a positive effect on risk-adjusted performance by using a variety of different hedge fund databases. They find that in some databases, there is no relationship between certain restrictions and fund performance. However, in their consolidated database (a combination of all their databases), they indeed find a positive relationship. Teo (2011) studies hedge funds that have relatively low funding restrictions. This would mean that a fund’s capital is relatively liquid. Among this group of liquid funds, the ones with high capital inflows exhibit greater risk-adjusted returns than those with low inflows.

1.9 Hedge Funds During Crisis Periods

The high discretion and investment flexibility offered to hedge funds leads them to exhibit quite diverse cross-sectional performance. The lack of regulation within the hedge fund industry can leave investors under-protected, especially during times of poor performance. Studies have examined the performance of hedge funds in crisis periods with respect to the hedge fund characteristics that I have previously mentioned.

Stafylas and Andrikopoulos (2020) take a look at the characteristics that drive hedge fund performance (determined by the alpha in this study) during different business cycles. During good times, young funds, small funds, and funds with redemption restrictions are found to have superior performance. During bad times, small funds and funds with restrictions underperform, while young funds outperform. Additionally, hedge funds are shown to decrease their risk exposures during bad times.

Clare et al. (2015) investigate the relationship between hedge fund size and performance across time, including crisis and non-crisis periods. As in most studies, they find an overall strong negative relationship between the size and performance, however, the relationship becomes insignificant or even positive at certain time periods. The authors conclude that in the two crisis periods studied, the collapse of the tech bubble and the 2008 financial crisis, smaller hedge funds had better performance than larger hedge funds.

Schaub and Schmid (2013) study how funding restrictions affect hedge fund returns during the 2008 financial crisis and prior to it. They find that in the pre-crisis period, funding restrictions are related to greater returns, which would suggest that investors are given an "illiquidity premium" when they invest in funds with redemption periods and lockups. However, during the crisis period, funding restrictions are associated with poorer performance. The authors find that this poor crisis performance may be remedied if managers are provided with high incentive fees.

Stoforos et al. (2017) test the performance of different hedge fund styles during crisis and non-crisis periods by using the S&P 500 as a benchmark. Their analysis spans across a large time period and includes 5 different crisis periods: the 1997 Asian crisis, the 1998 LTCM crisis, the 2000 dot com bubble burst, the 2008 financial crisis, and the 2011 European debt crisis. For the majority of fund styles tested, there is evidence of structural breaks across crisis and non-crisis periods. This would suggest that hedge funds were not able to hedge themselves against the systemic market risk during crises.

Sun et al. (2018) examine the performance persistence of individual hedge funds conditional on the general hedge fund market performance. Results show that individual fund performance persistence varies depending on if the hedge fund market performs well or poorly. Hedge funds that perform well during weak market performance are found to consistently outperform other funds in the following 3 months to 3 years. Hedge funds that perform well during strong market performance are not found to exhibit this performance persistence. These findings lead the authors to suggest that the "information-to-noise ratio is higher during weak markets", and that it is easier to identify skilled managers during poor market performance.

Brunnermeier and Nagel (2004) investigate hedge fund trading behaviour during the technology bubble of 2000. Their study challenges the theory of efficient markets, which suggests that rational investors would correct mispricing (in this case by trading against the bubble) and thus riskless arbitrage would be eliminated from the market. Their results show that hedge funds in fact amplified the mispricing by "riding" the bubble and skillfully liquidating their positions before prices dropped. Mitchell and Pulvino (2012) also study arbitrage and hedge funds, however, they focus on the 2008 financial crisis.

During the crisis, prime brokers pulled debt financing away from funds, which caused long-term debt to become overnight short-term debt. This caused a mismatch between hedge funds' assets and liabilities and thus forced arbitrage hedge funds to liquidate their positions through fire-sales. This destabilized prices and exacerbated the mispricing of securities.

CHAPTER 2: DATA & FUND CHARACTERISTICS

The main dataset for this study is sourced from the Lipper-TASS hedge fund database. The data contains monthly observations spanning from January 1974 to April 2017 for 18,818 global hedge funds, however, only data from January 1994 to June 2009 is used in my study. Included in this dataset are fund returns, assets under management (AUM), and fund characteristics such as the fund investment style and managerial incentives. I use two additional data sources: David Hsieh's Data Library[1] provides the Fung-Hsieh (2004) factors found in their 7-factor model along with an additional emerging market index factor, and the University of Chicago Booth School of Business provides the Pastor-Stambaugh[2] (2003) Liquidity Factor. These are used to compute risk-adjusted returns, hedge fund alpha, fund exposure to liquidity risk, and fund exposure to equity market risk.

All the data in the Lipper-TASS database is self-reported by hedge funds, which gives rise to a number of different issues such as missing data or false returns. Using the raw data could thus lead to incorrect conclusions that are not representative of the hedge fund industry. I mitigate these issues through the use of filters presented in section 2.1. Following this, in section 2.2, I give an overview of the data and various fund characteristics that I use for my analyses.

[1] Fung-Hsieh Factors are downloaded from the following link:
https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

[2] The Pastor-Stambaugh Liquidity Factor is downloaded from the following link
https://faculty.chicagobooth.edu/lubos-pastor/data

2.1 Data Filters

The data found in hedge fund databases, such as Lipper-TASS, is voluntarily reported by hedge fund managers. They choose which database to report to, when and how often they do it, and also what numbers they report (Almeida et al., 2018). This gives rise to many issues that are common when researching hedge funds. Unfortunately, many studies do not deal with some of these issues. This can potentially bias the results and lead to conclusions that may be incorrect. Therefore, it is important to implement certain filters that mitigate these problems.

In order to get the most accurate results possible when conducting an analysis, a number of different filters are implemented to the dataset. Some of these filters deal with innocuous issues such as a cross-fund mismatch of reporting frequency, while others deal with issues that arise due to either poor data management or possible data manipulation. Applying these filters is a crucial component in hedge fund research since analysis results would then reflect real-world results more accurately. The filters used in this study largely follow the methodology proposed by Almeida et al. (2018). There is a total of 18,818 funds in the initial unfiltered dataset obtained from Lipper-TASS. After applying all of the filters, we are left with 6,131 funds (32.6% of the original full sample) to conduct the analyses with. A breakdown of each filter's (other than the survivorship and backfill bias filters) impact on the dataset is presented on page 27 in Table 2.1.

2.1.1 Initial Filters

To start the data filtering process, I implement a number of filters whose main goal is to deal with survivorship and backfill bias, and issues related to inconsistent reporting across funds. Apart from the biases, these issues may or may not influence the results. However, precisely because of this uncertainty, they must be dealt with in order to obtain reliable results. These filters discard a total of 8,799 hedge funds from the dataset. This leaves 10,019 funds (53% of the initial dataset) that must then be further treated for poor data management or possible data manipulation. This sample of 10,019 funds will be referred to as the "partially-filtered dataset".

Filter for Net Returns

The first filter I implement is used to eliminate all funds that do not report returns net of all fees. These include funds that report either the gross return or return net of management fees but not incentive fees. Including these funds in the analyses would bias the results by using an inflated and overestimated measure of returns. There is a total of 74 (0.39% if the full sample) funds that are eliminated through the use of this filter.

Filter for Reporting Frequency

The second filter that is applied is a "monthly-reporting" filter. I discard all funds that do not report their returns on a monthly basis. A small portion of hedge funds only give out quarterly information and in order to maintain consistency across estimates, these funds are removed. This filters out a total of 77 funds (0.41% of the full sample). Some funds initially report on a quarterly basis and then subsequently start reporting on a monthly basis. During the quarterly-reporting period of these funds, returns and other characteristics take the value of zero in between quarters. These funds will be dealt with in a later filter.

Currency Filter

I implement a currency filter which removes all funds that do not report their returns or other characteristics in USD. If I were to include funds that report in other currencies, they would have to be converted into USD. However, because of the time variation of exchange rates, this could add additional noise to my analysis. This filter eliminates 8,388 funds (44.57%). Although a substantial portion of the sample is eliminated through this filter, it is vital to implement it in order to have a homogenous sample of hedge funds that report in USD.

Filter for Survivorship Bias

Survivorship bias and backfill bias are two common issues encountered when studying hedge funds (Agarwal et al., 2015). Prior to 1994, Lipper-TASS only contained information on live funds. Any measures that are taken from that period would bias the results since only surviving funds would be considered. This could lead to an overestimation of returns and AUM for the hedge fund industry. In order to eliminate this survivorship bias, all observations prior to 1994 are dropped. This is an important bias that must be mitigated since live hedge funds are not representative of all hedge funds. This eliminates the first 1.66% of observations in the time series.

Filter for Backfill Bias

Backfill bias is another prominent issue in hedge fund research. Many funds report their data to databases in order to "advertise" how good their performance is, which could attract potential investors. However, when providing information, hedge funds are allowed to fill in past returns. This could incentivize managers to provide inflated historic returns which, if included in an analysis, would cause biased results. A commonly used method to deal with this bias is to drop the first 12 months (sometimes 24 months) of observations of every fund. Aggarwal and Jorion (2010) propose an alternative method to deal with backfill bias, as they believe that the commonly used method can cause additional problems. They claim that on one hand, dropping the first 12 months of every fund can eliminate funds that do not suffer from backfill bias. On the other hand, it also may not eliminate all backfilled returns of other funds. They find that the median backfill period within the Lipper-TASS database is approximately 480 days (16 months). Their solution to deal with this bias is to split the sample into two parts: one with backfilled funds and the other with non-backfilled funds. They deem a fund to suffer from backfill bias if the difference between the inception date and the date when the fund started reporting to the database is larger than 180 days.

What I have done to deal with backfill bias is a combination of the commonly used method and the method proposed by Aggarwal and Jorion. If the difference between the two aforementioned dates is larger than 180 days, only then are the first 12 months of a fund's returns removed from the sample. This eliminates approximately 13.21% of observations in the initial sample and eliminates 553 funds (2.94%).

2.1.2 Filters for Poor Data Management and Duplicate Funds

This section of filters is largely meant to deal with hedge funds that may have mistakenly entered the wrong numbers when reporting to Lipper-TASS or may have purposely altered a few numbers in order inflate their performance. I also deal with mirror funds, which are essentially duplicate funds. Out of the 10,019 funds that were left after the previous filtering process, a further 3,888 are discarded. Once every filter is applied, we are left with 6,131 funds (32.6% of the initial dataset) with which the analyses in this paper are based on.

Zero-Return Filter

The main goal of this filter is to flag funds that might have started out by reporting on a quarterly basis but later on reported on a monthly basis. Similar to the previously mentioned "monthly-reporting" filter, this filter helps keep the frequency of data consistent. The first step is to pick out funds whose returns are equal to zero for at least 10% of the funds' total observations. These returns are then flagged for one of the following three reasons: if the AUM in the previous or subsequent month is the same as the AUM in the month of the zero-return, if the fund does not report the AUM at all, or if the return in the previous or subsequent period is also zero. Funds that have at least one flagged return are then filtered out of the sample. This filter applies to 51 funds (0.51% of the partially-filtered dataset). Furthermore, if the return and AUM in a certain period are both zero, this return is converted into "missing data".

Filter for Funds with Consecutive Identical Returns

This filter identifies and removes funds that have many consecutive identical returns. For example, suppose a fund has the following time-series of returns: +1.1, +1.1, -2.0, -3.4, -3.4, +0.8. The first, second, fourth, and fifth returns are all flagged. If over 5% of a fund's returns are flagged, then the firm is filtered out from the sample. Almeida et al. (2019) believe that these consecutive identical returns are caused by poor data management. These funds may also incorrectly report other statistics such as AUM and thus it is important to remove these funds from the sample. I filter out a total of 342 funds (3.41% of the partially-filtered dataset).

Filter for Funds with Blocks of Returns

Hedge funds sometimes report consecutive blocks of returns. If, for example, a fund reports certain returns for a period of 4 months, it might also report those exact same returns in the following 4 months as well (such as +2.3, +0.8, -0.5, -1.6, +2.3, +0.8, -0.5, -1.6). I identify if a fund reports consecutive returns in block sizes of 2 to 12 periods. If a fund is found to have at least two different repeated blocks, it is flagged and discarded from the sample. There is no threshold such as 5% or 10% that is used in other filters because, as Almeida et al. point out, the probability of naturally obtaining at least two different repeated blocks of returns is extremely low. This filter identifies and drops 69 funds (0.69% of the partially-filtered dataset).

Filter for Funds that Round Returns

It is impossible to know with certainty whether a hedge fund rounds their returns or not. Almeida et al. propose multiple ways to identify funds that may engage in this type of data manipulation. Rounded returns do not accurately represent naturally-occurring returns and so the funds must be removed from the dataset. I apply three different criteria found in Almeida et al.'s paper and if a fund's returns meet one of these criteria, the fund is flagged and dropped.

The probability that the second-decimal of a return takes the value of a specific number is 10%. The first criterion for the filter is that the distribution of the second-decimal of a fund's returns contains at least 35% of one specific number (for example, if the second-decimal contains the number "5" in 35% or more of the fund's returns). A relatively lenient threshold level is used in this case because some funds with short time series may be incorrectly flagged otherwise. If a fund meets this criterion, it is flagged.

The second criterion is met if the second-decimal of a fund's returns contains at most 5 different numbers. For example, if the second-decimal only contains the numbers 0, 2, 4, 6, 8, this fund is then flagged. The third criterion is the same as the second one, except that the distribution of the first-decimal is considered rather than the distribution of the second-decimal. The three criteria of this filter identify a total of 1,209 funds (12.07% of the partially-filtered dataset) who may possibly round returns.

Filter for Funds that do not Report AUM

Some hedge funds do not report their AUM at all. While this, in itself, is not an issue, it may signal a lack of information transparency. This behaviour may indicate that these funds slightly alter their reported returns. This filter flags all funds that do not report their AUM for any period. Before applying this filter, I change all observations where AUM is equal to zero, to a missing observation (since unless the fund is inactive and does not trade, a value of zero for AUM does not make sense). A total of 1,867 funds (18.63% of the partially-filtered dataset) are discarded using this filter.

Filter for Funds with a Mismatch of Reported and NAV-Implied Returns

A hedge fund's net return should be equivalent to its NAV-implied return, however, there exist funds where this is not the case. This filter serves to identify these funds. Some hedge funds provide rounded estimates for their NAV and thus, a slight inevitable mismatch with the reported returns can be permitted without discarding the fund from the sample. In order to allow for this small divergence, the difference in returns is rounded to the second-decimal before applying this filter.

Hedge funds must meet one of the following two criteria in order to be flagged by this filter. The first criterion is met when more than 5% of a hedge fund's observations have a mismatch in reported returns and NAV-implied returns. The second criterion is met if a fund has at least one observation where the difference in returns is greater than 0.5% (for example +0.24 and +0.87). A total of 104 funds (1.04% of the partially-filtered dataset) were identified by this filter and discarded.

Filter for Mirror Funds

This filter is a very important one to implement as it affects a significant portion of the dataset. Mirror funds are operated by the same management company and provide the same returns as another hedge fund. Essentially, they are copies of other funds. In order to filter out these funds, I must first identify which funds are similar to other funds. The first step of identifying mirror funds is to compute the return correlations of all combinations of pairs of funds that are managed by the same company. Some companies manage only a handful of funds while others manage hundreds of funds. Once the correlations are computed, I identify which pairs of funds have a correlation greater than 99%. Out of these funds, the fund with a greater number of observations is kept while the other is discarded from the dataset. If two funds have the same number of observations, one of these will randomly be discarded. The mirror fund filter removes 1,407 funds (14.04% of the partially-filtered dataset) from the sample.

Table 2.1: Amount of funds dropped by each filter

This table presents the amount and the percentage of funds dropped. The statistics on the first five filters (up until, and including, the backfill bias filter) are based on the original sample of 18,818 funds obtained from Lipper-TASS. The statistics on the remaining filters are based on the partially-filtered sample of 10,019 funds.

Note: The survivorship bias filter does not drop any funds since the removed observations (those prior to 1994) belong to funds that have survived until 1994.

Fund Filters	Funds Dropped	% of Funds Dropped
Net Returns	74	0.39%
Reporting Frequency	77	0.41%
Currency Filter	8388	44.57%
Survivorship Bias	0	0.00%
Backfill Bias	553	2.94%
Zero-Return	51	*0.51%
Consecutive Identical Returns	342	*3.41%
Blocks of Returns	69	*0.69%
Rounded Returns	1209	*12.07%
Funds With No AUM	1867	*18.63%
NAV-Implied Return Mismatch	104	*1.04%
Mirror Funds	1407	*14.04%

* indicates % dropped from the "partially-filtered dataset"

2.2 Overview of Data and Fund Characteristics

An important characteristic to include in any hedge fund analysis is the investment style of the fund or the fund type (used interchangeably throughout this paper). There are 11 styles that I consider: Convertible Arbitrage, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Funds of Funds, Global Macro, Long/Short Equity, Multi-Strategy, and Other. As shown in Table 2.2 and Figure 2.1, the behaviour of returns greatly varies across fund styles: some have higher means than others, some are more volatile, and some respond differently in certain market conditions such as the 2008 financial crisis. Therefore, evaluating fund performance with respect to the fund style is a vital component to include in my analysis. Each hedge fund's investment style is given in the Lipper-TASS dataset.

Researchers have debated on the existence of manager skill within funds and the consensus throughout hedge fund literature is that there indeed is skill, which is captured by the fund alpha. The alpha is not given directly by the Lipper-TASS dataset, and therefore, I must manually construct this measure of skill. By using Fung-Hsieh's 7-factor model (2004) along with the Emerging Markets Index and Pastor-Stambaugh Liquidity Factor (2003), I extract the idiosyncratic component of hedge fund returns by regressing fund raw returns on the 9 factors. Found in this idiosyncratic component is the constant, which is the fund alpha.

Hedge fund age and size are two fund characteristics that go hand-in-hand; as funds get older, they tend to grow. This leads to changes in performance since funds may change their strategies over time. Younger funds are typically thought to employ more aggressive trading strategies in order to establish a reputation within the industry while older funds are thought to be more cautious and preserve capital. The Lipper-TASS database provides the age (in months) and the size (in USD) of each hedge fund. Table 2.3 presents summary statistics for fund age and fund size.

Another characteristic I include in my analysis is the hedge fund historic return. I test if funds that historically perform well also perform well during the crisis. For this measure, I use a fund's average raw returns throughout the entire pre-crisis period. One can assume that hedge funds who generally perform well are more likely to outperform other funds during times of crisis. However, this may not be true; perhaps their strategies are better suited to stable economic periods but harmful during others. The summary statistics for historic returns is presented in Table 2.3 (these statistics are based on the average historic return of each fund, not the returns for each fund-month pair).

The Lipper-TASS database reports a fund's maximum leverage, average leverage, and presence of leverage (dummy variable) for each month. Unfortunately, using the maximum and average leverage in my analysis would cause a problem since both these measures are quite irregular throughout the dataset. Different funds report these differently and thus the actual leverage level of each fund is unknown. Therefore, I opt to use the presence of leverage as this is the most consistent measure of the three.

Hedge fund exposures are an interesting component to include when analyzing performance during the 2008 crisis. Funds with more exposure to liquidity risk and equity market risk are likely to suffer from poorer performance during a crisis than funds with less exposure. Like the fund alpha, these measures are not given directly and must be estimated by regressing fund returns on the Pastor-Stambaugh Liquidity Factor (2003) and the equity market factor (S&P 500 monthly returns). The loadings on these factors determine each fund's exposure to the respective risk.

Managers of funds are typically given incentives in order to encourage good fund performance. These come in the form of management fees, incentive fees, and a high watermark. The management fee is a bonus given for the management of a fund; this is typically 1-2% of the fund's AUM. The incentive fee is a performance-based bonus in which the manager receives a percentage of the fund's profits, usually 20%. The high watermark is the peak value that a fund has reached in a certain timeframe and bonuses to managers can only be given once this level has been passed. This forces managers to recover any previous losses before obtaining a bonus. Another incentive for managers to increase fund performance is whether or not they have their personal wealth invested in the fund. Although this is a more indirect incentive than the other three, it is still an important factor to include since it may cause fund performance to increase. All four of these incentives are reported in the Lipper-TASS dataset for each fund. Summary statistics for the management fees and incentive fees are reported in Table 2.3.

Hedge funds have funding restrictions that make it more difficult for investors to withdraw their money. This is done so that funds face less unexpected withdrawals and have more freedom when trading in the long-term. In times of crisis, investors may panic and decide to withdraw their capital, but through the use of restrictions, hedge funds have more time to mitigate any losses they would have faced had there been no restrictions. The funding restrictions include: the lockup period, the redemption frequency, and the redemption notice period. When an investor invests their capital into the fund, the lockup period prohibits them from withdrawing any capital for a pre-determined amount of time (typically 12 months). Redemption frequency indicates how often an investor can withdraw their capital from the fund (for example, a "quarterly" redemption frequency means that an investor can withdraw their capital once every quarter). If an investor decides to withdraw their capital, they must let the fund know a certain amount of days or months in advance, this is called the redemption notice period. The Lipper-TASS database provides information for all funding restrictions for each fund. Summary statistics for these are presented in Table 2.3.

Some hedge funds specialize and focus in certain areas of the economy. A number of different investment focuses are reported in the Lipper-TASS dataset, however, I opt to only use four that are related to the 2008 financial crisis: mortgage-backed securities (MBS), US real estate, distressed markets, and bankruptcies. The burst of the US housing bubble was a major factor that led to the financial crisis, therefore, including the MBS and US real estate focuses is important in my analysis.

A characteristic I briefly examine is the tendency of funds to engage in systematic or discretionary trading. Systematic trading is automated trading through the use of computer programs and statistical models while discretionary trading is a more inconsistent approach where the trader evaluates whether or not to make a trade based on the information set available to them at the time. The Lipper-TASS database identifies funds that use systematic trading and funds that use discretionary trading.

Table 2.2: Monthly raw returns for each fund style

This table presents performance statistics for each fund style. Reported are the total amount of funds, the mean, standard deviation, minimum value, and maximum value of each fund style's average monthly raw returns. The data is derived from the fully-filtered dataset. The data used for this table spans from January 1994 to June 2009

Investment Style	Total Funds	Mean	St. Dev.	Min.	Max.
Convertible Arbitrage	161	0.53%	3.888	-75.65%	108.39%
Dedicated Short Bias	29	0.18%	7.29	-56.76%	66.01%
Emerging Markets	520	0.70%	7.65	-85.49%	404.94%
Equity Market Neutral	292	0.48%	3.121	-100.00%	37.62%
Event Driven	444	0.72%	3.58	-43.87%	184.17%
Fixed Income Arbitrage	171	0.56%	3.1	-54.51%	50.28%
Fund of Funds	1860	0.36%	5.532	-94.84%	1282.20%
Global Macro	303	0.58%	4.955	-57.69%	137.67%
Long/Short Equity Hedge	1654	0.77%	6.213	-90.15%	953.31%
Multi-Strategy	386	0.56%	4.316	-90.49%	202.02%
Other	290	0.61%	4.775	-90.00%	342.13%

Figure 2.1: Monthly raw returns for each fund style

This figure presents average monthly raw returns for each fund type from January 1994 to June 2009. The dashed vertical line within each graph indicates the beginning of the financial crisis, December 2007. The data is derived from the fully-filtered dataset.

Table 2.3: Summary statistics for various hedge fund characteristics

This table presents summary statistics for different hedge fund characteristics from January 1994 until June 2009. The statistics include: the mean, standard deviation, minimum value, the 1st, 25th, 50th, 75th, and 99th percentiles, and the maximum value. These statistics are calculated based on all the individual observations in the dataset. The data is derived from the fully-filtered dataset.

Note: The minimum value of Size is indicated as "N/A" because the minimum value in the dataset is 1, which is not a realistic value. Therefore, the true smallest fund Size is unknown.

Characteristic	Mean	St. Dev.	Min	1%	25%	50%	75%	99%	Max
Age (in months)	62.44	47.91	0	3	27	49	85	220	475
Size (in millions, USD)	159	486	N/A	0.413	12.4	40.5	128	1900	79000
Historic Return (in %)	0.82	0.958	-10.71	-1.75	0.46	0.76	1.12	4.05	9.14
Management Fee (in %)	1.42	0.57	0	0	1	1.5	2	3	6
Incentive Fee (in %)	15.12	7.73	0	0	10	50	20	25	50
Lockup Period (in days)	3.24	6.68	0	0	0	0	2	24	90
Red. Frequency (in days)	74.30	80.9	0	1	30	30	90	365	1095
Red. Notice Period (in days)	38.66	31.89	0	0	15	30	60	112	365

CHAPTER 3: RESULTS & ANALYSIS

I examine the effects that the 2008 financial crisis had on hedge funds from two perspectives. The first perspective is how the crisis affected fund performance, while the second is how the crisis affected fund survivability. In each case, I examine fund characteristics (such as fund age or size) that are most likely to explain which kind of funds were most affected by the crisis or what characteristics of funds led to lower returns. Although some characteristics slightly differ across the two sections, mostly similar characteristics are used.

When examining how hedge fund characteristics relate to fund performance, I implement two approaches for most characteristics: a non-parametric approach which compares the average monthly returns of groups of funds, and a parametric approach which involves using linear regressions of individual fund raw returns on various characteristics. When analyzing the relationship between hedge fund characteristics and fund survivability, I also implement two different approaches: a non-parametric approach comparing the default rate of groups of funds, and a parametric approach which uses Cox proportional-hazards regressions that indicate if a certain characteristic is associated with increased or decreased fund survivability. When forming conclusions for a certain characteristic and its relationship with fund performance or survival, I consider the results of both the non-parametric and parametric analyses.

When analyzing fund survival, a hedge fund is considered to have defaulted if its last observation is in June 2009 (the final month of the financial crisis) or before. This gives rise to the problem of classifying a fund as "defaulted" even though it may have simply just stopped reporting to the database whilst still continuing its operations. The actual default rate of funds would thus be lower than the default rate calculated. However, this issue should not affect my conclusions since they are based on the relative default rate between groups of funds, not the absolute default rate. An assumption that must be made in this case is that the difference between the actual default rate and computed default rate of one group of funds is the same for another group of funds.

3.1: Effect of the 2008 Financial Crisis on Hedge Fund Performance

3.1.1 Hedge Fund Investment Style

Hedge funds can be classified into different categories based on their investment style. Each style has its own strategy where funds base their investments on different financial instruments and market conditions. For example, event-driven funds invest based on what they think the outcome of certain events (such as acquisitions or bankruptcies) will be, whereas global macro funds analyze macroeconomic trends around the world and tend to invest more in currencies or commodities. Consequently, some hedge fund styles exhibit superior performance than others depending on what the current market conditions are. Up to 20% of the cross-sectional variability of hedge fund performance can be explained by differences in investment style (Brown and Goetzmann, 2001). Global macro style funds are shown to have had superior performance than other styles during the 2008 crisis (Olmo and Sanso-Navarro, 2012). The equity market neutral, funds of funds, multi-strategy, and global macro styles adjust their risk exposures in bad times so that losses would be mitigated (Cao et al., 2015).

For each hedge fund style, I would like to see how those funds performed both before and during the crisis. Certain styles, such as Emerging Markets and Funds of Funds tend to thrive when the outlook on markets is bullish, while others, such as Dedicated Short Bias or Fixed Income Arbitrage, might have an advantage during bad times or times of high volatility. I follow a "portfolio" style approach where the monthly raw and risk-adjusted returns for each style are calculated based on the average return of all the appropriate funds within each month. This methodology allows for an equally-weighted index-like approach when comparing performance across fund styles. To create risk-adjusted returns, I perform a 24-month rolling regression of each fund's returns on Fung-Hsieh's 7 factors along with the Emerging Market Index factor, and the Pastor-Stambaugh Liquidity Factor (2003)). Following this, I add the constant and the residuals for each observation, which results in the risk-adjusted return. This methodology of creating risk-adjusted returns is followed throughout the rest of the paper. As a parametric analysis, I implement a regression approach in which I regress monthly returns during the crisis on dummy variables indicating the various hedge fund investment styles. I repeat this regression after controlling for the equity market (S&P 500 Index), however, this does not significantly alter the results. Since explaining returns using fund characteristics is fairly difficult, we cannot expect a high R^2 from the regressions. This holds true for the fund investment style and all other characteristics tested in this paper.

Panel A of Table 3.1 reports the average monthly raw returns of each hedge fund style. Prior to the crisis, the hedge fund styles with the highest average monthly raw returns are Long/Short Equity (1.17%), Emerging Markets (1.11%), and Multi-Strategy (0.94%). These hedge fund styles tend to implement strategies that work well when markets trend upwards in the long run. The hedge fund styles with the worst pre-crisis performance are the following: Dedicated Short Bias (0.03%), Fixed Income Arbitrage (0.65%), Global Macro and Funds of Funds (0.67%). Evidently, Dedicated Short Bias hedge funds do not perform well since their strategy works best when there is a market downturn. Furthermore, their standard deviation is highest out of all hedge fund styles. Hence, in addition to having the worst performance, they also seem to have the highest risk. When considering risk-adjusted returns (which are reported in Table 3.1 Panel B), Dedicated Short Bias goes from having the worst performance out of all styles, to having the second-best performance. The reason for this is that in relatively stable times (the pre-crisis period), these hedge funds limit their risk exposures since they trade in the opposite direction of the long-run bullish trends.

During the crisis, we see a reversal in which the worst-performing funds prior to the crisis become the funds with the highest raw returns during the crisis: Dedicated Short Bias (1.59%), Global Macro (0.53%), and Fixed Income Arbitrage (-0.20%). Since Dedicated Short Bias hedge funds rely on bearish markets, unsurprisingly this style performs best during the financial crisis, as can be seen in Panel C. Global Macro hedge funds are the only other style that averaged a positive raw return throughout the crisis. These funds tend to invest in foreign currencies or foreign financial instruments, and thus could have limited their exposure to U.S. markets and traded against them. Looking at the worst fund styles, we see that Emerging Markets was hit hardest by the crisis: its average monthly raw return fell from 1.11%, to -1.24% and had the highest standard deviation of all fund styles (5.89). In terms of risk-adjusted returns, we see that Dedicated Short Bias is ranked lowest, whereas previously it was ranked highest. This is as a result of an increased exposure to various risk factors that had bearish movement during the crisis. The risk-adjusted returns of Global Macro funds are second-highest among all styles, supporting the idea that these funds reduced their exposures to U.S. markets and U.S. financial instruments such as mortgage-backed securities. The regression results, reported in Table 3.2, show that the raw monthly returns were significantly impacted by four hedge fund styles: Dedicated Short Bias, Global Macro, Emerging Markets, and Other. The Dedicated Short Bias and Global Macro styles have positive coefficients, whereas the Emerging Markets style has a negative coefficient. These results support those found in the previous analysis. A positive coefficient is also found for Other, however, this category contains a broad set of fund types and therefore we do not know which exact fund types are causing this positive relationship.

Table 3.1: Monthly returns of each hedge fund style

This table presents performance metrics for the 11 types of hedge funds for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, the ranking of each fund type's mean returns, each fund type's share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds corresponding to each fund type during the crisis. The means and standard deviations shown in the table are based on the average returns of each fund type for each month, as opposed to being based on all the returns of all funds (within a fund type) for the whole pre-crisis or crisis period. The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns			
Fund Type	**Mean**	**St. Dev.**	**Ranking**
Convertible Arbitrage	0.70	1.27	7
Dedicated Short Bias	0.03	5.03	11
Emerging Markets	1.11	4.27	2
Equity Market Neutral	0.76	0.81	5
Event Driven	0.94	1.38	4
Fixed Income Arbitrage	0.65	1.20	10
Fund of Funds	0.67	1.56	8
Global Macro	0.67	1.78	9
Long/Short Equity Hedge	1.17	2.59	1
Multi-Strategy	0.94	1.22	3
Other	0.75	1.06	6

Panel B: Pre-Crisis Risk-Adjusted Returns			
Fund Type	**Mean**	**St. Dev.**	**Ranking**
Convertible Arbitrage	0.71	0.84	7
Dedicated Short Bias	1.03	2.10	2
Emerging Markets	1.23	1.37	1
Equity Market Neutral	0.68	0.62	9
Event Driven	0.93	0.62	3
Fixed Income Arbitrage	0.88	0.76	5
Fund of Funds	0.68	0.73	8
Global Macro	0.59	1.00	11
Long/Short Equity Hedge	0.83	0.76	6
Multi-Strategy	0.90	0.61	4
Other	0.65	0.60	10

Panel C: Crisis Raw Returns						
Fund Type	**Mean**	**St. Dev.**	**Ranking**	**Worst 500**	**Best 500**	**Total Funds**
Convertible Arbitrage	-0.76	5.73	9	5.00%	2.00%	58
Dedicated Short Bias	1.59	3.96	1	0.20%	1.20%	12
Emerging Markets	-1.24	5.89	11	27.80%	27.40%	303
Equity Market Neutral	-0.30	1.60	4	1.40%	1.20%	130
Event Driven	-0.69	3.01	8	3.60%	3.40%	221
Fixed Income Arbitrage	-0.20	2.77	3	2.60%	1.60%	68
Fund of Funds	-0.82	2.62	10	11.60%	6.20%	1217
Global Macro	0.53	1.66	2	1.40%	4.60%	125
Long/Short Equity Hedge	-0.67	3.89	7	34.20%	41.40%	839
Multi-Strategy	-0.33	2.43	6	6.20%	4.60%	271
Other	-0.32	2.45	5	6.00%	6.40%	160

Panel D: Crisis Risk-Adjusted Returns						
Fund Type	**Mean**	**St. Dev.**	**Ranking**	**Worst 500**	**Best 500**	**Total Funds**
Convertible Arbitrage	0.12	1.17	9	2.20%	2.00%	58
Dedicated Short Bias	-0.02	0.95	11	0.00%	0.00%	12
Emerging Markets	0.36	0.83	4	21.20%	22.60%	303
Equity Market Neutral	0.13	0.77	8	4.20%	1.00%	130
Event Driven	0.27	0.52	7	3.60%	2.40%	221
Fixed Income Arbitrage	0.32	0.64	6	3.00%	2.40%	68
Fund of Funds	0.03	0.72	10	11.40%	10.00%	1217
Global Macro	0.60	0.64	2	3.80%	6.40%	125
Long/Short Equity Hedge	0.37	0.47	3	36.40%	36.00%	839
Multi-Strategy	0.33	0.60	5	6.60%	9.40%	271
Other	0.69	0.76	1	7.60%	7.80%	160

Table 3.2: Regression results of fund performance on fund investment style during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on dummy variables indicating the fund investment style. The regressions are performed using data from December 2007 to June 2009. The second model controls for the equity market movement by using monthly S&P 500 returns. Robust t-statistics are reported in parentheses.

Variables	Model 1	Model 2
Convertible Arbitrage	-0.456	-0.429
	(-1.197)	(-1.201)
Dedicated Short Bias	2.349***	2.427***
	(-4.39)	(-3.911)
Emerging Markets	-0.702***	-0.695***
	(-2.791)	(-2.935)
Equity Market Neutral	0.305	0.332
	(-1.202)	(-1.328)
Event Driven	-0.169	-0.147
	(-0.747)	(-0.686)
Fixed Income Arbitrage	0.221	0.298
	(-0.771)	(-1.086)
Funds of Funds	-0.318	-0.277
	(-1.432)	(-1.298)
Global Macro	1.104***	1.115***
	(-4.5)	(-4.649)
Long/Short Equity Hedge	-0.125	-0.125
	(-0.570)	(-0.599)
Managed Futures	0.236	0.226
	(-0.988)	(-0.984)
Other	0.548**	0.519**
	(-2.104)	(-2.061)
Equity Market Factor		0.332***
		(-48.54)
Constant	-0.589***	0.166
	(-2.820)	(-0.833)
Observations	51,350	51,350
Number of Funds	3,387	3,387
R^2	0.00218	0.0689

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.1.2 Hedge Fund Alpha

There is an abundance of research papers that focuses on determining if hedge fund managers are "skilled" or if their returns are just "luck". While some researchers implement an alternative approach to identify skill, most papers focus on estimating a hedge fund's alpha, which is widely regarded as a measure of skill. Proposed by Fund and Hsieh (2004), this approach consists of regressing fund returns on a set of risk factors to estimate the alpha. The idea behind this multifactor approach is to eliminate as much of the systemic portion of the returns as possible. This leaves behind the idiosyncratic component of the returns, which is composed of the alpha (the constant) and the residuals.

I examine the effect that the 2008 financial crisis had on funds that previously exhibited high alpha versus funds that previously exhibited low alpha. I hypothesize that funds with higher alphas (indicating higher skill) are able to outperform funds with lower alphas (indicating lower skill). To estimate each fund's alpha, I use the multifactor approach proposed by Fung-Hsieh (2004). First, I take a fund's raw returns and regress them on 9 factors (Fung-Hsieh 7 factors, Emerging Market Index factor, and Pastor-Stambaugh Liquidity factor). This is performed at a 24-month rolling interval from the fund's first reported return until November 2007 (the month prior to the start of the financial crisis). This yields, for each 24-month period, the factor loadings, the constant (which is in fact the alpha, or skill, of the 24-month period), and the residuals. This results in many different alphas that pertain to various 24-month periods of a fund's return history. Each of these alphas indicates the skill of a fund within that 24-month period, but not of the whole history of a fund. Therefore, I calculate the average of the alphas in order to obtain the "historic alpha" of a fund (can also be considered a measure of the overall skill). This process is done for every fund in the dataset. The hedge funds are then sorted into five equal quintiles based on their "historic alpha". Each of these quintiles is regarded as a "portfolio" of hedge funds and my analysis is based on the return of each portfolio rather than the returns of each individual hedge fund within the portfolio. I also implement a linear regression in which I regress raw monthly returns onto the average alpha of each fund throughout the crisis. The average alpha, which is the same one computed for the portfolios, is held constant throughout the crisis period.

The methodology for estimating fund alphas is similar to the methodology I use for estimating risk-adjusted returns: the same 9 factors are used over a 24-month rolling interval, and the risk-adjusted returns are found by adding together the constant and residuals while the fund alpha is given directly by the constant. This would cause an endogeneity issue and therefore, I deviate from this methodology of calculating risk-adjusted returns and do the following: I regress a fund's returns on 9 factors (the factors do not change) using only returns from the crisis period (December 2007 to June 2009), and then I add the constant and residuals for each month in order to obtain the risk-adjusted return of the fund for each month. This regression acts as one lone “19-month window” and eliminates the issue of endogeneity because the crisis risk-adjusted returns are not mechanically related to the alphas upon which the funds were sorted on.

Prior to the crisis, the raw return of hedge funds increased monotonically with manager alpha (Table 3.3 Panel A). The portfolio which contains funds with the lowest alpha had an average return of 0.90% per month while the portfolio of the highest-alpha funds realized an average return of 1.59%. The standard deviations of these two portfolios are 3.41 and 2.60, respectively. However, the standard deviation does not move monotonically, instead, it is U-shaped: the middle three quintiles all have standard deviations no higher than 1.66. This may suggest that the funds with “highly skilled” managers obtain their returns as a result of undertaking more risk.

During the 2008 financial crisis, we observe in Panel B that the managers with high alpha were hit hardest by the crisis: their average monthly return dropped to -0.86% (the lowest return of all 5 portfolios, whereas they previously held the highest return) and their standard deviation increased to 4.96 (the highest out of all portfolios). Furthermore, we observe a general negative pattern between alpha and performance, although this is hindered by Portfolio 4 which causes a break in the pattern. The crisis risk-adjusted returns in Panel C do not show any clear pattern, however, the funds with the largest alphas have the highest risk-adjusted returns. This suggests that these funds are better able to hedge their clients during times of crises. The regression results, presented in Table 3.4, suggest that higher average alpha during the pre-crisis period led to inferior performance during the crisis. However, once controls are added, this relationship is not present. The failure to find a strong significance in the regression results may be as a result of the funds found in Portfolio 4. My findings suggest that if managers show a high level of skill during stable economic conditions, this skill may not translate into volatile economic crises. The strategies of high-skilled managers may only be viable when markets are relatively stable and when there is less economic uncertainty. My findings are conceptually similar to the findings of Andrikopoulos and Stafylas (2020): they find that hedge funds only deliver positive and significant alpha during good economic periods but do not deliver significant alpha when market conditions are bad and volatile. Combined together, our results imply that hedge fund managers exhibit skill when the global economic conditions are good, however, when the economic conditions are bad, the manager’s skill becomes irrelevant in producing superior returns and is even slightly related to inferior performance.

Table 3.3: Monthly returns of each portfolio of hedge funds, sorted from lowest to highest alpha

This table presents performance metrics for different portfolios of hedge funds for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each portfolio's share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each portfolio. The portfolios are constructed based on each fund's alpha. Portfolio 1 contains funds with the lowest alpha while Portfolio 5 contains funds with the highest alpha. Each fund's alpha is estimated by first regressing monthly raw returns on 9 factors at a 24-month rolling interval, and then computing the average of the constants obtained from these regressions. For each fund, these regressions are performed from their first available observation until November 2007. The means and standard deviations shown in the table are based on the average returns of each portfolio for each month, as opposed to being based on all the returns of all funds (within a portfolio) for the whole pre-crisis or crisis period. The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns		
Portfolio	**Mean**	**St. Dev**
P1	0.90	3.41
P2	0.71	1.38
P3	0.92	1.66
P4	1.05	1.54
P5	1.59	2.60

Panel B: Crisis Raw Returns					
Portfolio	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
P1	-0.61	2.48	13.60%	15.40%	160
P2	-0.60	2.21	7.00%	8.40%	159
P3	-0.71	2.74	13.20%	11.40%	161
P4	-0.51	2.91	18.80%	18.60%	161
P5	-0.86	4.96	47.40%	46.20%	161

Panel C: Crisis Risk-Adjusted Returns					
Portfolio	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
P1	0.01	0.82	15.80%	17.20%	160
P2	-0.11	0.66	6.80%	8.00%	159
P3	-0.01	0.78	10.40%	11.40%	161
P4	0.06	0.81	16.20%	15.00%	161
P5	0.22	0.81	50.80%	48.40%	161

Table 3.4: Regression results of fund performance on fund alpha during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on its alpha. The regressions are performed using data from December 2007 to June 2009. Each fund's alpha is estimated by first regressing monthly raw returns on 9 factors at a 24-month rolling interval, and then computing the average of the constants obtained from these regressions (this is performed from each fund's first available observation until November 2007). The alpha is held constant throughout the crisis period. The performance-alpha regressions are performed using data from December 2007 to June 2009. The second model controls for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2
Hedge Fund Alpha	-0.211*	-0.173
	(-1.816)	(-1.530)
Equity Market Factor		0.328***
		(-32.37)
Constant	-0.543***	-0.0678
	(-6.758)	(-0.186)
Observations	14,495	14,495
Number of funds	802	802
Fund Type FE	No	Yes
R^2	0.001	0.124

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.1.3 Hedge Fund Age

The age of hedge funds has been shown to be inversely related with fund performance (Howell (2001), Jones (2007), Mozes & Steffens (2016)). Younger funds tend to perform better in order to establish a good reputation within the hedge fund industry which would attract more investors and increase their assets under management (Aggarwhal & Jorion, 2010). However, at a certain age, this superior performance ceases to exist. Therefore, we may find that only the youngest of funds provide superior returns.

I test to see if there is evidence that these findings still hold throughout the 2008 crisis. Although the youngest of funds tend to provide higher returns than older funds, I hypothesize that the strong negative impact of the financial crisis might have been too difficult for young funds to manage, which would eliminate the return disparity between the youngest funds and the older funds. The reason for this is that older funds have gone through more economic downturns and therefore, have more experience in investing during volatile economic conditions. They may also have more stable funding and are, thus, more resilient. I implement the "portfolio" approach as I have done previously. I split the funds into portfolios according to their age (in months) on the month prior to the start of the crisis. Funds that enter the database during the crisis are not included in this analysis. As another test, I regress monthly raw returns during the crisis on the log-age of each fund. Since the age of a fund tends to be correlated with the size of the fund, I include fund size as a control variable in some of my regression models.

Prior to the crisis, Table 3.5 Panel A shows that the average performance of the youngest portfolio of hedge funds was highest among all portfolios (1.29% per month). However, this is closely followed by the fourth-youngest portfolio, at 1.24%. Although the raw returns do not indicate large outperformance by the portfolio with the youngest funds, the risk-adjusted returns do: the youngest portfolio generates a 1.33% monthly average risk-adjusted return which is much higher than the remaining four portfolios (0.42% higher than the second-highest).

During the crisis, both the average raw returns and the average risk-adjusted returns of the youngest funds are higher than those of older funds. Furthermore, out of the 500 highest return observations generated by funds during the crisis, the youngest portfolio of funds makes up 29.40% of those observations. Additionally, they contributed to 26.80% of the 500 lowest return observations. This highlights young funds' tendency to implement aggressive trading strategies in order to quickly establish a good reputation and attract more investors.

When looking at the regression results in Table 3.6, we see that the coefficient of the log-age is significant and negative in the first two models. This supports the findings of the non-parametric analysis. However, Models 3 and 4 show a different result: when controlling for fund size, the age of a fund does not have a significant negative relationship with performance. In fact, the results in Model 3 contradict those of the previous two models: fund age has a positive relation to fund performance. When adding more controls (the equity market and the fund investment style), there is no significant relationship found between age and performance (shown in Model 4).

The non-parametric analysis shows that both during the crisis and before it, fund performance is only related to fund age up to a certain point. Only the youngest portfolio of hedge funds consistently provides the highest raw returns and risk-adjusted returns. Once a fund reaches a certain age, this superior performance related to age decreases and is not as strong. The regression results are mixed: without controlling for size, the age of a fund is shown to be negatively related to performance, however, when controlling for size, this relationship is not found. The results of the non-parametric and parametric analyses show that even though fund age is negatively related to fund performance, this relationship is formed as a result of other factors, not the age itself. Therefore, although we can say younger funds perform better, we cannot say that age is the driver of this superior performance. Moreover, fund age can be considered as a proxy for fund experience; my results show that experience did not cause funds to exhibit superior or inferior performance during the crisis.

Table 3.5: Monthly returns of each portfolio of hedge funds, sorted from youngest to oldest

This table presents performance metrics for different portfolios of hedge funds for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each portfolio's share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each portfolio during the crisis. The portfolios are constructed based on the age of funds on November 2007. Portfolio 1 contains the youngest funds while Portfolio 5 contains the oldest funds. The means and standard deviations shown in the table are based on the average returns of each portfolio for each month, as opposed to being based on all the returns of all funds (within a portfolio) for the whole pre-crisis or crisis period. The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns		
Portfolio	**Mean**	**St. Dev**
P1	1.29	1.59
P2	1.09	1.36
P3	0.97	1.06
P4	1.24	1.54
P5	0.99	1.73

Panel B: Pre-Crisis Risk-Adjusted Returns		
Portfolio	**Mean**	**St. Dev**
P1	1.33	0.51
P2	0.78	0.41
P3	0.68	0.57
P4	0.82	0.81
P5	0.91	0.67

Panel C: Crisis Raw Returns					
Portfolio	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
P1	-0.54	3.26	26.80%	29.40%	598
P2	-0.66	2.83	17.00%	16.40%	543
P3	-0.74	2.92	16.60%	18.40%	588
P4	-0.74	3.08	17.60%	15.60%	568
P5	-0.68	3.56	22.00%	20.20%	561

Panel D: Crisis Risk-Adjusted Returns					
Portfolio	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
P1	0.41	0.60	28.40%	33.40%	598
P2	0.29	0.55	18.60%	23.00%	543
P3	0.14	0.55	16.40%	13.80%	588
P4	0.18	0.55	17.60%	14.80%	568
P5	0.17	0.64	19.00%	15.00%	561

Table 3.6: Regression results of fund performance on the age of hedge funds during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on its age (in months). A log transformation is applied on the age variable prior to the regression. The regressions are performed using data from December 2007 to June 2009. The second and fourth models control for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. The third and fourth models control for fund size (the AUM, on which a log transformation is applied) Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2	Model 3	Model 4
Age (log)	-0.0880*	-0.0931**	0.221**	0.113
	(-1.942)	(-2.132)	(-2.121)	(-1.107)
Size (log)			-0.0466*	-0.0468*
			(-1.816)	(-1.801)
Equity Market Factor		0.332***		0.362***
		(-48.68)		(-35.52)
Constant	-0.360*	0.542	-0.938**	0.681
	(-2.124)	(-2.06)	(-2.038)	(-1.359)
Observations	51,350	51,350	32,562	32,562
Number of funds	3,387	3,387	2,092	2,092
Fund Type FE	No	Yes	No	Yes
R^2	0.00001	0.069	0.00019	0.0601

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.1.4 Hedge Fund Size

Similarly to age, the size of hedge funds tends to be negatively correlated with fund performance. As hedge funds get larger, the phenomenon of "diseconomies of scale" comes into effect. One of the reasons this occurs is because as funds get larger, they cannot only select their top investment opportunities, they must also select their second-best or third-best opportunities (Jones 2007). However, this relationship between size and performance does not always hold and can at times be positive (Ammann and Moerth, 2005). Although evidence regarding the negative relation is mixed, there is still support for this found during times of crisis (Clare et al., 2015).

I examine if the inverse relationship between hedge fund size and fund performance is still present during the 2008 financial crisis. In terms of survivability, I believe that larger funds are better equipped to withstand the crisis because of their larger capital reserves, thus allowing them to survive longer. However, this section focuses purely on performance (rather than survivability) and we may indeed find that, just like Clare et al.'s findings, the size of a hedge fund is negatively related to its returns. Once again, I use the portfolio approach to split the funds into portfolios based on their average AUM of the 12 months prior to the start of the crisis. A regression of fund monthly raw returns during the crisis on fund log-size is implemented as well.

The pre-crisis average returns should not be considered since, for instance, funds within the portfolio of "largest" funds may previously have been considered "small" funds, yet they are still part of the largest portfolio. Therefore, the pre-crisis average returns of a portfolio may include funds that should not be a part of that portfolio.

The performance of hedge funds during the crisis (reported in Table 3.7) moves monotonically with respect to size: the portfolio with the smallest funds generates a monthly return of -0.58% while the portfolio with the largest funds generates a return of -0.87%. When risk-adjusted returns are considered, there is no clear increasing or decreasing pattern. However, the two portfolios with the smallest funds outperform the two portfolios with the largest funds, hence providing more evidence that smaller funds outperform larger funds. The results found here support those of Clare et al.: the average performance of hedge funds during the crisis is inversely related to the size of hedge funds.

However, when looking at the Worst 500 observations, we mostly find observations of smaller funds. Therefore, we can say that although the largest funds have, on average, worse performance, they offer a certain degree of protection to their investors. This will further be explored when analyzing the survivability of hedge funds in relation to their size. When examining the regression results in Table 3.8, we only find a negative significant relationship when controlling for the equity market factor and fund investment style. The failure to find strong significance may be because size is only a handicap for the largest of funds. Therefore, the non-linear size-performance relationship cannot adequately be captured by a linear regression.

There are a multitude of reasons as to why this negative relationship between fund size and performance can be observed. One of the main drivers of this is the presence of capacity constraints: as a fund becomes larger, its main investment strategy may not be scalable therefore resulting in the investment of “worse” strategies. To remedy this issue and increase performance, some hedge fund families opt to open up new hedge funds when their largest fund increases in size too much (Chakravarty and Deb, 2013). Another possible explanation is related to agency costs between the manager and the investors. Some hedge fund managers receive a management fee which is tied to the size of the fund; the larger the fund is, the greater the bonus a manager receives. This may cause managers to focus more on the growth of the fund (for instance, by attracting new investors) rather than maximizing return on investment.

Table 3.7: Monthly returns of each portfolio of hedge funds, sorted from smallest to largest

This table presents performance metrics for different portfolios of hedge funds for the crisis period. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each portfolio's share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each portfolio. The portfolios are constructed based on the average AUM of each hedge funds from December 2006 to November 2007 (the 12 months prior to the start of the crisis). Portfolio 1 contains the smallest funds while Portfolio 5 contains the largest funds. The means and standard deviations shown in the table are based on the average returns of each portfolio for each month, as opposed to being based on all the returns of all funds (within a portfolio) for the whole crisis period. The crisis period ranges from December 2007 to June 2009.

Panel A: Crisis Raw Returns					
Portfolio	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
P1	-0.58	3.11	23.20%	28.60%	420
P2	-0.66	4.15	26.20%	24.40%	419
P3	-0.65	3.35	19.80%	22.20%	419
P4	-0.67	2.85	13.00%	10.80%	419
P5	-0.87	3.18	17.80%	14.00%	419

Panel B: Crisis Risk-Adjusted Returns					
Portfolio	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
P1	0.21	0.54	28.80%	29.60%	420
P2	0.27	0.63	23.20%	22.60%	419
P3	0.29	0.50	16.40%	23.40%	419
P4	0.20	0.55	14.40%	10.80%	419
P5	0.11	0.63	17.20%	13.60%	419

Table 3.8: Regression results of fund performance on the size of hedge funds during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on its size (the AUM of a fund). A log transformation is applied on the size variable prior to the regression. The regressions are performed using data from December 2007 to June 2009. The second model controls for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2
Size (log)	-0.0328	-0.0397*
	(-1.419)	(-1.286)
Equity Market Factor		0.362***
		(-35.19)
Constant	-0.228	1.054**
	(-0.516)	(-2.236)
Observations	32,562	32,562
Number of funds	3,081	3,081
Fund Type FE	No	Yes
R^2	0.00003	0.06

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.1.5 Hedge Fund Historic Return

Another test I perform is whether funds with historically large returns also exhibit relatively large returns during the crisis. A similar hypothesis as with the alpha characteristic, I believe that funds with superior pre-crisis returns also provide superior returns during the crisis. The reason for that is because if a fund can continuously earn large returns throughout market conditions which constantly change from stable to volatile, the fund will, on average, also be able to realize large returns during the 2008 crisis. To perform this test, I split the hedge funds into five portfolios on the basis of their average monthly raw returns from the entire pre-crisis period. This is meant to separate funds that consistently do relatively well from those that consistently do relatively poorly. I also perform a regression similar to the one I did for hedge fund alpha: I regress raw monthly crisis returns on the average pre-crisis returns for each fund (which is held constant for each fund). Results for the portfolio analysis are presented in Table 3.9 and results for the regression analysis are presented in Table 3.10.

Naturally, the pre-crisis average raw returns of the portfolios move monotonically (since the portfolios were sorted on this basis). It is important to note that as the returns of the portfolios increase, so do their standard deviations. This suggests that funds with greater returns tend to adopt riskier investment strategies than funds with lower returns. When taking into account the pre-crisis mean of risk-adjusted returns, the same monotonic behaviour is observed.

During the crisis, the raw returns exhibit the opposite pattern: as the historic fund performance increases, the average raw return during the crisis decreases. However, this decrease in crisis returns is followed by an increase in standard deviation, suggesting that the funds with large historic returns implement risky strategies in both the pre-crisis period and crisis period. Another important observation is that out of both the top and bottom 500 monthly return observations (the extreme outliers), the portfolio with the greatest pre-crisis performance consists of over 60% of these observations, further supporting the idea that funds within this portfolio implement riskier strategies. When considering risk-adjusted returns during the crisis, we observe the same increasing and monotonic patterns for both mean returns and standard deviation as we did in the pre-crisis period. The regression results support those found in the portfolio analysis: there is a significant negative relationship between historical fund performance and fund performance during the crisis.

The results suggest that funds who tend to generate large raw returns prior to the crisis do not necessarily generate large returns during the crisis. In fact, both the portfolio and regression approaches suggest that the crisis and pre-crisis raw returns are inversely related. Additionally, the standard deviation of raw returns increases with respect to the mean of raw returns. In conclusion, the findings show that the high pre-crisis raw returns are generated as a result of riskier strategies, which could prove to be beneficial in the long-run and throughout changing market conditions, but are harmful during the 2008 crisis.

Table 3.9: Monthly returns of each portfolio of hedge funds, sorted from lowest historic returns to highest historic returns

This table presents performance metrics for different portfolios of hedge funds for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each portfolio's share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each portfolio. The portfolios are constructed based on average monthly returns of each fund from their first observation (since January 1994) until November 2007. Only funds with at least 12 observations are included in this analysis. Portfolio 1 contains funds with the lowest historic returns while Portfolio 5 contains funds with the highest historic returns. The means and standard deviations shown in the table are based on the average returns of each portfolio for each month, as opposed to being based on all the returns of all funds (within a portfolio) for the whole pre-crisis or crisis period. The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns

Portfolio	Mean	St. Dev
P1	0.39	1.15
P2	0.69	1.12
P3	0.87	1.39
P4	1.18	1.90
P5	1.91	3.50

Panel B: Pre-Crisis Risk-Adjusted Returns

Portfolio	Mean	St. Dev
P1	0.48	0.60
P2	0.70	0.59
P3	0.79	0.58
P4	1.01	0.72
P5	1.74	1.25

Panel C: Crisis Raw Returns

Portfolio	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	-0.53	1.92	8.80%	10.20%	504
P2	-0.70	2.21	6.80%	6.00%	504
P3	-0.72	2.54	7.40%	7.60%	504
P4	-0.80	3.04	16.20%	13.20%	504
P5	-0.85	5.78	60.80%	63.00%	503

Panel D: Crisis Risk-Adjusted Returns

Portfolio	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0.11	0.47	11.40%	10.80%	504
P2	0.10	0.56	8.40%	8.40%	504
P3	0.10	0.54	9.00%	6.60%	504
P4	0.21	0.56	12.20%	10.60%	504
P5	0.47	0.79	59.00%	63.60%	503

Table 3.10: Regression results of fund performance on fund historic return during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on its historical performance. The regressions are performed using data from December 2007 to June 2009. Each fund's historic return is computed by taking the average of all a fund's pre-crisis returns, starting from its first observation and ending on November 2007. The historic return is then held constant throughout the crisis period. The regressions are performed using data from December 2007 to June 2009. The second model controls for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2
Historical Return	-0.205***	-0.151*
	(-2.752)	(-1.779)
Equity Market Factor		0.344***
		(-40.72)
Constant	-0.596***	0.382*
	(-8.394)	(-1.788)
Observations	40,320	40,320
Number of funds	2,519	2,519
Fund Type FE	No	Yes
R^2	0.000347	0.064

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.1.6 Hedge Fund Leverage

Hedge funds implement risky trading techniques that can lead to large losses or large gains. By using leverage, funds are able to increase their gains even more, however, they face the risk of margin calls and significant losses. Funds must be wary when using leverage, especially during volatile times. Studies have shown that during the 2008 financial crisis, hedge funds reduced their leverage significantly (Ang et al., 2011; Zhao et al., 2018).

I examine if funds that use leverage perform better during the crisis than those that do not. Since funds are shown to reduce their leverage during the crisis, one can postulate that the funds that do use some leverage, believe that they have spotted good investment opportunities. Thus, these funds' confidence can be taken as an indicator of better future performance than that of funds with no leverage. To test this hypothesis, I implement both a parametric approach and non-parametric approach. First, I compare the average monthly raw returns and risk-adjusted returns of all leveraged funds to all non-leverage funds. Next, I run a regression of monthly raw returns during the crisis on leverage (a dummy variable indicating if a fund is leveraged or not).

We see in Table 3.11 that prior to the crisis, raw returns and risk-adjusted returns of leveraged and non-leveraged funds are quite similar, with not more than a 0.03% difference. However, during the crisis, there is a noticeable difference: leveraged funds have a higher average return than non-leveraged funds (-0.62% compared to -0.82%). The standard deviation of leveraged funds (10.48) is substantially higher than that of non-leveraged funds (5.90), supporting the theory that leveraged funds observe larger gains and larger losses. For risk-adjusted returns, the findings are the same: leveraged funds exhibit superior performance and a larger standard deviation. The regression results (reported in Table 3.12) paint a similar picture: leverage is positively and significantly related to raw returns during the crisis. Although this significance is lost when controlling for the equity market and fund investment style, the general regression results support those found in the portfolios. Both the parametric and non-parametric analyses show that leveraged funds produced better performance, on average, than non-leveraged funds. This supports the idea that perhaps leveraged funds had, on average, spotted better investment opportunities during the 2008 financial crisis than non-leveraged funds, which can be seen as an indicator of skill. The superior performance of leveraged funds is contrary to what we may expect, since leverage can cause large losses, especially during a financial crisis.

Table 3.11: Monthly returns of non-leveraged hedge funds and leveraged hedge funds

This table presents performance metrics for leveraged and non-leveraged hedge funds for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each group of funds' share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each group. The means and standard deviations shown in the table are based on all the returns of all funds (within each group) for the whole pre-crisis and crisis period, as opposed to being based on the average return for each month of each group of funds (the portfolio approach). The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns		
Leverage	**Mean**	**St. Dev**
Not Leveraged	0.86	3.97
Leveraged	0.89	4.81

Panel B: Pre-Crisis Risk-Adjusted Returns		
Leverage	**Mean**	**St. Dev**
Not Leveraged	0.70	2.59
Leveraged	0.73	3.28

Panel C: Crisis Raw Returns					
Leverage	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
Not Leveraged	-0.82	5.90	40.80%	35.00%	1642
Leveraged	-0.62	10.48	59.20%	65.00%	1762

Panel D: Crisis Risk-Adjusted Returns					
Leverage	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
Not Leveraged	0.19	2.96	41%	35%	1642
Leveraged	0.32	4.79	59%	65%	1762

Table 3.12: Regression results of fund performance on the presence of fund leverage during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on a dummy variable indicating whether or not the fund is levered. The regressions are performed using data from December 2007 to June 2009. The second model controls for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2
Leverage (Dummy)	0.204***	0.125
	(-2.746)	(-1.445)
Equity Market Factor		0.332***
		(-48.52)
Constant	-0.820***	0.13
	(-22.17)	(-0.647)
Observations	51,350	51,350
Number of funds	3,387	3,387
Fund Type FE	No	Yes
R^2	0.000143	0.0689

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.1.7 Hedge Fund Liquidity Risk Exposure

Investigating the relationship between a hedge fund's exposure to liquidity risk and its returns is a crucial component to include when analyzing hedge fund performance during the 2008 crisis. Brunnermeier (2009) offers insight into the various mechanisms that caused this to become a liquidity crisis. One explanation he proposes is that as asset prices drop, funds' capital also diminishes and lending comes with stricter terms. These effects lead to fire-sales which further decrease asset prices and tighten funding. As a result, markets dry up and less transactions occur. Hedge funds with more exposure to this liquidity risk may have exhibited different performance than funds with less exposure.

Hedge funds have been shown to provide an illiquidity premium on their returns. In his paper, Sadka (2010) has shown that funds with significant exposure to liquidity risk outperform funds with low exposure by approximately 6% per year (from 1994 to 2008). Furthermore, his results have shown that the high-loading portfolio outperforms the low-loading portfolio during non-crisis periods but underperforms during crisis periods. Since Sadka uses a different measure of liquidity risk than I do, it is worth examining whether my results support his results during the crisis.

In my study, I use the Pastor-Stambaugh (2003) liquidity factor when measuring risk exposure of hedge funds to liquidity risk. I perform a 24-month rolling regression of monthly raw returns on the equity market factor and the liquidity factor. I proceed with the portfolio approach and sort the hedge funds into five portfolios based on their last observed liquidity factor loading prior to the start of the crisis. Similarly to the analysis of fund size, I do not report the pre-crisis returns since some funds may have had different exposures in the past, therefore they would not belong in their current portfolios. Furthermore, I apply a linear regression in which the raw returns of each fund are regressed on the final liquidity factor loading prior to the crisis (this is the same one used in the portfolio approach).

The results for crisis raw returns (shown in Table 3.13 Panel A) do not show a clear increasing or decreasing pattern. Both the mean returns and the standard deviations are U-shaped: the first and fourth, and fifth portfolios have the worst performance and the highest volatility, while the middle portfolios perform the best, and with less risk. During the financial crisis, the risk-adjusted returns (Panel B) of the first portfolio (0.49%) are, on average, larger than that of all the other portfolios (ranging from 0.16% to 0.19%). However, these results may be faced with an endogeneity problem. Since the liquidity factor is used in estimating both the risk-adjusted returns and funds' exposure to liquidity risk (on which the portfolios are sorted on), the portfolios and their risk-adjusted returns may be mechanically correlated to each other. Therefore, I once again perform this test, however, when estimating risk-adjusted returns, I do not include the liquidity factor. This eliminates the issue of endogeneity. The results of this alternate risk-adjusted returns test (presented in Table 3.13 Panel C) show that the first and fifth portfolios exhibited the best performance (0.42 and 0.30, respectively), while the middle three portfolios underperformed. These results exhibit a U-shaped pattern, just like the ones for raw returns (Panel A), although the best-performing portfolios have now become the worst-performing portfolios and vice versa. It is difficult to identify a clear relationship between liquidity risk exposure and fund performance since there is no clear monotonic pattern. However, we can observe that funds with lower exposure (the first and second portfolios) tend to perform better than funds with high exposure (the fourth and fifth portfolios), and therefore, a negative non-linear relationship is found.

The regression results (presented in Table 3.14) show no evidence for a relationship between fund liquidity exposure and performance during the crisis. This holds regardless of whether or not controls are added to the model. The non-linear nature of fund performance (as shown in the portfolio analysis) might be the reason as to why the regression results do not show a significant effect. The overall results of my tests show that there is a negative non-linear relationship between fund performance and exposure to liquidity risk, and that investors would have been better off during the crisis by investing in hedge funds with low exposure rather than high exposure.

Table 3.13: Monthly returns of each portfolio of hedge funds, sorted from lowest to highest exposure to liquidity risk

This table presents performance metrics for different portfolios of hedge funds for the crisis period. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each portfolio's share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each portfolio. The portfolios are constructed based on each fund's liquidity risk exposure on November 2007. Portfolio 1 contains funds with the lowest exposure while Portfolio 5 contains funds with the highest exposure. Each fund's liquidity risk exposure is estimated by regressing monthly raw returns on the equity market factor (S&P 500) and the Pastor-Stambaugh liquidity factor (2003) at a 24-month rolling interval. The loading on the liquidity factor is then considered to be the fund's exposure to liquidity risk. For each fund, these regressions are performed from their first available observation until November 2007. The means and standard deviations shown in the table are based on the average returns of each portfolio for each month, as opposed to being based on all the returns of all funds (within a portfolio) for the whole crisis period. The crisis period ranges from December 2007 to June 2009.

Panel A: Crisis Raw Returns

Portfolio	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	-0.72	3.57	30.80%	31.80%	622
P2	-0.56	2.58	12.80%	12.80%	622
P3	-0.39	2.70	10.40%	8.80%	622
P4	-0.76	2.82	15.20%	14.60%	622
P5	-0.76	3.87	30.80%	32.00%	621

Panel B: Crisis Risk-Adjusted Returns

Portfolio	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0.49	0.62	33.00%	38.40%	579
P2	0.18	0.54	9.00%	9.00%	579
P3	0.17	0.46	10.00%	7.80%	578
P4	0.16	0.55	15.00%	11.80%	579
P5	0.19	0.61	33.00%	33.00%	578

Panel C: Crisis Risk-Adjusted Returns (Alternate Test)

Portfolio	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0.42	0.58	31.20%	34.60%	579
P2	0.15	0.58	11.80%	9.40%	579
P3	0.15	0.51	8.20%	5.00%	578
P4	0.18	0.52	14.00%	12.00%	579
P5	0.30	0.59	34.80%	39.00%	578

Table 3.14: Regression results of fund performance on fund exposure to liquidity risk during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on its exposure to liquidity risk. The regressions are performed using data from December 2007 to June 2009. Each fund's liquidity risk exposure is estimated by regressing monthly raw returns on the equity market factor (S&P 500) and the Pastor-Stambaugh liquidity factor (2003) at a 24-month rolling interval. The loading on the liquidity factor is then considered to be the fund's exposure to liquidity risk. For each fund, these regressions are performed from their first available observation until November 2007. The final liquidity risk exposure (November 2007) is then held constant throughout the crisis period. The regressions presented in this table are performed using data from December 2007 to June 2009. The second model controls for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2
Liquidity Risk Exposure	-0.0691	-0.0719
	(-1.379)	(-1.529)
Equity Market Factor		0.338***
		(-45.89)
Constant	-0.752***	0.102
	(-18.84)	(-0.427)
Observations	47,450	47,450
Number of funds	2,893	2,893
Fund Type FE	No	Yes
R^2	0.000045	0.0681

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.1.8 Hedge Fund Equity Market Exposure

I test whether hedge funds' exposure to the equity market is related to its returns during the crisis and before it. In non-crisis periods, markets tend to trend upwards, and so a higher exposure to the equity market can bring about higher returns. In crisis periods, the opposite can be found: equity markets trend downwards and a higher exposure could result in lower returns. I implement a similar approach as I did with the Liquidity Exposure: I perform a 24-month rolling regression of individual fund monthly returns on the equity market factor (the S&P 500). I then split the funds into five portfolios based on their last observed equity market exposure prior to the crisis. I omit the pre-crisis analysis since some funds belonging to one portfolio would not belong to the same portfolio throughout the whole pre-crisis period. Additionally, I implement a linear regression in which the raw returns of each fund are regressed on the final equity market factor loading prior to the crisis (this is the same one used in the portfolio approach).

During the crisis, the raw returns of the portfolios (reported in Table 3.15) exhibit a clear decreasing pattern. This evidence supports the fact that in a crisis, higher exposure to the equity market leads to lower returns. Looking at the standard deviation, we can see that it increases as the exposure increases. Also, the portfolio with the highest equity market exposure consists of more than 50% of the best and worst 500 observations during the crisis. These findings suggest that funds who have a high loading on the equity market factor have an increased exposure to the volatility and instability of markets as well. The risk-adjusted returns are U-shaped, although the first portfolio has a considerably higher return than all other portfolios. However, some degree of endogeneity can be found in these returns since the equity market factor was used in producing the risk-adjusted returns. As for the regression results (presented in Table 3.16), we see that although the coefficients of interest are negative, they are not significant. This may be because the funds with the highest exposure (those in portfolio 5) have a large variation in returns and they make up most of the observations on the extremities. This may reduce the power of the regression, making the coefficient insignificant.

Although the portfolio analysis implies a strong negative relationship, the regression analysis does not find support for this. However, this may be because of the large variation in returns of funds with high exposure. Therefore, I would conclude that on average, a higher exposure to the equity market led to lower returns during the 2008 crisis. Through the portfolio analysis, we also see that the high volatility of the equity market was transferred to funds as they increased their exposure to the equity market.

Table 3.15: Monthly returns of each portfolio of hedge funds, sorted from lowest to highest exposure to equity market risk

This table presents performance metrics for different portfolios of hedge funds for the crisis period. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each portfolio's share of the complete dataset's worst and best 500 return observations during a crisis, and the total amount of funds within each portfolio. The portfolios are constructed based on each fund's equity market exposure on November 2007. Portfolio 1 contains funds with the lowest exposure while Portfolio 5 contains funds with the highest exposure. Each fund's equity market exposure is estimated by regressing monthly raw returns on the equity market factor (S&P 500) at a 24-month rolling interval. The loading on the equity market factor is then considered to be the fund's exposure to the equity market. For each fund, these regressions are performed from their first available observation until November 2007. The means and standard deviations shown in the table are based on the average returns of each portfolio for each month, as opposed to being based on all the returns of all funds (within a portfolio) for the whole crisis period. The crisis period ranges from December 2007 to June 2009.

Panel A: Crisis Raw Returns					
Portfolio	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
P1	0.08	2.08	15.60%	16.40%	542
P2	-0.59	2.42	11.20%	7.20%	541
P3	-0.76	2.60	10.40%	8.60%	542
P4	-0.87	3.28	10.20%	13.00%	541
P5	-1.29	5.66	52.60%	54.80%	541

Panel B: Crisis Risk-Adjusted Returns					
Portfolio	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
P1	0.39	0.67	29.60%	36.00%	493
P2	0.15	0.55	12.60%	10.40%	492
P3	0.11	0.53	6.00%	7.00%	492
P4	0.09	0.59	10.40%	9.00%	492
P5	0.25	0.67	41.40%	37.60%	492

Table 3.16: Regression results of fund performance on fund exposure to the equity market during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on its exposure to the equity market. The regressions are performed using data from December 2007 to June 2009. Each fund's equity market exposure is estimated by regressing monthly raw returns on the equity market factor (S&P 500) at a 24-month rolling interval. The loading on the equity market factor is then considered to be the fund's exposure to the equity market. For each fund, these regressions are performed from their first available observation until November 2007. The final equity market exposure (November 2007) is then held constant throughout the crisis period. The regressions presented in this table are performed using data from December 2007 to June 2009. The second model controls for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2
Fund Equity Market Exposure	-0.116	-0.256
	(-0.349)	(-0.799)
Equity Market Factor (control)		0.344***
		(-40.32)
Constant	-0.821***	0.252
	(-18.02)	(-1.22)
Observations	39,681	39,681
Number of funds	2,461	2,461
Fund Type FE	No	Yes
R^2	0.000006	0.0634

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.1.9 Hedge Fund Managerial Incentives

Managers in hedge funds are often provided with incentives in order to align their objectives with that of the fund. These incentives are designed to reward managers for good performance and can therefore be seen as potential drivers of higher returns. There are three incentives given to managers: the management fee, the incentive fee, and the high watermark. Some managers decide to invest their own money into the fund and this provides yet another incentive for the fund to perform better. Although this is a more indirect incentive than the other three, it is still vital to include in the analysis.

I test to see if these four managerial incentives lead to improved performance during the crisis. I first implement a non-parametric test for each managerial incentive. Since the incentive fee and management fee have unusual distributions, forming equal-sized portfolios is not possible. Therefore, I manually select the cut-off points for each portfolio (these are reported in Tables 3.17 and 3.18). For the high watermark and personal capital incentives, I simply form two groups for each incentive: one group contains the funds without the respective incentive while the second group contains funds with the respective incentive. These are then used to compare the average monthly performances and check if a certain incentive relates to higher or lower performance. As a parametric test, I implement several linear regressions where the models' variables are different combinations of the incentives. In the linear regression, the numerical values of the incentive fee and management fee are used, while the high watermark and personal capital incentives are represented in the form of dummy variables.

Prior to the crisis, we observe that in general, managerial incentives were related to higher average raw returns (as reported in Panel A of Tables 3.19 – 3.22). Funds where managers had their personal capital invested exhibited 0.07% higher monthly returns than funds where managers had no personal capital invested. Looking at Table 3.20, we see that the mere presence of hedge fund incentive fees led to higher raw returns. We also observe that the higher the incentive fee, the better the performance, except for the fifth portfolio. Management fees (Table 3.21) are not shown to be related to positive or negative performance. Funds that had high watermarks produced 0.21% higher average monthly returns than funds with no high watermark. When taking into account the risk-adjusted returns (reported in Panel B of Tables 3.19 – 3.22), each managerial incentive is shown to be related to superior performance.

The results during the crisis are similar to those before the crisis. Every incentive, except for the management fee, is related to an average increase in performance for both raw returns and risk-adjusted returns (shown in Panels C and D of Tables 3.19 – 3.22). The differences are more pronounced during the crisis than they were before it: there is approximately a 0.3% difference in monthly raw returns for the personal capital and high watermark incentives and a 0.53% difference between the best-performing portfolio of incentive fees and the portfolio with no incentive fees (whereas it was previously 0.30%). When considering risk-adjusted returns, we also observe more pronounced differences just like we did with the raw returns. For personal capital, the difference is 0.21% (was 0.1% prior to the crisis), for the incentive fee, the difference between the best and worst-performing portfolios is 0.38% (was 0.22% prior to the crisis), for the high watermark, the difference is 0.17% (was 0.07% prior to the crisis). The results regarding the management fees (Table 3.21) do not show any clear increasing or decreasing pattern during the crisis. The non-parametric analysis therefore concludes that incentive fees, the presence of personal capital, and the presence of a high watermark are related to increased performance while management fees are not related to performance.

Upon close inspection of Panels A and C in Table 3.22, we see that during the crisis, the standard deviation of raw returns for funds with a high watermark (9.50) was much higher than the standard deviation of funds without a high watermark (5.88). Prior to the crisis, the standard deviation of funds with a high watermark (4.12) was actually lower than the standard deviation of funds without a high watermark (4.92). This is an interesting observation because one can posit that during the crisis, since funds dropped below the high watermark, managers decided to engage in risky investments. This would quickly bring the fund above the high watermark so that the managers can receive their bonuses. If the risky investments fail and the fund defaults, the manager would simply be able to start a new fund. This is reminiscent of the risk-shifting problem found in studies of corporate finance: if a firm has debt and is in financial distress, the manager would engage in risky investments where the rewards would mostly accrue to the shareholders while the risk would mostly be borne by the firm's creditors. This would allow the firm to quickly exit out of the financial distress or go bankrupt (which would not change much for the shareholders since the value of the firm in financial distress is mostly held by the creditors).

Looking at the linear regression (reported in Table 3.23), we see that the two incentives which are consistently significant are the personal capital and incentive fee. These two incentives are positively related to fund performance and they stay significant even after adding controls for the equity market and the fund style. Although the incentive fee loses some significance when combining all incentives and controls, it nevertheless remains significant at the 10% level. Both the management fee and the high watermark incentive cannot be said to explain fund performance as they are both insignificant in every regression model.

The strongest drivers of performance appear to be the incentive fee and the personal capital invested. Management fees do not appear to have any relationship with performance. This finding is plausible since management fees are not paid out according to fund performance, but rather fund size. Furthermore, funds with a high watermark engage in riskier investments during the crisis in order to quickly bring the fund above the high watermark so that the managers can receive their bonuses. This can be explored in further studies in order to confidently regard this claim as true.

Table 3.17: Breakdown of Incentive Fee Portfolios

This table presents the breakdown of the portfolios created regarding the incentive fees of funds. Reported in this table are the various values of incentive fees in the dataset (in %), the frequency (the amount of funds offering a certain incentive fee), the percent (the share of funds within the dataset that offer a certain incentive fee), the cumulative running sum of the "Percent" column, and the portfolio in which each incentive fee is included in. These portfolios were created based on the following two arguments: the most predominant incentive fees must be spread out across different portfolios and the amount of funds within each portfolio should be as equal as possible (given the restriction imposed by the first argument).

Incentive Fee (in %)	Frequency	Percent	Cumulative Percent	Portfolio #
0	545	16.12%	16.12%	Portfolio 1
0.1	1	0.03%	16.15%	Portfolio 2
0.3	1	0.03%	16.18%	
1	2	0.06%	16.24%	
2	2	0.06%	16.30%	
2.5	1	0.03%	16.33%	
3	3	0.09%	16.42%	
4	1	0.03%	16.45%	
5	153	4.53%	20.98%	
6	1	0.03%	21.01%	
7.5	19	0.56%	21.57%	
7.6	1	0.03%	21.60%	
8	9	0.27%	21.86%	
9	1	0.03%	21.89%	
10	534	15.80%	37.69%	Portfolio 3
12	3	0.09%	37.78%	
12.5	1	0.03%	37.81%	
15	167	4.94%	42.75%	
17	2	0.06%	42.81%	
17.5	3	0.09%	42.90%	
20	1864	55.15%	98.05%	Portfolio 4
22	1	0.03%	98.08%	Portfolio 5
25	45	1.33%	99.41%	
28	1	0.03%	99.44%	
30	11	0.33%	99.76%	
33	2	0.06%	99.82%	
33.33	1	0.03%	99.85%	
35	1	0.03%	99.88%	
40	1	0.03%	99.91%	
50	3	0.09%	100.00%	

Table 3.18: Breakdown of Management Fee Portfolios

This table presents the breakdown of the portfolios created regarding the management fees of funds. Reported in this table are the various values of management fees in the dataset (in %), the frequency (the amount of funds offering a certain management fee), the percent (the share of funds within the dataset that offer a certain management fee), the cumulative running sum of the "Percent" column, and the portfolio in which each management fee is included in. These portfolios were created based on the following two arguments: the most predominant management fees must be spread out across different portfolios and the amount of funds within each portfolio should be as equal as possible (given the restriction imposed by the first argument).

Management Fee (in %)	Frequency	Percent	Cumulative Percent	Portfolio #
0	64	1.88%	1.88%	
0.06	1	0.03%	1.91%	
0.1	3	0.09%	2.00%	
0.125	2	0.06%	2.06%	
0.13	1	0.03%	2.09%	
0.15	7	0.21%	2.30%	
0.166	2	0.06%	2.36%	
0.17	2	0.06%	2.41%	
0.2	3	0.09%	2.50%	
0.25	15	0.44%	2.94%	
0.3	7	0.21%	3.15%	
0.35	3	0.09%	3.24%	
0.375	9	0.26%	3.50%	
0.4	5	0.15%	3.65%	
0.4375	1	0.03%	3.68%	
0.45	1	0.03%	3.71%	Portfolio 1
0.5	40	1.18%	4.89%	
0.55	1	0.03%	4.92%	
0.6	6	0.18%	5.09%	
0.625	2	0.06%	5.15%	
0.65	13	0.38%	5.53%	
0.7	5	0.15%	5.68%	
0.75	54	1.59%	7.27%	
0.8	4	0.12%	7.39%	
0.83	2	0.06%	7.45%	
0.85	5	0.15%	7.59%	
0.88	1	0.03%	7.62%	
0.9	5	0.15%	7.77%	
0.94	1	0.03%	7.80%	
0.95	2	0.06%	7.86%	
0.98	1	0.03%	7.89%	
1	874	25.73%	33.62%	
1.1	2	0.06%	33.68%	
1.125	2	0.06%	33.74%	
1.13	2	0.06%	33.79%	
1.2	10	0.29%	34.09%	Portfolio 2
1.25	141	4.15%	38.24%	
1.3	10	0.29%	38.53%	
1.35	5	0.15%	38.68%	
1.4	6	0.18%	38.86%	
1.48	2	0.06%	38.92%	
1.5	1073	31.59%	70.50%	
1.55	5	0.15%	70.65%	
1.6	8	0.24%	70.89%	
1.61	1	0.03%	70.92%	
1.6125	1	0.03%	70.94%	
1.625	1	0.03%	70.97%	
1.65	16	0.47%	71.45%	
1.7	3	0.09%	71.53%	Portfolio 3
1.73	2	0.06%	71.59%	
1.75	78	2.30%	73.89%	
1.76	17	0.50%	74.39%	
1.7625	1	0.03%	74.42%	
1.8	9	0.26%	74.68%	
1.85	4	0.12%	74.80%	
1.9	3	0.09%	74.89%	
1.95	4	0.12%	75.01%	
2	759	22.34%	97.35%	Portfolio 4
2.05	6	0.18%	97.53%	
2.1	1	0.03%	97.56%	
2.15	6	0.18%	97.73%	
2.18	1	0.03%	97.76%	
2.2	2	0.06%	97.82%	
2.25	4	0.12%	97.94%	
2.3	2	0.06%	98.00%	
2.35	3	0.09%	98.09%	
2.4	2	0.06%	98.15%	Portfolio 5
2.45	1	0.03%	98.17%	
2.5	16	0.47%	98.65%	
2.7	1	0.03%	98.68%	
3	35	1.03%	99.71%	
3.6	1	0.03%	99.74%	
4	5	0.15%	99.88%	
4.5	1	0.03%	99.91%	
4.8	1	0.03%	99.94%	
5	2	0.06%	100.00%	

Table 3.19: Monthly returns of funds with and without personal investment from the manager

This table presents performance metrics for hedge funds where the manager does or does not have their personal capital invested in the fund for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each group of funds' share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each group. The means and standard deviations shown in the table are based on all the returns of all funds (within each group) for the whole pre-crisis and crisis period, as opposed to being based on the average return for each month of each group of funds (the portfolio approach). The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns		
Personal Capital	**Mean**	**St. Dev**
Not Invested	0.85	3.91
Invested	0.92	5.27

Panel B: Pre-Crisis Risk-Adjusted Returns		
Personal Capital	**Mean**	**St. Dev**
Not Invested	0.68	2.58
Invested	0.78	3.58

Panel C: Crisis Raw Returns					
Personal Capital	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
Not Invested	-0.80	6.21	69.40%	64.60%	2578
Invested	-0.49	13.21	30.60%	35.40%	826

Panel D: Crisis Risk-Adjusted Returns					
Personal Capital	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
Not Invested	0.20	3.06	71.60%	67.20%	2578
Invested	0.41	5.90	28.40%	32.80%	826

Table 3.20: Monthly returns of each portfolio of hedge funds, sorted from lowest incentive fee to highest incentive fee

This table presents performance metrics for different portfolios of hedge funds for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each portfolio's share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each portfolio. The portfolios are constructed based on the size of the incentive fee offered from hedge funds to their managers. Portfolio 1 contains funds that offer no incentive fee while Portfolio 5 contains funds that offer the highest incentive fees. The means and standard deviations shown in the table are based on the average returns of each portfolio for each month, as opposed to being based on all the returns of all funds (within a portfolio) for the whole crisis period. The crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns

Portfolio	Fee Range	Mean	St. Dev
P1	0%	0.67	1.81
P2	0.1 - 9%	0.75	1.47
P3	10 - 17.5%	0.80	1.68
P4	20%	0.96	1.78
P5	22 - 50%	0.76	1.47

Panel B: Pre-Crisis Risk-Adjusted Returns

Portfolio	Fee Range	Mean	St. Dev
P1	0%	0.70	0.79
P2	0.1 - 9%	0.69	0.66
P3	10 - 17.5%	0.75	0.60
P4	20%	0.86	0.57
P5	22 - 50%	0.91	1.00

Panel C: Crisis Raw Returns

Portfolio	Fee Range	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0%	-0.90	2.64	8.80%	6.80%	545
P2	0.1 - 9%	-0.84	2.55	1.80%	1.20%	195
P3	10 - 17.5%	-0.75	3.33	15.00%	14.80%	710
P4	20%	-0.52	3.18	70.60%	73.00%	1864
P5	22 - 50%	-0.37	2.96	3.80%	4.20%	66

Panel D: Crisis Risk-Adjusted Returns

Portfolio	Fee Range	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0%	-0.01	0.65	9.80%	7.40%	545
P2	0.1 - 9%	0.02	0.72	2.20%	3.20%	195
P3	10 - 17.5%	0.14	0.66	10.40%	9.00%	710
P4	20%	0.37	0.46	74.40%	76.80%	1864
P5	22 - 50%	0.37	0.66	3.20%	3.60%	66

Table 3.21: Monthly returns of each portfolio of hedge funds, sorted from lowest management fee to highest management fee

This table presents performance metrics for different portfolios of hedge funds for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each portfolio's share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each portfolio. The portfolios are constructed based on the size of the management fee offered from hedge funds to their managers. Portfolio 1 contains funds that offer the lowest management fees while Portfolio 5 contains funds that offer the highest management fees. The means and standard deviations shown in the table are based on the average returns of each portfolio for each month, as opposed to being based on all the returns of all funds (within a portfolio) for the whole crisis period. The crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns			
Portfolio	Fee Range	Mean	St. Dev
P1	0 - 0.98%	0.74	1.39
P2	1 - 1.48%	0.92	1.84
P3	1.5 - 1.95%	0.83	1.71
P4	2%	0.92	1.79
P5	2.05% - 5%	0.69	1.91

Panel B: Pre-Crisis Risk-Adjusted Returns			
Portfolio	Fee Range	Mean	St. Dev
P1	0 - 0.98%	0.72	0.62
P2	1 - 1.48%	0.79	0.59
P3	1.5 - 1.95%	0.83	0.70
P4	2%	0.87	0.68
P5	2.05% - 5%	0.69	1.04

Panel C: Crisis Raw Returns						
Portfolio	Fee Range	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0 - 0.98%	-0.49	2.35	3.40%	5.60%	268
P2	1 - 1.48%	-0.70	3.35	29.20%	31.60%	1054
P3	1.5 - 1.95%	-0.71	2.86	28.60%	27.00%	1226
P4	2%	-0.52	3.38	36.60%	34.40%	759
P5	2.05% - 5%	-0.72	2.28	2.20%	1.40%	90

Panel D: Crisis Risk-Adjusted Returns						
Portfolio	Fee Range	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0 - 0.98%	0.24	0.60	4.60%	3.60%	268
P2	1 - 1.48%	0.19	0.54	27.20%	27.80%	1054
P3	1.5 - 1.95%	0.24	0.51	23.80%	24.80%	1226
P4	2%	0.36	0.57	39.40%	39.40%	759
P5	2.05% - 5%	0.04	1.26	5.00%	4.40%	90

Table 3.22: Monthly returns of funds with and without a high watermark

This table presents performance metrics for hedge funds that do and do not have a high watermark for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each group of funds' share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each group. The means and standard deviations shown in the table are based on all the returns of all funds (within each group) for the whole pre-crisis and crisis period, as opposed to being based on the average return for each month of each group of funds (the portfolio approach). The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns		
High Watermark	**Mean**	**St. Dev**
No	0.75	4.92
Yes	0.96	4.12

Panel B: Pre-Crisis Risk-Adjusted Returns		
High Watermark	**Mean**	**St. Dev**
No	0.68	3.21
Yes	0.75	2.85

Panel C: Crisis Raw Returns					
High Watermark	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
No	-0.92	5.88	25.00%	21.40%	1032
Yes	-0.63	9.50	75.00%	78.60%	2366

Panel D: Crisis Risk-Adjusted Returns					
High Watermark	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
No	0.14	3.23	23.20%	24.20%	1032
Yes	0.31	4.30	76.80%	75.80%	2366

Table 3.23: Regression results of fund performance on managerial incentives during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on various combinations of managerial incentives. The managerial incentive variables in the model are: the presence of a manager's personal investment in the fund (indicated by a dummy variable), the management fee (in %), the incentive fee (in %), and the presence of a high watermark (indicated by a dummy variable). The regressions are performed using data from December 2007 to June 2009. The third, fourth, and fifth models control for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Personal Capital (Dummy)	0.320***		0.276***		0.245*	0.242*
	(-2.668)		(-2.085)		(-1.932)	(-1.873)
Management Fee		-0.0348		-0.00758	-0.0276	-0.00185
		(-0.463)		(-0.132)	(-0.481)	(-0.0327)
Incentive Fee		0.0175***		0.0137**	0.0151**	0.0122**
		(-3.13)		(-2.332)	-2.488	(-2.052)
High Watermark (Dummy)		0.149		0.134	0.137	0.12
		(-1.577)		(-1.543)	-1.51	(-1.446)
Equity Market Factor			0.332***	0.333***		0.333***
			(-48.62)	(-48.37)		(-60.34)
Constant	-0.797***	-1.015***	0.125	0.0243	-1.046***	-0.00292
	(-25.20)	(-7.929)	(-0.626)	(-0.11)	(-8.138)	(-0.00797)
Observations	51,350	51,010	51,350	51,010	51,010	51,010
Number of funds	3,387	3,364	3,387	3,364	3,364	3,364
Fund Type FE	No	No	Yes	Yes	No	Yes
R^2	0.0001	0.0001	0.0691	0.0689	0.00059	0.069

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.1.10 Funding Restrictions

Hedge funds are known to invest in illiquid assets, which can be a risky strategy if investors are allowed to withdraw their capital from the fund whenever they wish. This could cause problems for the hedge fund since they would be unable to execute their planned strategies as a result of a last-minute decrease in funds. Some hedge funds protect themselves against this through the use of three different mechanisms: lockup period, redemption frequency, and redemption notice period. These various mechanisms serve to provide hedge funds with some security by matching the liquidity of their funding to the liquidity of their investments. Studies have shown that these mechanisms are positively related to fund performance during non-crisis periods (Liang and Park, 2007; Agarwal et al., 2009; Schaub and Schmid, 2013). I test to see if this still holds during the 2008 financial crisis.

During the 2008 financial crisis, there were many panicked investors and these funding restrictions allowed hedge funds to operate with more freedom since they did not face large unexpected funding liquidity shocks. I test to see if these three mechanisms helped funds realize greater returns during the crisis. I first implement a non-parametric analysis, which largely follows the approach I have used thus far. Similarly to the managerial incentives, the funding restrictions have unusual distributions which make it difficult to form equal-sized portfolios. For the redemption frequency and redemption notice period, I manually select cut-off points that I believe best differentiate each of the five portfolios I have created (a breakdown of portfolios is presented in Tables 3.24 and 3.25). For the lockup period, I only create two groups: one where funds don't have a lockup period (approximately 74% of funds) and one where funds do have a lockup period (approximately 26% of funds). As a parametric analysis, I implement a linear regression of fund monthly raw returns on each of the following three variables: the log of the redemption notice period, the log of the redemption frequency, and a dummy variable indicating if a fund has a lockup period or not. I then regress the raw returns on all three variables at the same time and then repeat these four regressions but control for the equity market factor and the fund investment style.

Looking at the pre-crisis raw returns and risk-adjusted returns (reported in Panels A and B of Tables 3.26 to 3.28), we see that stronger restrictions tend to be related to superior returns. Even though this relationship is not quite monotonic when considering redemption frequency (Table 3.26), there is still a visible positive relationship. During the crisis, we do not see any clear relationship between the performance of hedge funds and the redemption notice period or lockup. However, we do observe that the first three redemption frequency portfolios outperform the last two redemption frequency portfolios (Panels C and D of Table 3.26). Therefore, we can suggest that stricter redemption frequencies were negatively related to fund performance during the crisis. This may be because hedge funds that allow frequent redemptions are under the constant threat of investor withdrawals. Therefore, they must constantly perform well, whereas funds that do not allow frequent withdrawals have less incentive to do so.

When looking at Table 3.29, we see that in general, none of the three funding restrictions had a significant effect on hedge fund performance during the crisis. However, for the redemption notice period, we observe a negative effect at the 10% significance level in the two regressions with no controls. The remaining two regressions that contain this variable and control variables do not show any significance. The overall regression results suggest that the funding liquidity restrictions did not provide hedge funds with any benefit that would have increased their returns during the 2008 crisis. The same regressions are repeated using the pre-crisis sample period to check if these restrictions were related to fund performance in the pre-crisis period. We see in Table 3.30 that the use of funding restrictions leads to an increased performance prior to the crisis, however, redemption frequency becomes insignificant when used in conjunction with the other two funding restrictions.

While the pre-crisis results show that the restrictions are tied to increased fund performance, the crisis results show that this relationship does not always hold. These results imply that while the restrictions may be useful in general, they do not lead to greater fund performance during the crisis. Although the restrictions may mitigate unexpected negative funding shocks, they do not bring about superior returns. Furthermore, the non-parametric analysis suggests that a more restrictive redemption frequency policy leads to inferior returns.

Table 3.24: Breakdown of Redemption Frequency Portfolios

This table presents the breakdown of the portfolios created regarding the redemption frequencies of funds. Reported in this table are the various values of redemption frequencies in the dataset (in days), the frequency of each redemption frequency (the amount of funds offering a certain redemption frequency), the percent (the share of funds within the dataset that offer a certain redemption frequency), the cumulative running sum of the "Percent" column, and the portfolio in which each redemption frequency is included in. These portfolios were created based on the following two arguments: the most predominant redemption frequencies must be spread out across different portfolios and the amount of funds within each portfolio should be as equal as possible (given the restriction imposed by the first argument).

Redemption Frequency (in days)	Frequency	Percent	Cumulative Percent	Portfolio #
0	1	0.03%	0.03%	Portfolio 1
1	53	1.65%	1.68%	
7	65	2.02%	3.70%	
14	9	0.28%	3.98%	
15	6	0.19%	4.16%	
30	1660	51.58%	55.75%	Portfolio 2
90	1191	37.01%	92.76%	Portfolio 3
180	90	2.80%	95.56%	Portfolio 4
365	139	4.32%	99.88%	Portfolio 5
730	2	0.06%	99.94%	
1095	2	0.06%	100.00%	

Table 3.25: Breakdown of Redemption Notice Period Portfolios

This table presents the breakdown of the portfolios created regarding the redemption notice period of funds. Reported in this table are the various values of redemption notice periods in the dataset (in days), the frequency of each notice period (the amount of funds offering a certain notice period), the percent (the share of funds within the dataset that offer a certain notice period), the cumulative running sum of the "Percent" column, and the portfolio in which each notice period is included in. These portfolios were created based on the following two arguments: the most predominant redemption notice periods must be spread out across different portfolios and the amount of funds within each portfolio should be as equal as possible (given the restriction imposed by the first argument).

Notice Period (in days)	Frequency	Percent	Cumulative Percent	Portfolio #
0	318	9.34%	9.34%	Portfolio 1
1	18	0.53%	9.87%	
2	11	0.32%	10.19%	
3	17	0.50%	10.69%	
4	5	0.15%	10.84%	
5	68	2.00%	12.84%	
6	3	0.09%	12.93%	
7	26	0.76%	13.69%	
8	1	0.03%	13.72%	
10	100	2.94%	16.66%	
11	1	0.03%	16.69%	
14	18	0.53%	17.22%	
15	99	2.91%	20.12%	Portfolio 2
16	15	0.44%	20.56%	
17	1	0.03%	20.59%	
18	1	0.03%	20.62%	
19	2	0.06%	20.68%	
20	90	2.64%	23.33%	
21	10	0.29%	23.62%	
22	1	0.03%	23.65%	
23	7	0.21%	23.85%	
24	2	0.06%	23.91%	
25	17	0.50%	24.41%	
28	2	0.06%	24.47%	
30	816	23.97%	48.44%	
31	12	0.35%	48.80%	
33	5	0.15%	48.94%	
34	9	0.26%	49.21%	
35	136	4.00%	53.20%	
36	1	0.03%	53.23%	
37	5	0.15%	53.38%	Portfolio 3
40	43	1.26%	54.64%	
41	1	0.03%	54.67%	
45	407	11.96%	66.63%	
46	7	0.21%	66.83%	
47	1	0.03%	66.86%	
48	1	0.03%	66.89%	
50	9	0.26%	67.16%	
60	388	11.40%	78.55%	
61	6	0.18%	78.73%	
62	6	0.18%	78.91%	
63	2	0.06%	78.97%	
64	2	0.06%	79.02%	
65	100	2.94%	81.96%	Portfolio 4
70	6	0.18%	82.14%	
75	32	0.94%	83.08%	
80	2	0.06%	83.14%	
82	1	0.03%	83.17%	
85	1	0.03%	83.20%	
90	401	11.78%	94.98%	
91	5	0.15%	95.12%	
92	3	0.09%	95.21%	
93	1	0.03%	95.24%	
94	3	0.09%	95.33%	
95	91	2.67%	98.00%	
96	2	0.06%	98.06%	Portfolio 5
97	5	0.15%	98.21%	
100	18	0.53%	98.74%	
105	4	0.12%	98.85%	
112	1	0.03%	98.88%	
120	6	0.18%	99.06%	
180	29	0.85%	99.91%	
365	3	0.09%	100.00%	

Table 3.26: Monthly returns of each portfolio of hedge funds, sorted from lowest to highest redemption frequency

This table presents performance metrics for different portfolios of hedge funds for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each portfolio's share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each portfolio. The portfolios are constructed based on the length of the redemption frequency (in days) offered from hedge funds to their investors. Portfolio 1 contains funds that offer the shortest redemption frequencies while Portfolio 5 contains funds that offer the longest redemption frequencies. The means and standard deviations shown in the table are based on the average returns of each portfolio for each month, as opposed to being based on all the returns of all funds (within a portfolio) for the whole crisis period. The crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns

Portfolio	Frequency	Mean	St. Dev
P1	0 - 15	0.69	2.55
P2	30	0.76	1.56
P3	90	0.99	1.75
P4	180	1.11	2.33
P5	365 - 1095	1.01	1.85

Panel B: Pre-Crisis Risk-Adjusted Returns

Portfolio	Frequency	Mean	St. Dev
P1	0 - 15	0.79	1.25
P2	30	0.73	0.60
P3	90	0.91	0.63
P4	180	0.86	0.93
P5	365 - 1095	0.86	0.61

Panel C: Crisis Raw Returns

Portfolio	Frequency	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0 - 15	-0.57	3.52	6.80%	8.80%	134
P2	30	-0.59	2.84	51.60%	53.60%	1660
P3	90	-0.69	3.36	37.60%	32.00%	1191
P4	180	-0.98	2.94	1.80%	2.00%	90
P5	365 - 1095	-0.81	3.57	2.20%	3.60%	143

Panel D: Crisis Risk-Adjusted Returns

Portfolio	Frequency	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0 - 15	0.47	0.43	6.20%	6.60%	134
P2	30	0.24	0.54	51.00%	52.80%	1660
P3	90	0.27	0.57	37.80%	35.80%	1191
P4	180	0.05	0.66	2.80%	1.00%	90
P5	365 - 1095	0.19	0.57	2.20%	3.80%	143

Table 3.27: Monthly returns of each portfolio of hedge funds, sorted from lowest to highest redemption notice period

This table presents performance metrics for different portfolios of hedge funds for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each portfolio's share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each portfolio. The portfolios are constructed based on the length of the redemption notice periods (in days) offered from hedge funds to their investors. Portfolio 1 contains funds that offer the shortest notice periods while Portfolio 5 contains funds that offer the longest notice periods. The means and standard deviations shown in the table are based on the average returns of each portfolio for each month, as opposed to being based on all the returns of all funds (within a portfolio) for the whole crisis period. The crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns			
Portfolio	Not. Period	Mean	St. Dev
P1	0	0.53	1.75
P2	1 - 28	0.81	1.86
P3	30 - 50	0.96	1.81
P4	60 - 85	1.01	1.70
P5	90 - 365	1.02	1.46

Panel B: Pre-Crisis Risk-Adjusted Returns			
Portfolio	Not. Period	Mean	St. Dev
P1	0	0.55	0.62
P2	1 - 28	0.79	0.72
P3	30 - 50	0.84	0.64
P4	60 - 85	0.93	0.67
P5	90 - 365	1.01	0.64

Panel C: Crisis Raw Returns						
Portfolio	Not. Period	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0	-0.73	2.36	4.20%	5.60%	318
P2	1 - 28	-0.62	3.42	22.80%	26.40%	515
P3	30 - 50	-0.60	3.05	46.00%	44.00%	1453
P4	60 - 85	-0.59	3.65	13.80%	14.60%	546
P5	90 - 365	-0.84	2.78	13.20%	9.40%	572

Panel D: Crisis Risk-Adjusted Returns						
Portfolio	Not. Period	Mean	St. Dev	Worst 500	Best 500	Total Funds
P1	0	0.10	0.63	7.20%	7.00%	318
P2	1 - 28	0.27	0.55	22.20%	24.80%	515
P3	30 - 50	0.27	0.49	46.80%	44.40%	1453
P4	60 - 85	0.22	0.67	11.00%	10.60%	546
P5	90 - 365	0.24	0.68	12.80%	13.20%	572

Table 3.28: Monthly returns of funds with and without a lockup period

This table presents performance metrics for hedge funds that do and do not have a lockup period for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each group of funds' share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each group. The means and standard deviations shown in the table are based on all the returns of all funds (within each group) for the whole pre-crisis and crisis period, as opposed to being based on the average return for each month of each group of funds (the portfolio approach). The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns		
Lockup	**Mean**	**St. Dev**
No	0.83	4.48
Yes	1.02	4.45

Panel B: Pre-Crisis Risk-Adjusted Returns		
Lockup	**Mean**	**St. Dev**
No	0.69	2.98
Yes	0.79	3.08

Panel C: Crisis Raw Returns					
Lockup	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
No	-0.71	9.05	68.40%	68.00%	2510
Yes	-0.75	6.90	31.60%	32.00%	893

Panel D: Crisis Risk-Adjusted Returns					
Lockup	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
No	0.25	4.01	64.20%	68.80%	2510
Yes	0.29	4.00	35.80%	31.20%	893

Table 3.29: Regression results of fund performance on funding restrictions during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on various combinations of funding restrictions. The funding restriction variables in the models are: the redemption notice period in days (natural log transformation), the redemption frequency in days (natural log transformation), and the presence of a lockup period (indicated by a dummy variable). The regressions are performed using data from December 2007 to June 2009. The fourth, fifth, sixth, and eighth models control for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Redemption Notice Period (log)	-0.0840*			-0.0173			-0.0845*	-0.00008
	(-1.779)			(-0.379)			(-1.701)	(-0.00177)
Redemption Frequency (log)		-0.0595			-0.0364		-0.0336	-0.0368
		(-1.525)			(-0.962)		(-0.632)	(-0.739)
Lockup Period (Dummy)			-0.0405			-0.109	-0.0149	-0.113
			(-0.534)			(-1.571)	(-0.154)	(-1.330)
Equity Market Factor				0.342***	0.337***	0.332***		0.341***
				(-46.37)	(-47.27)	(-48.52)		(-45.85)
Constant	-0.405**	-0.472***	-0.705***	0.338	0.317	0.17	-0.259	0.454
	(-2.368)	(-3.241)	(-15.26)	(-1.083)	(-1.298)	(-0.85)	(-1.132)	(-1.231)
Observations	46,871	48,667	51,350	46,871	48,667	51,350	46,238	46,238
Number of funds	3,078	3,208	3,387	3,078	3,208	3,387	3,037	3,037
Fund Type FE	No	No	No	Yes	Yes	Yes	No	Yes
R^2	0.00005	0.00004	0.00001	0.0688	0.0686	0.0689	0.00009	0.0681

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.30: Regression results of fund performance on funding restrictions before the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on various combinations of funding restrictions. The funding restriction variables in the models are: the redemption notice period in days (natural log transformation), the redemption frequency in days (natural log transformation), and the presence of a lockup period (indicated by a dummy variable). The regressions are performed using data from January 1994 to November 2007. The fourth, fifth, sixth, and eighth models control for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Redemption Notice Period (log)	0.0564***			0.0757***			0.0325**	0.0589***
	(-4.489)			(-5.883)			(-2.355)	(-4.231)
Redemption Frequency (log)		0.0690***			0.0657***		0.0194	0.00951
		(-7.004)			(-6.846)		(-1.446)	(-0.744)
Lockup Period (Dummy)			0.195***			0.190***	0.129***	0.109***
			(-10.15)			(-10.01)	(-6.115)	(-5.262)
Equity Market Factor				0.273***	0.270***	0.272***		0.272***
				(-87.85)	(-89.55)	(-91.39)		(-87.44)
Constant	0.711***	0.602***	0.824***	0.684***	0.625***	0.791***	0.680***	0.698***
	(-15.06)	(-14.78)	(-84.54)	(-5.61)	(-6.644)	(-9.988)	(-12.59)	(-5.432)
Observations	249,469	269,245	279,418	249,469	269,245	279,418	247,551	247,551
Number of funds	4,199	4,626	4,851	4,199	4,626	4,851	4,153	4,153
Fund Type FE	No	No	No	Yes	Yes	Yes	No	Yes
R^2	0.0001	0.00021	0.00036	0.0602	0.058	0.0582	0.00029	0.0603

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.1.11 Investment Focus

Hedge funds can also be classified into what their investment focus is. These focuses include statistical arbitrage, pairs trading, distressed bonds, and others. I select funds with certain investment focuses related to the 2008 financial crisis and test to see if they performed better or worse than funds that had focused on different types of investments. Since the financial crisis was partly caused by the subprime mortgage crisis and the collapse of the housing bubble, the investment focuses I include in my analysis are mortgage-backed securities (MBS), US real estate, distressed markets, and bankruptcies.

I hypothesize that hedge funds who invested in MBS and US real estate were hit hard by the crisis and had worse performance than funds who did not focus their investments in these two areas. As for the funds that focused on distressed markets and bankruptcies, the financial crisis presented them with more investment opportunities but there is uncertainty in what direction these funds' returns went compared to other funds. To test these hypotheses, I implement the same non-parametric approach as I have previously done, and I compare the average monthly performance of funds with each investment focus to funds with a different investment focus. I then implement a linear regression of each investment focus individually and then all four combined together.

As seen in Panel A of Tables 3.31 - 3.34, the pre-crisis average raw returns are higher for funds that focused on US real estate, distressed markets, and bankruptcies and are lower for funds that focused on MBS. When considering risk-adjusted returns (Panel B of Tables 3.31 - 3.34), these results hold for all investment focuses except for US real estate. Furthermore, we see that the standard deviation for funds that focus on bankruptcies is approximately half of the standard deviation for funds that do not focus on bankruptcies. While the other investment focuses also provide lower standard deviations, none of them provide quite a disparity like the bankruptcy focus.

When looking at the raw and risk-adjusted returns during the crisis, we observe that funds which invested in MBS still suffer from poorer performance than funds with other investment focuses. However, this difference in performance and the difference in standard deviations is of similar magnitude as it was prior to the crisis, thus suggesting that funds focusing on MBS did not suffer any more than funds with different investment focuses.

Results for funds that invested in US real estate are mixed: while the return disparity between funds with US real estate focus and funds with another focus decreases for raw returns, it increases for risk-adjusted returns. The returns for distressed markets and bankruptcy focuses are clearer: we see that prior to the crisis, these funds performed better than other investment focuses but during the crisis they performed worse. Furthermore, the standard deviation of the bankruptcy focus remains approximately half of that of funds with a different focus.

When looking at the regression results presented in Table 3.35, we see that MBS and distressed markets are the only investment focuses that have a negative relationship with fund performance. For both these variables, the negative relationship is found in three of four regressions containing the respective variables. These regression results support the results found in the portfolio analysis. For the US real estate and bankruptcy focuses, no significant relationship is found.

Fund performance is found to have a negative relationship with the MBS and distressed markets investment focuses. This is supported by both the parametric and non-parametric analyses. Funds focusing on distressed markets have also seen their returns drop more than the returns of other investment styles. This is also true for the bankruptcy investment focus. The results in Table 3.33 and Table 3.34 show that prior to the crisis, there is a positive relationship between funds with these two focuses (distressed markets and bankruptcies) and their performance, but a negative relationship during the crisis. Also, we observe that the standard deviation of funds that focused on bankruptcies is approximately half of that of other funds, suggesting that funds with this investment focus invest relatively more carefully both before and during the crisis. The performance of funds that focus on US real estate gives mixed signals when considering both raw returns and risk-adjusted returns. The regression results do not make things any clearer, as no relationship is found between this investment focus and fund performance.

Table 3.31: Monthly returns of funds that focus and that do not focus their investments in Mortgage-Backed Securities

This table presents performance metrics for hedge funds that that focus and funds that do not focus their investments in Mortgage-Backed Securities for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each group of funds' share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each group. The means and standard deviations shown in the table are based on all the returns of all funds (within each group) for the whole pre-crisis and crisis period, as opposed to being based on the average return for each month of each group of funds (the portfolio approach). The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns

Focus	Mean	St. Dev
Other	0.88	1.78
MBS	0.73	1.20

Panel B: Pre-Crisis Risk-Adjusted Returns

Focus	Mean	St. Dev
Other	0.89	4.60
MBS	0.72	2.56

Panel C: Crisis Raw Returns

Focus	Mean	St. Dev	Worst 500	Best 500	Total Funds
Other	-0.64	3.09	96.60%	98.60%	3171
MBS	-0.84	2.51	3.40%	1.40%	203

Panel D: Crisis Risk-Adjusted Returns

Focus	Mean	St. Dev	Worst 500	Best 500	Total Funds
Other	-0.71	8.75	96.60%	98.60%	3171
MBS	-0.87	4.82	3.40%	1.40%	203

Table 3.32: Monthly returns of funds that focus and that do not focus their investments in US Real Estate

This table presents performance metrics for hedge funds that that focus and funds that do not focus their investments in US Real Estate for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each group of funds' share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each group. The means and standard deviations shown in the table are based on all the returns of all funds (within each group) for the whole pre-crisis and crisis period, as opposed to being based on the average return for each month of each group of funds (the portfolio approach). The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns		
Focus	**Mean**	**St. Dev**
Other	0.88	4.48
US Real Estate	0.98	3.46

Panel B: Pre-Crisis Risk-Adjusted Returns		
Focus	**Mean**	**St. Dev**
Other	0.72	3.02
US Real Estate	0.70	1.98

Panel C: Crisis Raw Returns					
Focus	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
Other	-0.72	8.60	98.20%	98.20%	3340
US Real Estate	-0.71	5.94	1.80%	1.80%	64

Panel D: Crisis Risk-Adjusted Returns					
Focus	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
Other	0.25	4.01	97.80%	97.20%	3340
US Real Estate	0.40	4.00	2.20%	2.80%	64

Table 3.33: Monthly returns of funds that focus and that do not focus their investments in Distressed Markets

This table presents performance metrics for hedge funds that that focus and funds that do not focus their investments in Distressed Markets for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each group of funds' share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each group. The means and standard deviations shown in the table are based on all the returns of all funds (within each group) for the whole pre-crisis and crisis period, as opposed to being based on the average return for each month of each group of funds (the portfolio approach). The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns		
Focus	**Mean**	**St. Dev**
Other	0.87	4.57
Distressed Markets	0.90	4.03

Panel B: Pre-Crisis Risk-Adjusted Returns		
Focus	**Mean**	**St. Dev**
Other	0.69	3.09
Distressed Markets	0.81	2.63

Panel C: Crisis Raw Returns					
Focus	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
Other	-0.68	8.92	91.80%	93.60%	2946
Distressed Markets	-0.96	5.64	8.20%	6.40%	428

Panel D: Crisis Risk-Adjusted Returns					
Focus	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
Other	0.29	4.22	91.20%	91.40%	2946
Distressed Markets	0.09	2.36	8.80%	8.60%	428

Table 3.34: Monthly returns of funds that focus and that do not focus their investments in Bankruptcies

This table presents performance metrics for hedge funds that that focus and funds that do not focus their investments in Bankruptcies for the pre-crisis and crisis periods. These metrics include the mean of the monthly raw and risk-adjusted returns (reported in %), their standard deviations, each group of funds' share of the complete dataset's worst and best 500 return observations during the crisis, and the total amount of funds within each group. The means and standard deviations shown in the table are based on all the returns of all funds (within each group) for the whole pre-crisis and crisis period, as opposed to being based on the average return for each month of each group of funds (the portfolio approach). The pre-crisis period ranges from January 1994 to November 2007 while the crisis period ranges from December 2007 to June 2009.

Panel A: Pre-Crisis Raw Returns		
Focus	**Mean**	**St. Dev**
Other	0.87	4.57
Bankruptcy	0.92	2.35

Panel B: Pre-Crisis Risk-Adjusted Returns		
Focus	**Mean**	**St. Dev**
Other	0.71	3.08
Bankruptcy	0.78	1.48

Panel C: Crisis Raw Returns					
Focus	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
Other	-0.71	8.77	97.60%	97.20%	3178
Bankruptcy	-0.76	4.52	2.40%	2.80%	196

Panel D: Crisis Risk-Adjusted Returns					
Focus	**Mean**	**St. Dev**	**Worst 500**	**Best 500**	**Total Funds**
Other	0.26	4.13	98.20%	97.60%	3178
Bankruptcy	0.19	1.76	1.80%	2.40%	196

Table 3.35: Regression results of fund performance on investment focuses during the crisis

This table presents the linear regression results obtained when regressing monthly raw returns of each hedge fund on various combinations of investment focuses. The investment focus variables in the models all take the form of a dummy variable, where the value of 1 indicates a specific investment focus of a fund. The regressions are performed using data from December 2007 to June 2009. The sixth, seventh, eighth, ninth, and tenth models control for the equity market movement by using monthly S&P 500 returns and includes dummy variable fixed effects for the fund investment type. Robust t-statistics are reported in parentheses.

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Mortgage-Backed-Securities (Dummy)	-0.165*				-0.0664	-0.259**				-0.216**
	(-1.686)				(-0.631)	(-2.509)				(-2.070)
US Real Estate (Dummy)		0.00176			0.0529		-0.115			-0.0678
		(-0.00869)			(-0.259)		(-0.639)			(-0.375)
Distressed Markets (Dummy)			-0.281***		-0.322***			-0.172*		-0.163
			(-3.442)		(-3.359)			(-1.910)		(-1.644)
Bankruptcy (Dummy)				-0.0566	0.163				-0.015	0.133
				(-0.627)	(-1.571)				(-0.167)	(-1.374)
Equity Market Factor						0.332***	0.332***	0.332***	0.332***	0.332***
						(-48.3)	(-48.54)	(-48.31)	(-48.32)	(-48.31)
Constant	-0.703***	-0.715***	-0.677***	-0.709***	-0.679***	0.166	0.17	0.171	0.165	0.173
	(-17.64)	(-18.71)	(-16.00)	(-17.70)	(-15.71)	(-0.828)	(-0.851)	(-0.856)	(-0.828)	(-0.866)
Observations	50,986	51,350	50,986	50,986	50,986	50,986	51,350	50,986	50,986	50,986
Number of funds	3,357	3,387	3,357	3,357	3,357	3,357	3,387	3,357	3,357	3,357
Fund Type FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
R^2	0.00002	0.00001	0.00012	0.00001	0.00014	0.0686	0.0689	0.0686	0.0686	0.0686

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.1.12 Investment Approach Case Study

With the constant improvement of technology and computing power, some hedge funds have opted to use an algorithmic approach to trading. Also known as systematic trading or "quant" trading, this approach uses a set of pre-defined "rules" that determine whether or not a trader should enter into a position. These rules are determined typically through the use of statistical models which are created with computer programs. These trades can be automated and there is typically no emotion attributed to the choice of trades. Contrary to this, there is discretionary trading, which means that a trader executes trades based on the collection of different information available to them at the time. This approach to trading cannot be easily automated and can sometimes be influenced by the trader's emotions or other subjective factors (Milton, 2021). Although discretionary trading also involves the use of "rules", traders can still choose whether or not to execute trades regardless of if the rules have been fulfilled (unlike in systematic trading). I test if discretionary hedge funds perform better or worse than systematic hedge funds during the 2008 financial crisis.

Due to the small sample, my methodology for comparing discretionary versus systematic hedge funds is different than my methodology I have previously used in other tests (hedge fund leverage, managerial incentives, investment focus, etc.). I first select all hedge funds that have indicated whether they solely engage in discretionary trading or systematic trading. I then find pairs of funds that have near-identical performance in the 3 years prior to the crisis. The funds within these pairs must have a difference no larger than 0.02% in their mean monthly raw returns and return standard deviation in that 3-year period (this allows up to a 0.24% difference in yearly returns). Once these pairs have been identified, I eliminate pairs in which the smaller fund is less than half the size of the larger fund. This leaves 6 pairs of hedge funds upon which my analysis is based on. Within each pair, there is one fund that uses discretionary trading and one fund that uses systematic trading. I can make further restrictions based on selecting hedge funds with the same incentive fee, the presence of leverage, and whether or not the fund's manager is personally invested in the fund, however, this would reduce my sample size to only one pair of firms (pair #3, shown in Table 3.36). Attempting to apply any further constraints regarding the characteristics of funds would eliminate all pairs of funds – even after loosening performance restrictions from 0.02 to 0.05. However, loosening performance restrictions even more (to 0.10 or 0.20) would allow for more pairs to be included in the sample, but the funds would not be deemed to have similar performance. Once I have created my sample of firm pairs, I compare the performance of funds within each pair during the crisis to check if they had performed differently from one another.

Looking at Table 3.36, we see that in four out of the six pairs of hedge funds, the discretionary fund outperformed the systematic fund during the crisis. With close inspection, we observe that these four pairs contain relatively large hedge funds, while the other two pairs (in which the systematic funds have superior performance) are relatively small hedge funds. When looking at the difference in standard deviations, we find that the discretionary funds tend to have less volatility in their monthly returns. Pair #3 (the pair that has the same incentive fee, presence of leverage, and presence of a manager’s personal wealth) directly follows these results: the discretionary fund has superior performance and lower return volatility. These results suggest that during the 2008 crisis, a discretionary approach to trading led to higher returns while a systematic/algorithmic approach led to lower returns. The use of statistical models and algorithms may not be useful in volatile market conditions since the pre-determined “rules” may only be valid during stable economic times; funds would be better off using a discretionary approach during crisis periods. Parmar et al. (2020) analyze the performance of discretionary and systematic hedge funds during the COVID-19 pandemic and reach a similar conclusion: during 2020, most of the best-performing funds were those using a discretionary approach while most of the worst-performing funds were those using a quant-based approach.

Table 3.36: Performance comparison of hedge funds that engage in discretionary trading and systematic trading

This table presents performance metrics for hedge funds for the pre-crisis and crisis periods. The metrics include the mean of the monthly raw returns (reported in %), their standard deviations, and the differences of these metrics for each pair of funds. In order to create each pair, both funds within the pair must have a mean monthly return difference and standard deviation difference of no more than 0.02% in the three-year period prior to the crisis. The pre-crisis period starts in December 2004 and ends in November 2007 while the crisis period starts in December 2007 and ends in June 2006.

Fund ID	Pair ID	Investment Approach	Return (Pre-Crisis)	St. Dev (Pre-Crisis)	Return (Crisis)	Return Difference (Crisis)	St. Dev (Crisis)	St. Dev Difference (Crisis)
1	1	Discretionary	0.57	0.86	-0.61	0.27	3.24	-0.37
2	1	Systematic	0.56	0.87	-0.88		3.62	
3	2	Discretionary	0.82	2.46	1.34	0.84	2.42	0.43
4	2	Systematic	0.82	2.48	0.51		1.99	
5	3	Discretionary	0.86	1.40	0.05	0.17	1.11	-3.39
6	3	Systematic	0.87	1.38	-0.12		4.49	
7	4	Discretionary	0.66	1.20	-0.71	0.06	1.81	-0.72
8	4	Systematic	0.66	1.20	-0.77		2.53	
9	5	Discretionary	0.45	1.30	-1.20	-1.59	2.35	-0.35
10	5	Systematic	0.47	1.28	0.39		2.70	
11	6	Discretionary	0.76	1.73	-0.72	-0.81	6.24	5.40
12	6	Systematic	0.77	1.72	0.10		0.84	

Table 3.37: Characteristics of hedge funds from case study

This table presents characteristics for hedge funds for the pre-crisis period. The characteristics for each fund include the AUM (in millions of USD), the fund investment type, the incentive fee (in %), whether or not the fund is leveraged, and whether or not the manager of the fund has their personal wealth invested into the fund. The pre-crisis period starts in December 2004 and ends in November 2007 while the crisis period starts in December 2007 and ends in June 2006.

Fund ID	Pair ID	Investment Approach	AUM (in millions)	Fund Style	Incentive Fee (in %)	Leveraged	Personal Wealth Invested
1	1	Discretionary	$405.81	Fund of Funds	20.00	Yes	Yes
2	1	Systematic	$390.88	Fund of Funds	5.00	No	Yes
3	2	Discretionary	$174.00	Global Macro	20.00	Yes	No
4	2	Systematic	$100.21	Fund of Funds	0.00	No	No
5	3	Discretionary	$410.83	Long/Short Equity Hedge	20.00	Yes	No
6	3	Systematic	$371.38	Convertible Arbitrage	20.00	Yes	No
7	4	Discretionary	$217.16	Fund of Funds	10.00	Yes	No
8	4	Systematic	$134.12	Fund of Funds	10.00	No	No
9	5	Discretionary	$17.90	Multi-Strategy	0.00	Yes	No
10	5	Systematic	$18.58	Equity Market Neutral	20.00	No	No
11	6	Discretionary	$33.36	Fund of Funds	20.00	Yes	Yes
12	6	Systematic	$16.72	Long/Short Equity Hedge	20.00	Yes	No

3.2: Effect of the 2008 Financial Crisis on Hedge Fund Survivability

3.2.1 Hedge Fund Investment Styles

In the previous section, I have tested whether certain hedge fund investment styles perform better during the crisis than other hedge fund investment styles. I found that some styles, such as Dedicated Short Bias and Global Macro, performed better while other styles, such as Emerging Markets, performed worse. However, better or worse performance during the 2008 crisis does not necessarily translate to better or worse survivability.

I use the Cox proportional-hazards model to test how the survivability of hedge funds varies according to style. The hazard is set to be on the date where a hedge fund reports its last observation (this would indicate that a default possibly occurred some time between the month of the last observation and the subsequent month). As independent variables, I use a dummy indicating the 2008 financial crisis period (December 2007 to June 2009), a dummy indicating one specific hedge fund style, and an interaction term with the two dummy variables. This regression is performed a total of 11 times, once for each of the 11 hedge fund styles. If the coefficient of the interaction term is greater than 1, this would suggest that during the crisis, funds with the specific style (depends on which style is tested) had worse survivability than funds of other styles. If the coefficient is smaller than 1, this would suggest that they had greater survivability during the crisis. Furthermore, I compute the percentage of hedge funds from each fund style that defaulted during the crisis. This can be used to visualize what fund styles had a larger share of funds that defaulted.

When looking at the Cox proportional hazards results in Table 3.38, we see that the Emerging Markets, Equity Market Neutral, Global Macro, and Long/Short Equity Hedge styles lead to greater survivability for a fund. These results are surprising when examined along with the results for performance. While Emerging Markets provides better survivability during the crisis, it also provides the worst raw returns and the highest standard deviation. We also see that while Equity Market Neutral funds lead to better survivability though the Cox model, they have the second-highest default percentage during the crisis (shown in Table 3.39). Looking at Table 3.38, we find that Funds of Funds and Multi-Strategy lead to worse survivability. In the case of Funds of Funds, we observe both poor survivability during the crisis and poor performance. Furthermore, we see that while Dedicated Short Bias funds provide the best returns during the crisis, they do not lead to superior survivability. However, the results regarding survivability for Dedicated Short Bias have low power since there are only 12 of these funds present during the crisis.

We see that the hedge fund styles with the best performance do not necessarily show superior survivability than other funds, and fund styles with worse performance do not necessarily exhibit worse survivability.

Table 3.38: Cox Proportional-Hazards Regression results with respect to fund type

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their investment styles. On the top row of the table is the fund type used for each model. The variables in the models include: the financial crisis period (indicated by a dummy variable), the fund investment type (indicated by a dummy variable), and an interaction term between the financial crisis and fund type dummy variables. The regressions are performed using data from January 1994 to June 2009. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arbitrage	Funds of Funds	Global Macro	Long/Short Equity Hedge	Multi-Strategy	Other
2008 Crisis (Dummy)	2.626***	2.625***	2.692***	2.666***	2.598***	2.632***	2.166***	2.712***	2.966***	2.511***	2.621***
	(-24.6)	(-24.87)	(-24.81)	(-24.67)	(-23.77)	(-24.55)	(-15.89)	(-25.23)	(-24.34)	(-22.99)	(-24.64)
Fund Type (Dummy)	1.199*	1.236	1.004	1.779***	0.988	1.495***	0.603***	1.726***	1.302***	0.541***	0.591**
	(-1.79)	(-1.065)	(-0.0509)	(-6.165)	(-0.162)	(-4.034)	(-9.742)	(-6.394)	(-5.691)	(-4.327)	(-2.306)
2008 Crisis*Fund Type	1.072	0.707	0.696**	0.732*	1.129	1.003	1.893***	0.495***	0.641***	2.325***	1.342
	(-0.282)	(-0.549)	(-2.244)	(-1.800)	(-0.82)	(-0.0152)	(-7.849)	(-3.447)	(-4.945)	(-4.692)	(-0.988)
Observations	330,816	330,816	330,816	330,816	330,816	330,816	330,816	330,816	330,816	330,816	330,816

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.39: Default percentage of funds for each Fund Type

This table presents the share of hedge funds that have defaulted during the crisis for each of the 11 types of funds. The default rank is also provided, where the fund type with the highest default percentage is ranked first while the fund type with the lowest default percentage is ranked last. The crisis period ranges from December 2007 to June 2009.

Fund Type	Default %	Default Rank
Convertible Arbitrage	34.48%	3
Dedicated Short Bias	25.00%	7
Emerging Markets	19.47%	10
Equity Market Neutral	35.38%	2
Event Driven	31.67%	4
Fixed Income Arbitrage	42.65%	1
Fund of Funds	31.06%	5
Global Macro	24.00%	9
Long/Short Equity Hedge	24.79%	8
Multi-Strategy	30.63%	6
Other	16.88%	11

3.2.2 Hedge Fund Alpha

Previously, I have shown that high-alpha managers are able to better navigate through the 2008 financial crisis than managers with low alpha. The superior performance of funds with high alpha (a measure of skill) must also translate to superior survivability during the crisis, otherwise, we cannot truly claim that a manager is skillful.

To test if funds with high alpha have greater chances of surviving the 2008 financial crisis, I implement the Cox proportional-hazards model and compute the share of funds that defaulted within each of the 5 portfolios created in section 3.1.2 (the comparison of Hedge Fund Alpha and Performance). When estimating the Cox regression, I use three variables: a dummy variable indicating the crisis period, the alpha of a hedge fund, and an interaction term of these two variables. In order to estimate the alpha of each hedge fund, I follow the same procedure as in section 3.1.2. Once the alphas are estimated, I standardize them across all observations before proceeding with the Cox regression.

Reported in Table 3.40, the results for the Cox proportional-hazards regression indicate that a high alpha leads to a higher probability of survival during the 2008 crisis. This is to be expected since a manager's skill should not only be beneficial in terms of providing higher returns, but also in terms of avoiding defaults. In addition, the results in Table 3.41 exhibit a clear pattern that supports the results of the Cox regression: in portfolios of high-alpha funds, the share of funds that defaulted is lower than the share in portfolios of low-alpha funds.

The results for the Cox regression may be influenced by the length of the interval chosen when estimating hedge fund alpha (in this case, 24 months). This means that the survivability of a fund is only based on the manager skill that was exhibited in the previous 24 months. However, one can argue that a longer time period must be used since the 24-month alpha may sometimes capture luck, and not skill (a shorter time interval is more prone to "noise", which makes it more likely that luck is captured). Therefore, I repeat the Cox proportional-hazards regression, but I choose two different time intervals when estimating hedge fund alpha: a 48-month (4 year) rolling regression and a 96-month (8 year) rolling regression. The results for these robustness checks (presented in Table 3.42) support those found when using the 24-month interval for estimating alpha: higher alpha relates to better survivability during the 2008 financial crisis.

Table 3.40: Cox Proportional-Hazards Regression results with respect to hedge fund alpha

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their alphas. The variables in the models include: the financial crisis period (indicated by a dummy variable), the hedge fund alpha (standardized across all observations in the sample) and an interaction term between the financial crisis and fund alpha variables. Each fund's alpha is estimated by regressing monthly raw returns on 9 factors at a 24-month rolling interval. The regressions are performed using data from January 1994 to June 2009. The second model contains dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2
2008 Crisis	2.435***	2.529***
	(-22.85)	(-23.7)
Hedge Fund Alpha	0.943***	0.944***
	(-6.752)	(-6.681)
2008 Crisis*Hedge Fund Alpha	0.945**	0.931***
	(-2.347)	(-2.809)
Observations	278,976	278,976
Fund Type FE	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.41: Default percentage of funds for each portfolio of hedge funds, sorted from lowest alpha to highest alpha

This table presents the share of hedge funds within each portfolio that have defaulted during the crisis. Portfolio 1 contains funds with the lowest alpha while Portfolio 5 contains funds with the highest alpha. The portfolios are the same ones created in the previous section (when analyzing hedge fund performance). The crisis period ranges from December 2007 to June 2009.

Portfolio	Default %
P1	21.25%
P2	16.98%
P3	11.18%
P4	5.59%
P5	8.70%

Table 3.42: Cox Proportional-Hazards Regression robustness check results, Fund Alpha

This table presents robustness check results for the analysis of hedge fund survivability and fund alpha. The variables in the models include: the financial crisis period (indicated by a dummy variable), the hedge fund alpha (standardized across all observations in the sample), and an interaction term between the financial crisis and fund alpha variables. Each fund's alpha is estimated by regressing monthly raw returns on 9 factors at a 48-month or 96-month rolling interval. The regressions are performed using data from January 1994 to June 2009. The second and fourth models contain dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2	Model 3	Model 4
2008 Crisis	2.435***	2.528***	2.433***	2.523***
	(-22.83)	(-23.66)	(-22.74)	(-23.56)
Hedge Fund Alpha	0.950***	0.950***	0.952***	0.952***
	(-6.544)	(-6.484)	(-6.378)	(-6.323)
2008 Crisis*Hedge Fund Alpha	0.956*	0.942**	0.961*	0.946**
	(-1.921)	(-2.455)	(-1.648)	(-2.299)
Observations	278,976	278,976	278,976	278,976
Fund Type FE	No	Yes	No	Yes
Interval Used To Estimate Alpha	48 Months	48 Months	96 Months	96 Months

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.2.3 Hedge Fund Age

My paper has found support for the general hedge fund literature, which suggests that a hedge fund's age is inversely related to its performance: as hedge funds get older, their returns diminish. However, the relationship between fund age and its ability to survive may not be the same. Younger funds are not as well-established as older funds and they do not have as much experience in navigating through a financial crisis. Therefore, older funds may show superior survivability during the 2008 financial crisis than younger funds.

To test if the survivability of funds during the crisis is related to their age, I once again use the Cox proportional-hazards regression along with the share of funds that defaulted within each portfolio created in section 3.1.3. The preparation and implementation of the Cox model is different than the approach used in most of section 3.2. Since the results of the Cox regressions are formed on how long a fund survives based on a certain characteristic (for example, fund alpha or fund size), it would be incorrect to simply use the age of the fund as a variable. The results would show that as the age of the fund increases, so does its survivability, which is only natural since the two go hand-in-hand. Therefore, I opt to hold the age of the fund fixed at the start of the crisis and I use that as my sole variable in the regression. Additionally, I discard the pre-crisis period and only perform the Cox regression on observations pertaining to the crisis period. In the Cox regression, the age of each fund is standardized across all fund ages. I estimate four models: one using just the age as a variable, one using the age along with fund investment type fixed effects, one using the age and controlling for size (size is standardized), and one using age and controlling for both fund size and investment type.

The results for the Cox proportional-hazards regression, which are reported in Table 3.43, show that older funds had better survivability during the crisis than younger funds. Even when controlling for the fund type and the fund size, the significance of this result remains under the 1% level. Table 3.44 indicates that the two portfolios with the oldest funds had a lower share of funds that defaulted during the crisis (compared to the first three portfolios that contain younger funds). It is found that just like fund age and performance, the relationship between fund age and survivability is not linear: the youngest portfolio of funds, just like the oldest portfolio, has better survivability than the middle portfolios. This non-linearity is further demonstrated in Figures 3.1 and 3.2, which show the percentage of defaulted funds in the crisis of portfolios based on fund age at the start of the crisis. The funds are split into 5 portfolios in Figure 3.1 and 10 portfolios in Figure 3.2. Overall, my results show that during the crisis, older hedge funds exhibited greater survivability than younger hedge funds, except for the youngest group of funds, which also showed high survivability.

Table 3.43: Cox Proportional-Hazards
Regression results with respect to hedge fund age

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their age. The variable used in the model is the hedge fund age (in months, standardized across all observations). The age of the fund is taken in December 2007 and is held fixed throughout the crisis period. The regressions are performed using data from December 2007 to June 2009. The second and fourth models contain dummy variable fixed effects for the fund investment style. The third and fourth models control for fund size (given by the AUM and standardized across all observations in the sample). Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2	Model 3	Model 4
Fund Age	0.863***	0.849***	0.887***	0.878***
	(-4.251)	(-4.674)	(-3.067)	(-3.282)
Fund Size			0.623***	0.607***
			(-2.921)	(-3.005)
Observations	46,022	46,022	37,845	37,845
Fund Type FE	No	Yes	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.44: Default percentage of funds for each
portfolio of hedge funds sorted from youngest to oldest

This table presents the share of hedge funds within each portfolio that have defaulted during the crisis. Portfolio 1 contains the youngest funds while Portfolio 5 contains the oldest funds. The portfolios are the same ones created in the previous section (when analyzing hedge fund performance). The crisis period ranges from December 2007 to June 2009.

Portfolio	Default %
P1	30.94%
P2	37.57%
P3	36.73%
P4	28.35%
P5	26.56%

Figure 3.1: Share of funds that have defaulted, 5 portfolios

This figure presents the share of hedge funds within five portfolios that have defaulted during the crisis. The left-most portfolio contains the youngest funds while right-most portfolio contains the oldest funds. The crisis period ranges from December 2007 to June 2009.

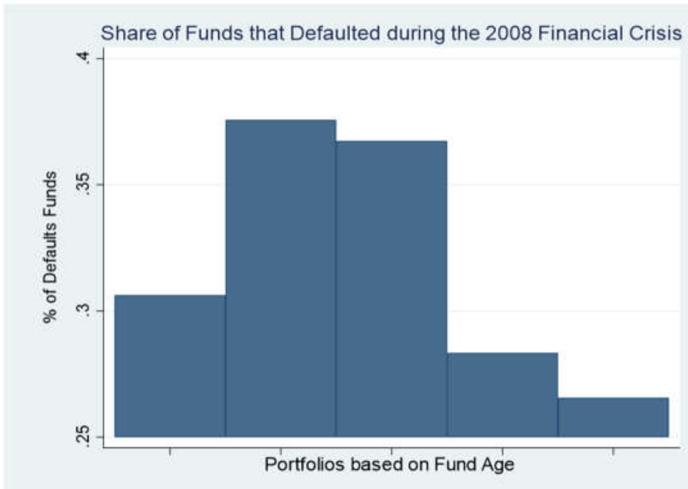
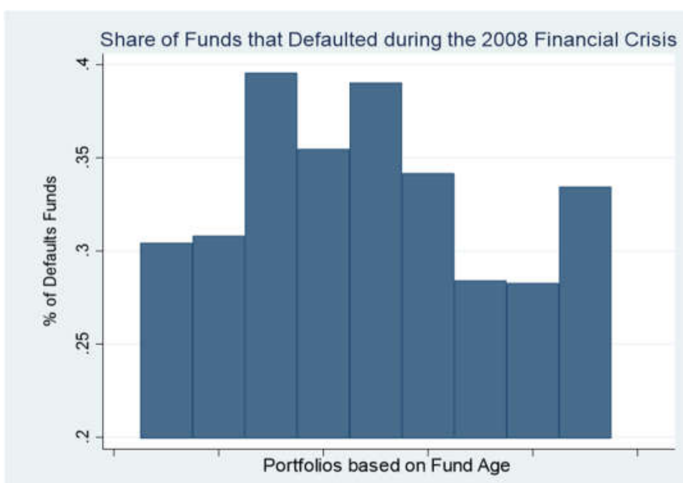


Figure 3.2 Share of funds that have defaulted, 10 portfolios

This figure presents the share of hedge funds within ten portfolios that have defaulted during the crisis. The left-most portfolio contains the youngest funds while right-most portfolio contains the oldest funds. The crisis period ranges from December 2007 to June 2009.



3.2.4 Hedge Fund Size

In the section regarding the performance of hedge funds during the 2008 crisis, I observed that smaller funds provided higher average monthly returns than larger funds. However, I believe that in terms of survivability, larger funds have an advantage since they have larger capital reserves and can therefore withstand greater losses. To test if my hypothesis is true, I use the Cox proportional-hazards model and I also compute the percentage of funds that defaulted in each of the five portfolios which I have created in the performance section of my analysis. For the Cox proportional-hazards model, I use similar specifications as before: a dummy variable indicating the 2008 crisis period, the size of the fund (the AUM standardized across all observations), and an interaction term of the two variables. I estimate the model once without any controls and once while controlling for fund investment style/type.

As reported in Table 3.45, the survivability of hedge funds is positively related to fund size, both prior to the crisis and during the crisis. Since the coefficient on the interaction terms is lower than 1, this means that the time to hazard (default) during the crisis is prolonged if a fund is large. When controlling for the fund type, the results still hold. Looking at Table 3.46, we see a clear and monotonic decreasing pattern: as the fund size increases from one portfolio to the next, the share of funds that have defaulted decreases. In the portfolio with the smallest funds, we see that approximately 45% have defaulted during the crisis while only 26% of the largest funds defaulted.

The results from these two tests suggest that during the 2008 crisis, larger funds did indeed have better survivability than smaller funds. Although larger funds are found to have worse performance, this does not mean that they have a higher chance of defaulting. Their larger capital reserves allow for greater losses and more opportunities for diversification or hedging. Thus, large negative shocks during the crisis have a lower chance of putting the fund in financial distress.

Table 3.45: Cox Proportional-Hazards Regression results with respect to hedge fund size

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their size. The variables in the models include: the financial crisis period (indicated by a dummy variable), the hedge fund size (given by the AUM and standardized across all observations in the sample), and an interaction term between the financial crisis and fund size variables. The regressions are performed using data from January 1994 to June 2009. The second model contains dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2
2008 Crisis	2.178***	2.239***
	(-13.56)	(-13.96)
Size	0.698***	0.696***
	(-7.420)	(-7.516)
2008 Crisis*Size	0.652***	0.655***
	(-6.571)	(-6.518)
Observations	250,821	250,821
Fund Type FE	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.46: Default percentage of funds for each portfolio of hedge funds, sorted from smallest to largest fund size

This table presents the share of hedge funds within each portfolio that have defaulted during the crisis. Portfolio 1 contains the smallest funds while Portfolio 5 contains the largest funds. The portfolios are the same ones created in the previous section (when analyzing hedge fund performance). The crisis period ranges from December 2007 to June 2009.

Portfolio	Default %
P1	44.52%
P2	39.38%
P3	36.04%
P4	35.32%
P5	25.78%

3.2.5 Hedge Fund Historic Return

Hedge funds who have performed well in the pre-crisis period are shown to perform badly during the 2008 financial crisis. This is a surprising result since one can expect that funds that perform well in general would perform better during the crisis than funds that perform poorly in general. Nonetheless, I now turn my focus onto the survivability of these funds. Hedge funds that performed well prior to the crisis may be expected to have better survivability, however, just like what was observed in the performance section of this paper, there is a possibility that the relationship between historic returns and survivability is negative.

I test how the survivability of hedge funds moves in accordance with their pre-crisis historical return. This is done through the use of the Cox proportional-hazards regression and the computation of the share of funds that have defaulted within each portfolio created in section 3.1.5. When performing the Cox regression, I use a similar approach to the one in section 3.2.3 (Hedge Fund Age and Survivability): I compute the historical average monthly return of a fund from its first observation up until the month prior to the financial crisis, I hold this number fixed for the remainder of the crisis, I then drop all observations prior to the crisis and any funds that had less than 12 months of observations, and finally I standardize the historical returns before implementing the Cox regression.

The Cox proportional-hazards regression results suggest that a higher historical return leads to greater survivability during the crisis (shown in Table 3.47). The significance of the result remains below the 1% level with or without the use of fund type controls. This result is further supported by Table 3.48: we see that the portfolio of funds with the lowest historical returns had a default rate of 51% while the portfolio of funds with the highest historical returns had a default rate of approximately 21%. Out of all characteristics tested in this paper, the historical return is one of the characteristics with the strongest positive relationship to fund survivability during the crisis. This is surprising when one considers the negative relationship between historic return and performance during the crisis.

Table 3.47: Cox Proportional-Hazards Regression results with respect to hedge fund average historic monthly raw returns

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their historic returns. The variable used in the model is the hedge fund historic return of each fund (in %). The historic return of a fund is computed by taking the average of all returns of a fund from its first observation since January 1994 to November 2007. This number is then standardized across all observations and held fixed throughout the crisis period. The regressions are performed using data from December 2007 to June 2009. The second model contains dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2
Historical Return	0.666***	0.667***
	(-5.744)	(-5.321)
Observations	40,328	40,328
Fund Type FE	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.48: Default percentage of funds for each portfolio of hedge funds, sorted from lowest to highest historic return

This table presents the share of hedge funds within each portfolio that have defaulted during the crisis. Portfolio 1 contains funds with the lowest historic returns while Portfolio 5 contains funds with the highest historic returns. The portfolios are the same ones created in the previous section (when analyzing hedge fund performance). The crisis period ranges from December 2007 to June 2009.

Portfolio	Default %
P1	50.99%
P2	35.12%
P3	27.18%
P4	28.77%
P5	20.68%

3.2.6 Hedge Fund Leverage

In the performance section of this paper, I found that hedge funds with leverage performed better during the 2008 financial crisis than hedge funds with no leverage. This may be as a result of more confident investments and better investment opportunities; funds may have decided to leverage themselves because they spotted certain investments that they believed would be profitable. Although leverage helps a fund realize larger profits, it may also lead to larger losses which can be enough to threaten the fund's survivability. I decide to test whether funds with leverage exhibit greater survivability (like they did with performance) or if they default more often. To test this, I follow the same approach as I have for the previous characteristics: a comparison of the default percentage of leveraged and non-leveraged funds and the implementation of the Cox proportional-hazards model. For the regression approach, I base my conclusions on the coefficient of the interaction term between a dummy variable indicating the crisis period and a dummy variable indicating if a fund is leveraged or not.

When looking at the default percentage of levered versus non-levered hedge funds (reported in Table 3.49), we do not observe a large difference as there is only 2% that separates these two groups of funds. However, the results reported in Table 3.50 for the Cox proportional hazards regression are much clearer: we find that during the crisis, funds with leverage exhibited better survivability than funds with no leverage. This result holds when controlling for the fund type. The results in this paper show that hedge funds with leverage tend to exhibit greater performance and greater survivability during the 2008 crisis compared to funds that do not have any leverage. As suggested before, this may be because funds with leverage have spotted better investment opportunities than funds with no leverage.

Table 3.49: Cox Proportional-Hazards Regression results with respect to the presence of leverage in a hedge fund

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and whether they are leveraged. The variables in the models include: the financial crisis period (indicated by a dummy variable), the presence of leverage in a fund (indicated by a dummy variable), and an interaction term between the financial crisis and the presence of leverage. The regressions are performed using data from January 1994 to June 2009. The second model contains dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2
2008 Crisis	2.914***	3.040***
	(-18.35)	(-19.08)
Leverage (Dummy)	1.311***	1.241***
	(-5.961)	(-4.702)
2008 Crisis*Leverage	0.852**	0.838**
	(-2.072)	(-2.287)
Observations	330,816	330,816
Fund Type FE	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.50: Default percentage of leveraged funds versus non-leveraged funds

This table presents the share of hedge funds within each group of funds that have defaulted during the crisis. One group contains funds that are not leveraged while the other group contains funds that are leveraged. The crisis period ranges from December 2007 to June 2009.

Leverage	Default %
Not Leveraged	26.92%
Leveraged	29.00%

3.2.7 Hedge Fund Liquidity Exposure

A hedge fund's exposure to liquidity risk is an important factor to consider when examining the relationship between a fund's survivability and its characteristics. During the 2008 financial crisis, markets were affected by large liquidity problems which negatively affected fund performance. Funds that had high exposure to liquidity risk saw their performance drop further than that of funds with lower exposure (Sadka, 2010). It is worth examining the relationship between fund exposure to liquidity risk and fund survival since this deterioration in performance may have led to more bankruptcies.

I test if high exposure to liquidity risk is related to worse hedge fund survivability during the crisis. To test this, I use the Cox proportional-hazards regression model in which I include three variables: a dummy variable for the financial crisis period, the liquidity exposure of each fund, and an interaction term of the two variables. In addition, I compute the percentage of funds that have defaulted within each of the 5 portfolios I have created in section 3.1.7. To estimate the liquidity risk exposure of each hedge fund, I implement the same approach as I have done when testing the relationship between liquidity risk exposure and fund performance. Once the liquidity risk exposures are estimated, I standardize them across all observations before proceeding with the Cox regression.

Looking at the results of the Cox regression presented in Table 3.51, we see that the coefficient of the interaction term is significant at the 1% level and is greater than 1. This suggests that during the financial crisis, hedge funds with a higher exposure to liquidity risk had greater chances of defaulting than funds with low exposure. This result is to be expected; liquidity was severely negatively impacted during the crisis and funds whose performance was overly exposed to this surely had more trouble surviving than funds who were not as exposed. When looking at Table 3.52, we see that funds with lower exposure to liquidity risk actually had a larger share of funds that defaulted during the crisis. This contradictory result may have occurred because I sorted the funds into portfolios based on their liquidity risk exposure from December 2005 to November 2007 (since this is the time period in which the rolling regression was performed on when creating the portfolios). The exposure of funds in this two-year period can be quite different from their exposure towards the end of the crisis, which is when some funds defaulted.

As a robustness check, I perform the Cox regression once again, however, this time I estimate the liquidity risk exposure by using shorter time periods: 12 months and 6 months. This would ensure that the Cox regression only includes recent exposure to liquidity risk, and not exposure from 2 years prior. However, this method leads to larger and more abrupt changes in liquidity exposure (since only 12 and 6 observations are used). This could resemble “noise”, which may cause the results of the Cox regressions to have lower significance. The results, reported in Table 3.53, show that high liquidity exposure is still related to worse fund survivability during the crisis when a time interval of 12 months is used. When using a 6-month time interval, the result becomes insignificant. My results imply that a fund’s long-term exposure to liquidity risk (12 months and 24 months) is negatively related to the fund’s survivability, however, the same cannot be said about short-term exposure (6 months).

Table 3.51: Cox Proportional-Hazards Regression results with respect to hedge funds' exposure to liquidity risk

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their exposure to liquidity risk. The variables in the models include: the financial crisis period (indicated by a dummy variable), exposure to liquidity risk, and an interaction term between the financial crisis and the exposure to liquidity risk. Each fund's liquidity risk exposure is estimated by regressing monthly raw returns on the equity market factor (S&P 500) and the Pastor-Stambaugh liquidity factor (2003) at a 24-month rolling interval. The loading on the liquidity factor is then considered to be the fund's exposure to liquidity risk. The exposure is then standardized across all observations in the sample. The regressions are performed using data from January 1994 to June 2009. The second model contains dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2
2008 Crisis	2.448***	2.548***
	(-23.21)	(-24.15)
Liquidity Risk Exposure	1.011	1.014
	(-0.485)	(-0.648)
2008 Crisis*Liquidity Risk Exposure	1.093***	1.100***
	(-3.028)	(-3.358)
Observations	315,580	315,580
Fund Type FE	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.52: Default percentage of funds for each portfolio of hedge funds, sorted from lowest to highest exposure to liquidity risk

This table presents the share of hedge funds within each portfolio that have defaulted during the crisis. Portfolio 1 contains funds with the lowest exposure to liquidity risk while Portfolio 5 contains funds with the highest exposure to liquidity risk. The portfolios are the same ones created in the previous section (when analyzing hedge fund performance). The crisis period ranges from December 2007 to June 2009.

Portfolio	Default %
P1	28.78%
P2	30.06%
P3	24.28%
P4	21.22%
P5	24.80%

Table 3.53: Cox Proportional-Hazards Regression robustness check results, Liquidity Risk Exposure

This table presents robustness check results for the analysis of hedge fund survivability and fund exposure to liquidity risk. The variables in the models include: the financial crisis period (indicated by a dummy variable), the exposure to liquidity risk (standardized across all observations in the sample), and an interaction term between the financial crisis and fund exposure to liquidity risk. In the robustness checks, each fund's exposure is estimated by using a 6-month or 12-month rolling interval. The regressions are performed using data from January 1994 to June 2009. The second and fourth models contain dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2	Model 3	Model 4
2008 Crisis	2.496***	2.601***	2.453***	2.554***
	(-23.84)	(-24.79)	(-23.25)	(-24.2)
Liquidity Risk Exposure	1.042	1.043*	1.047***	1.047***
	(-1.641)	(-1.747)	(-4.247)	(-4.361)
2008 Crisis*Liquidity Risk Exposure	0.975	0.975	1.064**	1.074***
	(-0.988)	(-1.020)	(-2.515)	(-2.943)
Observations	315,551	315,551	315,580	315,580
Fund Type FE	No	Yes	No	Yes
Interval Used To Estimate Liquidity Risk Exposure	6 Months	6 Months	12 Months	12 Months

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.2.8 Hedge Fund Equity Market Exposure

As a result of the huge losses faced by U.S. stock markets, hedge funds with high exposure to these markets saw their returns fall dramatically during the 2008 crisis. Consequently, there is cause to believe that these funds also had lower chances of surviving. I implement tests in order to see if this hypothesis is true. I first use a Cox proportional-hazards regression model to check if there is a relationship between a fund's exposure to the equity market and its ability to survive during the 2008 financial crisis. I then compute the proportion of funds that have defaulted during the crisis within each portfolio created in section 3.1.8. For the Cox regression, I use the same approach as I have done thus far: I include the dummy variable indicating the crisis period, the exposure to the equity market, and an interaction term between these two variables. To estimate the equity market exposure of a fund, I simply perform a 24-month rolling regression of the fund's monthly raw returns on the S&P 500 Index (the same approach as in section 3.1.8). I then standardize the loading on the equity market factor across all observations before proceeding with the Cox regression.

The results for the Cox proportional-hazards regression (presented in Table 3.54) suggest that funds with a higher exposure to the equity market had worse survivability during the crisis than funds with a lower exposure. When looking at Table 3.55, we cannot observe a clear increasing or decreasing relationship between the share of funds that have defaulted and the portfolios. Since these two tests do not support one another, I implement a robustness check just as I have done in section 3.2.7 (Hedge Fund Liquidity Risk Exposure and Survivability). When estimating a fund's exposure to the equity market, I use a 12-month and 6-month rolling regression. Once the new exposures to the equity market are estimated, I proceed with the same Cox regression as I have done when using the 24-month interval. The results of this robustness check, presented in Table 3.56, do not show any significant relationship between a fund's exposure to the equity market and its survivability during the crisis. Overall, my results cannot conclude that a higher exposure to the equity market clearly led to worse survivability during the 2008 financial crisis.

Table 3.54: Cox Proportional-Hazards Regression results with respect to hedge funds' exposure to the equity market

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their exposure to the equity market. The variables in the models include: the financial crisis period (indicated by a dummy variable), exposure to the equity market, and an interaction term between the financial crisis and the exposure to the equity market. Each fund's exposure is estimated by regressing monthly raw returns on the equity market factor (S&P 500) at a 24-month rolling interval. The loading on the equity market factor is then considered to be the fund's exposure to the equity market. The exposure is then standardized across all observations in the sample. The regressions are performed using data from January 1994 to June 2009. The second model contains dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2
2008 Crisis	2.478***	2.582***
	(-23.47)	(-24.44)
Equity Market Exposure	1.026	1.046*
	(-1.065)	(-1.905)
2008 Crisis*Equity Market Exposure	1.081*	1.075*
	(-1.776)	(-1.719)
Observations	320,911	320,911
Fund Type FE	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.55: Default percentage of funds for each portfolio of hedge funds, sorted from lowest to highest exposure to the equity market

This table presents the share of hedge funds within each portfolio that have defaulted during the crisis. Portfolio 1 contains funds with the lowest exposure to the equity market while Portfolio 5 contains funds with the highest exposure to the equity market. The portfolios are the same ones created in the previous section (when analyzing hedge fund performance). The crisis period ranges from December 2007 to June 2009.

Portfolio	Default %
P1	28.04%
P2	30.87%
P3	31.00%
P4	31.42%
P5	26.80%

Table 3.56: Cox Proportional-Hazards Regression robustness check results, Equity Market Exposure

This table presents robustness check results for the analysis of hedge fund survivability and fund exposure to the equity market. The variables in the models include: the financial crisis period (indicated by a dummy variable), the exposure to the equity market (standardized across all observations in the sample), and an interaction term between the financial crisis and fund exposure to the equity market. In the robustness checks, each fund's exposure is estimated by using a 6-month or 12-month rolling interval. The regressions are performed using data from January 1994 to June 2009. The second and fourth models contain dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2	Model 3	Model 4
2008 Crisis	2.502***	2.609***	2.492***	2.598***
	(-23.85)	(-24.82)	(-23.72)	(-24.69)
Equity Market Exposure	1.058***	1.068***	1.021	1.039
	(-2.804)	(-3.563)	(-0.778)	(-1.449)
2008 Crisis*Equity Market Exposure	1.016	1.011	1.076	1.064
	(-0.347)	(-0.255)	(-1.613)	(-1.426)
Observations	320,901	320,901	320,911	320,911
Fund Type FE	No	Yes	No	Yes
Interval Used To Estimate Equity Market Exposure	6 Months	6 Months	12 Months	12 Months

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.2.9 Hedge Fund Managerial Incentives

As previously analyzed, the presence of managerial incentives is related to increased hedge fund performance during the crisis. Funds in which managers have their personal wealth tied into the fund and funds that have an incentive fee are shown to clearly exhibit superior performance. When testing for survivability instead of performance, I expect to see similar results.

To test if funds with managerial incentives survive more than funds without them, I once again implement the Cox proportional-hazards model and compute the portion of funds that have defaulted during the crisis with respect to each incentive. For the Cox regressions, I estimate six models (three without any controls and three with controls for the fund type). The first model includes a dummy variable indicating whether the manager is personally invested in the fund, the second model includes the three different managerial incentives implemented by the fund (management fee standardized across all observations, incentive fee standardized across all observations, and a high watermark dummy variable), and the third model combines the two models and uses all four incentives.

In Table 3.57 (the Cox regression results), we see that hedge funds where the manager had their personal wealth invested in the fund had a higher probability of surviving the 2008 crisis than funds where the manager's personal wealth was not invested in the fund. This result holds for all the models in which personal capital is included. We can observe the same conclusion for funds that have incentive fees: these funds have a higher probability of surviving the crisis than funds with no incentive fees. When looking at funds with management fees, we do not observe any significant coefficient, therefore, these funds do not have superior or inferior survivability. As for hedge funds that have a high watermark, we see in Table 3.57 that they have worse survivability during the crisis than funds with no high watermark. This is further support for the explanation proposed in section 3.1.9: funds with a high watermark engaged in riskier investments. Alternatively, managers may have engaged in strategic default, which would cause managers to believe that setting up another fund, rather than trying to keep their current fund alive, would allow them to gain more personal wealth. Looking at Table 3.58 Panel A, we see that approximately 22% of funds in which the manager was personally invested in had defaulted during the crisis, compared to a 30% default rate for funds in which the manager did not have their personal wealth invested in the fund. Table 3.58 Panel B shows that funds who had an incentive fee had a lower default rate than funds with no incentive fee. Panel C (the management fee) shows that the middle three portfolios (consisting of nearly 90% of the sample) all have a similar default rate while the two portfolios on the extremes have a large disparity between their default rates. This suggests that unless a fund has a very high or very low management fee, their survivability is unaffected by the size of the fee. Furthermore, Table Panel D shows that funds with a high watermark only had a 1.50% better survival rate than funds with no high watermark, a minute difference.

The results for hedge fund survivability during the 2008 financial crisis are similar to the results found in the performance section. We see that funds containing a manager's personal capital perform better and have a higher chance of surviving during the crisis. This is also true for funds that have an incentive fee. The management fee is shown to have no relationship with fund performance and survivability during the crisis, although there is a negative relationship with survivability when only comparing the extremes. Interestingly, the Cox regression results imply that hedge funds with a high watermark exhibit a greater probability of default than funds without a high watermark. As mentioned before, this could be due to strategic defaulting or the tendency of managers to engage in high-risk investments that, if successful, would bring the fund above the high watermark target. This would be an interesting topic to analyze more closely in further studies.

Table 3.57: Cox Proportional-Hazards Regression results with respect to management incentives

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their managerial incentives. The variables in the models include: the financial crisis period (indicated by a dummy variable), the presence of a manager's personal investment in the fund (indicated by a dummy variable), the management fee (in %, standardized across all observations), the incentive fee (in %, standardized across all observations), the presence of a high watermark (indicated by a dummy variable), and an interaction term between the financial crisis and each managerial incentive variable. The regressions are performed using data from January 1994 to June 2009. The second, fourth, and sixth models contain dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
2008 Crisis	2.974***	3.113***	2.363***	2.410***	2.524***	2.583***
	(-24.16)	(-25.18)	(-12.29)	(-12.44)	(-12.53)	(-12.74)
Management Fee			1.001	1.006	1.000	1.007
			(-0.0514)	(-0.342)	(-0.0181)	(-0.352)
2008 Crisis*Management Fee			1.062	1.068	1.056	1.062
			(-1.439)	(-1.562)	(-1.307)	(-1.437)
Incentive Fee			1.420***	1.380***	1.423***	1.378***
			(-13.89)	(-11.51)	(-13.7)	(-11.36)
2008 Crisis*Incentive Fee			0.724***	0.715***	0.741***	0.731***
			(-7.014)	(-7.303)	(-6.419)	(-6.738)
High Watermark (Dummy)			0.676***	0.675***	0.675***	0.675***
			(-8.615)	(-8.661)	(-8.504)	(-8.542)
2008 Crisis*High Watermark			1.347***	1.359***	1.380***	1.395***
			(-3.38)	(-3.453)	(-3.637)	(-3.722)
Personal Capital (Dummy)	1.118**	1.087*			0.986	0.988
	(-2.475)	(-1.835)			(-0.298)	(-0.254)
2008 Crisis*Personal Capital	0.610***	0.586***			0.680***	0.669***
	(-5.269)	(-5.693)			(-3.998)	(-4.180)
Observations	330,816	330,816	328,562	328,562	328,562	328,562
Fund Type FE	No	Yes	No	Yes	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.58: Default percentage of funds with respect to the management incentive

This table presents the share of hedge funds within each group of funds that have defaulted during the crisis. Panel A contains two groups of funds: one where the manager does not have their personal capital invested in the fund and one where the manager does have their personal capital invested in the fund. Panel B contains five portfolios of funds which are formed depending on the incentive fee offered by funds (these portfolios were formed in the previous section). Panel C contains five portfolios of funds which are formed depending on the management fee offered by funds (these portfolios were formed in the previous section). Panel D contains two groups of funds: one contains funds with no high watermark and one contains funds with a high watermark. The crisis period ranges from December 2007 to June 2009.

Panel A: Personal Capital	
Personal Capital	**Default %**
Not Invested	30.02%
Invested	21.67%

Panel B: Incentive Fee	
Portfolio	**Default %**
P1	30.83%
P2	21.54%
P3	26.34%
P4	28.59%
P5	24.24%

Panel C: Management Fee	
Portfolio	**Default %**
P1	22.01%
P2	28.08%
P3	28.30%
P4	28.06%
P5	37.78%

Panel D	
High Watermark	**Default %**
No	28.97%
Yes	27.47%

3.2.10 Funding Restrictions

I have shown that the use of funding restrictions (lockup periods, redemption notice periods, and redemption frequency) does not have a positive relationship with fund returns during the crisis. However, since these mechanisms serve to protect hedge funds from unexpected withdrawals by investors, they may be related to greater survivability. By keeping capital in the fund, the restrictions allow hedge funds who are in financial distress to get out of this situation more easily rather than having capital taken away by panicked investors.

I implement a Cox proportional-hazards regression to test if funds with these mechanisms do indeed exhibit better survivability. I use 7 variables for my regression: the redemption notice period (first I applied a log transformation and then standardized across all observations), the redemption frequency (applied a log transformation and standardized across all observations), a dummy variable indicating if a fund has a lockup period, a dummy variable indicating the 2008 financial crisis period, and three interaction terms where the crisis period dummy variable is interacted with each of the three funding restriction variables. As a non-parametric analysis, I compute the share of funds that have defaulted in each of the portfolios created in section 3.1.10.

Looking at Table 3.59, we see that during the crisis, none of the funding mechanisms led to better or worse survivability: all the coefficients of the interaction terms are insignificant. When controlling for the fund type, these results remain unchanged. When looking at Panel A and Panel B of Table 3.60, the default shares of portfolios do not exhibit a clear increasing or decreasing pattern, therefore, supporting the results from the Cox regression. We do, however, see that funds with a lockup period (Panel C) had slightly worse survivability than funds with no lockup period, although this difference is quite small (approximately 3%).

Similarly to what I have done in the performance section of my analysis, I test to see if these funding restrictions are related to fund survivability prior to the crisis. I use the same regression specifications as I did for the crisis period with the exception of one variable: I use a dummy variable indicating the pre-crisis period rather than the crisis period. The results of this regression, reported in Table 3.61, show that funding restrictions were not related to superior survivability prior to the crisis. However, I do find that when I control for the fund type, the coefficient of the interaction term between the pre-crisis period and the redemption notice period is smaller than one and just barely significant at the 10% level. This suggests that funds that used this mechanism had greater survivability prior to the crisis than funds without that mechanism.

The combined results of my tests show that funds that use funding restrictions during the 2008 crisis do not have significantly better performance or survivability than funds who do not use restrictions. Prior to the crisis, it is observed that funds with these restrictions exhibited superior performance but not superior survivability.

Table 3.59: Cox Proportional-Hazards Regression results with respect to funding restrictions (focus on crisis period)

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their funding restrictions. The variables in the models include: the financial crisis period (indicated by a dummy variable), the redemption notice period in days (natural log transformation, standardized across all observations), the redemption frequency in days (natural log transformation, standardized across all observations), the presence of a lockup period (indicated by a dummy variable), and an interaction term between the financial crisis and each funding restriction variable. The regressions are performed using data from January 1994 to June 2009. The second model contains dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2
2008 Crisis	2.829***	2.938***
	(-20.06)	(-20.75)
Redemption Notice Period	0.901***	0.922***
	(-3.824)	(-2.865)
2008 Crisis*Redemption Notice Period	1.068	1.081
	(-1.338)	(-1.528)
Redemption Frequency	1.007	0.996
	(-0.245)	(-0.140)
2008 Crisis*Redemption Frequency	0.948	0.959
	(-1.055)	(-0.822)
Lockup Period (Dummy)	1.210***	1.156**
	(-3.269)	(-2.471)
2008 Crisis*Lockup Period	1.044	1.034
	(-0.451)	(-0.347)
Observations	293,834	293,834
Fund Type FE	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.60: Default percentage of funds with respect to the management incentive

This table presents the share of hedge funds within each group of funds that have defaulted during the crisis. Panel A contains five portfolios of funds which are formed depending on the redemption notice period offered by funds (these portfolios were formed in the previous section). Panel B contains five portfolios of funds which are formed depending on the redemption frequency offered by funds (these portfolios were formed in the previous section). Panel C contains two groups of funds: one contains funds with no lockup period, and one contains funds with a lockup period. The crisis period ranges from December 2007 to June 2009.

Panel A: Redemption Notice Period	
Portfolio	**Default %**
P1	28.30%
P2	26.80%
P3	29.04%
P4	28.02%
P5	26.22%

Panel B: Redemption Frequency	
Portfolio	**Default %**
P1	29.85%
P2	28.25%
P3	27.46%
P4	28.89%
P5	25.17%

Panel C: Lockup Period	
Lockup	**Default %**
No	27.17%
Yes	30.35%

Table 3.61: Cox Proportional-Hazards Regression results with respect to funding restrictions (focus on pre-crisis period)

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their funding restrictions. The variables in the models include: the pre-crisis period (indicated by a dummy variable), the redemption notice period in days (natural log transformation, standardized across all observations), the redemption frequency in days (natural log transformation, standardized across all observations), the presence of a lockup period (indicated by a dummy variable), and an interaction term between the pre-crisis period and each funding restriction variable. The regressions are performed using data from January 1994 to June 2009. The second model contains dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

VARIABLES	Model 1	Model 2
Pre-Crisis Period	0.362***	0.348***
	(-19.76)	(-20.42)
Redemption Notice Period	0.971	1.006
	(-0.742)	(-0.14)
Pre-Crisis Period*Redemption Notice Period	0.924	0.912*
	(-1.628)	(-1.827)
Redemption Frequency	0.964	0.964
	(-0.843)	(-0.830)
Pre-Crisis Period*Redemption Frequency	1.041	1.029
	(-0.793)	(-0.559)
Lockup Period (Dummy)	1.262***	1.193**
	(-3.016)	(-2.246)
Pre-Crisis Period*Lockup Period	0.957	0.967
	(-0.459)	(-0.356)
Observations	293,834	293,834
Fund Type FE	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.2.11 Investment Focus

I have previously tested whether a hedge fund's investment focus is tied to their performance during the crisis. My results suggest that funds focusing on distressed markets and bankruptcies exhibited lower performance during the crisis than funds with other investment focuses. In this section, I continue with my analysis, however, I examine the survivability of these funds rather than their performance. I use the same four investment focuses as before: mortgage-back-securities (MBS), US real estate, distressed markets, and bankruptcies. To test the funds' survivability, I implement a Cox proportional-hazards regression and for each investment focus, I compute the share of funds that have defaulted during the crisis. The specifications of the Cox models largely follow those found in previous sections of this paper.

Presented in Table 3.62, the results of the Cox proportional-hazards regressions indicate that funds who invested in MBS had a lower probability of surviving than other funds. This result remains significant in all model specifications. Funds investing in US real estate are not shown to have any significantly positive or negative relationship with survivability. Hedge funds who focused their investments in distressed markets have a higher tendency to default, however, upon adding more variables and controls in the model, the significance of this result falters. The coefficient of the variable of interest (interaction term between the crisis period and distressed markets), becomes insignificant in the final model in Table 3.62 (Model 10). However, the p-value regarding this coefficient is 10.7, which is just outside of the 10% significance range. Therefore, we may still conclude that in general, funds that focus on distressed markets have worse survivability. For the case of the bankruptcy focus, the models solely containing this investment focus show a negative relationship between bankruptcy focus and fund survivability. However, this relationship becomes insignificant once the other investment focuses are included in the model. When looking at the share of funds that defaulted during the crisis (reported in Table 3.63), we find that funds focusing on MBS had a default rate over 5% higher than funds not focusing on MBS. The remaining three investment focuses all had defaults rates approximately 3% higher.

The tests I have implemented show that funds investing in MBS may not be affected differently than other funds in terms of performance during the 2008 crisis, although they clearly suffer more in terms of survivability. The performance and survivability of funds focusing on US real estate (compared to those that focus on other investments) does not seem to move in neither a negative nor positive direction. Funds focusing on distressed markets are shown to exhibit both lower performance and worse survivability during the crisis than other funds. Funds investing in bankruptcies also seem to have worse performance and survivability, although this depends on the tests used and the specifications of these tests. As a result, a conclusion regarding this investment focus cannot be reached.

Table 3.62: Cox Proportional-Hazards Regression results with respect to a hedge fund's investment focus

This table presents the Cox proportional-hazards regression results obtained when analyzing hedge funds' survivability and their investment focus. The variables in the models include: the crisis period (indicated by a dummy variable), one dummy variable for each investment focus (Mortgage-Backed Securities, US Real Estate, Distressed Markets, and Bankruptcies), and an interaction term between the crisis period and each investment focus variable. The regressions are performed using data from January 1994 to June 2009. The second, fourth, sixth, eighth, and tenth models contain dummy variable fixed effects for the fund investment style. Robust z-statistics are reported in parentheses. If a variable's coefficient is greater than 1, that variable is associated with a higher hazard rate (in this case, worse survivability), while if the coefficient is less than 1, that variable is associated with a lower hazard rate (better survivability).

Table presented on the following page

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
2008 Crisis (Dummy)	2.524***	2.622***	2.610***	2.716***	2.464***	2.580***	2.538***	2.642***	2.435***	2.547***
	(-22.8)	(-23.63)	(-24.57)	(-25.45)	(-21.37)	(-22.36)	(-23.08)	(-23.94)	(-20.8)	(-21.74)
Mortgage-Backed-Securities (Dummy)	0.887	0.923							0.99	0.989
	(-1.308)	(-0.817)							(-0.105)	(-0.108)
2008 Crisis* MBS	1.482***	1.573***							1.326*	1.416**
	(-2.585)	(-3.013)							(-1.745)	(-2.185)
US Real Estate (Dummy)			0.89	0.965					0.99	1.04
			(-0.520)	(-0.164)					(-0.0447)	(-0.177)
2008 Crisis*US Real Estate			1.285	1.211					1.121	1.072
			(-0.801)	(-0.615)					(-0.36)	(-0.222)
Distressed Markets (Dummy)					0.781***	0.868**			0.837***	0.914
					(-3.833)	(-2.142)			(-2.605)	(-1.277)
2008 Crisis*Distressed Markets					1.381***	1.370***			1.242*	1.232
					(-2.882)	(-2.815)			(-1.675)	(-1.612)
Bankruptcy (Dummy)							0.618***	0.686***	0.693***	0.722**
							(-3.538)	(-2.759)	(-2.580)	(-2.285)
2008 Crisis*Bankruptcy							1.640***	1.586**	1.319	1.261
							(-2.641)	(-2.461)	(-1.319)	(-1.098)
Observations	325,987	325,987	330,816	330,816	325,987	325,987	325,987	325,987	325,987	325,987
Fund Type FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.63: Default percentage of funds with respect to the investment focus

This table presents the share of hedge funds within each group of funds that have defaulted during the crisis. Each panel contains one group of funds that have a certain investment focus and one group of funds that do not have that investment focus. The crisis period ranges from December 2007 to June 2009.

Panel A	
Investment Focus	**Default %**
Other	27.12%
MBS	32.51%

Panel B	
Investment Focus	**Default %**
Other	27.93%
US Real Estate	31.25%

Panel C	
Investment Focus	**Default %**
Other	27.05%
Distressed Markets	30.14%

Panel D	
Investment Focus	**Default %**
Other	27.25%
Bankruptcy	30.61%

CHAPTER 4: CONCLUSION

4.1: Summary of Results

The results of my paper have shown that while some hedge fund characteristics are related to performance or survivability in both the pre-crisis and crisis period, others are not. Some characteristics are shown to have a relationship prior to the crisis, however, this falters during the crisis, possibly as a result of the highly volatile market conditions. Furthermore, it is important to bear in mind that a negative relationship between a certain characteristic and fund performance does not necessarily mean that this characteristic also has a negative relationship with fund survival. Additional findings of this paper offer insight on how certain characteristics are related to the level of risk-taking or the aggressiveness or passiveness of investment strategies.

When comparing the performance of different hedge fund investment styles during the crisis, we see from the non-parametric analysis that the worst-performing funds from the pre-crisis period are ranked higher than the best-performing funds from the pre-crisis period. From the parametric analysis, the only two styles with a significant positive relationship with performance are dedicated short bias and global macro, while emerging markets is the only style with a negative relationship. These findings demonstrate that while a fund style may be prosperous in a long-term bullish market (the pre-crisis period), it may experience significant losses during bearish markets. Contrary to this, fund styles that perform relatively poorly in general, such as dedicated short bias, thrive when markets are plummeting. As for the survivability of hedge fund styles during the crisis, we see that they do not quite coincide with the performance of fund styles. Fund styles with high crisis returns, such as fixed-income arbitrage (ranked third-best in raw returns but with the highest default rate), may have poor survival ability while other styles with low crisis returns, such as emerging markets (ranked last in raw returns but have the second-lowest default rate), may have great survivability. The results in this paper illustrate how the behaviour of different hedge fund styles varies under different market conditions.

The hedge fund alpha, a commonly-used measure of skill, is found to generally have a negative relation to fund performance during the crisis. This suggests that the pre-crisis investment strategies of skilled managers do not translate well in the 2008 financial crisis period. However, when taking into account risk-adjusted returns, we see that funds with the highest alpha provide greater performance and are able to hedge their clients in times of crisis. Furthermore, the results show that the funds with the highest alpha have the largest volatility during the crisis. As for the survivability of funds, I find that the fund alpha does in fact lead to a lower default rate. Funds with higher-skilled managers survive more during the crisis. The overall results imply that manager skill did not help funds realize greater returns, however, it did help them survive through the crisis.

Fund age and fund size are both commonly thought to be negatively related to fund performance. I show that this is true, although the relationship tends to be non-linear. This non-linearity stops my regression results from showing a strong negative significant relationship, however, upon looking at this from another angle by using the portfolio approach, we do indeed see this negative relationship. Despite the fact that older and larger funds have inferior performance during the crisis, they are seen to have better survival rates. My results demonstrate that although their returns suffer more, the experience of old funds and the power of large funds helps keep them alive until the end of the crisis.

Hedge funds who have historically performed well prior to the crisis do not perform well during the crisis. In fact, when looking at the findings of both the portfolio and regression analyses, we see a clear negative relationship between historical performance and performance during the crisis. Another important observation is that the pre-crisis and crisis volatility increase as the historical performance increases. This suggests that funds with high historical performance implement risky strategies that are detrimental during the 2008 crisis. However, just like with fund age and fund size, a negative relationship with performance does not mean there is a negative relationship with survivability. Both the Cox regression results, and the portfolio default rates indicate that funds with superior historical performance also have superior survivability during the crisis.

The presence of leverage in a hedge fund is shown to have a positive relationship with fund performance during the crisis. An explanation for this would be that funds spotted certain investment opportunities in which they were confident in and they decided to lever themselves in order to maximize their returns. In this case, leverage can be viewed as an indicator of skill or the ability to spot better investments. The Cox regression results indicate that funds who are leveraged have better survivability during the crisis than funds with no leverage. This finding is not supported by the non-parametric analysis; however, the Cox regression results have strong significance while the non-parametric analysis does not show a large difference between leveraged and non-leveraged funds. Therefore, I conclude that leveraged funds have better survivability than non-leveraged funds.

Hedge funds' exposure to liquidity risk is shown to have a non-linear relationship with performance. Funds with low exposure outperform funds with high exposure, although this is only true when comparing returns of the first two quintiles of funds with the last two quintiles. Furthermore, funds with more exposure do suffer from worse survivability. In the case of fund exposure to the equity market, there is evidence to suggest that funds with higher exposure experienced lower returns. This finding is unsurprising since the equity market crashed and a high exposure to this would undoubtedly result in lower returns. However, fund survivability during the crisis was not related to the equity market exposure of funds. In sum, during the crisis, exposure to liquidity risk had no relationship with performance but had a negative relationship with survivability, while exposure to the equity market had a negative relationship with performance but no relationship with survivability.

Managerial incentives tend to lead to greater fund performance; however, this is not true for all incentives. The incentive fee and the presence of a manager's personal capital in the fund are the strongest incentives, as they both lead to an increase in performance and fund survivability during the crisis. The management fee has no effect on performance or survivability. However, it does have a negative relationship with survivability when the extremes are compared. Therefore, funds with the lowest management fees have better survivability than funds with the highest management fees. As for the high watermark, there is not enough evidence that allows us to claim that it is related to fund performance. However, during the crisis, funds with high watermarks considerably increased their risk, which gives the impression that these funds engaged in some form of "risk-shifting". This idea is further supported by the negative relationship found between high watermarks and fund survivability.

Funding restrictions (redemption frequency, redemption notice period, and the presence of a lockup period) are not shown to have any relationship with performance or survivability during the crisis. However, prior to the crisis, all three funding restrictions were related to increased performance. These results show that during normal times, funding restrictions can be useful, however, during a crisis, they are not able to provide enough financial security to the fund in order to increase performance or survival.

The four investment focuses I analyze, mortgage-backed securities (MBS), US real estate, distressed markets, and bankruptcies, were affected differently by the crisis. Funds focusing on MBS and distressed markets are found to exhibit superior performance and survivability than funds with other investment focuses. Funds focusing on US real estate are not shown to exhibit superior or inferior performance or survivability. There is some evidence pointing to a negative relationship between the bankruptcy investment focus and fund performance. Regarding the relationship between the bankruptcy focus and fund survivability, no conclusion can be reached since the results change with respect to the kind of test performed and the specifications of the tests. An additional result found was that funds focusing on distressed markets and bankruptcies have seen their returns drop more heavily than those of other investment focuses.

The comparison of discretionary versus systematic funds is a pertinent one since the use of mathematical models and strong statistical software for trading is on the rise. Because of a lack of observations, my approach to this fund characteristic is different than my approach to the other 11 characteristics. My results show that during the crisis, large discretionary funds outperformed large systematic funds while small systematic funds outperformed small discretionary funds. Furthermore, discretionary funds had less return volatility. Examining the relationship between the investment approach and fund survival was not performed since the lack of observations would cause results to be inaccurate and unrepresentative of the hedge fund industry.

4.2: Future Research

Through the various analyses I have performed, I have identified certain interesting areas that need further investigation. I have shown that both historical performance and hedge fund alpha (manager skill) may be negatively related to fund performance during the 2008 financial crisis. This is surprising since we expect funds that generally perform well to outperform, during the crisis, funds that generally perform poorly. The same can be said about funds that exhibit high manager skill. My results may be driven by the methodology I implement, and therefore, I would recommend that more research be done on this topic by using different measures of historical performance and fund alpha.

The presence of a high watermark in a fund is shown to increase fund volatility during the crisis. Although I mention that this may be due to the effect of risk-shifting, an in-depth analysis must be performed in order to confirm this. Future studies can research whether funds who are below their high watermark purposely engage in risky investments during crisis or non-crisis periods in order to bring the fund back above the high watermark.

In my paper, the majority of evidence suggests that the redemption frequency of a fund is not related to its performance during the 2008 crisis. However, the portfolio analysis indicates that a more restrictive policy leads to lower raw returns during the crisis. This finding does not hold much weight since the portfolios are highly unbalanced and my other tests do not support this relationship. Nevertheless, this is an area that requires further investigation since it is plausible to believe that if a fund offers frequent redemptions during bad times, it may be incentivized to consistently keep returns high in order to avoid investor withdrawals.

Comparing the performance of funds who typically rely on computer programs versus funds who do not is an area worthy of future research. This battle of "man versus machine" is becoming more relevant as funds are looking for ways to increase their returns, and automated trading allows for consistency and conveniency. A thorough examination must be performed regarding the performance of systematic and discretionary funds during both the non-crisis and crisis periods. This includes the need for the recent performance of hedge funds and a large sample size.

Table 4.1: Summary of Results

This table presents the main results found in my paper. These include each characteristic's relationship with fund performance and fund survival during the 2008 financial crisis.

Hedge Fund Characteristic	Performance During the 2008 Crisis	Survivability During the 2008 Crisis
Investment Style	Clear relationship, different fund styles perform differently	Clear relationship, survivability greatly varies according to fund style
Alpha	Some evidence for a negative relationship	Clear positive relationship
Age	Negative relationship, although this falters as funds get older	Positive non-linear relationship, the youngest group of funds have good survivability as well
Size	Slight negative relationship, only present when the extremes are compared	Clear positive relationship
Historical Performance	Clear negative relationship, better historical performance means worse performance during the crisis	Clear positive relationship
Presence of Leverage	Funds with leverage outperform those without leverage	Positive relationship
Liquidity Risk Exposure	Non-linear negative relationship Lowest-exposure funds outperform highest-exposure funds	Some evidence for a negative relationship
Equity Market Exposure	Some evidence for a negative relationship	Not enough evidence to confirm a relationship

Table continues on next page

Hedge Fund Characteristic	Performance During the 2008 Crisis	Survivability During the 2008 Crisis
Managerial Incentive: *Personal Capital*	Clear positive relationship	Clear positive relationship
Managerial Incentive: *Incentive Fee*	Clear positive relationship	Some evidence for a positive relationship
Managerial Incentive: *Management Fee*	No relationship	No relationship in general, although there is a negative relationship when the extremes are compared
Managerial Incentive: *High Watermark*	Unclear, however, funds with a high watermark have more volatile returns	Some evidence for a negative relationship
Funding Restrictions: *Redemption Frequency*	Not enough evidence to support a relationship, although further analysis may reveal a negative relationship	No relationship
Funding Restrictions: *Redemption Notice Period*	Not enough evidence to support a negative relationship	No relationship
Funding Restrictions: *Presence of Lockup Period*	No relationship	No relationship
Investment Focus: *Mortgage-Backed Securities*	Negative relationship	Negative relationship
Investment Focus: *US Real Estate*	No relationship	Not enough evidence to confirm a relationship
Investment Focus: *Distressed Markets*	Negative relationship	Negative relationship
Investment Focus: *Bankruptcies*	Some evidence for a negative relationship, was impacted more strongly than other focuses	Unable to reach conclusion, conflicting results
Investment Approach: *Systematic vs. Discretionary*	Large discretionary funds outperform large systematic funds, Small systematic funds outperform small discretionary funds	N/A

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