Copyright Declaration

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed: ______________________________

Date: ______________________________

Acknowledgements

Working as a Ph.D. student in Strathclyde was a magnificent and challenging experience for me. Completing this thesis has been a difficult, but rewarding, journey of self-discovery for someone who never thought that it to be possible. All good theses require companions and I am extremely fortunate in having had some of the best.

My gratitude goes first to my supervisor Dr Leiei Tang, who expertly guided me through my graduate education and who shared the excitement of discovery. His extraordinary patience and consistent encouragement gave me great help by providing me with the necessary materials, valuable advice and inspiring ideas. His suggestions drew my attention to a number of deficiencies and made many things clearer. Without his strong support, this thesis could not have been completed.

It has not always been the easiest or smoothest career ride for me over the last few years and I would like to thank various colleagues at Strathclyde Business School and beyond for their help, advice, support and friendship. To Dr Jun Qiu, and Dr Bibek, my seniors, thank you for listening and for your support. Special thanks go to my generous colleagues who have always been there when needed and have given up their time when I have been stressed. In no particular order, other colleagues who have been there for me at various times for supportive tea breaks, advice and encouragement (in no particular order): Dr Junyu Wu, Dr Yuanyuan Jiang, Dr Mei Liu, Dr Lu Huang, Dr Fengyang Jiang, Mingjun Rong and Dr Zishuo Shao.

I would like to thank my parents Gang Fang and Yi Zheng for their love and confidence in me throughout the years. I also owe my sincere gratitude to my friends who gave me their help and time by listening to me and helping me work out my problems.

Finally, to my wife Zoe; thank you for being a constant source of support, patience and motivation. You have kept me going through the many tough times and have dealt with the anxiety, elation, stress, panic and all the other emotions with the same love, assurance and tolerance – this is all for you.

Abstract

The purpose of this thesis is to examine the predictability of hedge fund performance by using survival risk and liquidity risk analyses. Institutional investors are interested in long-run investments in the hedge fund industry and the high liquidation rate in the hedge fund industry brings significant risk to their investors. This research not only estimates the relationship between hedge fund characteristics and failure risk, but also examines the relationship between hedge fund survival risk, liquidity risk and their relative performance. This thesis is relevant to both researchers and practitioners in exploring a tangible analysis of hedge fund performance.

The sample of this study derives from the TASS database from January 1984 to July 2014. The sampling time period covers the Asian crisis in 1997, the Russian crisis in 1998, the collapse of the sub-prime mortgage crisis in the US in 2007 and the subsequent credit crunch. The original database contains 14,031 hedge funds for this period, of which 6,505 are live funds and 7,526 are liquidated funds. The first empirical chapter estimates the predictability of hedge fund performance by use of a semi-parametric procedure. The results suggest that hedge fund monthly returns are predictable with proper identification of fund failure. The identification of fund failure can extract funds that are liquidated because of poor performance. The empirical evidence suggests that fund failure risk has strong explanatory power regarding hedge fund performance.

The second empirical chapter estimates the predictability of hedge fund performance by using investor-induced liquidity. It suggests that hedge fund liquidity risk derived from investors is an important factor of hedge fund performance analysis. The result also confirms that investor-induced liquidity in the more recent past has more explanatory power regarding its post-performance. Moreover, incubation bias could influence the predictability of hedge fund performance significantly. The result from fund performance shows that the fire sale problem was more significant in the recent financial crisis period but not significant in a normal period.

The last empirical chapter investigates the predictability of hedge fund performance by using a combined prediction model. The result indicates that a model combining survival risk and liquidity risk exhibits more detail and performs better than using a prediction model with a single dimension. The result also indicates that incubation bias influences the predictability of hedge fund performance. Moreover, more recent data influences the predictability of hedge fund performance more significantly. On the other hand, long distance past data can provide a more significant result in estimation of covariates by using the Cox proportional hazard model. It is helpful to investigate the interactions between the risk of hedge fund characteristics and their performance practically.

Content

Chapter 1: Introduction

Absolute return managers have attracted significant interest in recent times. Small and non-institutional investors seek exposure in this alternative asset class. Currently, the popularization of hedge fund and funds of hedge funds has allowed high net-worth individual and institutions to reward premiums and it has increased their value in hedge fund investment analysis. By using an unconventional trading strategy, hedge funds have experienced a low correlation of hedge funds' performance with different financial institutions. The investment strategy of hedge funds has outperformed other trading strategies for a long period (Ding, Shawky, and Tian, 2009). However, hedge funds have a significant risk of liquidation leading to many hedge funds experiencing very low performance. This boosts the interest in studying hedge fund survival risk. With the development of the hedge fund market, hedge fund data vendors provide substantial information on their performance. This study is related to two aspects of literature on hedge funds: (i) thesis focusing on hedge fund survival risk analysis and liquidity risk analysis, and (ii) thesis investigating the predictability of hedge fund performance.

1.1 Motivation

1.1.1 Hedge fund

Hedge fund managers have attracted more attention in recent years and hedge funds have exhibited influential power in the financial market. Hedge funds can influence liquidity by using of relatively low funds. Brown, Goetzmann and Ibbotson (1999) report that one hedge fund manager is able to change the Dow Jones by 10 points. By using a wide variety of tactics, a hedge fund could achieve its purpose for corporate governance in target companies, despite holding a relatively low proportion of the stakes (Brav et al., 2008).

Capital investment in the hedge fund industry has resumed to pre-crisis period levels. Barclay Hedge Research Alternative Investment Databases reported that assets under management of the hedge funds industry and the funds of hedge funds which belong to it grew rapidly from 1997 to 2007. After a sharp decrease in 2008, the total size of the hedge funds' industry returned to pre-crisis levels at the end of 2013 and increased to over USD 2.3 trillion by the end of 2014. However, total assets of the fund of hedge funds kept on experiencing outflows after the financial crisis. The reason for this could be the disintermediation in this market. However, more significantly, the funds of hedge funds have a lower entry threshold for investors and their managers can add value through active management. Funds of hedge funds managers embrace the shorter term for the strategic allocation process more than typical ways (Agarwal and Naik, 2000a, Baquero et al., 2005, Malkiel and Saha, 2005). Moreover, this adds value to a long-term period and provides adequate resilience for investors' needs (Darolles and Vaissie, 2012). Darolles and Vaissie (2012) also report that hedge fund added value depends on their fund picking ability dramatically, in which during the pre-crisis period (Jan 2000 to June 2007), value added by successful fund of hedge fund managers was 3.48% (4.19% during the crisis period from July 2007 to July 2009) and failures were -2.11% (-4.3% during the crisis period). With the right identification of hedge funds, it is possible to construct an investable strategy and then the fund of hedge funds could experience an increase of total asset under management.

1.1.2 Hazard model

Hedge funds have the ability to leverage their investment, thereby creating significant risk. Hedge fund performance is different from standard asset classes (Gregoriou and Duffy, 2006) and could be the reason that investors are interested in it (Fung and Hsieh, 1997a, Siegmann and Lucas, 2002). Hedge fund investors face high searching costs and it is hard to gain enough information from the hedge fund industry. Allocating the right managers to investments becomes a very important issue because there is a high cost involved in both entry to and exit from an active hedge fund. Moreover, it takes a long time to understand a manager's skills. Furthermore, hedge funds often have a significant lock-up period. It is important to identify how best to construct a portfolio of hedge funds. Agarwal and Naik (2001), Kat and Brooks (2002), and Fung and Hsieh (1997a) report that standard methods can be inappropriate when constructing portfolios for hedge funds. More significantly, hedge funds experienced a high attrition rate (8.7%) from 1995-2004 (Liang and Park 2010) and dead hedge funds can cause extreme losses.

This study considers an investment issue that estimates the expected survival risk of a hedge fund before making any decision on investment. Using of hazard model can provide warning signal of liquidation risk. Furthermore, a hazard model helps to identify the causal relationship between the characteristics of hedge funds and relative longevity. Investors and fund of hedge funds could construct their models on performance together with the hazard model, which is helpful to improve the investment instrument. Moreover, the forecasting system related to the hazard model could predict performance together with survival risk. This method would not only be useful to direct investors and hedge fund managers, but also valuable for a broader set of stakeholders. Hedge funds with a strong ability to stay alive are expected to perform better than hedge funds with a weak ability to stay alive. As a result, buying hedge funds with the lowest failure risk and selling hedge funds with the highest failure risk could lead to abnormal returns that outperform market returns in the hedge fund industry.

1.1.3 Liquidity model

Bali, Brown, and Caglayan (2012) estimate the influence of tail risk, residual risk and market risk on hedge fund performance. The authors indicate that systematic risk has strong explanatory power on cross-sectional of hedge fund returns. Minamihashi and Wakamori (2014) document that if the hedge fund industry could decrease systematic risk, the timing ability of that systematic risk could be an important factor in the prediction of hedge fund performance. Many of the studies estimate different risk measures that explain the cross-section of hedge fund returns. Therefore, the hedge fund could have the function of minimizing systematic risk. Bali et al., (2012) document that residual risk and tail risk are not significant factors that could explain hedge fund returns. It is widely known that the hedge fund industry could be a market-neutral investment and it could experience significant positive returns in different market conditions. However, Bali et al., (2012) indicate that market factors play an important role in hedge fund performance. Tiu (2011) argues that hedge funds that are market-neutral investments experience a low R-square. Only the hedge funds with low R-square generate positive returns in both good and bad market conditions. Fung and

Hsieh (1997a), Fung et al., (2008) and Agarwal and Naik (2004) document that hedge funds experienced high tail risk exposure. The hedge fund with high dynamic trading and arbitrage trading strategies experience high tail risk exposure. Bali et al., (2012) further document that tail risk including skewness and kurtosis has no explanatory power on hedge fund performance. Consequently, traditional methods could not capture the hedge fund tail risk effectively and could mean missing the estimation of hedge fund performance. The authors further estimate the explanatory power of systematic variables and unsystematic variables individually. The results indicate that systematic risk measurement is better than residual risk measurement for predicting hedge fund returns. This suggests that a prediction model based on systematic risk could perform better than the residual risk measure.

Liquidity concerns are considered to be a leading indicator in the systematic risk that could predict hedge fund returns (Savona, 2014). There are few studies that explore the prediction model of hedge fund performance. Savona (2014) first builds early warning systems for the hedge fund extreme negative returns by use of a novel regression tree algorithm, documenting that liquidity concerns are important leading characteristics of hedge fund extreme negative returns. Savona (2014) explores how an early warning system would work for the extreme negative returns and could help to predict the risk that causes market-wide crises. Sadka (2006) and Teo (2011) also report that hedge funds embrace high liquidity risk for a smooth performance. The results also indicate that managers deliberately report their performance with less volatility (Bollen and Whaley, 2009). This thesis employs hedge fund liquidity risk as an indicator that could predict hedge fund performance. Hedge fund managers which embrace a lower investor-induced liquidity are expected to perform better. In contrast, managers which expierence higher investor-induced liquidity are expected to perform worse.

1.2 Background

The hedge fund market, a privately organized financial vehicles, has developed rapidly in last decades. Adrian (2007) reports that the hedge fund industry estimated that hedge fund' assets under management amount to $1.5 trillion. Hedge funds are administered by professional investment managers and the managers gather their assets from institutional investors and high net worth individuals. The institutional investors include pension funds, endowments and foundations. The best definition of hedge funds is that they are free from certain regulatory controls of mutual funds (Brown and Goetzmann, 2003). On the one hand, this gives priority to hedge funds so that hedge funds managers can construct unique fee structures and use particular strategies that are unavailable to mutual funds. On the other hand, the main reason for investing in hedge funds is for their high absolute returns and hedge fund performance has low correlation with market returns. In addition, because hedge funds have low liquidity and it is hard to obtain information about new hedge funds, institutional investors are in favour of long-term relationships with hedge funds (Casey, Quirk, &Acito and the Bank of New York, 2004). So it is important to locate hedge funds that are likely to perform better and last longer.

1.2.1 Governance environment

Hedge funds have different regulatory environments in different areas. The US has the most amount of hedge funds that are limited liability companies or limited partnership (Ackermann, McEnally and Ravenscraft, 1999). Hedge funds located in the US do not follow the governance of Investment Company Act of 1940, which regulate a fund's power to use derivatives and leverage (Fung and Hsieh, 1999). Furthermore, hedge funds have little obligation to disclose their information. The SEC list on hedge fund regulatory filings that are publicly available include sale of securities by an issuer exempt from registration, secondary sale of restricted and control securities, ownership of equity securities publicly traded in the United States and registered and unregistered institutional investment managers. The CFTC set requirements on hedge fund year-end financial reports and position reports but the form is not publicly available. However, to gain such benefits, there is a limitation on the number of hedge funds investors in a particular hedge fund (500 today but only 99 before 1996). Moreover, there is also a restriction on investors, in that individual investors cannot have more than five million assets and institutions cannot have more than twenty-five million assets. In addition, hedge funds are restricted from advertising for and soliciting investors publicly (Brown and Goetzmann, 2003).

1.2.2 Strategy employed

Hedge fund regulation is set for the protection of investors' interests, in case managers take on inappropriate levels of risk. However, regulation also limits the opportunities could maximize profit (Ackermann et al., 1999). The strategy employed by hedge funds is derived from the capability of how it generates returns and how much risk it bears. Hedge funds are free to use leverage, derivatives and short selling because they are exempt from certain regulations. This makes hedge fund strategies significantly different from traditional investment vehicles that are non-leveraged and long-only (Kat and Brooks, 2002).

1.2.3 Cost of hedge fund investment

Hedge funds possess the freedom of fees setting, which utilizes an extreme managerial incentive fee structure. Lee, Lwi and Phoon (2004) report that the percentage of hedge funds employing management fees and incentive fees is 96.6% and 98.9% respectively, of which hedge fund managers earn management fees of about 1.5% of assets under management and incentive fees equating to 18.5% of annual positive performance above the high water mark and/or pre-selected hurdle rate. Use of the "high water mark" indicates the incentive fee is based on the recuperation of previous losses. The hurdle rate is normally a fixed benchmark. Brown, Goetzmann and Park (2001) document that fees are causal factors of hedge fund failure.

1.2.4 Data in the hedge fund industry

Disclosure is an important consideration for hedge funds. On the one hand, hedge funds are different from mutual funds in that they have no regular responsibility to publish their information to an official institution. Hedge fund managers believe that full disclosure of a superior investment strategy would cause a negative effect on hedge funds' performance. On the other hand, hedge funds are forbidden from raising funds publicly. Consequently, hedge funds are self-selected to disclose information to private data vendors in order to provide information to their investors (Kat and Brooks, 2002).

Over half of hedge funds have not reported their monthly performance to any data vendor. Some of the hedge funds argue that they invest in illiquid assets that are hard to assess so they have difficulty in updating the valuation of their monthly assets. This flaw decreases the transparency of hedge funds activity and increases investors' risk.

1.1.5 Hedge fund liquidity

Investors in hedge funds often follow the fund's cancellation policy that relates to capital withdrawals. Most cancellation policies are comprised of a redemption period, notice period and lock-up period. The redemption period indicates that investors must wait for a period of time before receiving their money. Before the redemption period, investors have to give advance notice of withdrawal as a notice period. Moreover, the start of the notice period often asks for a previous lock-up period that indicates a guarantee of the minimum amount of time during which the investment cannot be taken out (Agarwal, Naveen and Naik, 2007). The restrictions of redemption influence liquidity negatively (Baquero, Horst and Verbeck, 2005). Aragon (2007) argue that on the one hand, the restriction of capital withdrawals in the hedge fund industry causes illiquidity for investors. On the other hand, the restrictions allow hedge funds to manage illiquid assets effectively and brings abnormal returns. Pulvino (1998) and Mitchell, Pedersen and Pulvino (2007) also report that the restriction of capital withdrawals can protect investors liquidating at fire sale prices.

1.3 Major findings and contributions

This section presents an overview of the main findings of this thesis. This study examines the predictability of hedge fund performance by using failure risk and liquidity risk. Failure risk is estimated by using the Cox proportional hazard model and liquidity risk is based on investor-induced liquidity. Moreover, this study estimates the combined predictability of the effects of both risks. Existing literature has treated failure risk as the fixed property of a hedge fund; virtually no research has studied how failure risk of hedge funds varies over time. In addition, previous studies of failure risk typically use whole life length as the estimation period of hedge fund failure risk. In contrast to the extant literature, this thesis estimates the failure risk of hedge funds by using a rolling window for the estimation period. Furthermore, empirical findings from this study extend prior literature findings on the link between hedge fund failure risk and its performance. Estimation of failure risk is based on the Cox proportional hazard model and the result suggests that hedge funds with low failure risk experience significantly high performance in the following period. This study also provides empirical findings on the link between hedge fund liquidity risk and performance. This study estimates hedge funds liquidity risk by using investor-induced liquidity. Hedge funds with high investor-induced liquidity experience low performance in the following period. This is consistent with the concept that the dilution impact influences fund performance in the long term. The combined prediction model provides more details of the two dimensions. Hedge funds with both low failure risk and low investor-induced liquidity experience high performance in the following period. The combined prediction model provides more details of the two dimensions. Hedge funds with both low failure risk and low investor-induced liquidity experience high performance in the following period. Moreover, the combined model illustrates hedge funds that are at different levels of failure risk and liquidity risk group. Investors could analyze hedge funds with more information in portfolios with more specific failure risks and liquidity risk level.

1.4 Thesis structure

This thesis, which investigates three issues, is organized into seven chapters. Chapter 2 presents a literature review of hedge fund analysis regarding survival risk and liquidity risk analysis. It includes analysis of macroeconomic risk factors and early studies on survival risk analysis. Chapter 3 provides the data and research employed in this thesis. The main research method is to estimate the relationship between fund characteristics and failure risk. Chapter 4 investigates the hedge fund failure risk and their related performance. Chapter 5 examines the relationship between investor-induced liquidity and hedge fund performance. Chapter 6 examines the predictability of hedge fund performance by using a combined prediction model. Finally, Chapter 7 provides the conclusions and limitations of this thesis.

Chapter 2: Literature review

2.1 Prediction of hedge fund performance

Literature focusing on the risk-return characteristics of hedge funds has developed considerably, in terms of the dramatic increase both in the size and number of hedge funds, in the last decade. There has been a large amount of research documenting the predictability of a hedge fund's performance in recent years.

2.1.1 Hedge fund performance analysis

The first strand of studies provides a plethora of linear relation analyses, the majority of which uses simple linear factor models. Early studies employ traditional risk measure for analysis of hedge fund performance. However, hedge funds with specific factors are hard to capture using these models. Hedge fund performance can be driven by many characteristics with significant explanatory power. Furthermore, the methods assessing risk exposures are not stable in the small samples of hedge funds, in terms of the majority of hedge funds that have between 30 and 40 months' length of life. As a result, the traditional linear models would not be appropriate to predict hedge fund performance due to their low ability to select the best hedge funds for investors.

Slavutskaya (2013) reports on hedge fund performance in the investment strategy categories in order to improve the prediction model of the hedge fund industry. The empirical analysis shows that due to the short length of a hedge fund life time, the cross-sectional time series analysis could provide a more significant result. This study assumes that hedge funds with a similar investment strategy could be influenced by the same level of risk exposure. Slavutskaya (2013) documents that the prediction ability of cross-sectional analysis is significantly overwhelming in commonly used linear factor models and suggests that the persistency of hedge fund performance is hard to identify. This is consistent with Brown et al. (1999) who employ the CAPM model to estimate risk-adjusted returns of hedge funds' performance. However, Edwards and Caglayan (2001) report significant performance persistence in the whole hedge fund industry. Using non-parametric analysis on style category returns, Agarwal and Naik

(2000a, b) report that hedge fund performance shows persistency in 3-month cycle returns. Interestingly, they point out that failure funds perform in a more stable way than winners in the hedge fund industry. Similarly, using the bootstrap procedure and Bayesian Econometrics, Kosowski et al. (2007) also report that hedge fund performance shows persistency in 1-year cycle returns. In contrast, using the model of Agarwal and Naik (2004) and Carhart's (1997) four-factor model, Capocci and Hubner (2004) report that persistence of hedge fund's performance only exists in middle performed hedge funds with limited evidence. Kat and Menexe (2003) further report that the predictability of hedge fund performance is not significant. The persistence, however, is not well explained but it is important to both investors and hedge fund managers. To investors, persistence is important because the redemption barriers could cause delays in withdrawals. Persistence of performance is a fund manager's motivation in that good performance can attract capital inflow significantly.

The controversial results in previous studies can be explained by the various biases that are mentioned in This Chapter the method employed in this group solves a part of the bias and provides a step towards improvement in the hedge fund performance analysis. Slavutskaya (2013) documents a higher persistency of hedge fund performance in the investment strategy category.

2.1.2 Macroeconomic risk factors

The second group of the literature focuses on financial and macroeconomic risk factors' effects on hedge fund performance (Bali et al., 2011; Bali et al., 2012; Titman and Tiu, 2011; Sun et al., 2012). Estimating the macroeconomic risk factors, Bali et al. (2011) document a positive relationship between inflation beta and hedge fund future returns. Bali et al. (2012) further estimate that the magnitude of cross-sectional dispersion returns is drawn by financial and macroeconomic risk. Their study documents that systematic risk plays an important role in predicting hedge fund performance and is consistent with Titman and Tiu (2011) who report that funds with low P-value of returns on risk factors tend to have higher Sharpe ratios. Timan and Tiu estimate relationships between a group of risk factors and hedge fund returns. Furthermore, Sun et al. (2012)

estimate hedge fund performance based on funds' strategy and report that funds with the higher distinctiveness of investment strategy tend to perform better. This group of studies estimates on macroeconomic risk factors that could guide investors to allocate capital between hedge fund and other options. For investment within the hedge fund industry, it could be more important to focus on the characteristics of hedge funds, such as leverage used and minimum investment. Moreover, the model to predict hedge fund performance could be different from the traditional investment asset.

2.1.3 Predictability of hedge fund performance

The third group of literature (Amenc et al., 2003; Avramov et al., 2011; Capocci and Hubner, 2004; Hamza et al., 2006; Wegener et al., 2010) further investigates the return predictability of hedge fund returns. The first thesis that investigates the predictability of hedge fund returns is Amenc et al. (2003) who estimate the relationship between macroeconomic risk factors and hedge fund return predictability. Their study is based on the concept that systematic risk and other recognized macroeconomic factors play an important role in predicting hedge fund performance. The authors document a remarkable predictability in the hedge fund industry; however, they could only estimate on an 84 months' time period return that the accuracy of both regression parameters and prediction results are limited.

In the subsequent literature, Agarwal and Naik (2004) and Capocci and Hubner (2004) also report that hedge fund index returns can be predicted and various risk factors show explanatory power for the cross-sectional analysis include buy and write strategy on equity, equity index and bond returns. The results indicate that a single characteristic could not be the only explanation of hedge fund returns, such as the skill of specific hedge fund managers. In contrast, hedge fund performance is driven by a variety of economic risk factors. Based on the notion that hedge fund returns can be predicted from various economic variables, Hamza et al. (2006) estimate return predictability in the hedge fund investment strategy category; their study employs a wider set of risk factors and takes advantage of a longer time series database. The results are consistent with Agarwal and Naik (2004) and Capocci and Hubner (2004) that hedge fund returns can be predicted by financial and macroeconomic factors. The more recent studies take advantage of more abundant data and provide specific details of predictability analysis. Wegener et al. (2010) suggest that non-normality of hedge fund returns and time-varying risk exposure present explanatory power for hedge fund return predictability. Avramov et al. (2011) further report some of the factors could improve the hedge fund return predictability of the linear pricing model, such as default spread and exchange volatility index.

Most of the previous studies employ models that focus on the macroeconomic risk factors to forecast return patterns. Multifactor models which encompass the macroeconomic factors are widely accepted among traditional securities. These studies document that the hedge fund index is predictable and subsequent studies focus on the relative performance within the hedge fund industry

2.1.4 Predictability of relative performance in hedge fund industry

The prediction of hedge fund performance within the hedge fund industry is a relatively new field of research. The fourth group of studies (Avramov et al., 2013 Olmo and Sanso-Navarro, 2012; Panopoulou and Vrontos, 2015; Sanso-Navarro, 2012) is most closely related to this chapter, which investigates the predictability of relative performance in the hedge fund industry. Olmo and Sanso-Navarro (2012) construct a time-varying conditional randomized controlled trial to estimate the relative performance of hedge funds in the investment strategy category; they find that hedge funds that employ a global macro investment strategy perform much better than others who employ a directional strategy. This indicates that hedge fund characteristics matter for future performance within the hedge fund industry. More recently, Avramov et al. (2013) estimate hedge fund return predictability by employing both an in- and out-of-sample method. This study identifies hedge fund characteristics that could influence the predictability of their performance. Furthermore, Avramov et al. (2013) report that leverage and capacity constraints are important factors to estimate hedge fund performance one period ahead. This result enlightens a new area of study that hedge fund characteristics could be the decisive factor of hedge fund relative returns.

Some of studies further analyse different models and their explanatory power to predict hedge fund performance. Panopoulou and Vrontos (2015) test two sets of models: one is a combination of forecasts and the other a combination of information. The former employs simple models and estimates future returns based on a part of the whole information; the latter employs a complicated model to estimate future returns with the whole information set. By employing both kinds of model, the authors assessed the models' power of predictability covering the period from 2004 to 2013. The estimation period contains the financial crisis period that suppressed the growth of the hedge fund industry. The authors suggest that the simple model (combination of forecast models) performs better than the sophisticated model (combination of information models). However, the results indicate that both kinds of model could bring economically and significantly abnormal returns. Panopoulou and Vrontos (2015) also estimate their model by constructing hedge fund portfolios and test them on mean-CVaR. The result indicates that the construction of forecast models experienced both higher earnings and lower variance than the construction of information models. Their study also tests the performance of selected portfolios in the financial crisis period separately. The authors document models to see what combination of information performs better during crisis periods. The constructed portfolios still experience high return and low volatility under relatively high systemic and credit risk.

The previous studies analyse the predictability of hedge fund performance comprehensively. They employ both simple and relatively complicated models that include mean-variance and CAPM approaches, OLS model, Multivariate GARCH models, non-parametric models, Ridge model, Univariate and Multivariate Fama-Macbeth cross-sectional regression models, Cross-sectional regressions by hedge fund investment style, Lagged return of the hedge fund strategy model, ombination of forecast models and Combination of information models. Most of the individual models are commonly appreciated in traditional asset classes. A large number of studies document that hedge fund characteristics, such as investment strategies, play an important role in hedge fund performance.

2.1.5 Survival analysis in hedge fund industry

The literature referred to above focuses on mean-variance performance analysis and therefore could neglect extreme loss in the hedge fund industry. On the one hand, Brown, Goetzmann and Park (2001) document that the annual attrition rate is 15% of the whole hedge fund industry. Fung and Hsieh (1997b) report that the Commodity Trading Advisors' (CTAs) hedge fund has 20% of the annual attrition rate. Furthermore, Brown, Goetzmann and Ibbotson (1999) report that the offshore hedge fund annual attrition rate is 20%. To predict performance in terms of the extreme loss, it is worth applying models of survival analysis to measure the risk term. On the other hand, Agarwal and Naik (2001), Fung and Hsieh (1997a, 2000a) and Kat and Brooks (2002), point out that in using a standard method it is hard to estimate hedge fund performance because the distribution of hedge fund returns often has high kurtosis and positive or negative skewness. This is consistent with Wegener et al. (2010) who state that forecasting of hedge fund abnormal returns presents non-normality, time-varying risk exposures and heteroskedasticity. Using Monte Carlo and portfolio optimization models based on the normal-to-anything method, Morton et al. (2006) construct portfolios in the hedge fund industry with a downside risk measure. They employ the CSFB/Tremont database and select data from April 1994 to March 2003. Using survival analysis models could provide a method to estimate non-normal distributions.

Similarly to the literature in the previous section, Morton et al. (2006) are limited to the analysis of the hedge fund industry. Taking smooth reporting into consideration, many hedge funds hold less liquid securities that are hard to price and the securities often do not trade at the end of the month, and it is also often difficult to obtain publicly available prices for illiquid securities. Furthermore, hedge fund managers could value smoothing upside returns less than downside returns. Morton et al. (2006) do not compare lagged return techniques so the explanatory power of their efficient frontier has its limitations.

Furthermore, hedge funds often ask for a lock-up period, redemption period and notice period that would need a long time to get out of a hedge fund, it could therefore be hard to follow the portfolio on the efficient frontier.

2.2 Early study of survival analysis

Differently from standard methods, the survival risk model could take hedge funds' extreme failure performance into consideration. However, it is crucial to remove significant bias from the hedge fund industry. Differently from survivorship bias, survival analysis is concerned with the analysis of lifetime data or failure-time data (Keifer, 1988). Many factors influence the risk to hedge fund survival to a certain extent, such as fund size, fee, returns, investment style, leverage, lock-up periods and redemption period. Survivorship bias shows influence the result significantly when estimate returns in hedge fund database. Survival analysis shows greater detail on how hedge funds are likely to survive depending on the covariates.

2.2.1 Survival analysis in mutual funds

Using a semi-parametric model, Chevalier and Ellison (1997) test the relation between the growth of flow and performance and funds' income in the mutual fund industry. The outcome of this study would be related to the hedge fund industry. Chevalier and Ellison (1997) utilize data from Morningstar Incorporated and the Center for Research in Security Prices (CRSP). They report that mutual fund managers could decide on different risk exposures depending on their career concerns. Their study points out that fund managers quit or are terminated but appear later frequently managing different funds. Chevalier and Ellison (1997) tracked their performance and documented that the systematic and unsystematic risk these fund managers experienced would influence their ability to be employed in the industry in the future. It would be better if a similar situation were to happen between hedge fund managers. However, the hedge fund industry is different from the mutual fund industry. Hedge fund managers not only work on performance or payoffs, like mutual fund managers, but also need to attract new investors and be able to start a new fund in the future. Employing a hedge fund manager has more complicated conditions than employing a mutual fund manager. Compared with the mutual fund manager, the nature of a hedge fund manager makes it harder to predict the performance of new hedge funds with managers who have been in a hedge fund. One of the principal differences between mutual funds and hedge funds is that the latter do not have to conform to the standards set up by the Investment Company Act in 1940. However, hedge funds have restrictions on the number of their accounts. Then any client who withdraws from a hedge fund would influence hedge fund performance significantly and it is important to have communication with a few large clients for hedge fund managers.

Using the Offshore Funds Directory database, Brown et al. (2001) report factors that impact on the survival risk of hedge fund managers. They also report that the attrition rates for hedge fund managers are significant. Interestingly, hedge fund managers who drop out with low performance find it hard to obtain re-employment. Chevalier and Ellison (1997) report that seasoning influences mutual fund survival risk significantly; the more seasoned funds are less likely to die. Brown et al. (2001) also report that seasoning plays an important role in the hedge fund industry.

Chevalier and Ellison (1997) are limited to data matching of security records. The Morningstar data have 7.5% of the securities that are unmatched, which includes foreign securities, funds with shares in other mutual funds, securities that reported incorrect prices in the Morningstar database and securities that are not even in the CRSP data. After removing new funds and the funds without enough historical return data, only 89% of the records are available, which means the sample size of the hedge fund was about 350. Furthermore, similarly to the hedge fund database, the Morningstar database may have a back filling problem with mutual fund records. The study also points out that mutual funds report portfolio data voluntarily, which could cause selection bias. Brown et al. (1999) also pointed that hedge fund databases have back filling problems. Similarly, the hedge fund database is also faced with self-selection bias.

2.2.2 Style analysis in hedge fund industry

Fung and Hsieh (1997a) document that hedge fund strategies are different from mutual fund strategies in that the latter are not as dynamic. To extend the location factors in previous studies, Fung and Hsieh (1997a) start to analyse the effect of investment strategy factors on the hedge fund industry. They create five investable styles that duplicate five principal components. The investable style factors were related to the different style categories in their database. This method can preserve the density of managers in all style factors effectively. Agawal and Naik (2000b) provided a distinct model of passive option strategies in order to improve location factor analysis. Both of those studies indicate that investment style explains hedge fund returns significantly.

The assumption of the style analysis in Fung and Hsieh (1997a) is that the investment style consists of a period of time. However, Bares, Gibson and Gyger (2001) report that the real investment style is actually changing over time, and could be different from what hedge fund managers have reported to data vendors. Moreover, principal component analysis dos not quite fit the hedge fund industry. Firstly, there is less than 50% of cross-sectional return variance of the sample used in the five dominant investment styles. Secondly, there is a drawback in the procedure that associates investable style factors with one of the style categories in the database. Bares et al. (2001) document that the indices could miss the main capital of the principal components from this additional step.

Style consistency is also significantly related to survival probability. Bares et al. (2001) report on the relationship between hedge funds' style consistency and survival probability. Their study uses FRM's hedge fund database at the end of April 1999. The database includes 1500 hedge fund managers who managed 2992 hedge funds. FRM's hedge fund database obtains information from hedge funds or their administrators directly. The information includes asset under management, management fees and incentive fees, and even a detailed strategy description. The FRM database uses different categories to list observations on hedge fund management style. Some of the categories have clear style characteristics, such as Trading (468), Long and short market hedged (660), Event Driven (273), Relative Value (377), Market Directional (331) and

Multi-Strategy (199). Some of the categories have fewer levels of style characteristics, for example, Trading groups Discretionary, Marco and Systematic Trading subcategories. Their study also keeps on tracking hedge fund performance in both offshore and onshore funds that are run by the same hedge fund managers, which helps to link appropriate funds between them.

Bares et al. (2001) describe a new quantitative method to estimate the style consistency of hedge fund managers; they applied hard and fuzzy clustering to related cost function analysis in the hedge fund industry and report that hedge fund managers could change real investment styles over time and that this is different from what manager reported to the hedge fund database. Malkiel and Saha (2005) also report this situation in the TASS hedge fund database. To the best of the author's knowledge, this is the first report of using hard and fuzzy clustering with related cost function analysis of hedge fund investment styles. Fung and Hsieh (1997a) only estimate distinct clusters in their report that the clusters were distinct based on different of the hedge fund returns. Someone might argue that principal component analysis has higher explanatory power than cluster analysis. However, Bares et al. (2001) document that when contrasting hedge fund indices, cluster analysis has its benefits.

The study also applies hard clustering analysis to track for consistency of leverage in the hedge fund industry. The study analyses four major investment styles, i.e. Trading, Long/Short, Event Driven and Relative Value in 12 clusters-based sub-indices. The results are consistent with Nicholas (1999), i.e. that Event Driven managers are more likely to hold consistent leverage. In contrast, Trading Exhibits use the largest range of leverage (4:1) of all styles.

The study also applies a method of hedge fund survival analysis which is the other problem that influences hedge fund investment strategy. The estimation is based on the Kaplan-Meier estimator and the method take right-censorship of data into consideration. The conditional survival analysis indicates that investment style, fund size, beta and style consistency influence their survival probability significantly. In the four major investment styles, Relative Value shows a higher survival risk than other styles. Bares et al. (2001) document that hedge fund managers who changed their investment style are more likely to keep on changing their investment style. Their study reports that hedge funds with larger size and lower beta have a lower probability of disappearing.

This thesis decided to estimate hedge fund managers rather than the funds. It is beneficial to classify new funds with existing mangers that would have similar performances. Moreover, one manager could be hired by several funds in his career. Therefore, the study could have more observations within one sample for statistical accuracy. As a result, Bares et al. (2001) set an entry level of samples where there were at least 36 monthly returns for a manager under management. The data chosen for survival risk analysis are helpful to retain high statistical accuracy. However, the number of samples became small for this reason. The number of managers in a trading group is fewer than 200 on peak time on 1st January 1998. Moreover, there were fewer than 200 sample sizes in every investment style before 1994. Therefore the number of samples could not be big enough to estimate style consistency and survival risk; in addition, several managers who do not reach 36 month returns are also important in the hedge fund industry, as their funds could also have a significant size and flow. Another flaw in this method is that many of the hedge fund companies have more than one manager, so the performance of a hedge fund could not represent the strategy of the target manager. On the other hand, managers may choose not to report because the fund has reached an appropriate size or they do not want to attract new investors. This reason could also reduce the size of the sample.

More specific to this chapter, the characteristics of hedge funds in TASS is the most recent reported situation. As a result, the characteristics of funds include lock-up period, notice period and redemption period, and the investment strategy could change during their lifetime. For example, Schaub and Schmid (2013) report that the restrictions on hedge funds could change during a financial crisis period and the resultant changing situation is not shown in the TASS database. This is also called an endogeneity problem that could cause bias. Therefore, the characteristics of restriction and strategy should not be taken into account when calculating the estimation model.

Chapter 3: Data and methodology

3.1 Data description

The hedge fund has no regular obligation to publish their information to the official governing body and they are forbidden from raising funds publicly. Normally, hedge fund managers are self-selected to disclose information to private data vendors that data vendors can provide information to existing and potential investors. Kat and Brooks (2002) point out that the data from these providers are not independently verified. Although data vendor tends to perform regular report, the information provided are unaudited. As discussed in Chapter 2, TASS database could fit for this thesis because it contains more of dead funds information. Using of TASS database could cause lower self-selection bias. Moreover, the use of monthly return improve the accuracy of variance measure of risk and TASS database could provide better information that could reduce survivorship and backfill bias to a certain extent. In addition, the TASS database collects relatively more observations than other databases. This research can apply access to one database and TASS database is the most appropriate option.

There are two separate databases contained in the Lipper TASS. One includes information that hedge funds keep reporting to TASS which is live fund database. The other includes hedge funds that are liquidated and stop reporting to TASS database. The database provides monthly returns, total net assets, and other fund characteristics. For example, minimum investment, leverage, management fee and performance fee are reported.

Table 3.1 summarizes the number of hedge funds reported in the TASS database from January 1984 to July 2014. Using of data before 1994 could cause survivorship bias because TASS started collecting data in 1994 that the hedge funds died before 1994 are not included in the database. Importantly, the sampling time period covered the Asian crisis in 1997, Russian crisis in 1998, the collapse of the sub-prime mortgage crisis in the United States in 2007 and the following credit crunch. The original database contains 14031 of hedge funds in this period, of which 6505 are live funds and 7526 are liquidated funds. Table 3.1 illustrates the characteristic data in the database for active funds, liquidated funds, and all funds. The minimum investment is the average requirement that the hedge fund asks for initial investment from their investors. In comparison, there is a higher minimum investment in active funds and it is about 2 times higher than the liquidated funds. Redemption frequency signifies the average times per year that hedge funds redeem their assets. There is little difference in this characteristic between active funds and liquidated funds. Fund using leverage refers to the percentage of funds which use debt to leverage their capital. Similarly, domiciled in the U.S. is the percentage that hedge funds registered in the United States.

Table 3.1 Administrative Data

This table provides a comparison of the fund characteristic data provided by the Lipper TASS hedge fund database. The first 2 rows represent averages from each group of funds. The bottom rows indicate the percentage of funds within each group that exhibit that characteristic

	Active		Liquidated		All	
	mean	std	mean	std	mean	std
Mean of Minimum investment ($)	2008391	35959243	1295911	20467370	1621932	28445408
Redemption frequency (per year)	28.77	82.64	23.95	67.92	25.99	47.56
Funds using Leverage (%)	61.51		59.46		60.41	
Domiciled in the U.S (%)	0.73		0.68		0.7	
Total number of hedge fund	6505		7526		14031	

As discussed in Chapter 2, many biases exist in the hedge fund database because of the weak regulation in the hedge fund industry. Hedge funds often operate a period before attracting outside investors. Funds with a successful history will report their performance to the database and funds with bad performance will not report to the database. Furthermore, reported data of hedge funds often include performance before the time it listed on the database. The backfilled performance can be much better than the hedge fund actual returns. In order to reduce this incubation bias, I deleted first 12 months' return for each hedge fund. Previous studies indicate that incubation bias significantly influences the estimation of hedge fund performance (Baba and Goko, 2006; Malkiel and Saha, 2005).

Table 3.2 presents the main time series data considered in this study and these independent variables show the difference between the active fund and liquidated funds. Duration is the average life length of hedge funds in each group. The average duration of the live fund is about half a year longer than dead funds. Total Net Assets (TNA) of the fund represent the total funds under management for a net of fees and expenses on average in each group. Baba and Goko (2006) reported that average assets under management of the active fund (102.34 million US$) are over two times higher larger than that of the liquidated fund (45.61 million US$). However, TNA provided by the TASS database shows that the total net asset between active funds and liquidated funds are not significantly different. The time series data for four different return moments shows that active funds experienced higher means of return than liquidated funds. According to the risk aversion theory, investments with high first and third moments and low second and fourth moments are more preferred. Live funds experienced a higher mean of return and lower kurtosis than liquidated funds. However, their variance is higher and skewness is lower than liquidated funds. The descriptive statistics do not show clear support of this theory.

Table 3.2 Administrative Data

This table provides a comparison of the fund characteristic data provided by the Lipper TASS hedge fund database. The first 2 rows represent averages from each group of funds. The bottom rows indicate the percentage of funds within each group that exhibit that characteristic

	Active		Liquidated		All	
	mean	std	mean	std	mean	std
Mean of Minimum investment ($)	2008391	35959243	1295911	20467370	1621932	28445408
Redemption frequency (per year)	28.77	82.64	23.95	67.92	25.99	47.56
Funds using Leverage (%)	61.51		59.46		60.41	
Domiciled in the U.S (%)	0.73		0.68		0.7	
Return	2.45%	0.098	1.15%	0.096	1.7%	0.098
Skewness	-4.44%		-1.5%		-1.58%	
Kurtosis	5.93%		7.02%		6.35%	
Duration	36.8		30.7		33.5	
TNA	24.2		23.7		23.92	
Total number of hedge fund	6505		7526		14031	

3.2 Definition of variables

The analysis of covariates based on the hypothesis of their relationship with fund failure risk. The set of covariates includes size, return measures, leverage and minimum investment. Table 3.3 illustrates the expected relationship between covariates and fund's failure risk:

Table 3.3: Expected relationship between covariates and fund failure

The Table 3.3 lists the covariates intended for use in this study. The column labeled expected relation indicates the expected relationship with fund failure. The presence of an asterisk "*" denotes that the covariate is represented as a dummy variable.

Covariate	Expected Relation
Fund size	Negative
Mean of Return	Negative
Return on t	Negative
Average return from t-2 to t	Negative
Variance of return	Positive
Kurtosis of return	Positive
Skewness of return	Negative
Leverage*	Positive
Minimum investment	Positive

3.2.1 Size

The fund size is based on the sample mean of the total net asset (TNA) over the lifetime of the estimation period. This information is reported on a monthly basis for every fund after the sampling process. United States dollars is selected as common currency because the majority of the hedge funds reported in it. Using exchange rate on July 31st, 2014, this study converts total net assets to US dollars in order to place meaningful comparison. Consistent with the extant literature, this study takes the natural logarithm of TNA in United State dollars. It is expected that funds with large size could withstand the big impact from market change. Fund size is supposed to negatively relate to failure risk because funds with insufficient size present higher attrition rate (Amin and Kat, 2003). Amin and Kat (2003) documented that funds lack of capital is hard to perform managerial expectations and bear the burden of fixed cost. This opinion is supported by study employing the proportional hazards model (Gregoriou, 2002; Baba and Goko, 2006) and the research using the probit regression analysis (Baquero, Horst, and Verbeek, 2005; Liang, 2000; Malkiel and Saha, 2005).

On the other hand, Ammann and Moerth (2005) argue that large funds perform worse than small funds because an investment fund has to diversify away with the growth of fund size. It makes large funds' return more stable and moves closer towards a market portfolio as a poorer performance. On contrary, smaller funds have more flexible and dynamic investment strategies. Large funds present better stability and smaller funds show higher return, the overall effect of fund size on failure risk must be determined empirically.

3.2.2 Return

Fund returns are reported on a monthly basis and net of all fees. It is difficult to calculate returns after fees accurately because incentive fee structure is complex together with hurdle rate, high water marks and different calculation periods. Incentive fee increases with a higher return on investment. For example, incentive fees are 5% when the return higher than hurdle rate and it increases to 10% when the return over 5% higher than hurdle rate. Moreover, Hedge funds calculate their incentive fees annually, semi-annually or even quarterly and it also changes the length of time to reset high water mark. Typically, fees are assessed on an annual basis and allocate estimated fee charges to monthly returns. Using of monthly returns net of fees, this study composes six of return based measures that are mean of return, return on t-1, the average return from t-2 to t, the variance of return, the skewness of return and kurtosis of return.

Mean of return is calculated as the average monthly return over the life of the fund in the estimation period. It is expected that funds with low returns present a higher risk of failure. Funds with negative returns will experience a decreasing of fund TNA. Moreover, negative returns could cause a lower expectation of incentive fee and it could further influence propensity for the fund manager to close down the fund. In addition, Baba and Goko (2006) reported that capital outflow from poor performing funds to funds with good performance. Many of previous research (Baba and Goko, 2006; Baquero, Horst, and Verbeek, 2005; Brown, Goetzmann, and Park, 2001; Gregoriou, 2002; Liang, 2000; Malkiel and Saha, 2005) find strong evidence to support that fund return is negatively related to the risk of failure. Morover, Amin, and Kat (2001) document that average return in the last 12 month of dead funds are negative or do not differ significantly from zero. Baba and Goko (2006) document significant result using of average monthly return both on the latest 3 months and latest month. This indicates that performance in the less distance past is of more importance. It is consistent with Rouah (2005), Liang and Park (2008) and Malkil and Saha (2005) that contemporary measures of mean return have more explanatory power on fund failure than mean returns over the life of the fund.

The variance of return is the sample variance of monthly return over the lifetime of the estimation period. On one hand, increasing of variance increases the probability of higher return. On the other hand, high variance increases the risk of low return. A plethora of previous studies including Brown, Goetzmann, and Ibbotson (1999), Brown Goetzmann and Park (2001), Gregoriou (2002), Malkiel and Saha (2005) all provide evidence to suggest that negative effects of downside risk outweigh the gains from upside risk. As the result, the variance is expected to positively relate to funds' failure. Gregoriou and Duffy (2006) reported that the most of the hedge fund returns experienced negative skewness and high kurtosis. Liang and Park (2008) also reported that 43.4% of the hedge funds returns reject the null hypothesis of normality at 5% significance level by using of Jarque-Bera test of normality. Therefore, tests only use variance could underestimate the tail risk of hedge funds. According to investors' utility function, investors will prefer high mean and skewness and low variance and kurtosis. It is expected that funds with high kurtosis and low skewness will have a higher risk of failure.

3.2.3 Leverage

The use of leverage is an option to hedge fund managers. Funds with leverage could magnify their return and help managers to control the volatility of returns. Simultaneously, using of leverage could cause high fees and even fail to serve creditors. Gregoriou (2002) document that funds employing leverage matter for failure risk. Leveraged funds are expected to have higher failure risk as it embraces greater return volatilities. Baba and Goko (2006) documents that fund with high leverage shows no significant difference compare to lower-leveraged funds. Fang and Hsieh (1997), Gregoriou (2002) and Liang (2000) document that leverage can contribute to a negative effect on hedge fund performance and length of duration. Hedge fund managers can change amount or margin rates of leverage over time. Moreover, non-debt instruments include derivatives can provide leverage to hedge funds. However, TASS database only provides whether the fund use leverage. Therefore, leverage is treated as a dummy variable in this study - 0 if the fund does not use leverage and 1 otherwise.

3.2.4 Minimum investment

Minimum investment in TASS database is the threshold for new investors entering into the fund. A certain level of minimum initial investment can impact fund liquidity in two ways and matters to fund duration time. Firstly, funds with high minimum investment are likely to reject a big amount of small-scale investors. It indicates that stability of investment in funds is weaker and consequently a lower duration. Secondly, high minimum investment allows redemption from single investor influence constancy of fund size. As the result, funds with high minimum investment are expected to have high failure risk. TASS database provides minimum investment in a different currency. Using exchange rate on July 31st, 2014, this study converts minimum investment into US dollars in order to place meaningful comparison. TASS database provide all performance of list hedge fund. There is no particular data that hedge fund set their minimum investment. This study utilize the date that data is available to convert minimum investment into dollar.

3.3 Methodology

Prior empirical studies on survival risk analysis identified the relation between fund characteristics and the risk of death. This Chapter aims to identify the empirical value of survival risk analysis. I tend to use survival analysis based on Cox (1972) proportional hazard (PH) model to predict hedge fund failure and then construct portfolios of hedge funds based on their historical failure risk. The hypothesis is that buying top sort of hedge funds (lowest failure risk) and selling bottom sort of hedge funds (highest failure risk) could obtain an abnormal return that outperforms market return in the hedge fund industry. I could roll the failure risk estimation every six months and restructure the portfolio.

3.3.1 Survival risk analysis

Survival analysis aims to detect the relationship between factors of individuals and their life length until they meet a specific event. The event is a transformation from one status to another that can be identified on time. Quantitative methods are generally used such as hazard models. This study defines the event as the failure of hedge funds that due to poor performance. Accordingly, the life length is the duration of time from the first time monthly return reported for the last month. The basic setting is as follows. Suppose that the life length is a random variable T and the time to failure is a cumulative probability to failure $F(t)$.

(3.1) $$F(t) = P(T \leq t)$$

Where T and t are time and $P(T \leq t)$ is the probability that lifetime of a hedge fund is shorter or equivalent to t. On contrary, the probability of a lifetime of a hedge fund is longer than t. The survival function is given by:

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

The relation between survivor function and cumulative probability to failure express as:

(3.3) $$S(t) = 1 - F(t)$$

Given the survivor function, we can ascertain the hazard function that expresses the time to failure. The hazard function estimates the probability that life length of a hedge fund is t. It is defined as:

(3.4) $$\lambda(t) = \lim_{\Delta \to 0} P(t \leq T < t + \Delta t), T \geq t$$

Consequently, the survivor function can be deduced as follows:

(3.5) $$S(t) = \exp[-\int_0^t \lambda(\mu) d\mu]$$

Where $\lambda(\mu)$ is also called hazard ratio because it measures the number of failures per interval time. $\lambda(\mu)$ is unobservable but it can be estimated by the number of failures divided by the number of actives in the time intervals. It is important to define scale and origin of time to proceed to explain the hazard ratio.

This thesis estimate hedge fund failure risk by using of hazard model. The estimation of the coefficient for covariates based on Cox proportional hazard model. It is the most commonly employed semiparametric model in hazard regression. The conditional hazard function is assumed to be of the form:

(3.6) $$\lambda(t, z) = \lambda_0(t) e^{(\beta' z)}$$

Where z is observed value of covariate. $\lambda(t, z)$ is hazard rate and $\lambda_0(t)$ is the baseline hazard rate function. $\beta = (\beta_1, \beta_2, \dots, \beta_q)^T$ is the vector of regression coefficients. There is no particular function assumed for baseline hazard and it is estimated non-parametrically. The hazard model present probability of a hedge fund failed in time t conditional upon the firm surviving until time t. The hazard function is constructed by two factors. Firstly, the exponential of covariates z and the coefficients β. Secondly, an underlying hazard function denotes the hazard function for the hedge fund without covariates$\lambda_0(t)$ which is unspecified and it cannot be negative. The Cox proportional hazards model relates the value of hazard rate for observations to the baseline value of hazard rate for observations. The output finally assess the hazard ratio as follow:

$$\text{(3.7)} \qquad \mathrm{HR} = {\lambda(t,z)}/{\lambda_0(t,z^*)}$$

The hazard ratio represents the relative risk of instant failure for observations having independent variable value z compared to the ones having the baseline values. For a baseline relative to vector z^* and the vector of independent variable value z, the hazard ratio is shown as follow:

$$\text{(3.8)} \qquad \mathrm{HR} = {\lambda(t,z)}/{\lambda_0(t,z^*)} = \exp[\textstyle\sum_{j\in R(t)}(z-z^*)\beta']$$

The hazard rates are related to survival rates that survival rate at time t for an observation with the vector of independent variable z is

$$\text{(3.9)} \qquad \mathrm{S(t,z)} = S_0(\mathrm{t})^{HR(t,z)}$$

Where $S_0(t)$ is the survivor function with the baseline hazard rate function $\lambda_0(t)$ and $\mathrm{HR(t,z)}$ is the hazard ratio of the independent variable value z relative to the baseline value. The coefficient estimates are found by maximizing the likelihood function of the model. Partial maximum likelihood function is the major calculation to complete Cox proportional hazards model and is based on the observed order of events. Essentially, this model vanish baseline hazard $\lambda_0(t)$ and estimate the vector of covariates as an ordinary likelihood function. The calculations are based on standard partial likelihood methods in the Cox proportional hazards model. The partial likelihood function is given by

$$\text{(3.10)} \qquad \mathrm{P(\beta)} = \textstyle\prod_{i=1}^{n}\{{\exp(\beta' z_i)}/{\sum_{j\in R(t_i)}\exp(\beta' z_j)}\}^{\mu_i}$$

Where $\mathrm{R}(t_i) = \{\mathrm{j}: t_j \geq t_i\}$ represents the risk set on time t_i. Only event times contribute their own factor to the partial likelihood. Both of censored and uncensored observations are in the denominator. All individuals that are still at risk immediately prior to t_i are still in the risk set. Let $\hat{\beta}$ represent the maximum partial likelihood estimate of β that is estimated by maximizing the partial likelihood function

$\mathrm{p(\beta)} = \mathrm{LnP(\beta)}$ from equation 3.10.

(3.11) $$\mathrm{p}(\beta) = \sum_{i=1}^{n} \mu_i(\beta' z_i) - \sum_{i=1}^{n} \mu_i \ln\{\sum_{j\epsilon R(t_i)} \exp(\beta' z_j)\}$$

The first derivative of $\mathrm{p}(\beta)$ with respect to β is called vector of gradient scores, given by

(3.12) $$\Omega(\beta) = {}^{dp}\!/_{d\beta} = \mu' Z - \sum_{i=1}^{n} \mu_i \, {}^{\sum_{j\in R(t_i)} \exp(\beta' z_j)\, Z_{(j,\cdot)}}\!\Big/_{\sum_{j\in R(t_i)} \exp(\beta' z_j)}$$

Where $\mu = (\mu_1, \dots, \mu_n)'$represent the vector of censoring observations, Z is $(\mathrm{n} \times \mathrm{p})$ matrix of covariate values, with the j-th row containing the covariate values of the j-th individual, $Z_{(j,\cdot)} = z_j'$.

The information matrix $\mathrm{M}(\beta)$ is given by the second derivative of $\mathrm{p}(\beta)$. Let $p_{R(i)} \in M(R)$represent the indicator vector of the risk set $\mathrm{R}(t_i)$, this means the j-th observation of $p_{R(i)}$is 1when $t_j \geq t_i$, and 0 otherwise. Then the hessian matrix is shown as follows:

(3.13) $$\mathrm{M}(\beta) = {}^{d^2 p}\!/_{d^2\beta}$$

$$= \sum_{i=1}^{n} {}^{\mu_i}\!/_{\varpi_i(\beta)^2}\, \bar{Z}(i)' [\varpi_i(\beta) D\{\exp(Z\beta)\} - \exp(Z\beta)\exp(Z\beta)'] \, \bar{Z}(i)$$

Where the $\varpi_i(\beta) = p_{R(i)}' \exp(Z\beta)$ are scalars; for any vector $\mathrm{Z}\beta$, $D\{\exp(Z\beta)\}$ represent the diagonal matrix with the main diagonal $\mathrm{Z}\beta$, and $\exp(Z\beta)$ is defined element. In $\bar{Z}(i) = D\{p_{R(i)}\}Z$, the matrices $\bar{Z}(i)$ are modifications of the design matrix Z, setting the rows of $\bar{Z}(i)$ to zero when the observations is not in the risk set on time t_i.

3.3.2 Liquidity risk analysis

Liquidity risk analysis aims to detect the relationship between investor induced liquidity and hedge fund post performance. This approach can capture liquidity pressures that hedge fund managers face with investors under same market liquidity condition. It indicates that this aspect of liquidity is most likely to influence hedge fund performance. Hedge fund managers embrace a lower investor-induced liquidity will carry out better performance. In contrast, managers experiencing higher investor-induced liquidity will have lower performance. High net investment flow could scale in active portfolio management, it could the subsequently cause adversely impact on hedge fund future performance. Firstly, this study evaluate investment flows of all hedge funds in each month as follow:

$$\text{(3.14)} \qquad \mathrm{NIF_t} = \mathrm{TNA_t} - \mathrm{TNA_{t-1}} * (1 + \mathrm{r_t})$$

Where $\mathrm{NIF_t}$ is the net investment flows into the fund in period p. The net investment flows of an individual fund represent the investor-induced liquidity. It is supposed that hedge fund manager should consider if they keep the investment flow in cash or invest it when they experience positive NIF. It could cause dilution when its direction correlates to the following return and further reduce the hedge fund performance. On the contrary, the hedge fund will short the low priority investment and fix investment portfolios when the hedge fund experiences negative NIF. It could subsequently cause a positive impact on fund performance. Then I estimate the investor-induced liquidity as follows:

$$\text{(3.15)} \qquad \mathrm{IL_t} = \frac{\mathrm{NIF_t}}{\mathrm{TNA_{t-1}}} = \frac{\mathrm{TNA_t}}{\mathrm{TNA_{t-1}}} - (1 + \mathrm{r_t})$$

Where $\mathrm{IL_t}$ is the investor-induced liquidity in month t. It is expected that aggregate investor induced liquidity in past n month have explanatory power on hedge fund post-performance. The aggregate investor induced liquidity is estimated as follow.

$$\text{(3.16)} \qquad \sum_{n=0}^{t-1} \mathrm{IL_{t-i}} = \sum_{n=0}^{t-1} \frac{\mathrm{NIF_{t-n}}}{\mathrm{TNA_{t-1-n}}} = \sum_{n=0}^{t-1} [\frac{\mathrm{TNA_{t-n}}}{\mathrm{TNA_{t-1-n}}} - (1 + \mathrm{r_{t-n}})]$$

Chapter 4: Survival risk analysis

4.1 Introduction

Using of publicly available data, This Chapter aims to build a forecasting system that's capable of constructing investable portfolios of hedge funds based on the historical time varying likelihood of survival risk in individual hedge funds. Much of previous research on hedge fund survival risk analysis has focused on causal factors of hedge fund failure, few of them analyzed the relation between hedge fund performance and their survival risk. Previous studies report predictability of hedge fund performance by using of traditional risk measure. Some of the studies further report predictability in different strategy categories. However, the most of the recent research indicates that hedge fund investors faced with significant downside risk exposure that is hard to control by traditional risk measure. Many studies reported that hedge fund performance has extremely low correlations with traditional asset classes. Some studies indicate that hedge fund failure could be predicted by the Cox proportional hazard model (Gregoriou, 2002; Baba and Goko, 2006; Rouah, 2006 and Liang and Park, 2008). In this regards, this chapter aims to explore the relation between hedge fund performance and their relative failure risk.

This chapter estimated the predictability of hedge fund performance by using a semi-parametric procedure. Firstly, it estimated causal factors that influence hedge fund failure risk. Using a Cox proportional hazard model, this chapter estimated the characteristics that could influence hedge fund failure risk. TNA, leverage, minimum investment, return, average return in the past three months, variance, kurtosis and skewness of return, are the main characteristics that influence hedge fund failure risk. Secondly, this chapter estimate predictability of hedge fund performance based on hedge fund failure risk. Empirical findings suggest that hedge fund monthly returns are predictable. The results suggest that hedge funds with low failure risk outperform hedge funds embracing high failure risk. Remarkably, this chapter also provides identification of fund failure. The results also suggests that fund failure predicts hedge fund performance better than fund liquidation. The influence of failure risk and hedge fund returns is helpful to investigate interactions between the risk of hedge funds and their performance practically. The result provides evidence that hedge fund with low failure risk outperforms hedge fund market. The constructed portfolio based on the hedge fund failure risk leads to economically and statistically significant performance.

In this chapter, Section 4.2 provide literature reviews about the prediction of hedge fund performance and survival risk analysis applied in the hedge fund industry. Section 4.3 describes the data and sampling method for this study. Section 4.4 explains the methodology. Section 4.5 presents the empirical results. Section 4.6 provides Robustness checks and Section 4.7 concludes this chapter.

4.2Literature review

4.2.1Methods in survival risk analysis

Brown, Goetzmann, and Park (2001) investigate the impact of historical performance on changes of risk profile in hedge funds. The study was based on data from TASS hedge-fund database for the period 1994 to 1998. The sample size of the cross-sectional analysis is 1,241 and 168 of dead funds to be used as failure times. Using the contingency table test, they suggest that hedge fund manager with relatively poor performance more likely to increase their volatility. In addition, they find performance relative to high water mark is not associated with risk. Eventually, risk embrace also increases the risk of death. However, Baba and Goko (2006) argue that hedge funds with high water mark have a higher survival probability. Moreover, Brown, Goetzmann, and Park (2001) found that funds with young age or negative returns over one or two years are at increased risk of survival. It consistents with the findings of Liang (2000) that funds with small size, low incentive fee, low manager personal investment, young age, low return and incentive fee has high survival risk.

Notwithstanding that Brown, Goetzmann, and Park (2001) concentrated on the relationship between performance and volatility, they also point out that CTA fund with poor absolute performance in two years has high survival risk. It is consistent with Liang (2000) who report that the main reason for the fund’s disappearance is related to the significant underperformance of live funds. Moreover, Brown, Goetzmann, and Park (2001) report that the fund with longer lifetime has a lower risk of discontinuation.

Consistent with Chevalier and Ellison (1997), Brown, Goetzmann and Park (2001) suggest that seasoning is a considerable role in fund survival. Although, Lunde, Timmermann, and Blake (1999) argue that restrictive probabilistic analysis is hard to achieve, Brown, Goetzmann, and Park (2001) used Cox semi-parametric hazard rate regression to confirm that funds existing longer are more likely to survive. The study also reports that the attrition rate in hedge fund was about 15 percent per year from 1994.

Boyson (2002) points out that a limitation of Brown, Goetzmann, and Park (2001) stems from the use of absolute probability of failure. Conditional failure could be more accurate. Furthermore, the study treated all funds appearing in the 'Graveyard' as failures. Consequently, other reasons include discontinuation of reporting was examined as a failure. Graveyard in TASS refers to funds that have stopped reporting, however, there are different reasons that funds stop reporting. The reason could not be examined as failures such as liquidated, merge or purchased and the fund base has reached an appropriate level and they do not wish to attract new capital. Moreover, the sample of dead funds is too small to be used as failure times. In addition, in Brown, Goetzmann, and Park (2001) study, volatility and individual investment were used as covariates. I tend to agree with Liang and Park (2010) who report on a more reliable method and argue that manager tenure does not explain the survival of hedge fund.

4.2.2 Take live fund into consideration

Gregoriou (2002) assess dynamic performance properties on survival probabilities of hedge funds based on Zurich Capital Markets database. The dataset covering the period 1994 to 2005 consist of 1,503 live fund and 1,273 funds that have discontinued reporting. Using of Product-Limit estimation, Life table method, Accelerated Failure Time Model and the Cox proportional hazards models, Gregorious (2002) find certain classifications of hedge fund more likely have longer survival time, which includes millions managed, redemption period, incentive fee, leverage, monthly returns and minimum purchase.

Without consideration of drop reason, Boyson (2002) reported that fund in Graveyard was under-performing and probably closed. The data of Boyson (2002) shows that 57 of the 288 funds in the sample were considered dead, 5 of them had merged, 31 of them ceased reporting and 21 of them closed. The sample of dead funds is too small to be used as failure times. Gregoriou (2002) reported that in the 1,273 dead funds, 531 has closed, 558 stopped reporting,62 had merged, 12 of those reached capacity limits in terms of capital under management and other funds did not report their reason for discontinuation of the report. Furthermore, Gregoriou (2002) pointed out that it is necessary to take live funds into estimation process because they also contribute information about their survival time in the hedge fund database. The analysis of Brown, Goetzmann and Park (2001) and Boyson (2002) could suffer from a downward bias because they did not combine live funds into estimation period.

The study report that large hedge funds and capital of hedge funds that the size higher than median could have better performance. The funds with Minimum purchase which higher than $250,000 embraced the high risk of death. Gregoriou (2002) highlight that funds with annual redemptions have a positive effect on survival. They also report that leverage has a negative effect on survival, with high leverage funds exhibition shorter duration times.

However, Gregoriou (2002) only incorporated the funds dropped out the reporting mechanism. The underlining failures of hedge fund should be extended. In addition, the critical weak of Gregoriou (2002) as same as Brown, Goetzmann, and Park (2001) is the way they select failure funds. The study also uses entire dead fund database as failure times. It includes liquidated and assets returned to investors, merge or purchased by larger funds, the funds with good records that reached capacity limits and stop reporting. Fung and Hsieh (2000a) also report that many hedge funds which were not liquidated in dead fund database are actually alive and perform well.

Gregoriou and Rouah (2002) also report that size may have a negative impact on hedge fund performance. This drawback could mislead the result. Baba and Goko (2006) reported that leverage has low power to explain the survival of hedge fund and high leverage fund will survival longer. Liang and Park (2010) also report that leverage does not significantly influence survival probabilities

4.2.3 Separate liquidation from death

Using of Semi-parametric Cox proportional hazard analysis, non-parametric Kaplan-Meier analysis, and the discrete-time hazard Logit model, Baba and Goko (2006) focus on survival analysis and examines whether terminates of a hedge fund can be predicted by information available from TASS database. The covariates include returns, incentive fees, redemption period and frequency, the number of total hedge funds, leverage, liquidity and minimum invest. Their result indicated that funds leverage has low explanatory power on survival probability. A number of hedge funds have a negative effect on survival probability. Funds with shorter redemption period, higher incentive fees, low water mark, lower assets under management and recent funds flows, funds with higher volatilities and lower skewness of return and higher frequency of redemption have increased the risk of death. The process of this analysis is more effective than the two prior studies.

Nonetheless, using of duration models, this study can estimate covariates of survival risk in a regression-like framework. It compensates the Cox proportional hazard model that test on the very restrictive assumption of hazard ratio. In comparison, the previous study use Logit and probit models to estimate survival risk, duration model has an advantage on handling the problem of right censoring that a huge number of hedge fund were not liquidated at the end of the sample period.

The TASS database consists of over 4000 live funds and 2000 dead funds from February 1997 to 2005. Moreover, TASS database divides up dead funds into seven categories: (i) Stop reporting to TASS; (ii) Liquidated, (iii) Closed to new investment, (iv) Restructured; (v) Merged with other hedge funds; (vi) Unable to contact; (vii) Unknown. Baba and Goko (2006) chose the hedge funds which report all necessary information continuously over two years. They finally get 952 live funds and 270 liquidated in 511 dead funds. The 270 liquidated funds were selected as failures. TASS database has larger amount of data and more detailed data classification than ZCM database compared to previous research.

However, the number of dead funds to be used as failure times is too small in this study. The cross-sectional analysis consists of 270 liquidated funds as failure times in sample size of 1,222 funds. Furthermore, Liang and Park (2010) report that liquidated is not necessarily mean failed. One liquidated in his sample has a high cumulative return (1,139%) and until it is liquidated, there is no negative return in 44 months. There is a group of study focus on hedge fund liquidation and the covariates in the previous study of Baba and Goko (2006) ought to be determinants of liquidation. In addition, Agarwal and Naik (2000b) suggest that analysis of fund failure in dollar value is more reliable than on a percentage basis.

4.2.4 Time-varying covariates for risk analysis

Rouah (2005) provides further analysis of different types of drop out the reason. This study examines covariates of fund performance in four categories: All exits, Liquidate, Close and Stop reporting. The study also reports about determinants of survivorship bias and attrition rate. The thesis utilizes HFR database on both live and dead fund, covering the period January 1994 to December 2003. It consists of 2,371 of live funds and 1,224 dead funds. Moreover, HFR database divides dead fund into three categories: liquidated, closed to a new investor and simply stop reporting.

Rouah (2005) point out it is necessary to separate dead fund into different categories because the explanatory of covariates would be imprecise if all exits funds are treated as a single group. Compare with Baba and Goko (2006), this study uses a similar way to defining failure so the result of this study also not ought to be interpreted as a study of failure. However, Rouah (2005) extend the failure times by exploring stop reporting category and report that many funds closed to new investors may have good performance. Furthermore, using a competing risk model, Rouah (2005) provides a proper way to compare different exit types more effectively.

The study by Rouah (2005) also improved the method of the test by time-varying covariates. Using of time-dependent variants of the Cox proportional hazard model, Rouah (2005) can estimate the new value of covariates in each interval of the time period. Baba and Goko (2006) also use this model to predict liquidation. The model is capable of predictor variables change over time. On contrary, previous study test single value per covariate per fund that cannot provide precise signals to predict liquidation because of the timeliness of the impact of the predictor variables.

The result of the previous studies estimates the explanatory of predictor variables on hedge fund survival. Report attrition rate, survival time and survivorship bias. However, their results differ materially. Rouah (2005) point out that all dead funds have been treated as one group is a possible reason, as same as Baba and Goko (2006), this study attempt to isolate liquidation from dead fund database and Rouah (2005) further divided dead fund database into three categories. This enabled Rouah (2005) to separate funds with very good returns from dead fund database.

The result in this study has two aspects, survivorship bias and survival analysis aspect. In survivorship bias part, Rouah (2005) find that the group of funds closing to new investment experienced an increased attrition rate from 0.17 percent in 1994 to 1.47 percent in 2003. This result suggests that more funds closed recent years than one decade ago and overall increased attrition rate stems from stop reporting of some funds. More interesting thing is that dead funds upward bias soar up from 1.51 per cent to 3.28 per cent when estimate exclude the group of funds closing to new investment. It indicates that the group of funds closed to new investment experience good returns. Consist with Baba and Goko (2006), Rouah (2005) report that liquidated funds has negative returns and high volatility. On the opposite, because of voluntarily reporting, the live fund has high returns. This could be a reason why survivorship bias in Rouah (2005) is much higher than studies before that Rouah (2005) isolate the influence of a different group of exits on survivorship bias.

Rouah (2005) report that survival time until exits the database is shorter than the time until the fund liquidated. It suggests that hedge funds could experience other kinds of exits. Consistent with Brown, Goetzmann, and Park (2001), Rouah (2005) reported that large fund live longer than small fund expects funds in Merger Arbitrage group. The finding in Rouah (2005) indicate that the decisive factors of liquidation are different are different with other exits categories. The real failure is different with liquidation in hedge fund industry. Furthermore, Liang and Park (2010) reported that there are three cases of liquidated funds that could be considered as successful samples. Firstly, some of the hedge funds could detect the downward market movement early and liquidated successfully. For example, Global macro funds managed about one-third of assets in hedge fund industry after 1994. Due to the financial crisis in 2000, the magnitude of global macro funds decreased to only 3% of total hedge fund assets before 2001. Successful hedge funds are able to detect the crisis and liquidated in time. Secondly, some of the fund managers could launch a new fund after a good performance of the old fund. Liang and Park (2010) reported that 44.6% of liquidated hedge funds experienced a positive monthly return for the last half year before their liquidation. Moreover, some of the hedge funds experienced positive cumulative return and increased asset under management. These hedge funds could liquidate after new funds are well established by the same company and same manager (Liang and Park 2010). It could probably because the new funds could raise more fees due to their historical remarkable performance. Thirdly, some of the risk adverse hedge funds could liquidate in order to avoid downside risk of their portfolios. It shows the importance that we should separate exit types of a hedge fund from dead fund database.

4.2.5 Real death of, hedge fund failure

It is necessary to have a clear definition of failure in order to make survival analysis better. Liang and Park (2010) provide a more thorough way to define real death of hedge fund. Although the study aims to clarify the most effective driver of downside risk, Liang and Park (2010) implement the method of survival analysis by applying calendar time construction into Cox proportional hazard model. More significantly, the study clarifies the shortcoming of both types of data selection: Use all dead fund in the graveyard as failure times and just use liquidated funds as failure times. Based on method of previous research (Agarwal and Naik, 2000b and Baquero, Horst and

Verbeek, 2005), Liang and Park (2010) choose performance and fund flow filter system to test the drivers of failure funds.

Liang and Park (2010) select funds in TASS database carefully and 2,134 funds were taken into the sample. There are 1,362 live funds and 772 dead funds in different investment style categories. In order to avoid managed futures and double counting, Liang and Park (2010) exclude funds-of-funds to focus on hedge funds. Then test covariates that relate to failure. The results suggest that performance and HWM are main drivers of hedge fund failure. Interestingly, the lockup provision shows low power to prevent real failure of a hedge fund that it could only reduce attrition rate during its lockup period. Moreover, they prove that fund with long lifetime and large asset under management has no advantage underestimation of real failure.

Liang and Park (2010) reported new criteria of failure should have three characteristics. First of all, it should be listed in a graveyard once because of stopped reporting. Secondly, it has negative average rate return during last 6 months. Lastly, it experienced a decreased asset under management during last 12 months. Via this framework, the live fund also could be taken into the estimation. Furthermore, liquidated funds will not be entirely treated as failures. Liang and Park (2010) test the model and argue that both high water mark and performance impact failure significantly. The test uses both traditional and new definition of failure and suggests that the impact of performance was significant at 1% level after controlling for other covariates. Moreover, funds with high water mark provision have a low probability of failure. However, the variable representing age, size, and the lockup provision differ from the definition of failure.

Consistent with Liang (2000) and Getmansky, Lo, and Mei (2004), Liang and Park (2010) reports that attrition rate between 1995 and 2004 is 8.7 percent per year. Furthermore, the annual failure rate is much lower, about 3.1 percent per year. Interestingly, a practical study by Derman (2006) also reports that 3% of hedge fund moved to dead fund database because of its poor performance. However, Derman (2006) did not provide the basement of his result. Liang and Park (2010) support this result with a new definition of real failure. Furthermore, Feffer and Kundro (2003) also report that liquidated hedge fund often dead due to redemption that depends on the market expectation of fund managers or some business consideration. It suggests that select entire liquidated funds as failure times could be not reliable. Previous studies identify that returns fall in the bottom 10% of hedge fund monthly returns is extreme negative returns in the hedge fund industry (Boyson, Stahel and Stulz, 2010; Savona,2014). Consequently, this thesis will use both top 10% and bottom 10% of hedge fund returns as extreme performance in the hedge fund industry.

Liang and Park (2010) make contributions to the hedge fund literature in two aspects. On one hand, Liang and Park (2010) contribute to recent research by identifying the failure funds in dead fund database. It is difficult to define hedge fund failure because of self-selection of reporting. Dead fund often hides detailed information for some reasons. The regulation of reporting makes it difficult to extract real dead fund from dead fund database. It is the reason that early studies treat all funds in dead fund database as a failure (Brown, Goetzmann, and Park, 2001; Gregoriou, 2002). Subsequently, in order to avoid this problem, Baba and Goko (2006) and Rouah (2005) employ liquidated funds as failure times. However, Liang and Park (2010) report shortcoming of using liquidated funds as failure times. One of the reasons is hedge funds with good performance could voluntarily liquidate for investor redemption. Liang and Park (2010) report that in HFR database, the different categories of drop reason are not adequate to define failure of a hedge fund. More interestingly, based on Baquero, Host, and Verbeek (2005) who extract failures from stop reporting category, Liang and Park (2010) sorted the entire dead fund database into failures and non-failures. This achievement stems from testing four quarters of hedge fund money flows before it disappearing from the database. Liang and Park (2010) classified the hedge funds with negative flows in the final year of reporting as failures, where Baquero, Host, and Verbeek (2005) use this method to hedge funds which stop reporting.

On the other hand, Liang and Park (2010) analysis different measure on predicting hedge fund failure. The result shows that expect to return and tail risk is superior to variance. This result is consistent with Agarwal and Naik (2004) that variance underestimated left tail risk significantly. Using downside risk measures instead of standard deviation, this finding implement method used in Liang (2000), Brown, Goetzmann, Gregoriou (2002) and Rouah (2005) in predicting hedge funds failure. As mentioned above, Liang and Park (2010) use new criteria to define hedge fund failure and separate failure rate from attrition rate.

Although Liang and Park (2010) report downside risk measures perform better than a variance, the study limited to explaining the drivers of hedge fund failure. Follow the approach used in Liang and Park (2010) and construct portfolios of hedge funds based on their historical survival risk exposure. The performance of the decile portfolios can be evaluated relative to the Cox (1972) proportional hazard (PH) model. Based on new criteria of failure defined by Liang and Park (2010), the performance of last 6-month return and asset under management for the last 12 months could be an important signal to predict future return.

4.2.6 Prediction of real failure

Chapman (2007) provides a more thorough way to predict the occurrence and timing of failure. Consistent with Gregoriou (2002), Chapman (2007) also imported live funds together with dead funds from HFR database to test the drivers of hedge funds failure. Using of Cox proportional model, Chapman (2007) estimate variables representing of return, size, minimum investment, leverage, fee structure, investment style and liquidity. The study by Chapman (2007) was flawed by the way in which these data entered the model. Prior to estimation, Chapman (2007) exchanged the management fees and incentive fees to the dollar. This measure is based on Baquero, Horst and Verbeek (2005) that returns were estimated on absolute value and also compare to benchmarks include S&P 500 index and the United States ten year Treasury bond index. However, a large proportion of hedge funds set up outside of the Unite state could make a significant bias into the test.

The methodological improvement offered by this study derives from the use of the model output. Chapman (2007) exam prediction skill of the model based on survival curves of each hedge fund and report that it is possible to evaluate the time series of survival probabilities for each fund. The study suggests that both survival and failure risk could be predicted by using the cut-off threshold to convert the risk. Chapman (2007) imposed a threshold on the end of the second year after fund inception. The funds in sample period have a higher probability of survival than the cut-off threshold was forecast to survival and those lower than cut-off threshold were forecast to fail. The prediction of classified failed funds was correctly against the number of live funds that were incorrectly classified as failures. The results indicate that it is theoretically feasible to forecast failure of a hedge fund by integrating of Cox proportional hazard modeling and forecasting theory.

The drawback of this test process is the timing mismatch and double counting issue. Based on HFR database, Chapman (2007) selected live fund from January 1990 up until July 2007. The dead fund database covers a longer period than the live fund database. It could cause an over-representation of the number of dead funds in the risk set. In addition, some of the hedge funds could be taken into estimation in both the live fund and the dead fund database. Moreover, Chapman (2007) did not remove fund of hedge funds from the data set. Previous research has pointed out that funds of hedge funds were much different with hedge funds on their way of operation and their nature of risk. Furthermore, Chapman (2007) tested on the problem of failures by financial distress, which arises from not using of leverage. The study did not point out a clear definition of failure. Lastly, Chapman (2007) evaluated the forest ability of model on the point of the 120th month. An improvement of robustness test is essential that the model should carry a range of evaluation times.

4.2.7 Summary

In the light of the discussion, although literature on hedge fund performance is vast, there are few studies focus on the relation between hedge fund failure risk and performance. I tend to use TASS database from January 1994 through July 2014. Because TASS start distributing data in 1994, the funds dead before 1994 were not contained in TASS database. Using of data before 1994 in TASS database could cause survivorship bias. According to Liang and Park (2010), Discontinuation of reporting does not necessarily mean the fund is failed. As the result, it is important to identify failure case based on poor performance. In this study, liquidated hedge funds that satisfied certain conditions could be treated as non-failed fund: 1.Total net assets increased in last two years. Total net assets increased in last year 3. Average monthly return in last year is more than 0.25%. 4. Average monthly return in last two years is more than 0.25%. I tend to use survival analysis based on Cox (1972) proportional hazard (PH) model to predict hedge fund failure and then construct portfolios of hedge funds based on their historical failure risk. The hypothesis is buying top sort of hedge funds (lowest failure risk) and selling bottom sort of hedge funds (highest failure risk) could obtain abnormal returns that outperform market return in the hedge fund industry.

4.3 Data analysis

4.3.1 Data description

As mentioned in section 1.2.4 that hedge fund has no regular obligation to publish their information to an official governing body. Moreover, they are forbidden from raising funds publicly. However, hedges funds are self-selected to disclose information to private data vendors in order to provide information to their existing and indirect advertisement to their potential investors. Kat and Brooks (2002) point out that the data from these providers are not independently verified and not audited although some of them tend to perform a regular report. As discussed in Chapter 2 that many of the previous study documents that TASS database could fit for this thesis because more of dead funds are collected in it. Therefore, using the TASS database could cause lower selection bias. Moreover, the use of monthly return improves the accuracy of variance measure of risk and TASS database could provide better information that could reduce survivorship and backfill bias to a certain extent. In addition, TASS database collect relatively more observations than other databases. Firstly, I give the definitions of the prediction model in this chapter before analysis of database (Table 4.1).

Table 4.1: Definitions in Prediction model

i. Definition of testing period

Estimation period	The period for estimation of hazard index for samples.
Evaluation period	The holding period for estimation of Buy-and-Hold abnormal return test (6-month period after estimation period).

ii. Definition of Covariates

Return Property	
Mean	The sample mean of monthly return over the estimation period
Variance	Sample variance of monthly return over the estimation period
Skewness	Sample skewness of monthly return over the estimation period
Kurtosis	Simple catharsis' of monthly return over the estimation period
Return on t-1	Sample last monthly return over the estimation period
Average return in last 3 months	The sample mean of monthly return over the last 3 months in the estimation period
Mean of TNA	Mean of the sample's total net asset (TNA) over the estimation period in U.S. dollars. TNA denominated in other currencies are converted by exchange rate on July 31st, 2014
Leverage used	Leverage is treated as a dummy variable that is 0 if the fund does not use leverage and 1 otherwise.
Minimum investment	Minimum subscription amount in US dollars. Minimum subscription amount in other currencies is converted by exchange rate on July 31st, 2014.

In this thesis, I employ the Lipper TASS database. There are two separate databases contained in the Lipper TASS. The first one includes information that hedge funds keep reporting to TASS which is a live fund database. The second one includes information that hedge funds are liquidated and stop reporting to TASS database. The database provides monthly returns, total net assets and other fund characteristics such as minimum investment, leverage, management fee and a performance fee.

4.3.2 Sampling process

Before proceeding to an empirical analysis, it is necessary to identify an appropriate sample of funds in order to estimate the Cox proportional hazard model proposed by this chapter. The available information on hedge fund is insufficient because hedge fund managers report their data voluntarily. This section describes the step by step filtering process to rule out funds without sufficient information.

There is a big proportion of hedge funds that do not report their information of administrative data (Table 4.2) or the monthly time series of returns and total asset under management. Typically, there are two approaches to address the missing administrative data problem:

1. Delete the funds from the samples.
2. Delete the covariate from the testing model.

The TASS database began to collect dead funds information from January 1994. Using of data before 1994 could cause selection bias in estimation. As the result, I collect data from January 1994 to July 2014 in this study. Observations before 1994 are excluded. Previous studies reported that the fee structure is an important factor that could relate to funds' survival risk. However, there are only 593 funds reported their fee information to the TASS database (Table 4.2) after January 1994. Therefore, I should exclude the fee as a covariate from estimation model or the result would lose its representation. As compensation, I use total net asset instead of the asset under management that was used in previous studies. Total net assets represent the total funds under management for a net of fees and expenses that aggregate the factors of fees and asset under management. Although redemption frequency is considered as a liquidity factor of the hedge fund, there are only 4487 of funds reported their redemption frequency after above filtering process, in which 1704 are active funds and 2783 are liquidated funds (Table 4.2). There is no sufficient observation on this factor, which lead me to delete the covariate from the testing model. Similarly, as is shown in Table 4.2, only 593 of hedge funds reported their fees and covariate of fees should be excluded from estimation model.

For time series data, I list the solutions to address the missing data as follows:

1. Delete the funds from the samples.
2. Reserve the funds in the samples and infer the vacancy data points.
3. Delete the covariate from the testing model.

Funds without minimum investment information are deleted from samples (Option 1). Minimum investment and fund size sometimes are reported in different currencies. Using an exchange rate on July 31st, 2014, I converted all minimum investments and total net assets to US dollars in order to place meaningful comparison. Then, I will remove funds that do not report their monthly return (Option 1). The TASS database starts to collect data on defunct funds from 1994. So analysis based on the TASS database includes data before 1994 could cause significant survivorship bias and the data before 1994 is not fit for precise estimation of hedge fund risk and return. Moreover, the use of monthly return improves the accuracy of variance measure of risk. As the result, I delete all observations before 1994 and funds do not report their monthly performance (Option 1). Similarly, funds with missing data on the total net asset are excluded from the samples (Option 1). Option 2 is selected when funds with insufficient data to estimate precise result. After filtering process, the total number of hedge funds in my sample is 6294, in which 2846 are active funds and 3448 are liquidated funds.

Table 4.2: sampling process

Table 4.2 shows the variation on a number of observations step by step after sampling process. The number of funds who reported their redemption frequency and fees information is limited so that I decide to delete these two covariates from the vector.

	Total	Active	Liquidated
Total number of hedge funds	14031	6505	7526
Minimum investment reported	13817	6405	7412
Monthly return reported	6510	2713	3797
TNA reported	6294	2846	3448
Redemption frequency reported	4487	1704	2783
Fee reported	593	-	-

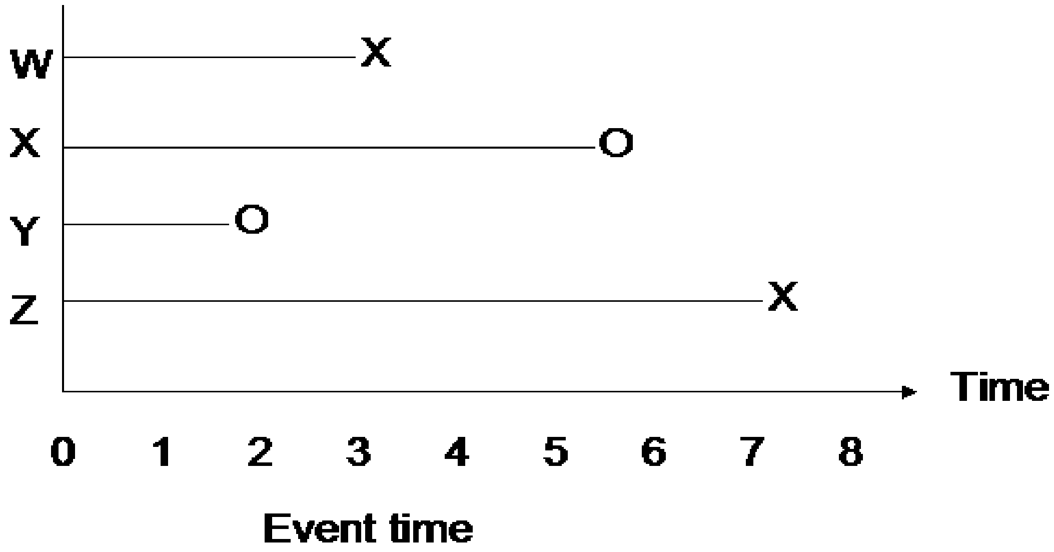
4.4 Research method

4.4.1 Timescale

The time scale measures the units of time that are taken into the estimation. The time series data of return and total net asset in this thesis are reported monthly. Therefore, it is necessary to match the definition of time scale with a resolution of data. The original time is the first time to run the model where t=0. Typically, there are two ways to define the original time. The first way measure the origin time as the life length that time 0 is defined as the fund established month and it is called "event time" method (Chart 4.1).

Chart 4.1: Event time method

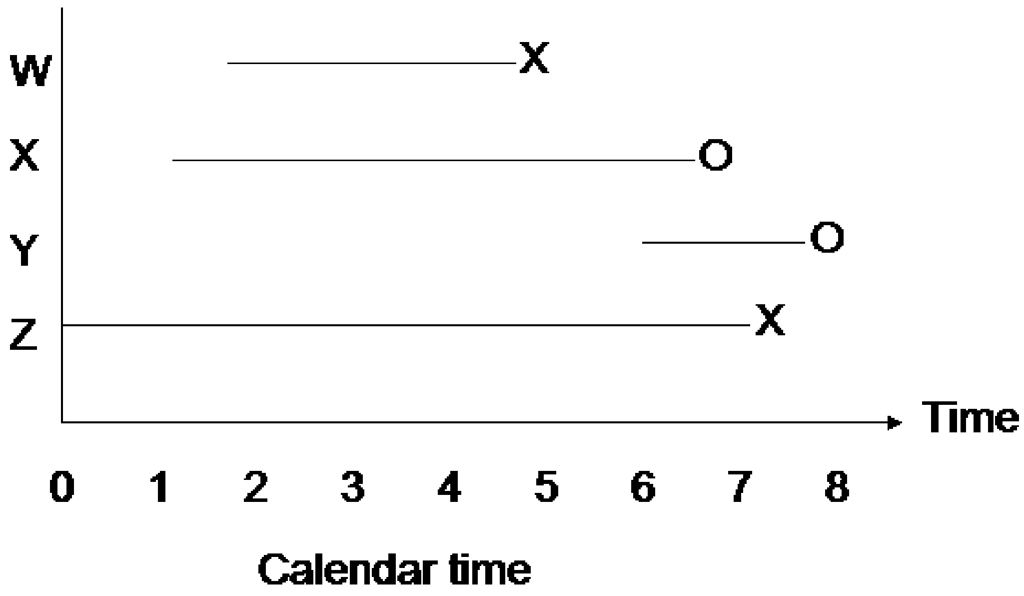
The Chart 4.1 presents samples of W, X, Y, Z are measured by event time method. Each of the samples enters the study on time 0. The duration of the time indicates the life length of the sample. "X" symbolizes the sample is a failure and "O" symbolizes the sample stop reporting for other reasons.



The second way defines the original time as calendar month that the first sample is observed in the dataset. For example, the origin time would be set in January 1994 if the dataset starts in this month (t=0). As a result, t=1 in February 1994, t=2 in March 1994 and so on. It is also called "calendar month" model.

Chart 4.2: Calendar time

The Chart 4.2 presents samples of W, X, Y, Z are measured by Calendar time method. Samples enter the study at a different time. The duration of the time indicates the life length of the sample. “X” symbolizes the sample is a failure and “O” symbolizes the sample stop reporting for other reasons.



When samples are arranged in a second way, both of calendar effect and duration effect are included into the hazard model. As the result, other time-varying covariates and economic indicators that are specific in time are comparatively pointless in the model. Furthermore, this model cannot test the effect of duration on failure alone. This chapter aims to forecast future performance outside the estimation sample that the calendar effects included in the model are unexpected. The calendar time model allows forecast only within the time period modeled because it is inevitably specific to the time period of the estimation sample. Therefore, the event time model is more appropriate for the objective of this chapter.

4.4.2 Setting of risk and censoring

Risk set is crucial to survival analysis as it set all hedge funds that are at risk of fail on every month. There is a big amount of active funds at the end of the study that could cause a censoring problem. As a result, it is important to estimate live funds and dead funds together. Moving out live funds could cause downward bias of survival time since a large number of live funds in the database could contribute information about hedge funds' survival experience (Rouah, 2005).

Censoring of samples means the funds are removed from the risk set for other reasons that they do not fail. Essentially, censoring is a tool to tackle the missing information. It occurs because there is not enough information on each fund until the time when they fail. The fundamental function of methods in survival analysis is their ability to deal with censored lifetimes. A sample of a variable T is right-censored if the T should be more than the date of censoring. There are two types of censoring that occur in the study. The first type of censoring exists when the censoring time is fixed. In this study, the data start from January 1994 to July 2014. The lifetime of hedge funds that belong to this period is completely known since the failed hedge fund is located in the database. On the contrary, hedge funds keeping alive until the end of the observation period are right censored. Because the actual fail date is unknown and will occur after July 2014. The second type of censoring exists when the censoring time is stochastic. Funds may stop reporting during the observation period for different reasons other than fail. For example, a fund could hold sufficient capital and drop out from TASS database.

4.4.3 Identification of real failure

As discussed in section 4.2.4, the real failure is different with liquidation in the hedge fund industry. Firstly, some hedge funds could detect the downward market movement early and liquidated successfully. Secondly, some fund managers could launch a new fund after a good performance of the old fund. These hedge funds could experience a positive monthly return for the last half year before their liquidation. Moreover, some of these funds experienced a positive cumulative return and increased asset under management. It could because the new funds could raise more fees due to their historical remarkable performance. Thirdly, some of the risk adverse hedge funds could liquidate in order to avoid downside risk of their portfolios. These funds could also experience positive cumulative rate of return and asset under management. As a result, it is necessary to establish new criteria to define the real failure due to poor performance. This thesis estimates different criteria and finally filters out a more reliable identification (see section 4.8, Robustness test,). Different with Liang and Park (2010), this method aims to identify successful funds among liquidated funds. Hedge funds satisfy following criteria would be considered as censored funds that are not failures and the left liquidated funds would be considered as real failures. 1) The hedge fund should be reported as liquidated funds. 2) The total net asset is increased in the last 12 month. 3) The total net asset is increased in the last 24 month. 4) Mean of monthly return over last 24 month is higher than 0.25%. 5) Mean of monthly return over last 12 month is higher than 0.25%. This scenario is aimed to identify liquidated funds with good performance that will be considered as successful ones. This scenario is helpful to pick the second case of funds that launch new funds after a good performance of old funds. The first and the third cases of successful hedge funds could not satisfy this scenario and it is hard to identify. For the first case of successful funds, it is hard to identify because it is hard to determine the influence of financial crises in different markets that hedge funds are established. For the third case of successful funds, it is hard to identify because the data providers could not choose to illustrate the allocation of their portfolios.

4.4.4 Model construction

Duration model and discrete-time model are two kinds of hazard models that are broadly applied to estimate longitudinal data. Extant studies mainly use duration models, although both kinds of model are similar in a statistical sense. Using of duration models can capture a non-monotonic relationship between the probability of fund failure and duration. Discrete-time hazard model such as logit model, for example, based on an assumption that fund failure monotonically increases or decreases with funds' duration time if it is included as an explanatory variable. Moreover, it is better to execute right-censoring problem and time-dependent covariates by using of duration models. This study uses the Cox proportional hazards model which are a semi-parametric duration model.

Cox proportional hazard model test on the very restrictive assumption of hazard ratio. Moreover, a huge number of hedge fund were not liquidated at the end of the sample period. Cox proportional hazard model has advantage on handling the problem of right censoring than other survival risk models. Nonparametric models such as Kaplan-Meier analysis make few explanatory variables about the distribution of time that funds failure. Parametric estimators make an arbitrary assumption that time until funds' failure follows a specific distribution format. Cox proportional hazard model is a semi-parametric model that becomes the main bridge between these models. The Cox proportional hazard model is able to adjust survival rate estimates to quantify the effect of independent variables. There is a specific functional form in the regression model and it does not set an exact form of the failure time distribution. Without applying a specific function for the dependency of a fund's failure rate on its age, it is appropriate to set this relationship in a nonparametric way. This chapter aims to build a forecasting system that capable of constructing investable portfolios of hedge funds based on the historical time varying likelihood of survival risk in individual hedge funds. In this effort, I construct portfolios of hedge funds based on their hazard index. Every 0.5 year, starting in January 2004, 10 hedge fund portfolios are formed based on hedge fund hazard index. Simultaneously, the identification of real failure (in Section 4.5.4) will be estimated each time. Based on Cox proportional hazard model, hedge fund hazard ratio is estimated from the equation as follows:

$$\mathrm{HI} = e^{(\beta' z)} \tag{4.1}$$

As discussed in Section 4.4.2, performance in the less distant past is of more importance for hedge funds. This study uses past 60 months of return as estimation period to test the failure rate. The post-formation returns on these sorted portfolios during the next 6 months are linked across years to set a single return series for every portfolio. Furthermore, to test for robustness, I also use past 120 months as estimation period to test the hazard index and get the post-formation returns on the sorted portfolios.

4.4.5 Empirical value of hazard index

This study uses the abnormal return appetites of hedge funds that grant a favorable interest to their investors. To gauge the practical significance of this failure risk measure, this chapter investigates the investment value based on selecting low failure risk hedge funds. Every six months starting from January 1999, I estimate the hazard index for each fund using the past 60-month estimation period data and then form ten decile portfolios based on their hazard index. These portfolios are held subsequently for six month holding period. This process is repeated every six months until December of 2013. All of the funds' returns are included in the evaluation of portfolio return if the fund stops reporting over the holding period. This yields a time series of returns for the ten portfolios of varying levels of failure risk from 1999 to 2013. Furthermore, I follow the Buy-and-Hold abnormal return approach used in Barber and Lyon (1997) to test if the return is statistically significant to the market return. Buy-and-Hold abnormal return could be more practical to assess abnormal return for the sake of this study. The BHAR method observes the difference between holding period return of sample funds and holding period return of the market return of all hedge funds. Accordingly, the Buy-and-Hold abnormal return function is

(4.2) $$BHAR_{iT} = \prod_{t=1}^{T}(1 + r_{it}) - \prod_{t=1}^{T}(1 + r_{mt})$$

The Buy-and-Hold abnormal return supposed to estimate investors experience directly. On the contrary, CAR method is a biased parameter of investors' experience. Blume and Stambaugh (1983) point out that transaction cost behind CAR method could be significant to firms with low capitalization. Furthermore, the redemption policy in the hedge fund industry makes it hard to invest in every hedge fund with the form of CAR method. As the result, the Buy-and-Hold abnormal return could be more practical to assess abnormal return for hedge fund investors. This study also uses the CAR method to do robustness test.

4.4.6 Limitation of research procedure

Although this research procedure is more efficient in the use of data and it bound by fewer assumptions, much of the advantages are reduced upon practical application. The major issue stems from raw of information that is available in TASS database. The existing study shows that estimation on hedge fund managers could be more accurate in the testing of fund failure. However, the TASS database does not have information on hedge fund managers. Bares Gibson and Gyger (2001) is an example of estimation on hedge fund managers. This study shows the benefit on classifying new funds with existing managers that could have similar performance. Moreover, some hedge fund managers could launch new funds after a good performance of old funds. The new funds could be considered as the same fund with higher fees and it could significantly accurate the estimation of fund failure.

4.4.7 Summary of research process

The prediction model of this chapter involves Section4.3 (Data analysis), Section 4.4 (Covariates) and Section 4.5 (Research method). This section provides a concise summary of the steps in order to clarify the prediction model. As can be seen in Chart 4.3, the first 5 procedures are set for filtering process of the sample. After that, procedures 6 to 10 provide integral ordered estimation in survival risk analysis. Subsequently, procedures 11 to 12 externalize the construction of prediction model. Then procedure 13 shows the method I used to test the empirical value of this prediction model and finally procedure 14 does the robustness test (Section 4.8).

Chart 4.3: Summary of research process

1. Collect estimation samples.
2. Delete first 12 months return of each fund.
3. Delete the covariates with insufficient observations.
4. Remove funds with insufficient data.
5. Convert currency into US dollar.
6. Set the raw data into vector of covariates.
7. Format the event time risk set.
8. Estimate and redefine funds' failure every 6 months from January 1999.
9. Estimate Coefficient by Cox ph model using of 60-month historical data.
10. Calculate hazard index for each hedge fund.
11. Form 10 decile portfolios based on estimated hazard index.
12. Hold each portfolio for six months.
13. Estimate Buy-and-Hold abnormal return of holding portfolio.
14. Robustness test on procedure2, 8, 9 and 13.

4.5 Empirical findings

4.5.1 Drivers of fund failure

The first outcome of the research procedure is the result of new identification of fund failure. It is discussed in Section 4.2.5 that it is important to identify the liquidated funds that are not liquidated because of poor performance. Table 4.3 illustrates the number of live funds and failure fund before and after the new identification of fund failure. As reported in the third column, the average amount of failure funds after new identification of fund failure is 111 lower than the original database. It indicates that there are 111 of liquidated hedge funds are not liquidated due to poor performance in the estimation period. Using of ten years estimation period there is more liquidated hedge funds are identified as non-failure. It is because there are more hedge funds reporting their performance in the longer estimation period. As the result, more of hedge funds are able to be estimated as non-failure.

Table 4.3: Original liquidated funds and new identification of fund failure

Hedge funds with sufficient data terms are estimated every 6 months by new fund's failure identification. A live fund is a number of funds that are not failures. The estimation period for the 5-year test is 60 months' data. The estimation period for the 10-year test is 120 months' data. The evaluation period is from January 2004 to January 2014. Using of a new identification of fund's failure, an average number of live funds is 111 higher than the original database.

	5 years test		10 years test		Original database	
Date	Live fund	Failed fund	Live fund	Failed fund	Live fund	Dead fund
01/2004	7418	6613	7804	6227	7384	6647
07/2004	7515	6516	7964	6067	7475	6556
01/2005	7622	6409	8069	5962	7580	6451
07/2005	7696	6335	8178	5853	7645	6386
01/2006	7791	6240	8214	5817	7735	6296
07/2006	7861	6170	8270	5761	7791	6240
01/2007	7919	6112	8288	5743	7831	6200
07/2007	7919	6112	8358	5673	7823	6208
01/2008	8002	6029	8377	5654	7878	6153
07/2008	8015	6016	8341	5690	7857	6174
01/2009	7992	6039	8305	5726	7825	6206
07/2009	7925	6106	8101	5930	7760	6271
01/2010	7797	6234	8048	5983	7642	6389
07/2010	7746	6285	7998	6033	7602	6429
01/2011	7659	6372	7921	6110	7517	6514
07/2011	7590	6441	7819	6212	7459	6572
01/2012	7442	6589	7616	6415	7289	6742
07/2012	7304	6727	7436	6595	7165	6866
01/2013	7166	6865	7269	6762	7046	6985
07/2013	6964	7067	7101	6930	6838	7193
01/2014	6818	7213	6978	7053	6694	7337
Mean	7627	6404	7926	6105	7516	6515

The Cox proportional hazard model examines the Coefficient of each driver to determine the magnitude of their effects on hedge fund failure. The magnitude and direction of each covariate in the vector represent the strength of this driver and if it increases or decreases the funds' failure rate. Positive coefficient of covariate indicates that the covariate positively relates to failure. On the contrary, the negative coefficient of covariate indicates that the driver negatively relates to failure.

Table 4.4 shows the output of the Cox's proportional hazard model using cross-sectional data. Firstly, the estimation results in Table 4.4 show that an average of coefficient on the Mean of TNA, Mean of return, Average return in last 3 months, Variance of return, Average return in last 3 months, Variance, Kurtosis of return, Skewness of return, leverage used and minimum investment are consistent with expected directions. Secondly, the strength of covariates fluctuated over time and some of the covariates even change their directions of relationship with failure over time. The magnitude of hedge fund failure effect could change due to market condition. For example, mean of return in bull market could not as important as it is in the bear market. Because most of the hedge funds could earn a remarkable return in a bull market, however, it could be more important to keep good performance in a bear market. The relation between covariates and failure rates also could change. Covariates like variance and leverage, for example, extant research point out that fund with high risk presents both high risks of death and high probability to perform better than others (Brown, Goetzmann, and Park, 2001). Therefore, which side overwhelms the other could change due to market condition.

It has discussed in Section 4.4.2 that less distance past data influence more significantly on fund failure. However, using of longer distance data, the Cox proportional hazard model could estimate covariates with a more significant result. As is shown in Table 4.4, a majority of standard deviation decreased from a test using 5 years data to using 10 years data (Mean of TNA, Mean of Return, Return of t-1, Average return in last 3 months, Kurtosis of return, Skewness of return, Leverage used and Minimum investment). Therefore, this study uses 10 years' historical data to do a robustness test of the prediction model.

Table 4.4: Cox Proportional Hazard Analysis

Hedge funds with sufficient data terms are modeled by Cox proportional hazard model every 6 months. The Hazard is the average of the Beta estimated by the Cox proportional hazard model during the estimation period. The std is average standard deviation estimated by the Cox proportional hazard model during the estimation period. The estimation period for the 5-year test is 60 months' data. The evaluation period is from January 1999 to January 2014.The estimation period for the 10 years test is 120 months' data. The evaluation period is from January 2004 to January 2014. Using of longer distance data, the Cox proportional hazard model could estimate covariates with a more significant result.

	5 years test		10 years test	
Covariates	Coe	Std	Coe	Std
Mean of TNA	-0.31	0.32	-0.40	0.21
Mean of Return	-13.56	26.99	-17.83	25.90
Return of t-1	1.32	4.15	0.25	3.66
Average return in last 3 months	-3.91	16.50	-2.90	5.54
Variance	0.84	3.20	1.04	3.31
kurtosis of return	0.35	0.50	0.41	0.31
skewness of return	-0.80	1.91	-0.05	1.69
leverage used	2.53	6.25	0.54	4.11
Minimum investment	0.05	0.21	0.02	0.11

4.5.2 Empirical value of prediction model

To test the effect of funds' failure risk on fund performance, I use the portfolio based approach and Buy and hold abnormal return method to estimate if failure risk influence fund’s post-performance. Every six months starting from January 1999, I estimate the hazard index for each hedge fund using past 60 months’ estimation period and then sort hedge funds into 10 portfolios based on their hazard index. These portfolios are held subsequently for the six-month holding period. BHAR is difference between holding period return of funds in portfolio and holding period return of the market return of all hedge funds. Table 4.5 presents the output summary on the empirical value of the prediction model. The Buy and hold abnormal return reveals corresponding differences between return in the hedge fund market and return on portfolios. The portfolios are sorted by historical failure risk. The P-values are derived from standard errors of BHAR. Specifically, Hedge funds in Portfolio 1 with low failure risk present economically and statistically significant positive Buy and hold abnormal return. It indicates that the holding of Portfolio 1 delivers economically significant return higher than average return on the hedge fund market in the post-ranking periods and it is at 3% significance level. Interestingly, hedge funds in Portfolio 10 with a higher failure risk do not present a significantly lower return. Take commonly used risk factors into consideration, this chapter calculate sharp ratio for each portfolios. The most of portfolios′ sharpe ratio are between 3.2 to 3.8 and bot portfolio shows lowest sharp ratio (2.6). It indicates that risk adjust returns of bot portfolio is lower than other portfolios. Hedge funds embracing higher failure risk increase the probability of getting high returns. The bot portfolio experienced lowest risk adjusted return.

The Chart 4.4 presents more details on the empirical value of the prediction model. The aggregate half year return reveals actual return on each portfolio sorted by historical failure risk. Normally, hedge funds in lower risk portfolios present higher performance. Interestingly, estimation on the 21st time shows that high-risk portfolio presents extremely higher return. That is the aggregate return between January 2009 and June 2009. The evaluation period of this time is the first test after the collapse of Lehman Brothers on September 15, 2008. Moreover, the estimation period for this time covered the collapse of the sub-prime mortgage crisis in the United States between 2007 and

2009. The hedge funds embracing higher failure risk increase the probability of getting extremely high returns during this time. On the other side, hedge funds in the Portfolio 1 also perform well at this time and the financial crisis time period. The prediction model maintained its empirical value in both normal period and financial crisis period. The next section explores alternative model specifications in an effort to estimate the robustness of the model and to explore other avenues for implementing the prediction model.

Table 4.5: Prediction model

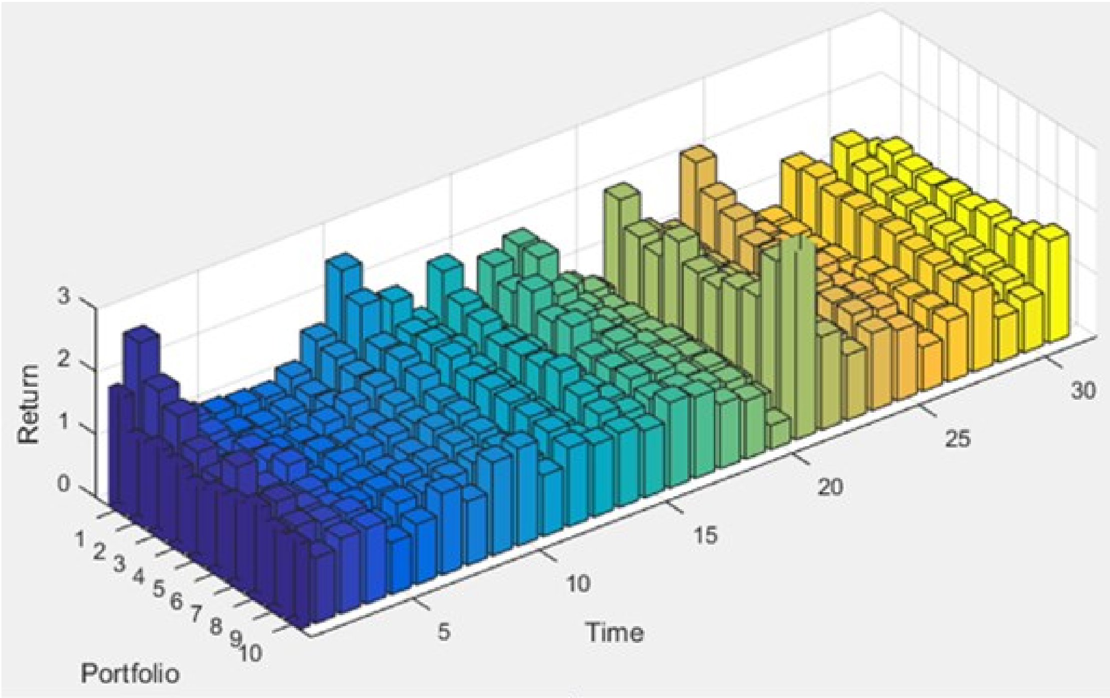
Sorts on hazard index.

Hedge funds with hazard index terms are sorted every 6 months into 10 deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 4.5.4. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2). The evaluation period is from January 1999 to June 2014.

	Portfolio	Return	BHAR	P-value	Sharpe ratio
	1	35%	13%	0.03***	3.8
Average return	2	23%	1%	0.71	3.0
22%	3	18%	-4%	0.13*	2.8
	4	20%	-2%	0.17	3.5
	5	16%	-6%	0.01****	2.9
	6	19%	-3%	0.23	3.2
	7	17%	-5%	0.04***	3.3
	8	18%	-4%	0.12*	3.5
	9	18%	-4%	0.27	3.6
	10	19%	-3%	0.55	2.6

Chart 4.4: Performance of each portfolio

Hedge funds with hazard index terms are sorted every 6 months into 10 deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 4.5.4. Return is the aggregate six months' return for each portfolio. Each time of the test produces a return for every portfolio. The evaluation period is from January 1999 to January 2014.



4.6 Robustness test of prediction model

Testing the predicting ability of the Cox proportional hazard model is central to ascertain the stability and flexibility of the model. This section includes different types of robustness test. Firstly, this chapter use different estimation period to do robustness test. This test could tell if longer estimation period has less explanatory power on current economic condition. Secondly, this chapter test on alternative failure identification. Using of alternative failure identification, we can make sure the test is work on a scope of failure type. Thirdly, this chapter test on data with backfilled bias. This test will show if the backfill bias influence predictability of hedge fund performance. Finally, this chapter test on CAR for theoretical value of this model.

4.6.1 Robustness test on hazard model

Table 4.6 illustrates the test on 10 years historical information. It shows that the magnitude and significance of prediction model are both reduced in this test. However, the direction keeps the same. Hedge funds in Portfolio 1 with lowest failure risk shows highest and positive buy and hold abnormal return. The buy and hold abnormal return decreased from 13% to 7% and the abnormal return is at 20% significance level. It supports the hypothesis that performance in the more distant past is of less importance.

The Chart 4.5 presents more details on the empirical value of the prediction model based on 10 years estimation period. The aggregate half year return reveals actual return on each portfolio sorted by historical failure risk. Normally, hedge funds in lower risk portfolios present higher performance. Estimation of the 11th time is the first test after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher failure risk increase the probability of getting extremely high returns on time 2, 4, 6, 7 and 20. On the other side, hedge funds in the Portfolio 1 also perform well in these times and the financial crisis time period. The prediction model maintained its empirical value in both normal period and financial crisis period.

Table 4.6: Prediction model in 10-year estimation period

Sorts on hazard index.

Hedge funds with hazard index terms are sorted every 6 months into deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 120 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 4.5.4. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2). The evaluation period is from January 2004 to June 2014.

	Portfolio	Return	BHAR	P-value
	1	26%	7%	0.18
Average return	2	23%	4%	0.20
19%	3	18%	-1%	0.55
	4	16%	-3%	0.14*
	5	15%	-4%	0.01****
	6	13%	-6%	0.02***
	7	15%	-4%	0.03***
	8	14%	-5%	0.04***
	9	16%	-3%	0.48
	10	18%	-1%	0.90

Chart 4.5: Performance of each portfolio (10-year estimation period)

Hedge funds with hazard index terms are sorted every 6 months into 10 deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 120 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 4.5.4. Return is the aggregate six months' return for each portfolio. Each time of the test produces a return for every portfolio. The evaluation period is from January 2004 to January 2014.

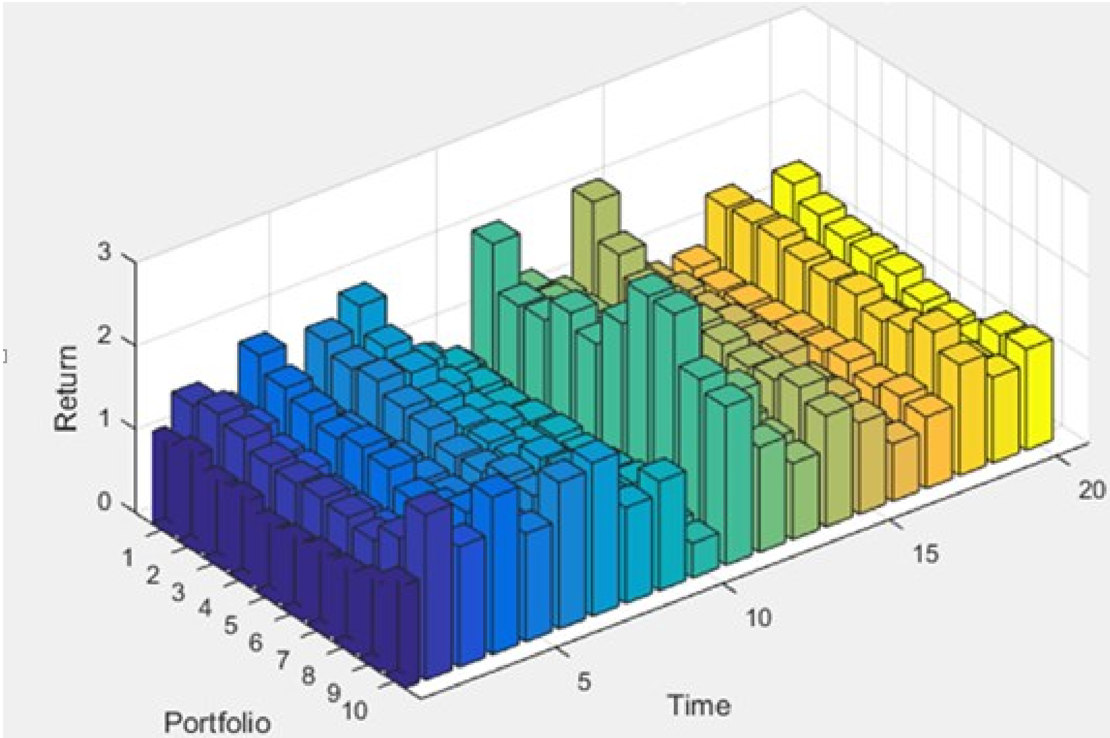


Table 4.7 shows the test of a prediction model with alternative failure identification. Liquidated hedge funds satisfy one of following criteria would be considered as censored funds that are not a failure and the left liquidated funds would be considered as real failures.

1) Positive return in last 6 months, total net asset increased in last 12 months;

3) Total net asset increased in the last 24 months, the average return in last 24 months is higher than 0.25%.

4) Total net asset increased in last 24 months, average return increased in last 24 months.

5) Total net asset increased in last 24 months, average return increased in last 12 months.

I repeat the test on both 5 years historical data and 10 years historical data. The Table 4.7 shows the test in 5 years historical data. It indicates that the prediction model robustness to the alternative failure identification that Portfolio 1 experienced positive and significant abnormal return in the hedge fund industry.

The Chart 4.6 presents more details on the empirical value of the prediction model based on alternative failure identification. The aggregate half year return reveals actual return on each portfolio sorted by historical failure risk. Normally, hedge funds in lower risk portfolios present higher performance. It is similar to the prediction model of the estimation on the 21st time shows that high-risk portfolio presents extremely higher return. That is the aggregate return between January 2009 and June 2009. The evaluation period of this time is the first test after the collapse of Lehman Brothers on September 15, 2008. The result indicates that the prediction model is robust to this alternative failure identification. The hedge funds embracing higher failure risk increase the probability of getting extremely high returns during this time. On the other side, hedge funds in the Portfolio 1 also perform well at this time and the financial crisis time period. The prediction model maintained its empirical value in both normal period and financial crisis period.

Similar to the robustness test on the length of historical data, the Table 4.8 shows that the magnitude and significance of result in alternative failure identification are also diminished when the test on 10 years historical data. It also supports the hypothesis that performance in the more distant past is of less importance.

Table 4.7: Alternative failure identification (5-year estimation period)

Sorts on hazard index.

Hedge funds with hazard index terms are sorted every 6 months into deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real failure follows the alternative failure identification. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2). The evaluation period is from January 1999 to January 2014.

Start year 2004	Portfolio	Return	BHAR	P-value
	1	33%	11%	0.10**
Average return	2	26%	4%	0.58
22%	3	21%	-1%	0.16
	4	24%	2%	0.91
	5	22%	0	0.28
	6	22%	0	0.32
	7	16%	-6%	0.01****
	8	19%	-3%	0.07**
	9	17%	-5%	0.02***
	10	22%	0	0.77

Chart 4.6: Performance for Alternative failure identification

Hedge funds with hazard the index terms are sorted every 6 months into 10 deciles based on their hazard ratio last month. The hazard ratio is the estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows the alternative failure identification. Return is the aggregate six months' return for each portfolio. Each time of the test produces a return for every portfolio. The evaluation period is from January 1999 to January 2014.

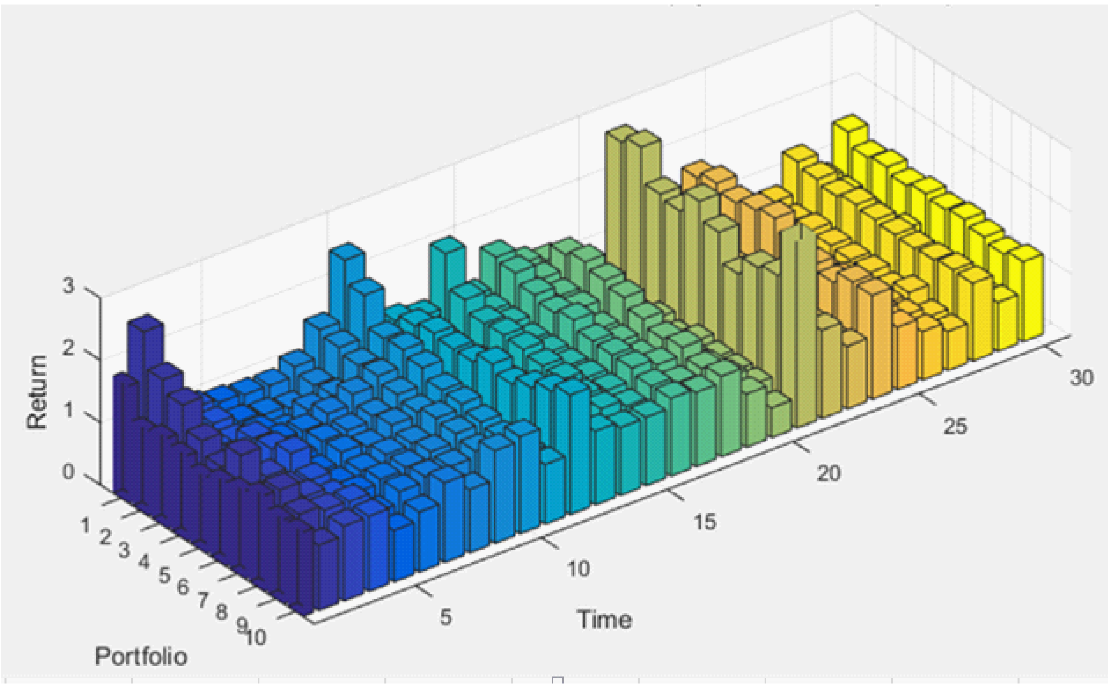


Table 4.8: Alternative failure identification (10-year estimation period)

Sorts on hazard index.

Hedge funds with hazard index terms are sorted every 6 months into deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 120 months' data and z is the vector of covariate for each fund. The identification of real failure follows the alternative failure identification. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2). The evaluation period is from January 2004 to June 2014.

	Portfolio	Return	BHAR	P-value
	1	27%	8%	0.17
Average return	2	23%	4%	0.19
19%	3	18%	-1%	0.64
	4	14%	-5%	0.09**
	5	16%	-3%	0.04***
	6	15%	-4%	0.02***
	7	14%	-5%	0.02***
	8	16%	-3%	0.14*
	9	14%	-5%	0.25
	10	18%	-1%	0.85

The Chart 4.7 presents more details on the empirical value of the prediction model when running for 10 years historical data based on alternative failure identification. The aggregate half year return reveals actual return on each portfolio sorted by historical failure risk. Normally, hedge funds in lower risk portfolios present higher performance. Estimation of the 11th time is the first test after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher failure risk increase the probability of getting extremely high returns on time 1, 2, 3, 4, 6, 7, and 9. On the other side, hedge funds in the Portfolio 1 perform well in some of these times and the financial crisis time period. Although outperformance of Portfolio 1 is not as clear as the original model, the prediction model based on alternative failure identification maintained its empirical value to some extent.

The identification of funds' failure in this study could be rejected by some researchers. Therefore, this study also does robustness test on original data without filtering non-failure funds from the liquidated funds. The Table 4.9 and Table 4.10 report the summary of the prediction model test for 5 years historical data and 10 years historical data respectively. The result shows that the prediction model is robustness to this method and has a similar trend of the result of using 5 years historical data to 10 years historical data.

Chart 4.7: Performance for Alternative failure identification (10-year estimation period)

Hedge funds with hazard index terms are sorted every 6 months into 10 deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 120 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows the alternative failure identification. Return is the aggregate six months' return for each portfolio. Each time of the test produces a return for every portfolio. The evaluation period is from January 2004 to January 2014.

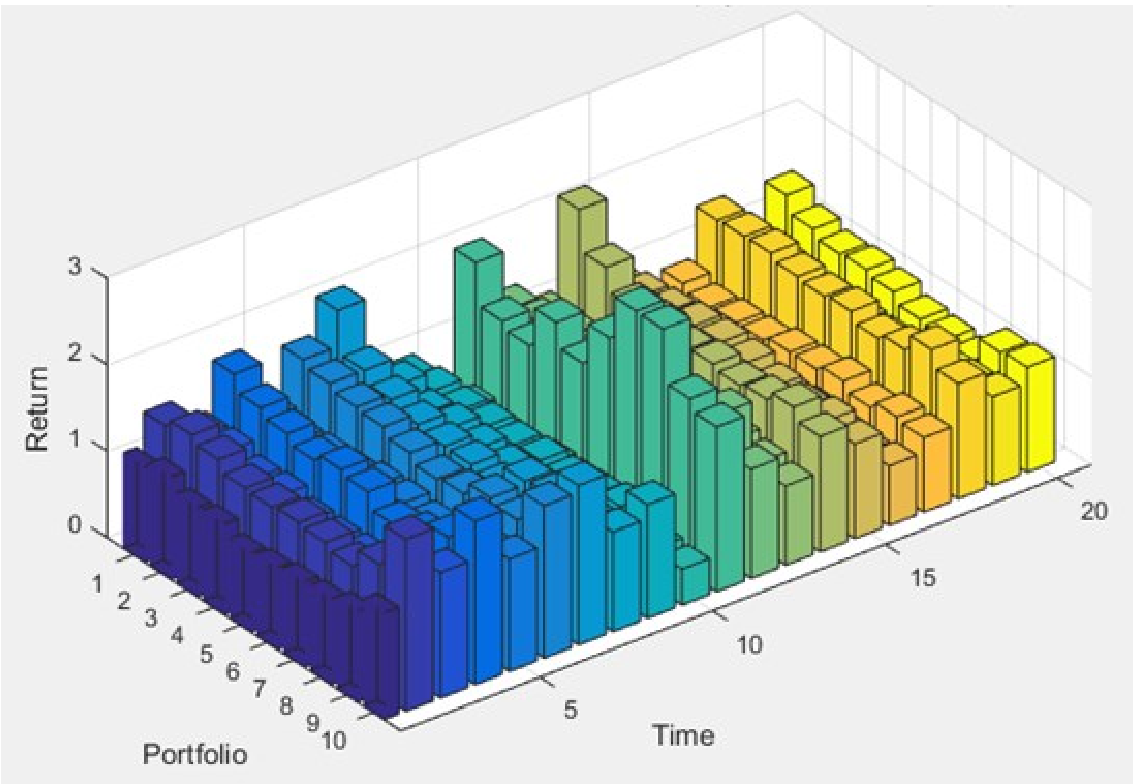


Table 4.9: No filter on fund failure (5-year estimation period)

Sorts on hazard index.

Hedge funds with hazard index terms are sorted every 6 months into deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real failure follows the original database that liquidated funds are considered as failures. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation 12). The evaluation period is from January 1999 to June 2014.

Start year 2004	Portfolio	Return	BHAR	P-value
	1	34%	12%	0.04***
Average return	2	24%	2%	0.58
22%	3	19%	-3%	0.26
	4	20%	-2%	0.24
	5	16%	-6%	0.00****
	6	19%	-3%	0.15*
	7	18%	-4%	0.08**
	8	18%	-4%	0.09**
	9	18%	-4%	0.25
	10	19%	-3%	0.57

The Chart 4.8 presents more details on the empirical value of the prediction model without filtering non-failure funds from the liquidated funds? The aggregate half year return reveals actual return on each portfolio sorted by historical failure risk. Normally, hedge funds in lower risk portfolios present higher performance. It is similar to the prediction model that estimation on the 21st time shows that high-risk portfolio presents extremely higher return. That is the aggregate return between January 2009 and June 2009. The evaluation period of this time is the first test after the collapse of Lehman Brothers on September 15, 2008. The result indicates that the prediction model is robust to this alternative failure identification. The hedge funds embracing higher failure risk increase the probability of getting extremely high returns during this time. On the other side, hedge funds in the Portfolio 1 also perform well at this time and the financial crisis time period. The prediction model maintained its empirical value in both normal period and financial crisis period.

Chart 4.8: Performance for no filter on fund failure

Hedge funds with hazard index terms are sorted every 6 months into 10 deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real failure follows the original database that liquidated funds are considered as failures. Return is the aggregate six months' return for each portfolio. Each time of the test produces a return for every portfolio. The evaluation period is from January 1999 to June 2014.

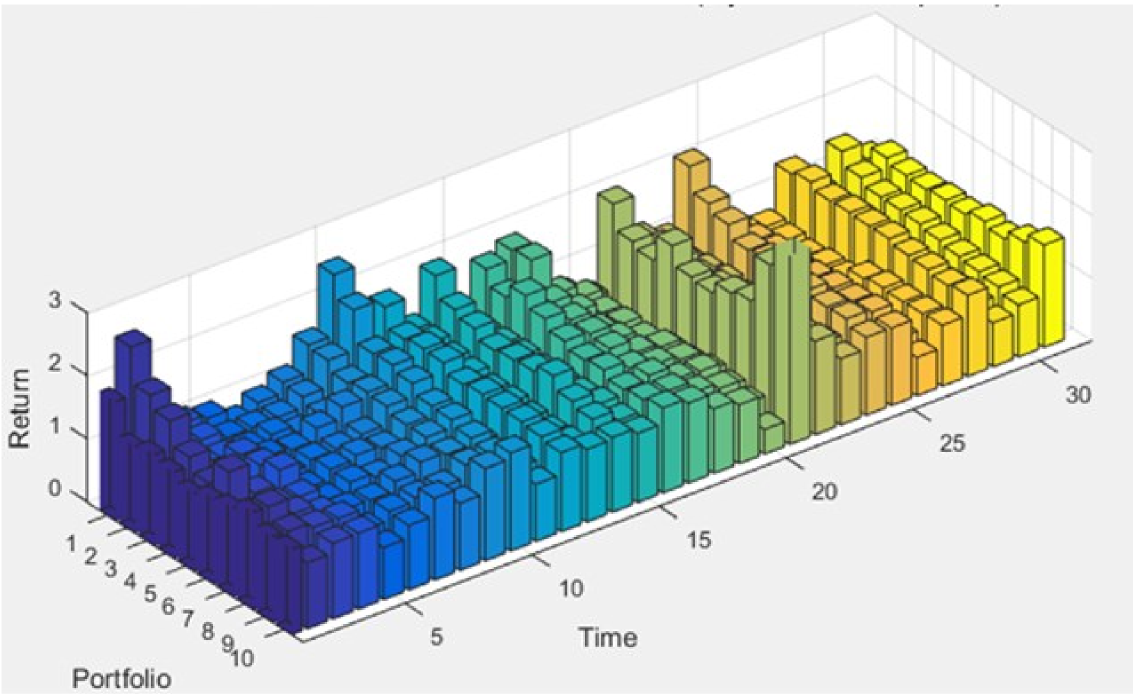


Table 4.10: No filter on fund failure (10-year estimation period)

Hedge funds with hazard index terms are sorted every 6 months into deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 120 months' data and z is the vector of covariate for each fund. The identification of real failure follows the original database that liquidated funds are considered as failures. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2). The evaluation period is from January 2004 to June 2014.

Start year 2004	Portfolio	Return	BHAR	P-value
	1	27%	7%	0.15
Average return	2	22%	3%	0.27
19%	3	18%	-1%	0.72
	4	15%	-4%	0.06**
	5	15%	-4%	0.01****
	6	14%	-5%	0.03***
	7	14%	-5%	0.03***
	8	14%	-5%	0.03***
	9	16%	-3%	0.47
	10	18%	-1%	0.88

The Chart 4.9 presents more details on the empirical value of the prediction model when running for 10 years historical data without filtering non-failure funds from the liquidated funds. The aggregate half year return reveals actual return on each portfolio sorted by historical failure risk. Normally, hedge funds in lower risk portfolios present higher performance. The hedge funds embracing higher failure risk increase the probability of getting extremely high returns on time 2, 4, 6, 7, 9 and 20. On the other side, hedge funds in the Portfolio 1 perform well in some of these times and the financial crisis time period. Although outperformance of Portfolio 1 is not as clear as the original model, the prediction model based on alternative failure identification maintained its empirical value to some extent.

In order to check the backfill bias effect on the prediction model, this study also tests the model include backfill biased data. Table 4.11 and Table 4.12 illustrate the output summary of the prediction model under different failure identification with 5 and 10 years estimation period respectively. Chart 4.10 and Chart 4.11 show correspond details on the empirical value of the prediction model. It is shown in Table 4.11 and Table 4.12 that hedge funds in Portfolio 10 with higher failure risk can earn positive BHAR even all of the result are not significant. This result suggests that hedge fund self-selected reporting could influence the prediction accuracy of this prediction model. The backfill bias influences the prediction accuracy on the performance of hedge funds with high failure risk the most significant. This evidence indicates that some of the high-risk hedge funds with low performance do not report their performance after the incubation period.

Chart 4.9: Performance for no filter on fund failure (10-year estimation period)

Hedge funds with hazard index terms are sorted every 6 months into 10 deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 120 months' data and z is the vector of covariate for each fund. The identification of real failure follows the original database that liquidated funds are considered as failures. Return is the aggregate six months' return for each portfolio. Each time of the test produces a return for every portfolio. The evaluation period is from January 2004 to June 2014.

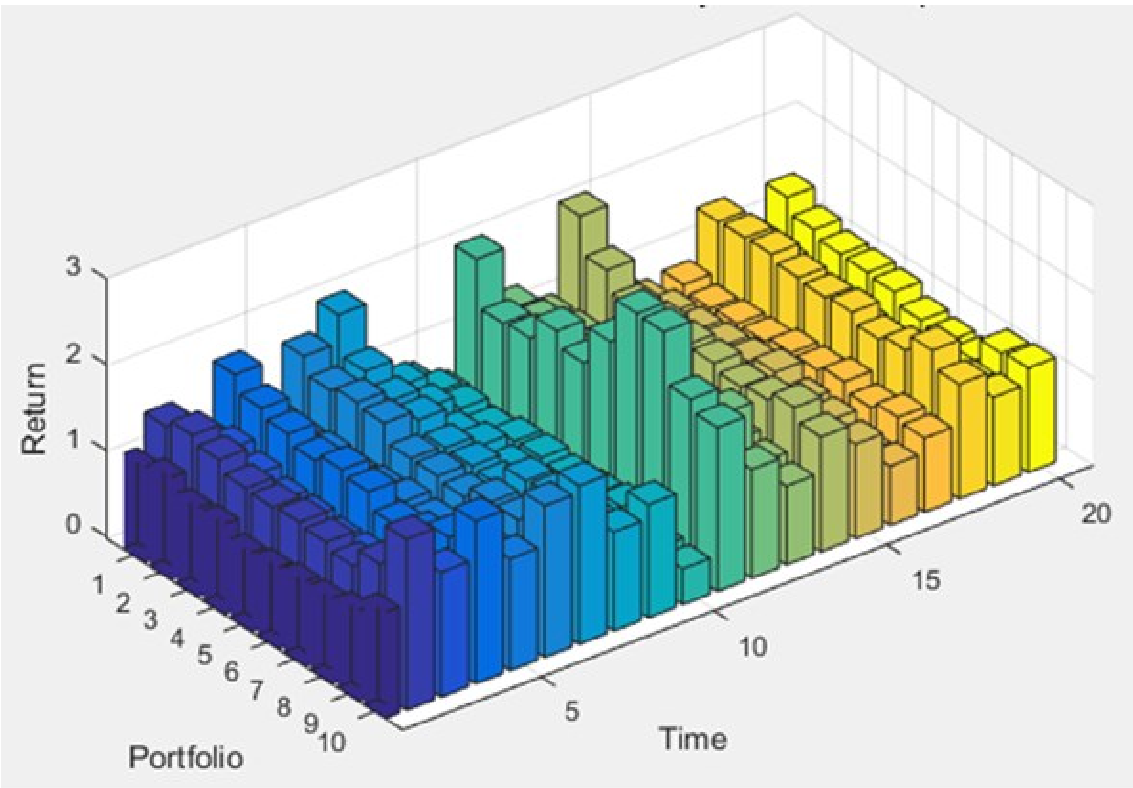


Table 4.11: Test with backfill bias information (5-year estimation period)

Sorts on hazard index.

Hedge funds with hazard index terms are sorted every 6 months into deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows three methods (no filter, alternative identification, and prediction model) respectively. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2). The evaluation period is from January 1999 to June 2014.

No filter	Portfolio	Return	BHAR	P-value
	1	33%	12%	0.05***
Average return	2	23%	2%	0.53
21%	3	19%	-2%	0.48
	4	17%	-4%	0.01****
	5	16%	-5%	0.01****
	6	16%	-5%	0.04***
	7	15%	-6%	0.01****
	8	15%	-6%	0.02***
	9	18%	-3%	0.53
	10	22%	1%	0.90

Alternative Identification	Portfolio	Return	BHAR	P-value
	1	33%	12%	0.07**
Average return	2.	23%	2%	0.51
21%	3	20%	-1%	0.61
	4	16%	-5%	0.00****
	5	16%	-5%	0.02***

	6	16%	-5%	0.08**
	7	15%	-6%	0.02***
	8	16%	-5%	0.05***
	9	18%	-3%	0.48
	10	22%	1%	0.92

Prediction model	Portfolio	Return	BHAR	P-value
	1	33%	12%	0.04***
Average return	2	23%	2%	0.53
21%	3	20%	-1%	0.68
	4	17%	-4%	0.01****
	5	16%	-5%	0.01****
	6	16%	-5%	0.01****
	7	14%	-7%	0.01****
	8	16%	-5%	0.03***
	9	18%	-3%	0.49
	10	22%	1%	0.88

Table 4.12: Test with backfill bias information (10-year estimation period)

Sorts on hazard index.

Hedge funds with hazard index terms are sorted every 6 months into deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 120 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows three methods (no filter, alternative identification, and prediction model) respectively. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) The evaluation period is from January 2004 to June 2014.

No filter	Portfolio	Return	BHAR	P-value
	1	34%	14%	0.02***
Average return	2	24%	3%	0.21
21%	3	21%	0	0.99
	4	17%	-4%	0.04***
	5	14%	-7%	0.01****
	6	15%	-6%	0.00****
	7	14%	-7%	0.00****
	8	16%	-5%	0.02***
	9	17%	-4%	0.38
	10	22%	1%	0.91

Alternative Identification	Portfolio	Return	BHAR	P-value
	1	1.34	13%	0.04***
Average return	2	24%	3%	0.26
21%	3	20%	-1%	0.72
	4	16%	-5%	0.03
	5	16%	-5%	0.01****

	6	15%	-6%	0.00****
	7	15%	-6%	0.01****
	8	16%	-5%	0.04***
	9	18%	-3%	0.48
	10	22%	1%	0.89

Prediction model	Portfolio	Return	BHAR	P-value
	1	34%	13%	0.03***
Average return	2	25%	4%	0.10**
21%	3	20%	-1%	0.70
	4	18%	-3%	0.05***
	5	14%	-7%	0.01****
	6	15%	-6%	0.00****
	7	13%	-8%	0.00****
	8	16%	-5%	0.03****
	9	18%	-3%	0.46
	10	21%	0	0.98

Chart 4.10: Performance with backfill bias (5-year estimation period)

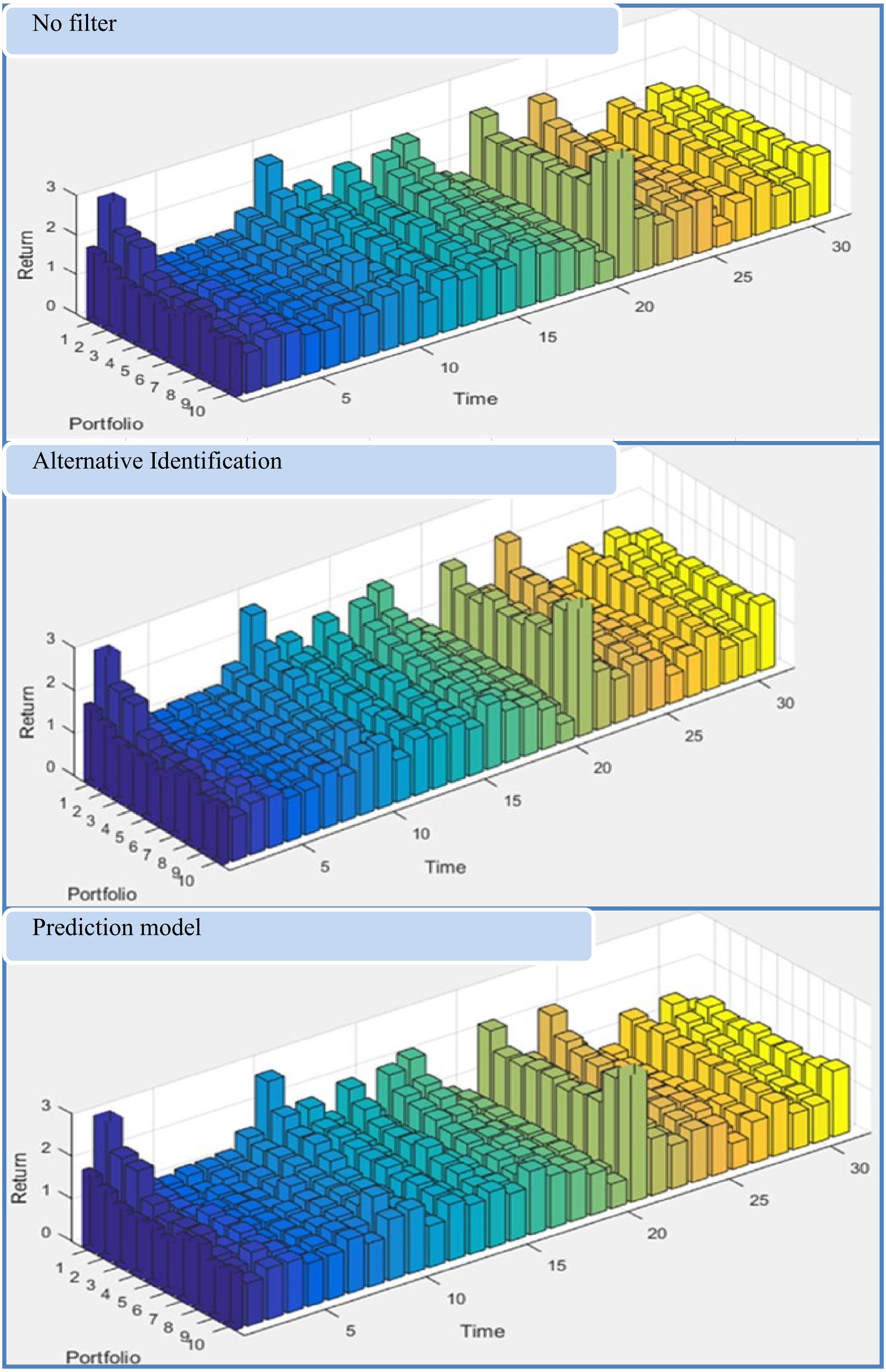
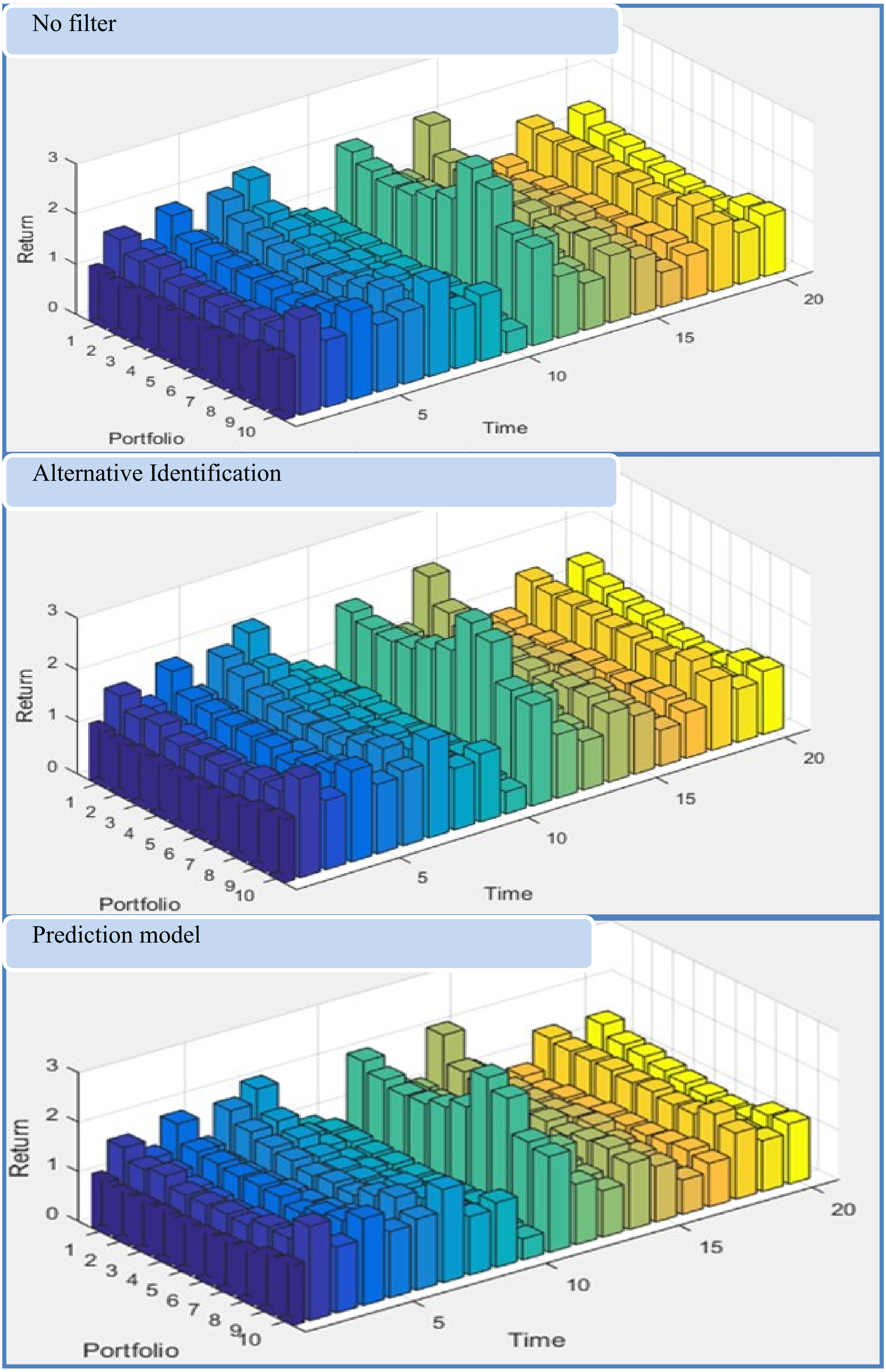


Chart 4.11: Performance with backfill bias (10-year estimation period)



4.6.2 Robustness test on abnormal return method

There are different methods to estimate abnormal return. This study does robustness test on the prediction model by cumulative abnormal return. The Table 4.13 reports that the prediction model robust to CAR method and the excess return is at 15% significance level. The alternative identification shows the less significant result at 25% significance level. Chart 4.12 shows correspond details on the empirical value of the prediction model. This result indicates that the original prediction model robust to CAR method. The alternative identification method is not significant. BHAR method is practically fit for hedge fund performance estimation. CAR method is not practically available in most of the hedge funds. Abnormal return in CAR observes the difference between portfolios′ monthly return and market return of all hedge fund. CAR is cumulative abnormal return for six months′ period.

Table 4.13: Robustness test on CAR method

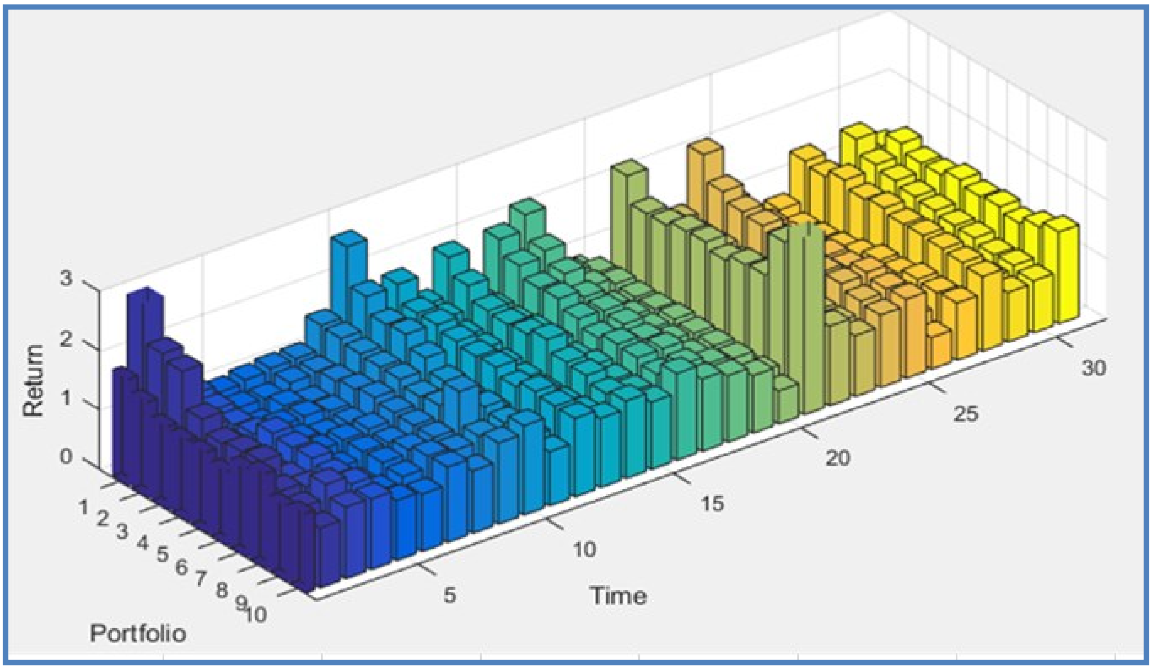
Hedge funds with hazard index terms are sorted every 6 months into deciles based on their hazard ratio last month. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows two methods (alternative identification and prediction model) respectively. Return is the aggregate six-month cumulative return for each portfolio. The P-values are derived from standard errors. Excess return is estimated by cumulative abnormal return. The evaluation period is from January 1999 to June 2014.

Alternative identification		Portfolio	CAR	P-value	Excess return
		1	1.39	0.25	18%
Average return		2	33%	0.4	12%
	21%	3	29%	0.54	8%
		4	23%	0.88	2%
		5	17%	0.71	-4%
		6	16%	0.67	-5%
		7	16%	0.62	-5%
		8	12%	0.35	-9%
		9	13%	0.4	-8%
		10	9%	0.23	-12%

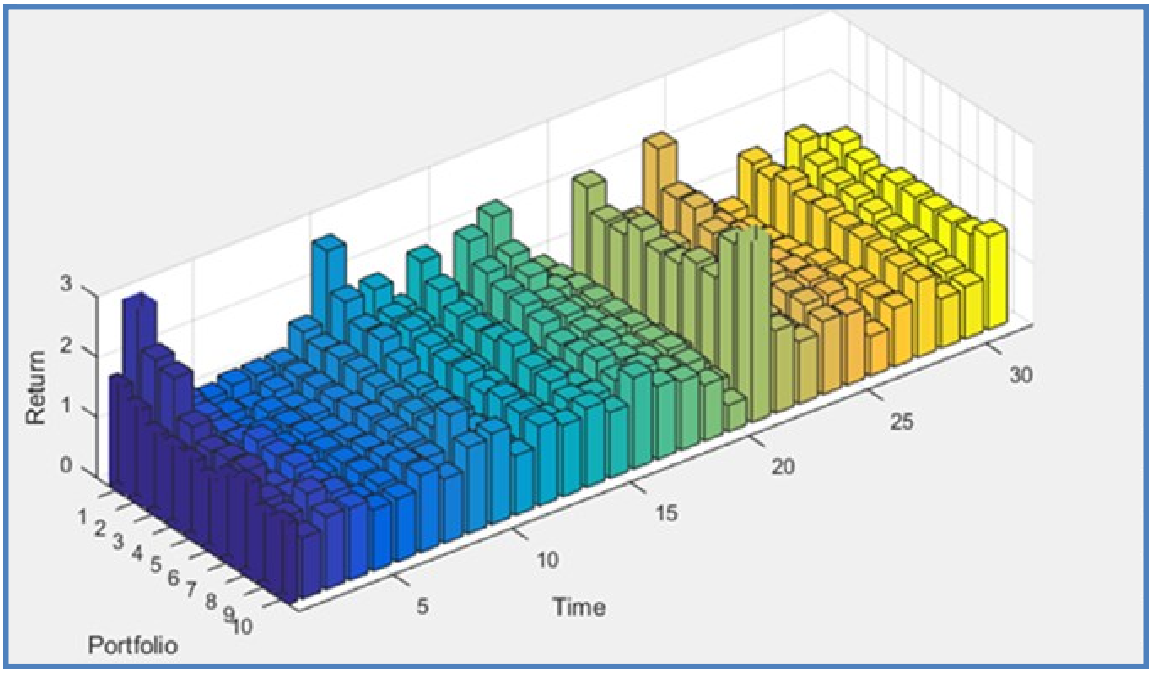
Prediction model		Portfolio	CAR	P-value	Excess return
		1	40%	0.15*	19%
Average return		2	32%	0.37	11%
	21%	3	26%	0.66	5%
		4	21%	0.99	0.00
		5	17%	0.75	-3%
		6	17%	0.76	-4%
		7	13%	0.46	-8%
		8	13%	0.4	-8%
		9	14%	0.53	-6%
		10	13%	0.53	-8%

Chapter 4.12: Performance for CAR method

Alternative Identification



Prediction model



4.6.3 Summary

Prediction model can allocate a portfolio of hedge fund portfolio with the significantly high return and low failure risk. Moreover, the result is robust to a different form of Cox proportional hazard model with different failure identification and CAR abnormal return methods. The most successful method is the prediction model with 5 years estimation period. The alternative identification and no filter of fund failure process present similar result. Furthermore, estimation on 10 years historical data could decrease the significance level of the result because of long distance of past data. The result also indicates that incubation bias influence performance analysis on high-risk hedge fund the most significantly. In long term running, a hedge fund with low failure risk outperforms in the hedge fund industry through 1994-2014.

4.7 Conclusion

This chapter provides empirical evidence that it is possible to predict the performance of hedge funds using data purchased from hedge fund data vendor such as Lipper TASS. The difficulty of finding out quality data of hedge fund is well recognized both within industry and academia. The reason of liquidation of some observations in the database are not clear and extant literature documented that the information about the exit reason is imprecise in the database. This study identifies a multi-component filter system to identify the real failure of hedge funds. Then a fixed specification of the Cox proportional hazard model was estimated using the selected failure times filtering system every half year. The Cox proportional hazard model examined a range of covariates suspected to be significant to hedge fund failure risk including fund size, return, leverage and minimum investment. The estimated coefficients provided quantitative information for the causal factors of hedge fund failure. This information was employed to generate failure risk for the estimated hedge funds. Based on the estimated failure risk, I form hedge fund portfolio with both economically and statistically significant abnormal return. Importantly, the results are robust against variations in evaluation timing, thresholds used to identify failure times and different method to estimate abnormal return.

The result of this chapter will allow investors to estimate the expected performance of a hedge fund before allocation of portfolios and also provide warning signals to investors who have invested in the hedge funds. Furthermore, credit crises become an important factor to investors and hedge fund failure could cause extreme loss. A model capable to predicts the risk of funds failure and further estimates their performance will prove to be invaluable to the broad set of stakeholders far beyond that of direct investors and creditors of hedge funds.

Chapter 5: liquidity risk analysis

5.1 Introduction

This chapter investigates whether the expected returns are related to investor-induced liquidity in the hedge fund industry. The research objective is to build a forecasting system that's capable of constructing investable portfolios of hedge funds based on historical investor-induced liquidity. The results suggest that investor-induced liquidity negatively influence hedge fund performance in the long term. The results are robust for different evaluation periods and estimation periods. The result supports a stream of previous empirical reports that state a high net inflow of hedge funds shows a negative effect on performance in the long term. The results suggest that hedge fund liquidity risk derived from investors is an important factor of hedge fund performance analysis for the risk management department. The results also confirm that investor-induced liquidity in the more recent past has more explanatory power regarding its post-performance. Moreover, incubation bias could influence the predictability of hedge fund performance significantly. Taking liquidity risk management into consideration, large amounts of investment inflow to individual hedge funds could place a heavy burden on hedge fund performance. Large amounts of investment outflow from individual hedge funds could cause fire sale problems when market liquidity is tight. The results from fund performance show that the fire sale problem was more significant in the recent financial crisis period and high investment inflow influence is more significant in normal periods.

Previous studies on liquidity analysis focused on the systematic risk effect that hedge fund industry brings to financial market (i.e. Aragon, and Strahan, 2012; Bianchi, Drew and Wijeratne, 2010. Fung and Hsieh, 2000b; Miniamihashi and Wakamori 2014). There are few studies focus on the relationship between investor-induced liquidity and hedge fund performance. Many previous studies have indicated that the hedge fund industry plays a vital part in the systematic risk of the collapse of Long Term Capital Management during 1998 (Edwards, 1999; President’s Working Group of Financial Market, 1999 and Chan, Getmansky, Haas and Lo, 2006). Few studies discussed the relationship between systemic risk and hedge fund performance. The mainstream of research pointed out that the hedge fund industry can increase systematic risk. The main reason is that hedge is not under well regulation. The indicators of systematic risk could have explanatory power on hedge fund performance.

Previous research has demonstrated that liquidity problems are considered to be the main indicators of systemic risk, which can predict the performance of hedge funds. Ding, Shawky and Tian (2009) report that hedge fund experienced high investor-induced liquidity in the last month performs better than hedge funds with low investor-induced liquidity one month forward. However, Friesen and Sapp (2007) document that return-chasing behavior is not conducive to active fund trader's performance. Investor liquidity shows a negative impact on the long-term performance of hedge funds. Additionally, hedge funds often set long redemption gates that are indeed more than one month. It is difficult for investors to recover their capital within a month. This chapter will estimate the relationship between investor-induced liquidity and hedge fund performance in the longer term. There are many researchers investigate the relationship between investor-induced liquidity and mutual fund performance. Few of study analysis the influence of investor-induced liquidity on hedge fund performance. According to Warther (2005) and Fortune (1998), investor-induced liquidity affects the asset trading of mutual fund managers. Actual fund flows have influenced stock prices and interest rates, which may also affect the monetary value. Dubofsky (2010) documents that trading cost may be one of the reasons for the scale of the non-economies. Therefore, the investment could cause a negative impact on the future performance of the fund if the high net inflow catches up with superior past performance (Chevalier and Ellison, 1997; Tufano, 2007). Furthermore, Friesen and Sapp (2007) show that the return-chasing behavior is not conducive to the performance of traders active fund. More importantly, investor-induced liquidity may result in dilution of mutual fund returns. Greene and Hodge (2002) also indicate that the mutual fund's investment may lead to dilution of asset returns, thereby affecting the fund's return. The authors also show that even if long-term investors may lead to moderate dilution in mutual funds and short-term investment strategies. Fund managers may decide whether or not to keep in money or to invest in the current portfolio. This evidence shows that investor-induced liquidity is negatively related to mutual fund performance. The impact of investment flows in the hedge fund industry could be different. Sadka (2006) report that hedge funds experienced positive investor-induced liquidity performs better than hedge funds with negative investor-induced liquidity. According to Teo (2011) and Sadka (2006), liquidity shocks from investors can lead to significant fire sales problems. The price of the asset could reduce because of tight short-term market liquidity. In the hedge fund market, managers can report their low liquidity assets in return for high prices and the redemption of investors may drag down prices below market value. The smooth reporting behavior could bias actual performance. Ding, Shawky, and Tian (2009) show that hedge funds have experienced high investment induced liquidity in the last month, the performance is higher than the low investor-induced liquidity 1 month forward from 1994 to 2005. Practically, hedge fun often set redemption gate more than 1 month. Moreover, the time period of this study does not include the recent financial crisis. Therefore, this thesis will investigate the liquidity of hedge funds based on the cash withdrawal, rather than taking share limit as the main feature for the estimation of hedge fund liquidity.

In this chapter, Section 5.2 I provide literature reviews about the estimation of hedge fund liquidity condition. Section 5.3 describes the data and sampling method for this study. Section 5.4 explains the methodology and research process. 4.7 presents the empirical results. Section 5.6 provides Robustness checks and Section 5.7 concludes this chapter.

5.2 Literature review

Hedge funds have a deep influence on market liquidity. Kathleen Casey of IOSCO and Ben Bernanke of the US Federal Reserve both agree that hedge funds become more and more significant in all kinds of markets as liquidity providers. Traditionally, the main duty of financial institutions is to serve as intermediation for liquidity provision. For the past few years, these financial institutions have got their earnings from agent fees instead of engaging in high-risk projects. More specifically, even the global banking sector has weakened its high-risk projects with the migration towards the Base II Accord. At the same time, the global hedge fund industry has been attracted by these high-risk projects of liquidity provision. The systematic level of liquidity and liquidity shock in firm's level could explain hedge fund performance to a certain extent. Previous study analysis on the different level of liquidity effect on hedge fund performance from several aspects.

5.2.1 Systematic risk and hedge fund performance

Systematic risk refers to an event or macroeconomic shocks that undermine the macro economy. It is well recognized that the undermine effect that systematic risk has an influence on banks, equities and credit markets are examined by previous studies. Previous studies document that the hedge fund industry plays an important role in systematic risk since the collapse of Long Term Capital Management in 1998 (President's Working Group of Financial Market. 1999; Edwards,1999 and Chan, Getmansky, Haas and Lo, 2006). There are few studies explore the relationship between systemic risk and hedge fund return. The mainstream of studies reports that the hedge fund industry exacerbates the effect of systematic risk in 1998. The main reason is hedge fund are not regulated as well as other financial industries. Chan, Getmansky, Haas and Lo (2006) document that the hedge fund managers are able to use aggressive investment strategy under the weak regulation. It includes getting profit from decreasing of stock price and using of leverage to increase their asset size. Consequently, the hedge fund industry provides specific investment style to their investors and draw a large amount of investment. Hedge fund industry invests in the financial market constantly with these tools and finally provide liquidity to the financial market. However, the systematic risk could increase from fail of one hedge fund because the fail of one hedge fund could not only influence its customers but also its creditors and trading competitors. Large financial institutions and the financial market could be involved in this increase of systematic risk. Consequently, a group of studies holds the argument that government should carry out tighter regulation on hedge fund since the collapse of Long-Term Capital Management in 1998. The hedge fund with a high level of leverage could cause a negative effect on systematic risk. Furthermore, repurchase market in 2008 provokes more researchers to analysis if the tighter regulation on fund leverage could prevent hedge fund from increasing of systematic risk.

The hedge fund industry is one of the important financial systems in the global financial market. It could play an important role in systematic risk. However, Eichengreen and Mathieson, Chadha, Jansen, Kodres and Sharama (1998) and Eichengreen and Mathieson (1998a, 1998b) Fung and Hsieh (2000a) and Ferguson and Laster (2007) hold the argument that the hedge fund industry is not the main reason of market turmoil that causes systematic risk in financial crisis period. Furthermore, Wijeratne Bianchi and Drew (2010) point out that Long Term Capital Management is a special hedge fund that the total size of an asset in this fund is much higher than normal hedge funds. The mean of hedge fund total asset under management is lower than US$82 million. Moreover, the competition in the hedge fund industry is very intense that attrition rate in the hedge fund market is over 10% every year (Wijeratne, Bianchi and Drew, 2010). Hedge fund managers are under pressure of competition in the industry and it causes a big number of hedge funds fail and quit the industry. However, Wijeratne, Bianchi and Drew (2010) document that the fail and quit of hedge funds did not increase market-wide systematic risk. On contrary, the competitive hedge fund market could provide liquidity to the financial market and decrease global systematic risk in another financial market. It is different with the argument of 'too big to fail' that many banks with strong market power that can hardly become a failure. Market forces function in the hedge fund market is very strong that no single hedge fund company could possess this kind of power. Consequently, many hedge fund fails and quit the hedge fund industry without increase systematic risk. Hedge fund fails because of competition with the different asset-management industry. The systematic risk could not be influenced from fail of hedge fund only if the size of the hedge fund industry or a hedge fund reach the level that can influence market liquidity.

The negative effect of systematic risk derives from the fail of a hedge fund are taken into consideration by policymakers after the collapse of Lehman Brother in 2008. The fail of hedge fund could cause financial contagion through other financial market and it could finally turn into globule financial crisis. Minamihashi and Wakamori (2014) point out that the governance of the hedge fund industry influence investor behavior significantly after the recent financial crisis. The restrict regulation of leverage use in the hedge fund industry could decrease investment in highly risky investment strategy and lead to a lower systematic risk. The author document that a small portion of investors in the hedge fund industry prefer to use leverage (20%). Furthermore, the author document that limitation of leverage usage on 200% could reduce investment in high-risk strategy effectively. It could minimize the negative effect of systematic risk from the hedge fund industry.

Bali, Brown, and Caglayan (2012) estimates the influence of tail risk, residual risk and market risk on hedge fund performance. The author indicates that systematic risk has strong explanatory power on cross-sectional of hedge fund returns. Minamihashi and Wakamori (2014) document that if hedge fund industry could decrease systematic risk, timing ability of systematic risk could be an important factor in prediction of hedge fund performance. Many of studies estimate different risk measure that explains the cross-sectional of hedge fund return. Therefore, the hedge fund industry could have the function of minimizing systematic risk. Bali, Brown, and Caglayan (2012) document that residual risk and tail risk are not significant factors that could explain hedge fund returns. It is widely known that the hedge fund industry could be a market-neutral investment and it could experience positive the returns significantly in different market conditions. However, Bali, Brown, and Caglayan (2012) indicate that market factors play an important role in hedge fund performance. Tiu (2011) hold the argument that the hedge funds that is market-neutral investment experienced low R-square. Only the hedge funds with low R-square generate the positive return in both good and bad market conditions. Fung and Hsieh (1997a), Fung, Hsieh, Naik, and Ramadorai (2008) and Argwal and Naik (2004) document that hedge funds experienced high tail risk exposure. The hedge fund with high dynamic trading and arbitrage trading strategies experienced high tail risk exposure. However, Bali, Brown, and Caglayan (2012) document that tail risk includes skewness and kurtosis have no explanatory power on hedge fund performance. Consequently, the traditional method could not capture hedge fund tail risk effectively and it could cause miss estimation of hedge fund performance. The author further estimates the explanatory power of systematic variables and unsystematic variables individually. The result indicates that systematic risk measurement is better than residual risk measurement on predicting of hedge fund return. It suggests that prediction model based on systematic risk could perform better than residual risk measure. There are several indicators related to the systematic risk that some of them present stronger explanatory power than others. Following part is the analysis of leading indicators.

5.2.2 Influence of liquidity on hedge fund performance

Liquidity concerns are considered as leading indicators using the systematic risk that could predict hedge fund returns (Savona, 2014). There are few studies explore prediction model of hedge fund performance. Savona (2014) first build early warning system for the hedge fund extreme negative returns by using a regression tree algorithm. Previous studies investigate different indicators of systematic risk. Stein (2009) report that crowd trading and using of leverage are two main indicators of systematic risk. It is consistent with Brunnermeier and Pedersen (2009) and Morris and Shin (2004) that investigate the influence of liquidity risk and leveraged arbitrageurs respectively. Following that, a group of studies focuses on co-movement of hedge fund investment behavior. Boyson, Stahel, and Stulz (2010) capture the hedge funds with worst returns based on contagion effect. The author suggests that the group of a hedge fund with the worst returns is correlated with contagion. Billio, Getmansky, Lo and Pelizzon (2012) also investigate the influence of connectivity between financial institutions of spillover effects and contagion. Adrian (2007) further document that similarities of hedge fund investment styles could be an important indicator of systematic risk. Besides leverage, strategy, and contagion, Savona (2014) document that liquidity concerns are important leading characteristics of hedge fund extreme negative returns. This thesis will employ hedge fund liquidity risk as an indicator that could predict hedge fund performance. Previous studies identify that returns fall in the bottom 10% of hedge fund monthly returns is extreme negative returns in the hedge fund industry (Boyson, Stahel and Stulz, 2010; Savona,2014). Consequently, this thesis will use both top 10% and bottom 10% of hedge fund returns as extreme performance in the hedge fund industry. Savona (2014) only explore how an early warning system could work for the extreme negative returns that could help to predict the risk that could cause market-wide crises. In this thesis, I focus on detecting both sides of extreme returns of hedge fun on specific characteristics that help to restructure of investment portfolios in the hedge fund industry.

Previous studies the investigate liquidity effect on fund performance in two aspects. On one hand, a group of studies focus on the concept of market-wide liquidity and emphasize that liquidity is an asset risk factor (Pastor and Stambaugh, 2003, Acharya and Pedersen, 2005 and Sadka, 2006). Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) both document that return is sensitive to stock market liquidity and hedge fund liquidity condition has explanatory power on the prediction of market return. Using of aggregate liquidity estimation, the author report that asset whose price highly correlated to the market-wide liquidity experienced higher return than assets whose priceless correlated to the market-wide liquidity. Many studies mainly the concentrated on the systematic influence of liquidity risk rather than on its special practical function from the liquidity level. This group of study focus on market liquidity fluctuations and report that firm level liquidity experienced similar change (Amihud, 2002; Chordia, Sarkar and Subrahmanyam, 2005). They estimate liquidity with different liquidity measure which focuses on the risk of the fluctuation of liquidity. Most of the studies document that hedge fund with high covariation of performance and liquidity experienced high post returns. Moreover, the importance of systematic liquidity variations in the evaluation of hedge fund performance is put forward to in other related studies. Sadka (2010) shows that liquidity, as measured by the fluctuations of fund returns without foreseeing, is a decisive factor in the aspect of hedge fund returns. According to the findings, hedge funds that take high liquidity risks perform about 6% higher than the funds that take low liquidity risks per year from 1994 to 2008. However, a hedge fund with high liquidity risk experienced negative returns during financial crisis period due to the low market liquidity. Systematic risk plays an important role in hedge fund performance.

On the other hand, a group of studies investigates firm-specific liquidity effect in fund market. For investors, this group of studies holds the argument that investors demand illiquid assets for a higher profitability in long term investment (Amihud and Mendelson, 1986). Using of bid-ask spreads measurement, Amihud, and Mendelson (1986) document that holding of the illiquid asset could cause an excess return. The liquidity is considered as a characteristic of stocks. According to Coval and Stafford (2007), mutual funds as investors could cause coordinated demand shocks to stocks they hold and it is an important source of price pressure. Mitchell, Pedersen, and

Pulvino (2007) report that a large amount of investment withdraws from convertible arbitrage hedge funds brought obvious departure of convertible bonds from the price it should be theoretically. In hedge fund market, Bollen and Whaley (2009) find that hedge funds managers tend to avoid to consider losses for the purpose of absorbing and keeping investors. Teo (2011) proclaims that the excessive liquidity risk exposure could be interpreted to some extent by agency matters of hedge funds. He shows that hedge funds, which are easy to affect by agency problems, are prone to increase liquidity risks extremely and hence to produce considerable returns and obtain the property of investors. He contends that hedge funds incline to put an excessive impact on liquidity risk so that it may generate significant returns and attract investors. It indicates that hedge fund with low liquidity could perform better on its reported return. More specifically, Sadka (2010) finds that the cross-section of hedge fund returns is highly determined by the liquidity risk which is estimated by the covariation of fund pay-backs with total liquidity. The findings demonstrate that the funds with liquidity risk usually perform 6 % higher than low-loading funds averagely. However negative performance is discovered during financial crises from the year 1994 to 2008. Ding, Shawky, and Tian (2009) investigate the performance of hedge fund with different liquidity risk exposure. The author report that hedge funds invested more in illiquid securities presented a more stable performance. It could because the pricing of the illiquid asset is on a long time span. As the result, Hedge fund invested more in illiquid asset could execute their strategy in long term running and report a more attractive performance. Sadka (2006) and Teo (2011) also report that hedge fund embraces high liquidity risk for a smooth performance. The result also indicates that managers purposefully report their performance with less volatility (Bollen and Whaley 2009). Therefore, analysis of hedge fund performance should include liquidity condition rather than only focus on reported return. Literature in hedge fund liquidity analysis also point out that hedge fund managers often set redemption gate to investors include lockup period and notice period (Sadka, 2006, Teo, 2011 and Ding, Shawky and Tian, 2009). The setting of redemption gate could release the stress of liquidity shock under tight market liquidity condition. It can also reduce fire sale problem for hedge funds embracing heavy liquidity risk. Ding, Shawky, and Tian (2009) and Teo (2011) also document that hedge fund with bigger size could embrace higher liquidity risk as they could set a longer lockup period and consequently hedge fund manager could manage their fund under a more stable investment environment. Consequently, large fund managers could allocate more in illiquid assets for a more attractive performance.

5.2.2.1 Influence of liquidity shock

Many of studies report the liquidity shock effect on mutual fund market. Warther (2005) and Fortune (1998) report that investor-induced liquidity influence mutual fund managers on their asset trading. The actual fund flows subsequently effect on stock price and interest rate and it could also impact currency values. One of possible reason is the size of mutual fund industry is similar to the US banking industry that it growth to $15.8 trillion in July 2014. Furthermore, in 2014, the non-money market inflow in the mutual fund industry reached $102 billion. In comparison, hedge fund capital reached $2.95 trillion at the end of 2014. The hedge fund industry experienced over $76.4 billion flowed into and about $28 billion flowed out of hedge fund market. The liquidity shock effect of hedge fund industry to systematic risk could be less than mutual fund industry and the firm level liquidity shock could be more noteworthy. The effect of investor-induced liquidity to the mutual fund industry have well explored. Dubofsky (2010) analysis the influence of investor-induced liquidity to portfolio trading of assets in the mutual fund industry. The author indicates many conditions that could vary the performance of mutual funds. Specifically, firm-level investment flow could increase the cost of liquidity service and cost of transaction fees. Moreover, fund inflow could cause portfolio purchases performs lower than managers' benchmarks. On contrary, fund outflow could cause portfolios sales performs higher than managers' benchmarks (Alexander et al., 2007). Berk and Green (2004) also documents that return of mutual fund are lower owing to decreasing returns to scale if net investor inflows follow the superior performance in active portfolio management. Dubofsky (2010) indicate that the cost of trading could be one reason of the non-economies of scale. As a result, it will totally adversely influence the fund's future performance if high net inflow catches up with superior past performance (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). There is an argument that prior fund performance explains only a small section of the trading decision that made by existing fund owners. However, Friesen and Sapp (2007) demonstrate that returns-chasing behavior is detrimental to active fund trader's performance. More importantly, investor-induced liquidity could cause dilution of mutual fund returns. Greene and Hodges (2002) also point out that mutual fund investment could cause dilution of asset return and consequently influence fund return. The author documents that even long-term investors could cause mild dilution to mutual funds with short-term investment strategies. Mutual fund managers could decide whether the investment should be kept as money or invest into current portfolio allocation. This evidence suggests that mutual funds with lower investor-induced liquidity could performance better than mutual funds with higher investor-induced liquidity.

The impact of investment flow in the hedge fund industry could be different. Sadka (2006) report that hedge funds experienced positive investor-induced liquidity performs better than hedge funds with negative investor-induced liquidity. The result is same in one and three month's lag. Teo (2011) and Sadka (2006) report that liquidity shock from investor redemption could cause significant fire sale problem that hedge fund has to short their asset with low price in the market because of tight market liquidity. The performance of hedge fund could bias more serious together with the problem of smooth-reported return. Hedge fund manager could report the high price of their return on low liquid asset and the redemption from investor could drag the price down to lower than market value. Ding, Shawky, and Tian (2009) also indicate that hedge fund with conservative strategy in coping with liquidity shock often performs worse than a fund with aggressive strategy in coping with liquidity shock. Ding, Shawky and Tian (2009) report that hedge fund experienced high investor-induced liquidity in the last month performs higher than hedge funds with low investor-induced liquidity 1 month forward from 1994 to 2005. On one hand, the time period of this research did not include recent financial crisis period. Sadka (2010) indicate that liquidity risk could conversely effect on hedge fund performance during financial crises period. On the other hand, hedge fund managers could hold an illiquid asset in order to smoothly present their performance. Moreover, the setting of redemption gate of hedge fund could help them to more smoothly presenting their return. Using of 1 month past performance to test 1 or 3 months forward return could not investigate the real effect of investor-induced liquidity. In addition, with increasing of hedge fund size and fund flows, the influence of investor-induced liquidity could close to the mutual fund. Take the characteristic of hedge fund management into consideration, it is important to test the impact of investment flow to hedge fund performance more reasonable. This study would examine on a longer set of past investor-induced liquidity and forward returns in order to test if the decrease of investor-induced capital flow to hedge fund had a negative impact on hedge fund performance from 1994 to 2014.

5.2.2.2 Redemption restriction and hedge fund performance

Many studies concentrate on the characteristic of specific asset liquidity of hedge fund. Liang (1999) document that redemption gate could play an important role in hedge fund liquidity condition. The author indicates that redemption gates prolong investor cash withdraw and it could consequently increase stability on long-term asset holding and reduce the amount of cash reserve. Specifically, Liang (1999) report that hedge fund performance is positively related to lockup period. The result indicates that lock-up periods are effective for the prevention of withdraws in the early period, the decrease of fund size and support hedge fund managers with relatively long term investment. Consequently, hedge fund managers could benefit from relatively long horizons and high investment flexibility. It is helpful to get profit from arbitrage investment because of noise trader risk. Moreover, a with more stable fund size, hedge fund managers could undertake lower pressure of fire sales problem in both crisis period and normal period. Interestingly, Aiken, Clifford, and Ellis (2015) report that hedge funds with discretionary liquidity restrictions impose the cost of illiquid investment to investors. The performance of hedge funds with strict share restrictions significantly worse than hedge funds with fewer share restrictions during the financial crisis period. As the result, a hedge fund with discretionary liquidity restrictions experienced a negative effect on their reputation after financial crisis period. This group of hedge funds faced difficulties to keep the size of asset and management fees. The change of market condition and reputation could influence the effect of fund share restrictions of their performance.

Aragon (2007) document that hedge fund with more restricted redemption gate could allow hedge fund managers to allocate illiquidity asset more effectively. As a result, investors could get profit from share illiquidity premium. The excess payback of hedge funds with lockup period is significantly higher (4.7% per year) than the funds without lockup periods. Ding, Shawky, and Tian (2009) also point out that large hedge fund has a competitive advantage in controlling asset redemption gate. When trying to control the capital outflows, a hedge fund with larger asset size is more easily to provide stable investment environment for their fund managers. They can set a longer lockup periods than small hedge funds and higher redemption fees for prevention of early withdraws. Aragon (2007) document that hedge fund with strict share restriction is more likely to invest in illiquid assets. It constent with Liang and Park (2007) and Khandani and Lo (2011) that share restriction is negatively associated with the fund liquidity. Consequently, a hedge fund with lockup period could get an excess return from illiquid assets. On contrary, Sadka (2006) estimate the relation between hedge fund liquidity loading and share restriction conditions (assessed by lockup period and notice period). The result indicates that hedge fund liquidity is not significantly related to its share restriction. The author further documented that hedge fund share restrictions (assessed by lockup period and notice period) are not significantly related to fund performance.

Using of market-wide liquidity measurement (Pastor and Stambaugh, 2003). Teo (2011) documents that hedge fund managers with less strict share restrictions are more likely to take a high liquidity risk. The liquidity restrictions are not often considered as liquidity risk exposure that hedge fund manager could take. Hedge funds with lockup period perform better than those without lockup period could due to the effect of fund size. Ding, Shawky, and Tian (2009) report that large fund is more likely to provide strict redemption gate for their investors. Furthermore, previous studies report the positive relation between fund size and the funds' asset portfolio performance (Liang, 2000; Ding, Shawky, and Tian, 2009). The results show that small hedge fund presents higher entire return. However, a hedge fund with large assets size presents higher risk-adjust return. Large funds hold the more illiquid asset and embrace lower burden of systematic and idiosyncratic risk than small funds. Sadka (2010) also reported that redemption gate that hedge fund managers set for their investors are not significantly related to their return and the result robust to commonly used characteristics in hedge fund analysis. As the result, this thesis is going to investigate hedge fund liquidity based on cash withdraw from investors directly rather than taking share restrictions as the main characteristic for the estimation of hedge fund liquidity.

5.2.3 Summary

Although the literature on systematic risk in the hedge fund industry is vast, there are few studies focus on the analysis of investor-induced liquidity and hedge fund performance. Prior studies have documented that liquidity concerns are considered as leading indicators of the systematic risk that could predict hedge fund returns. Ding, Shawky, and Tian (2009) report that hedge fund experienced high investor-induced liquidity in the last month perform higher than hedge funds with low investor-induced liquidity 1 month forward from 1994 to 2005. However, Friesen and Sapp (2007) demonstrate that returns-chasing behavior is detrimental to active fund trader's performance. Investor induced liquidity could negatively influence hedge fund performance in long term. In addition, practically, hedge fund often set redemption gate that is more than 1 month. It is hard to investors to withdraw capital within a month. This chapter would estimate the relationship between investor-induced liquidity and hedge fund performance in longer term running.

5.3 Data

5.3.1 Data description

This chapter employs TASS database and estimate liquidity based on hedge fund monthly return and total net asset. As mentioned in section 1.2.4 that hedge fund has no regular obligation to publish their information to the official governing body. Moreover, they are forbidden from raising funds publicly. However, hedge funds are self-selected to disclose information to private data vendors in order to provide information to their existing and indirect investors. Kat and Brooks (2002) point out that the data from these providers are not independently verified and not audited although some of them tend to perform regular report. As discussed in Chapter 2 previous studies prove that TASS database could fit for this thesis because more of dead funds are collected according to previous studies. Therefore, using of TASS database could cause lower self-selection bias. Moreover, the use of monthly return improve the accuracy of variance measure of risk and TASS database could provide better information that could reduce backfill bias to a certain extent. In addition, the TASS database collects relatively more observations than other databases. The definition of the prediction model in this chapter is shown as follows (Table 5.1).

Table 5.1: Definitions in Prediction model

Estimation period	The period for estimation of historical liquidity for observations.
Evaluation period	The holding period for estimation of Buy-and-Hold abnormal return test
Mean of return	The sample mean of monthly return over the estimation period
Mean of TNA	Mean of the sample's total net asset (TNA) over the estimation period in U.S. dollars. TNA denominated in other currencies are converted by exchange rate on July 31st, 2014

This chapter estimates hedge fund liquidity using the monthly reported return and total net asset in the TASS database. Similar to Chapter 4, I collect data from January 1994 to July 2014 in this chapter. Using of data before 1994 could cause survivorship bias because TASS started collecting data in 1994 that the hedge funds died before 1994 are not included in the database. Importantly, the sampling time period covered Asian crisis in 1997, Russian crises in 1998, the collapse of the sub-prime mortgage crisis in the United States in 2007 and the following credit crunch.The original database contains 14031 of hedge funds in this period, of which 6505 are live funds and 7526 are liquidated funds.

As discussed in Chapter 2 that many biases exist in hedge fund database because of the weak regulation in the hedge fund industry. Hedge funds often operate a period before attracting outside investors. Funds with successful history will report their performance to the database and funds with bad performance will not report to the database. Furthermore, reported data of hedge funds often include performance before the time it listed on the database. The backfilled performance can be much better than hedge fund actual returns. In order to reduce this incubation bias, I delete first 12 months' return for each hedge fund. Previous studies prove that incubation bias significantly influences the estimation of hedge fund performance (Baba and Goko, 2006; Malkiel and Saha, 2005).

Table 5.2 presents the main time series data considered in this Chapter and these independent variables show the difference between the active funds and liquidated funds. Duration is the average life length of hedge funds in each group. The average duration of the live fund is about half a year longer than dead funds. Total Net Assets (TNA) of the fund represent the total funds under management for a net of fees and expenses on average in each group. Baba and Goko (2006) reported that average asset under management of the active fund (102.34 million US$) are over two times larger than that of the liquidated fund (45.61 million US$). However, TNA provided by the TASS database shows that the total net asset between active funds and liquidated funds are not significantly different. The time series data for four return moments shows that active funds experience a higher mean of return than liquidated funds. According to the risk aversion theory, investments with high first and third moments and low second and fourth moments are more preferred. Active funds experienced a higher mean of return and lower kurtosis than liquidated funds. However, their variance is higher and skewness is lower than liquidated funds. The descriptive statistics do not show clear support of this theory.

Table 5.2: Time series data

Table 5.2 provides key statistics for the size and return based times series data in each database. Duration measured in a month refers to the difference between the date of inception and the date of the last report, TNA indicates the mean of a total net asset for each fund.

	Active	Liquidated	All
Duration	36.8	30.7	33.5
TNA	24.2	23.7	23.92
Mean of return	2.45%	15%	1.70%
Standard deviation	0.098	0.096	0.098
Skewness	-4.44%	-1.50%	-1.58%
Kurtosis	5.93%	7.02%	6.35%

5.3.2 Sampling process

Before proceeding to an empirical analysis, it is necessary to identify an appropriate sample of funds in order to estimate the liquidity of hedge fund supposed by this chapter. Hedge fund manager reports their data voluntarily that some of their available information from the database is insufficient. This chapter estimates hedge fund liquidity based on total net asset and monthly returns. For time series data, there are normally three solutions to address the missing data.

1. Delete the funds from the database.

2. Reserve the funds in the samples and infer the vacancy data points.

3. Delete the covariate from the testing model.

There is a big proportion of hedge funds do not report their monthly return or total net asset. Furthermore, the TASS database starts to collect data on defunct funds from 1994. So analysis based on the TASS database includes data before 1994 could cause significant survivorship bias and the data before 1994 is not fit for precise estimation of hedge fund liquidity and return. Moreover, the use of monthly return improves the accuracy of variance measure of risk. As the result, I delete all observations before 1994 and funds do not report their monthly performance (Option 1). Similarly, funds with missing data on the total net asset are excluded from the samples (Option 1). Option 2 is selected when funds with insufficient data to estimate precise result. After filtering process, the total number of hedge funds in my sample is 6294, in which 2846 are active funds and 3448 are liquidated funds.

Table 5.3: Sampling process

Table 5.3 shows the variation on a number of observations step by step after sampling process.

	Total	Active	Liquidated
Total number of hedge funds	14031	6505	7526
Monthly return reported	6510	2713	3797
TNA reported	6294	2846	3448

5.4 Research method

This chapter aims to build a forecasting system that is capable of constructing practically investable portfolios of hedge funds based on their historical investor-induced liquidity. To investigate the effect of investor-induced liquidity, I employ 6 months' hedge fund performance between estimation and evaluation periods. The measure of investor-induced liquidity follows Ding, Shawky and Tian (2009) and construct portfolios of a hedge fund based on an aggregate of historical fund liquidity. The following section will illustrate the model of investor-induced liquidity and scale and origin of time to proceed.

5.4.1 Model of investor-induced liquidity

This chapter focus on the aspect of investor directly induced liquidity. Existing literature indicates that redemption shocks from investors could lead to a price change in the short term for the holding asset of hedge funds who embrace excessive market liquidity risk (Gromb and Vayanos, 2002; Campbell, Grossman, and Wang, 1993 and Morris and Shin, 2004). Furthermore, the effect of fire sales becomes more significant when market liquidity and fund liquidity are both tight (Teo, 2011). Subsequently, the tight market liquidity could amplify the decreasing of hedge fund return. This Chapter is going to construct a model to forecast a longer period hedge fund performance based on investor-induced liquidity. To investigate the effects of liquidity under the same market condition, I follow the measure that Ding, Shawky and Tian (2009) estimate investor-induced liquidity. This approach can capture liquidity pressures that hedge fund managers face with investors under same market liquidity condition. Furthermore, this approach estimated investor-induced liquidity present significant relationship with the subsequent reaction of hedge fund managers (Ding, Shawky and Tian, 2009). It indicates that this aspect of liquidity is most likely to influence hedge fund performance.

The main hypothesis in this chapter is hedge fund managers embrace a lower investor-induced liquidity will carry out better performance. In contrast, managers experiencing higher investor-induced liquidity will have lower performance. It is consistent with Sadka (2010) and Teo (2011) that hedge fund embraces high liquidity risk could perform better. Furthermore, high net investment flow could scale in active portfolio management, it could the subsequently cause adversely impact on hedge fund future performance. For example, hedge funds with high net investment flows could cause dilution when its direction correlates to the following return and further reduce the hedge fund performance.

To estimate the effect of investor-induced liquidity on hedge fund returns, I first evaluate net investment flows of an individual hedge fund in each month as:

(5.1) $$\mathrm{NIF_t} = \mathrm{TNA_t} - \mathrm{TNA_{t-1}} * (1 + \mathrm{r_t})$$

Where NIF_t is the net investment flows into the fund in period p. It equals to the total net asset in period t (TNA_t) minus the sum of TNA_{t-1} plus the returns achieved during that period. Therefore, the calculated net investment inflows combine both asset market and shareholder liquidity pressure. The nature of managers held specific assets represent the market liquidity. The net investment flows of an individual fund represent the investor-induced liquidity. It is supposed that hedge fund manager should consider if they keep the investment flow in cash or invest it when they experience positive NIF. It could cause dilution when its direction correlates to the following return and further reduce the hedge fund performance. On the contrary, the hedge fund will short the low priority investment and fix investment portfolios when the hedge fund experiences negative NIF. It could subsequently cause a positive impact on fund performance.

Then I estimate the investor-induced liquidity as follows:

(5.2) $$IL_t = \frac{NIF_t}{TNA_{t-1}} = \frac{TNA_t}{TNA_{t-1}} - (1 + r_t)$$

Where IL_t is the investor-induced liquidity in month t. It is consistent with the approach that Fung, Hsieh, Naik and Ramadorai, (2008) and Ding, Getmansky, Liang and Wermers (2007) employed. I measure investor-induced liquidity in order to evaluate fund flows by investors. Furthermore, I use the past 6 months of aggregate investor-induced liquidity as an estimation period to test the aggregate investor-induced liquidity.

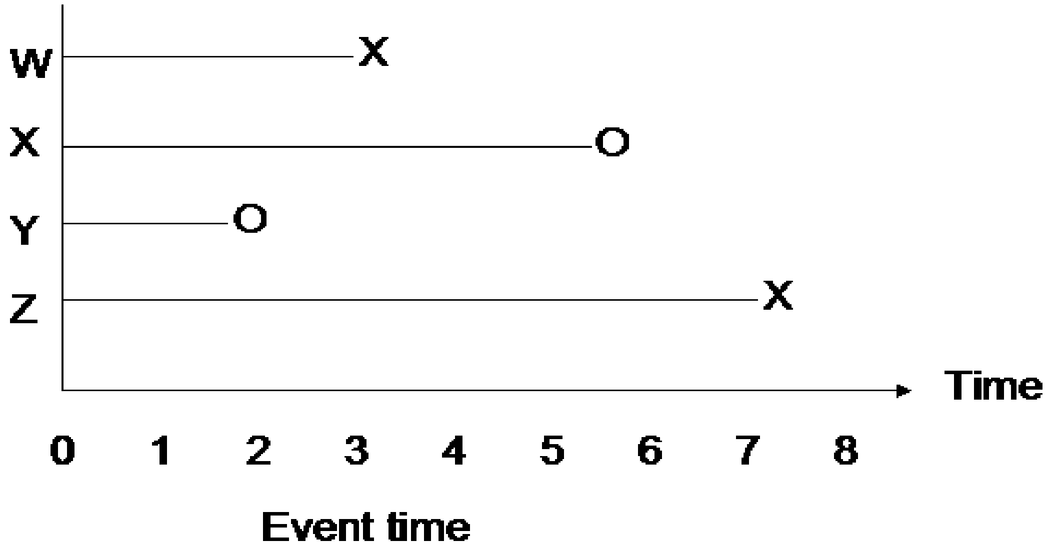
(5.3) $$\sum_{i=0}^{t-1} IL_{t-i} = \sum_{i=0}^{t-1} \frac{NIF_{t-i}}{TNA_{t-1-i}} = \sum_{i=0}^{t-1} [\frac{TNA_{t-i}}{TNA_{t-1-i}} - (1 + r_{t-i})]$$

5.4.2 Timescale

The time scale measures the units of time that are taken into the estimation. The time series data of return and total net asset in this thesis are monthly reported. Therefore, it is necessary to match the definition of time scale with the resolution of data. The original of time is the first time to run the model where t=0. Typically, there are two ways to define the origin time. The first way measure the origin time as the life length that time 0 is defined as the fund established month and it is called “event time” method (Chart5.1).

Chart 5.1: Event time method

The Chart 5.1 presents samples of W, X, Y, Z are measured in event time method. Each of the samples enters the study at time 0. The duration of the time indicates the life length of the sample. “X” symbolizes the sample is a failure and “O” symbolizes the sample stop reporting for other reasons.

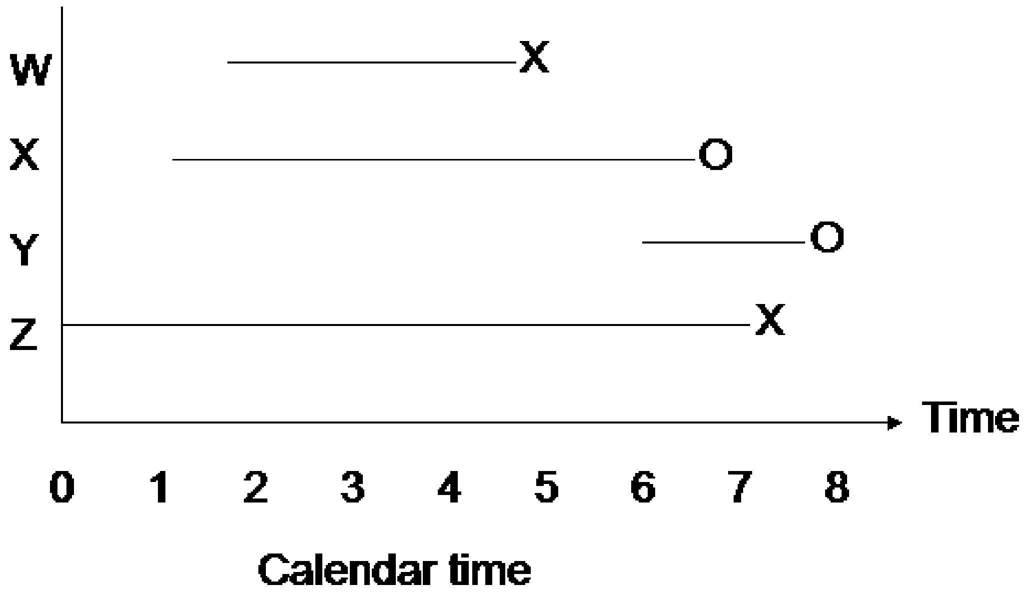


The second way defines the origin time as calendar month that the first sample is observed in the dataset. For example, the origin time would be set in January 1994 if the dataset starts in this month (t=0). As a result, t=1 in March 1994, t=2 in March 1994 and so on. It is also called “calendar month” model. As is shown in Chart 5.2

When samples are arranged in a second way, both of calendar effect and duration effect are included into the liquidity forecast model. This chapter aims to forecast future performance based on same market liquidity condition. The calendar time model allows forecast in the same calendar time that investor-induced liquidity of hedge fund under the same market condition. As the result, the calendar time model is more appropriate for the aims of this chapter.

Chart 5.2: Calendar time

The Chart 5.2 presents samples of W, X, Y, Z are measured in Calendar time method. Samples enter the study at a different time. The duration of the time indicates the life length of the sample. “X” symbolizes the sample is a failure and “O” symbolizes the sample stop reporting for other reasons.



5.4.3 Empirical value of investor-induced liquidity

This study employs the abnormal return appetites of hedge funds that grant a favorable interest to their investors. To gauge the practical significance of this liquidity risk measure, I investigate the investment value based on selecting hedge funds with different liquidity groups. Every month starting from July 1994, I estimate the hedge fund net investment flow for each fund using the past 6-month estimation period data and then form ten decile portfolios based on their aggregate net investment flow. These portfolios are held subsequently for six month holding period. This process is repeated every month until December of 2013. All of the funds’ returns are included in the evaluation of portfolio return if the fund stops reporting over the holding period. This yields a time series of returns for the ten portfolios of varying levels of liquidity risk from 1999 to 2013. Furthermore, I follow the Buy-and-Hold abnormal return approach used in Barber and Lyon (1997) to test if the return is statistically significant to the market return. Buy-and-Hold abnormal return could be more practical to assess abnormal return for the sake of this study. The BHAR method observes the difference between holding period return of sample funds and holding period return of the market return of all hedge funds.

The Buy-and-Hold abnormal return supposed to estimate investors experience directly. On contrary, CAR method is a biased parameter of investors' experience. Blume and Stambaugh (1983) point out that transaction cost behind CAR method could be significant for firms with low capitalization. Furthermore, the redemption policy in the hedge fund industry makes it impossible to invest in every hedge fund with the form of CAR method. As the result, the Buy-and-Hold abnormal return could be more practical to assess abnormal return for hedge fund investors. This study also uses a CAR method to do robustness test.

5.4.4 Limitation of research procedure

This research procedure focuses on the aspect of investor-induced liquidity, the major issue stems from raw of information that is available in TASS database. The existing study shows that estimation on hedge fund managers could be more accurate in the testing of fund liquidity. However, the TASS database does not provide information on hedge fund managers. Some hedge fund managers could launch new funds after a good performance of old funds. The new funds could be considered as the same fund that could present more accurate estimation of fund flows and investor-induced liquidity. Another concern is the high net investment flow could scale in active portfolio management, it could subsequently cause adversely impact on hedge fund future performance. Consequently, the timing strategy produced by this chapter could reduce investors' return that the hedge fund manager should consider if they keep the investment inflow in cash or invest it. Teo (2011) employs investor-induced liquidity to measure the aggregate fund flows. In terms of the redemption gate that hedge fund managers grant to investors, withdraw from capital often forewarned to hedge fund managers. The influence of fund flow could exist before the actual fund flow.

5.4.5 Summary of research process

The prediction model of this chapter involves Section5.3 (Data analysis) and Section 5.4 (Research method). This section provides a concise summary of the steps in order to clarify the prediction model. As is shown in Chart 5.3, the first 5 procedures are set for filtering process of the sample. After that, procedures 6 to 8 provide integral ordered aggregate liquidity for estimation. Subsequently, procedures 9 to 10 externalize the construction of the prediction model. Then procedure 11 shows the method I used to test the abnormal return of this prediction model. Finally, procedure 12 does the robustness test (Section 5.8).

Chart 5.3: Summary of research process

1. Collect estimation samples.
2. Delete first 12 months return of each fund.
3. Delete the covariates with insufficient observations.
4. Remove funds with insufficient data.
5. Convert currency into US dollar.
6. Format the calendar time risk set
7. Calculate investor induced liquidity from January 1999.
8. Calculate past 6 months' aggregate investor induced liquidity every month.
9. Form 10 decile portfolios based on estimated aggregate liquidity.
10. Hold each portfolio for six months.
11. Estimate Buy-and-Hold abnormal return of holding portfolio.
12. Robustness test on procedure2, 8, 10 and 11.

5.5 Empirical findings

To test the effect of investor-induced liquidity on fund performance, this chapter employs the portfolio based approach and use Buy and hold abnormal return method to test if investor-induced liquidity influence fund's post-performance. Using of 6-months rolling window, I sort hedge funds into ten portfolios based on their past aggregate investor-induced liquidity from January 1999. Then I calculate the abnormal return for each portfolio six months forward. Table 5.4 present the output summary on the empirical value of the prediction model. The Buy and hold abnormal return reveals corresponding differences between return in the hedge fund market and return on portfolios. The portfolios are sorted by historical investor-induced liquidity. The P-values are derived from standard errors. Specifically, Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. It indicates that the holding of the portfolio with the lowest liquidity delivers economically significant return higher than average return in the hedge fund market in the post-ranking periods and it is at 0.1% significance level. More importantly, this model is different with the Cox proportional hazard model on the output of hedge fund performance in Portfolio 10. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative Buy and hold abnormal return. It indicates that investors can avoid a low return in the hedge fund market by not choosing hedge funds with high investor-induced liquidity and it is at 2% significance level. Take commonly used risk factors into consideration, this chapter calculate sharp ratio for each portfolios. The most of portfolio's sharpe ratios are between 3.2 to 3.7 and bot portfolio shows lowest sharp ratio (2.4). This results indicates that risk adjust returns of top portfolio is higher than other portfolios. The results support Berk and Green (2004) Chevalier and Ellison, (1997); Sirri and Tufano (1998) that the high net inflow will ultimately adversely influence the performance of a fund and hedge fund after high net outflow experienced higher performance in the hedge fund market.

The Chart 5.4 presents more details on the empirical value of the prediction model. The aggregate half year return reveals actual return on each portfolio sorted by historical investor-induced liquidity. Normally, hedge funds in lower liquidity portfolios present higher performance. Interestingly, the result between 173th and 177th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between November 2008 and March 2009. The evaluation period of these times are the first 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. It is consistent with the fire sale story (Teo, 2011). However, Portfolio 1 performs well during other periods. In total, the prediction model maintained its empirical value and the result suggests that the opposite position should be takeN in the financial crisis period. The next section explores alternative model specifications in an effort to estimate the robustness of the model and to explore other avenues for implementing the prediction model.

Table 5.4: Prediction model

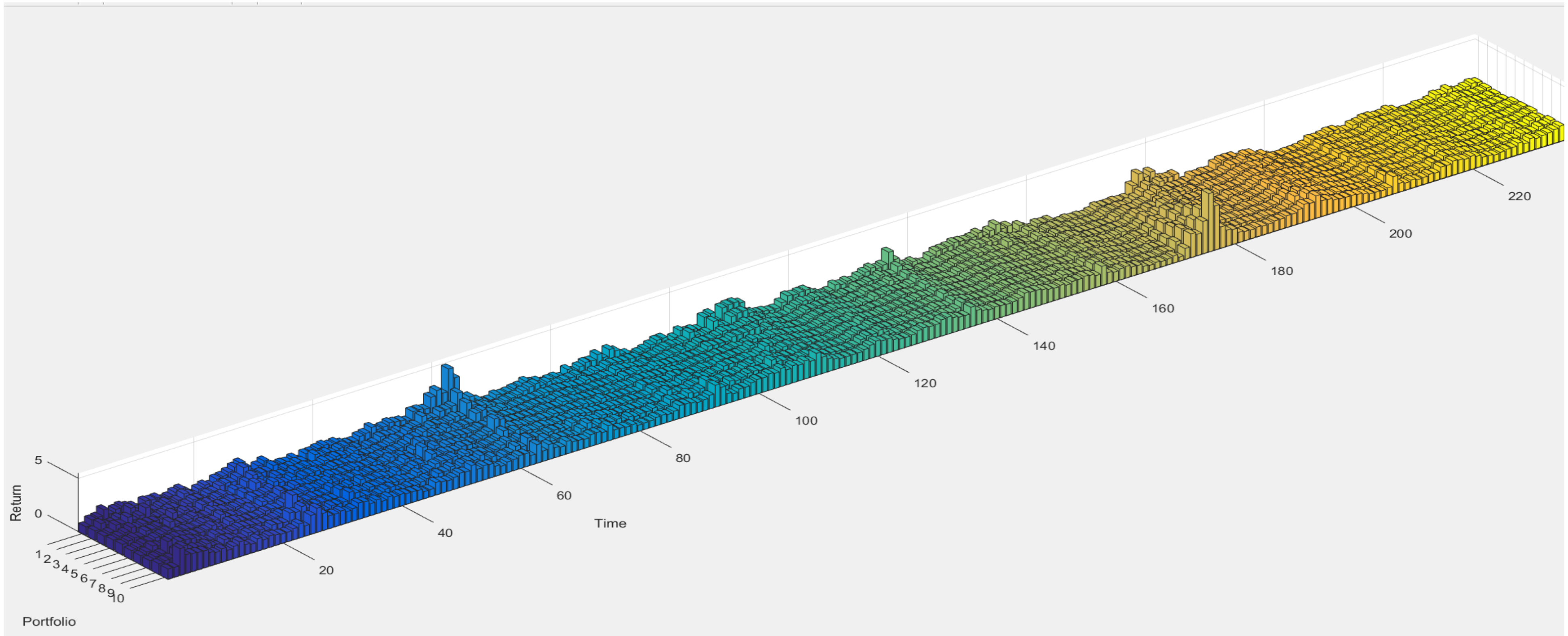
Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 6 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from July 1994 to July 2014.

	Portfolio	Return	BHAR	P-value	Sharpe ratio
	1	37%	13%	0.00****	3.7
Average return	2	28%	4%	0.00****	3.2
	3	25%	2%	0.09**	3.4
24%	4	24%	1%	0.48	3.1
	5	22%	-2%	0.01***	3.6
	6	21%	-2%	0.00****	3.2
	7	20%	-4%	0.00****	3.6
	8	20%	-4%	0.00****	3.4
	9	21%	-3%	0.04***	3.0
	10	19%	-5%	0.02***	2.4

Chart 5.4: Performance of each portfolio

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 6 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate six months' return for each portfolio. The evaluation period is from July 1994 to July 2014.



5.6 Robustness test of prediction model

This section employs robustness test on four aspects of testing of stability and flexibility of this model. First, an alternative measure of aggregate investor-induced liquidity is introduced to the prediction model. Second, the alternative length of portfolios holding period is introduced into the prediction model. Third, this chapter does robustness check on the impact of backfill bias data on a prediction model. Last, an alternative measure of abnormal return method is introduced to the prediction model. Section 5.8.1 is a combination of first two robustness test. Section 5.8.2 and Section 5.8.3 are the third and the fourth robustness test respectively.

5.6.1 Robustness test on liquidity measure

Practically, more than 95% of hedge fund set redemption frequency shorter than six months according to TASS database. However, the information of notice period and lock up period is not available from TASS database. As the result, it is important to take a different length of evaluation period into consideration. I first do robustness test of evaluation period on 3, 9 and 12 months respectively. Table 5.5 illustrate the empirical value of the prediction model when evaluation period is 3 months. It shows that the prediction model is robust to this test. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. The Buy and bold abnormal return for 3-month holding period are 5%. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative Buy and hold abnormal return. The value of negative Buy and bold abnormal return is -3% and the absolute value of monthly abnormal return of portfolio 10 from this model is higher than the original prediction model (-5% for six months).

The Chart 5.5 presents more details on the empirical value of the prediction model when evaluation period is 3 months. Normally, hedge funds in lower liquidity portfolios present higher performance. The result between 175th and 177th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between December 2008 and March 2009. It shows that the collapse of

Lehman Brothers on September influenced hedge fund performance three months later. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, it is robust to prediction model with a 3-month evaluation period.

Table 5.5: Prediction model (3-month BHAR)

Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 6 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 3 months' forward return. The evaluation period is from July 1994 to July 2014.

	Portfolio	Return	BHAR	P-value
	1	16%	5%	0.00****
Average return	2	13%	2%	0.05***
	3	11%	0	0.47
11%	4	11%	0	0.61
	5	11%	0	0.30
	6	10%	-1%	0.14*
	7	9%	-2%	0.00****
	8	9%	-2%	0.00****
	9	9%	-2%	0.01****
	10	8%	-3%	0.01****

Chart 5.5: Performance of each portfolio (3-month BHAR)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 6 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate 3 months' return for each portfolio. The evaluation period is from July 1994 to July 2014.

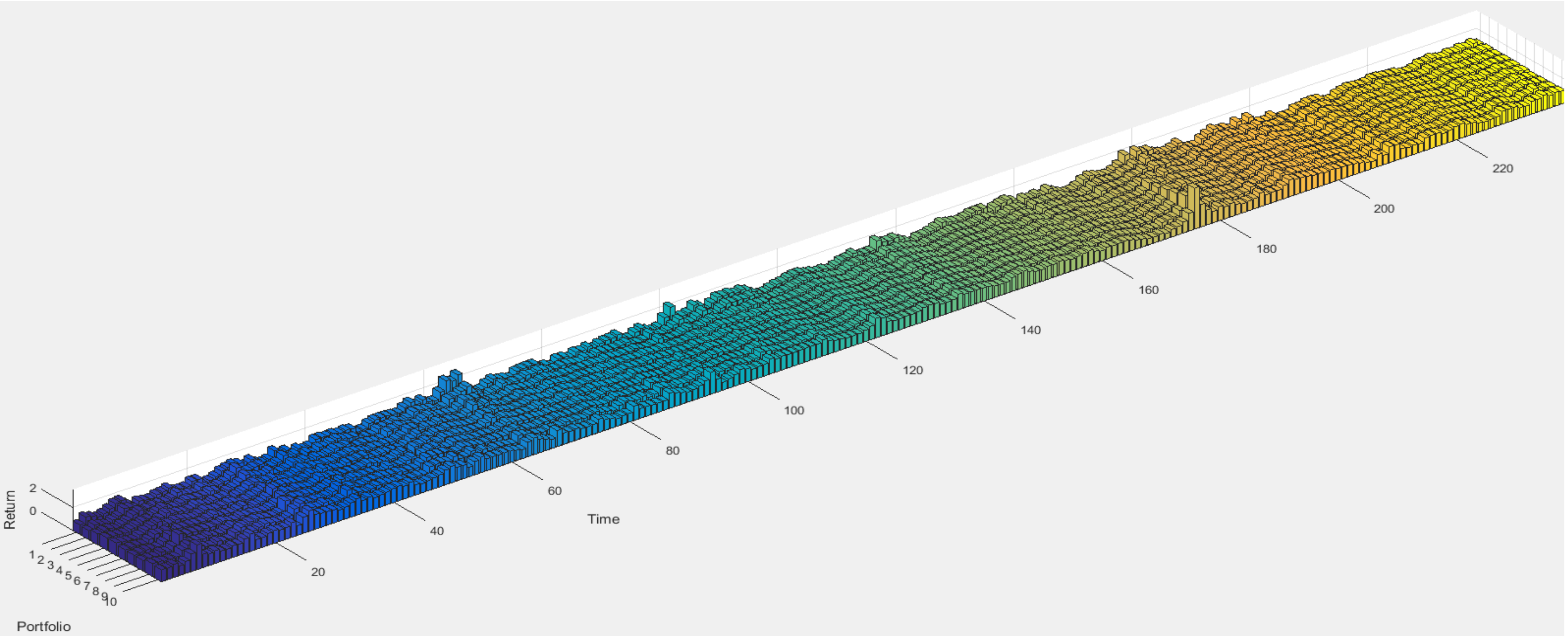


Table 5.6 illustrate the empirical value of the prediction model when evaluation period is 9 months. The prediction model is robust to this test. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. The Buy and bold abnormal return for 9-month holding period are 18%. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative Buy and hold abnormal return. The value of negative Buy and bold abnormal return is -11%.

The Chart 5.6 presents more details on the empirical value of the prediction model when evaluation period is 9 months. Normally, hedge funds in lower liquidity portfolios present higher performance. The result between 172th and 177th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between September 2008 and March 2009. It shows that the collapse of Lehman Brothers on September influenced hedge fund performance three months later. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, it is robust to prediction model with a 9-month evaluation period.

Table 5.6: Prediction model (9-month-BHAR)

Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 6 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 9 months' forward return. The evaluation period is from July 1994 to July 2014.

	Portfolio	Return	BHAR	P-value
	1	65%	18%	0.00****
Average return	2	47%	0	0.84
	3	41%	-6%	0.00****
47%	4	39%	-8%	0.00****
	5	34%	-13%	0.00****
	6	34%	-12%	0.00****
	7	33%	-14%	0.00****
	8	33%	-14%	0.00****
	9	33%	-14%	0.00****
	10	36%	-11%	0.00****

Chart 5.6: Performance of each portfolio (9-month BHAR)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 6 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate nine months' aggregate return for each portfolio. The evaluation period is from July 1994 to July 2014.

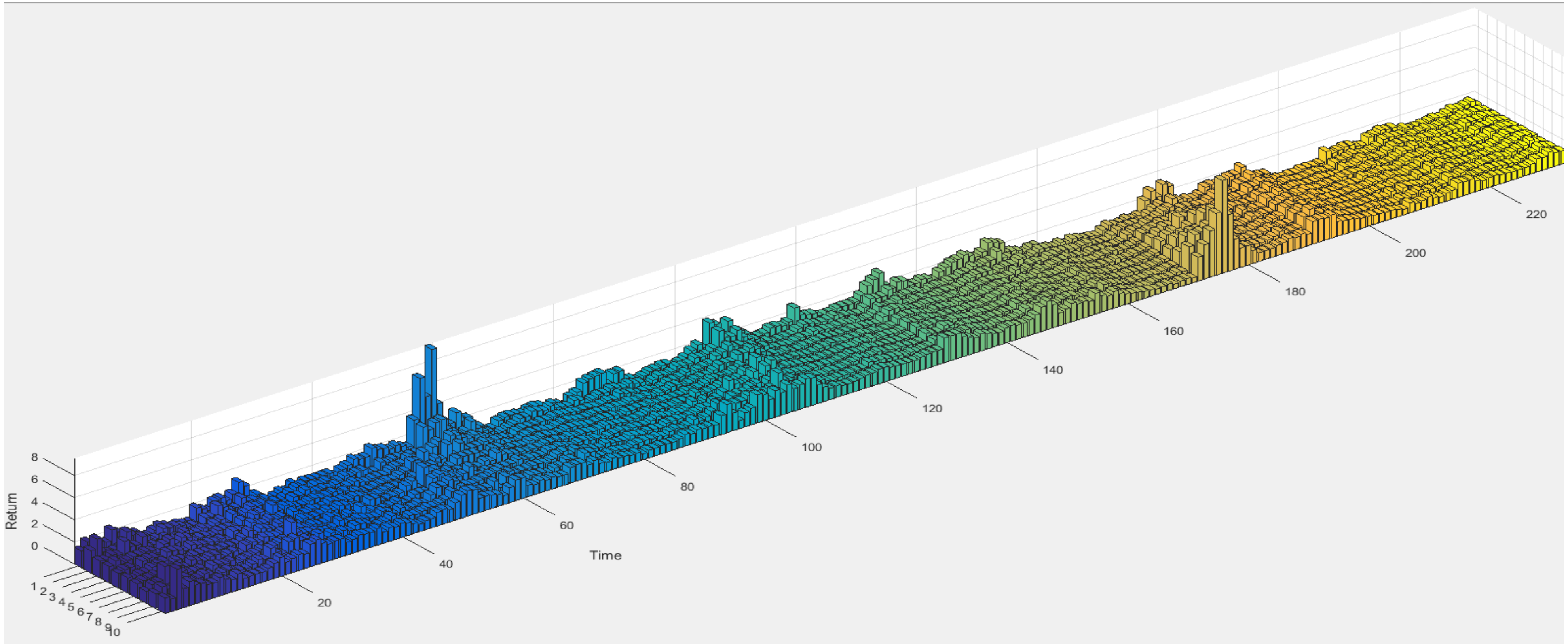


Table 5.7 illustrate the empirical value of the prediction model when evaluation period is 12 months. The prediction model is robust to this test on the part of low investor-induced liquidity. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. The Buy and bold abnormal return for 12-month holding period are 32%. However, Buy and hold abnormal return for a hedge fund in Portfolio 10 with high investor-induced liquidity is not different significantly. It indicates that the investor-induced liquidity in the less distance past has more explanatory power on fund performance.

The Chart 5.7 presents more details on the empirical value of the prediction model when evaluation period is 12 months. Normally, hedge funds in lower liquidity portfolios experience higher performance. Similar to original prediction model, the result between 172th and 177th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between September 2008 and March 2009. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, it is robust to prediction model with a 12-month evaluation period.

Table 5.7: Prediction model (12-month BHAR)

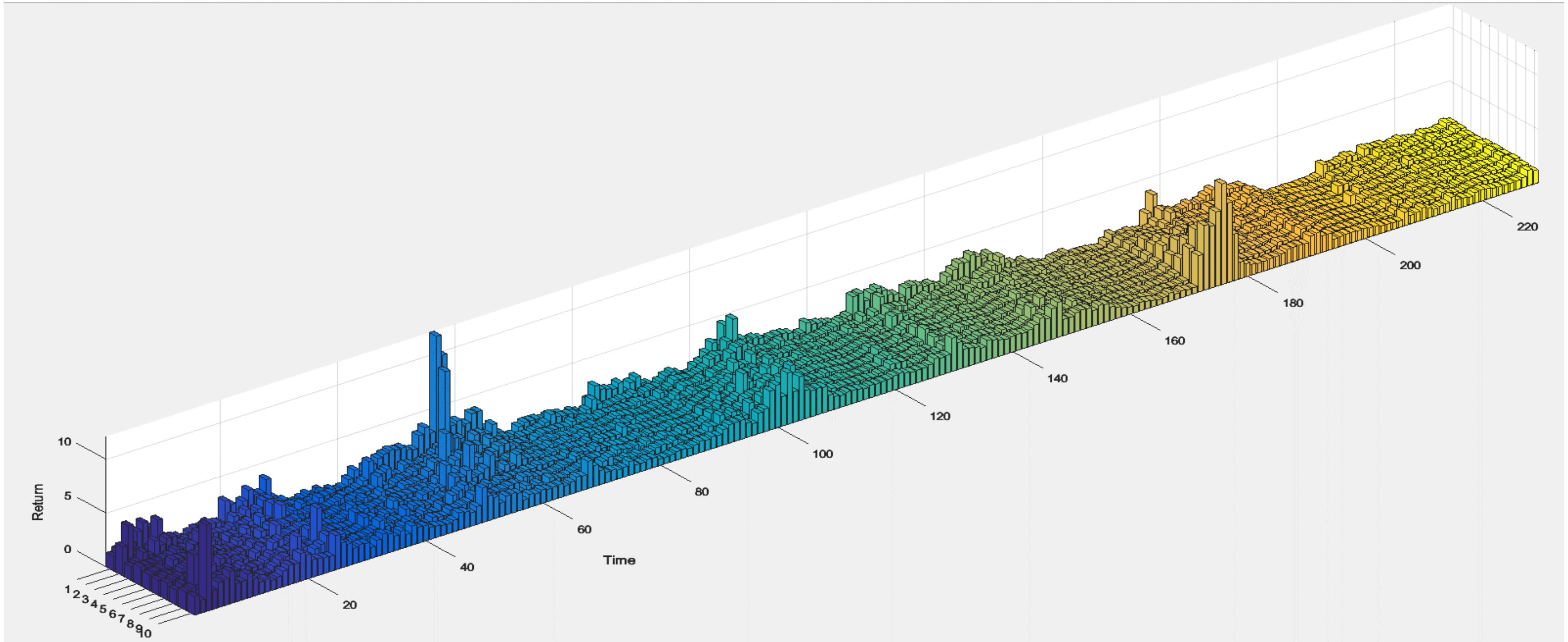
Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 6 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 12 months' forward return. The evaluation period is from September 1994 to July 2014.

	Portfolio	Return	BHAR	P-value
	1	90%	32%	0.00****
Average return	2	68%	10%	0.01****
	3	59%	1%	0.68
58%	4	56%	-1%	0.55
	5	48%	-10%	0.00****
	6	51%	-7%	0.00****
	7	50%	-8%	0.00****
	8	48%	-10%	0.00****
	9	49%	-8%	0.01****
	10	59%	1%	0.89

Chart 5.7: Performance of each portfolio (12-month BHAR)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 6 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate 12 months' aggregate return for each portfolio. The evaluation period is from July 1994 to July 2014.



According to previous 3 robustness tests, the investor-induced liquidity in the less distance past present more explanatory power on fund performance. It is important to do robustness test on a different length of the estimation period. This chapter does robustness of estimation period on 3, 9 and 12 months respectively. Table 5.8 illustrate the empirical value of the prediction model when estimation period is 3 months. It shows that the prediction model is robust to this test. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative Buy and hold abnormal return. The significance level decreases slightly from 2% to 8%.

The Chart 5.8 present more details on the empirical value of the prediction model when estimation period is 3 months. Normally, hedge funds in lower liquidity portfolios experience higher performance. Similar to original prediction model, the result between 176th and 180th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between November 2008 and March 2009. The evaluation period of this period is the first 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, it is robust to prediction model with 3-month estimation period

Table 5.8: Prediction model (3-month estimation period)

Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 3 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from April 1994 to July 2014.

	Portfolio	Return	BHAR	P-value
	1	34%	10%	0.00****
Average return	2	29%	5%	0.00****
	3	25%	1%	0.31
24%	4	23%	-1%	0.22
	5	22%	- 2%	0.01****
	6	21%	-3%	0.00****
	7	21%	-2%	0.01****
	8	21%	-3%	0.00****
	9	22%	-2%	0.16
	10	21%	-3%	0.08**

.

Chart 5.8: Performance of each portfolio (3 month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 3 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate six months' return for each portfolio. The evaluation period is from April 1994 to July 2014.

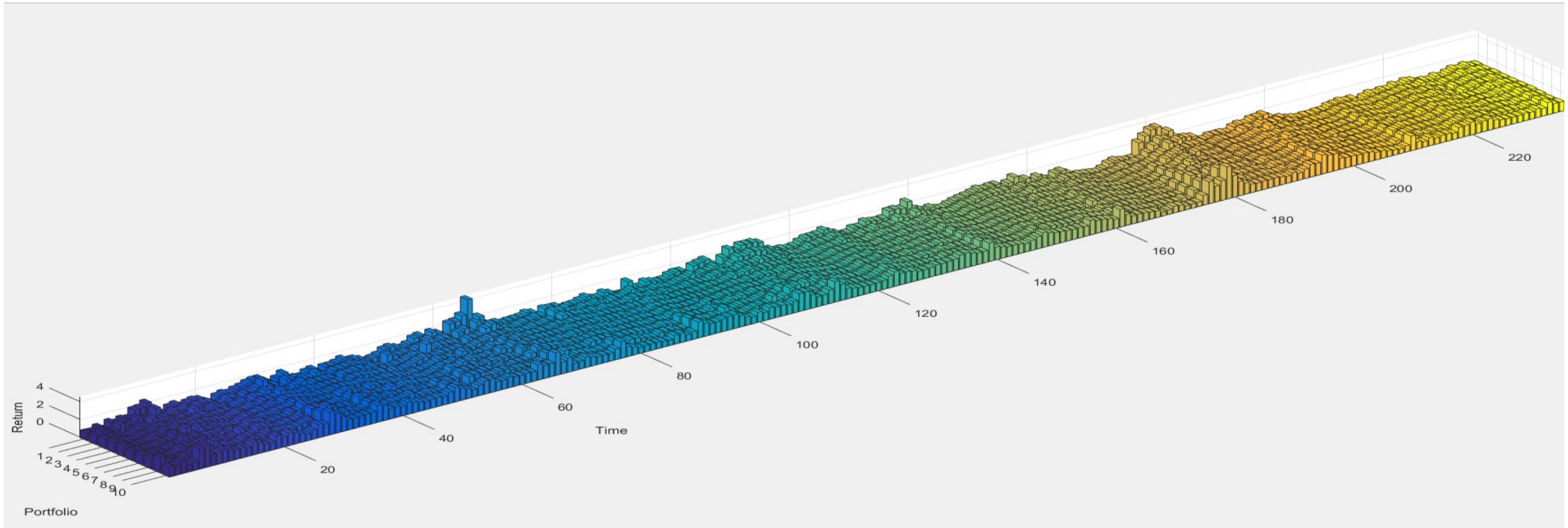


Table 5.9 illustrate the empirical value of the prediction model when estimation period is 9 months. It shows that the prediction model is robust to this test. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative Buy and hold abnormal return. The significance level decreases slightly from 2% to 5%.

The Chart 5.9 presents more details on the empirical value of the prediction model when estimation period is 9 months. Normally, hedge funds in lower liquidity portfolios experience higher performance. Similar to original prediction model, the result between 170th and 174th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between November 2008 and March 2009. The evaluation period of this period is the first 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, it is robust to prediction model with 9-month estimation period

Table 5.9: Prediction model (9-month estimation period)

Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from September 1994 to July 2014.

	Portfolio	Return	BHAR	P-value
	1	39%	15%	0.00****
Average return	2	27%	3%	0.03***
	3	24%	1%	0.34
23%	4	24%	0%	0.89
	5	22%	-1%	0.24
	6	21%	-2%	0.02***
	7	19%	-4%	0.00****
	8	19%	-5%	0.00****
	9	20%	-3%	0.02***
	10	19%	-4%	0.05***

Chart 5.9: Performance of each portfolio (9-month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 9 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate six months' aggregate return for each portfolio. The evaluation period is from September 1994 to July 2014.

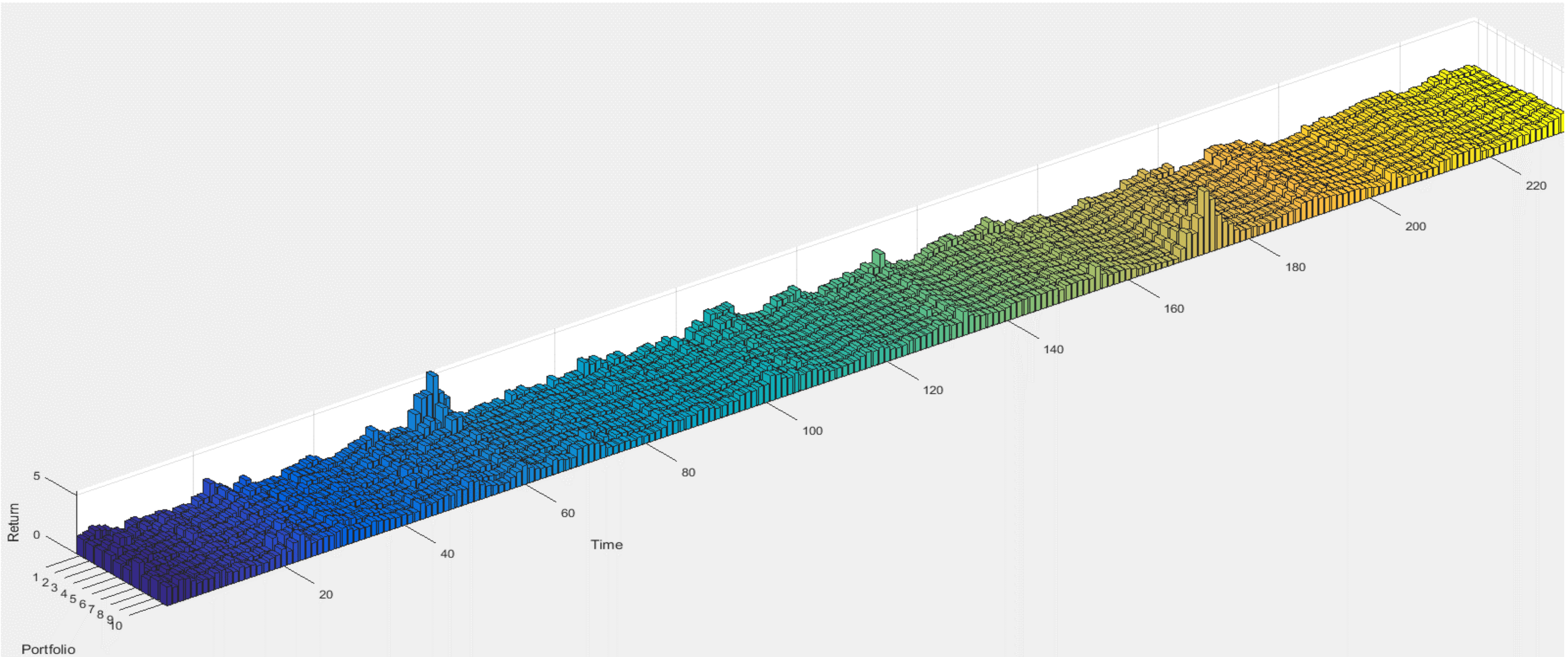


Table 5.10 illustrate the empirical value of the prediction model when estimation period is 12 months. It shows that the prediction model is robust to this test on the part of low investor-induced liquidity. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. The Buy and bold abnormal return for 6-month holding period are 13%. However, Buy and hold abnormal return for a hedge fund in Portfolio 10 with high investor-induced liquidity is not different significantly. It indicates that the investor-induced liquidity in the less distance past has more explanatory power on fund performance.

The Chart 5.10 presents more details on the empirical value of the prediction model when estimation period is 12 months. Normally, hedge funds in lower liquidity portfolios experience higher performance. Similar to original prediction model, the result between 167th and 171th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between November 2008 and March 2009. The evaluation period of this period is the first 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, it is robust to prediction model with 12-month estimation period.

Table 5.10: Prediction model (12-month estimation period)

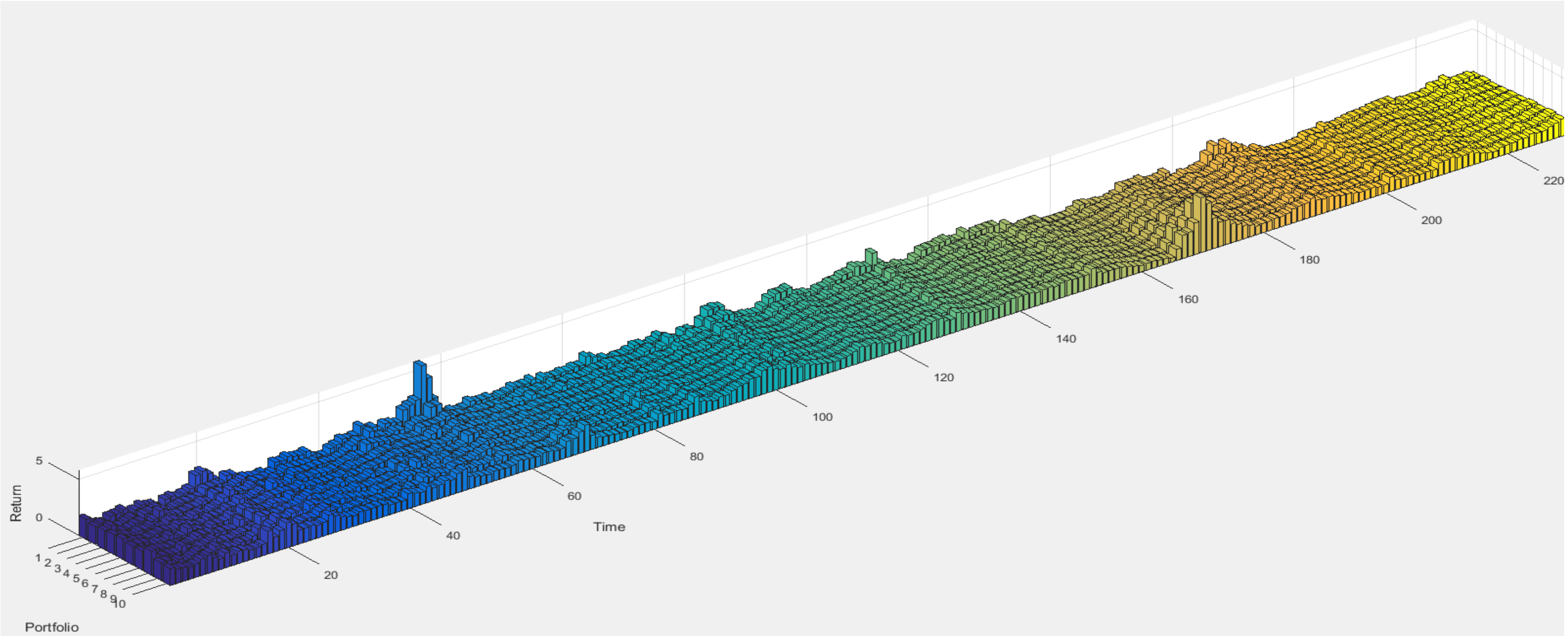
Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 12 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 12 months' forward return. The evaluation period is from December 1994 to July 2014.

	Portfolio	Return	BHAR	P-value
	1	36%	13%	0.00****
Average return	2	23%	1%	0.60
	3	23%	1%	0.47
23%	4	22%	0%	0.72
	5	21%	-1%	0.06**
	6	20%	-2%	0.00****
	7	20%	-3%	0.00****
	8	19%	-3%	0.01****
	9	20%	-2%	0.15*
	10	20%	-2%	0.27

Chart 5.10: Performance of each portfolio (12-month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 12 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate six months' aggregate return for each portfolio. The evaluation period is from December 1994 to July 2014.



5.6.2 Robustness test on backfill bias effect

In order to check the backfill bias effect on the prediction model, this study also tests the model include backfill biased data. Table 5.11, 5.12 and Table 5.13 illustrate the output summary of the prediction model with 3, 6, 9 and 12 month estimation period respectively. Chart 5.10, 5.12 and Chart 5.13 show correspond details on the empirical value of the prediction model. It is shown in Table 5.11 that the prediction model is robust to this test on the part of low investor-induced liquidity. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. The Buy and bold abnormal return for 6-month holding period are 12%. However, Buy and hold abnormal return for a hedge fund in Portfolio 10 with high investor-induced liquidity is not different significantly. This evidence also supports that some of the hedge funds with low performance do not report their performance after the incubation period.

The Chart 5.11 presents more details on the empirical value of the prediction model with backfill bias data when estimation period is 3 months. Normally, hedge funds in lower liquidity portfolios experience higher performance. Similar to original prediction model, the result between 176th and 180th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between November 2008 and March 2009. The evaluation period of this period is the first 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, it is robust to prediction model with 3-month estimation period for low investor-induced liquidity portfolios.

Table 5.11: Prediction model (3-month estimation period)

Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 3 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from March 1994 to July 2014.

	Portfolio	Return	BHAR	P-value
	1	38%	12%	0.00****
Average return	2	31%	4%	0.00****
	3	26%	5%	0.82
23%	4	25%	-1%	0.15*
	5	24%	-2%	0.00****
	6	23%	-3%	0.00****
	7	23%	-3%	0.00****
	8	23%	-3%	0.01****
	9	24%	-3%	0.05***
	10	25%	-1%	0.54

Chart 5.11: Performance of each portfolio (3-month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 3 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate six months' aggregate return for each portfolio. The evaluation period is from March 1994 to July 2014.

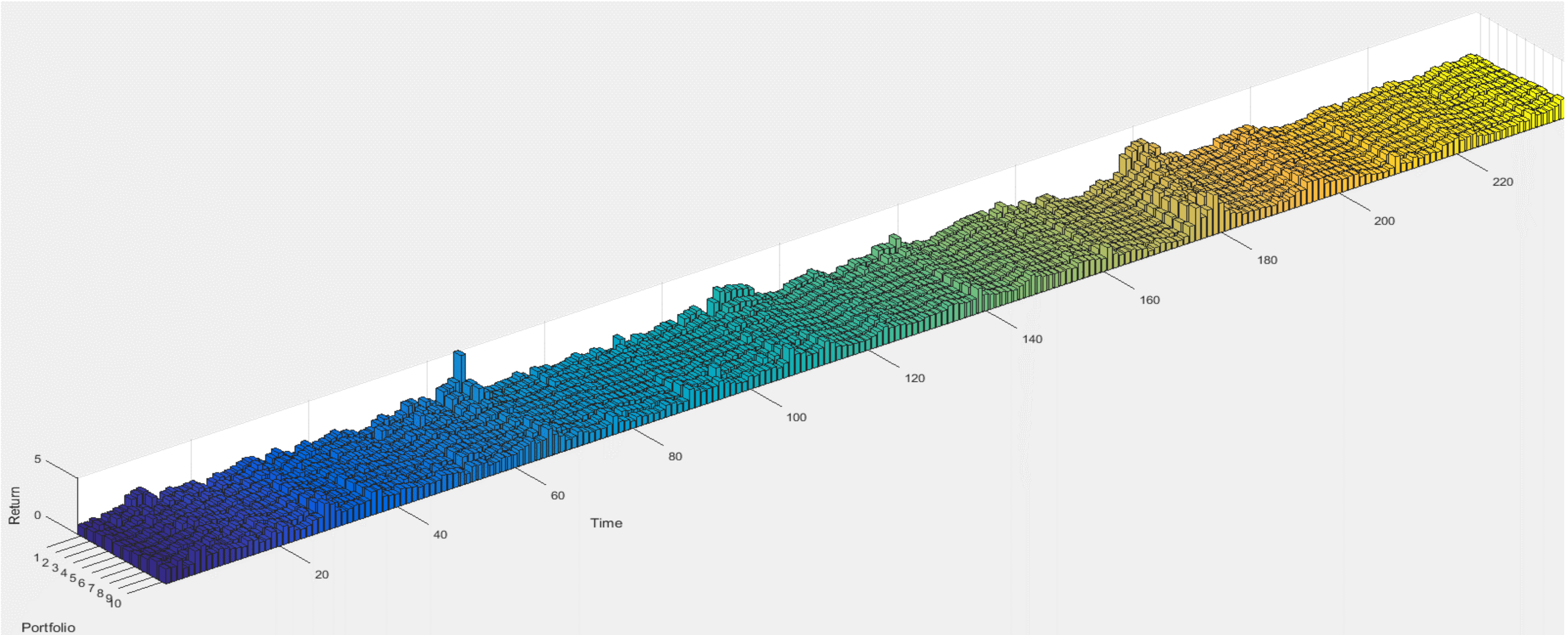


Table 5.12 illustrate the empirical value of the prediction model with backfill bias when evaluation period is 6 month. It shows that the prediction model is robust to this test. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. The Buy and bold abnormal return for 6-month holding period are 12%. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative Buy and hold abnormal return. The value of negative Buy and bold abnormal return is -3%

The Chart 5.12 presents more details on the empirical value of the prediction model with backfill bias data when estimation period is 6 months. Normally, hedge funds in lower liquidity portfolios experience higher performance. Similar to original prediction model, the result between 173th and 177th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between November 2008 and March 2009. The evaluation period of this period is the first 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, it is robust to prediction model with 6-month estimation period.

Table 5.12: Prediction model (6-month estimation period)

Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 6 months' data. Return is the aggregate 6 months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from July 1994 to July 2014.

	Portfolio	Return	BHAR	P-value
	1	38%	12%	0.00****
Average return	2	30%	5%	0.00****
	3	27%	2%	0.12*
23%	4	25%	-0%	0.81
	5	23%	-2%	0.00****
	6	22%	-3%	0.00****
	7	22%	-4%	0.00****
	8	22%	-4%	0.00****
	9	24%	-2%	0.14*
	10	22%	-3%	0.07**

Chart 5.12: Performance of each portfolio (6-month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 6 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate six months' aggregate return for each portfolio. The evaluation period is from July 1994 to July 2014.

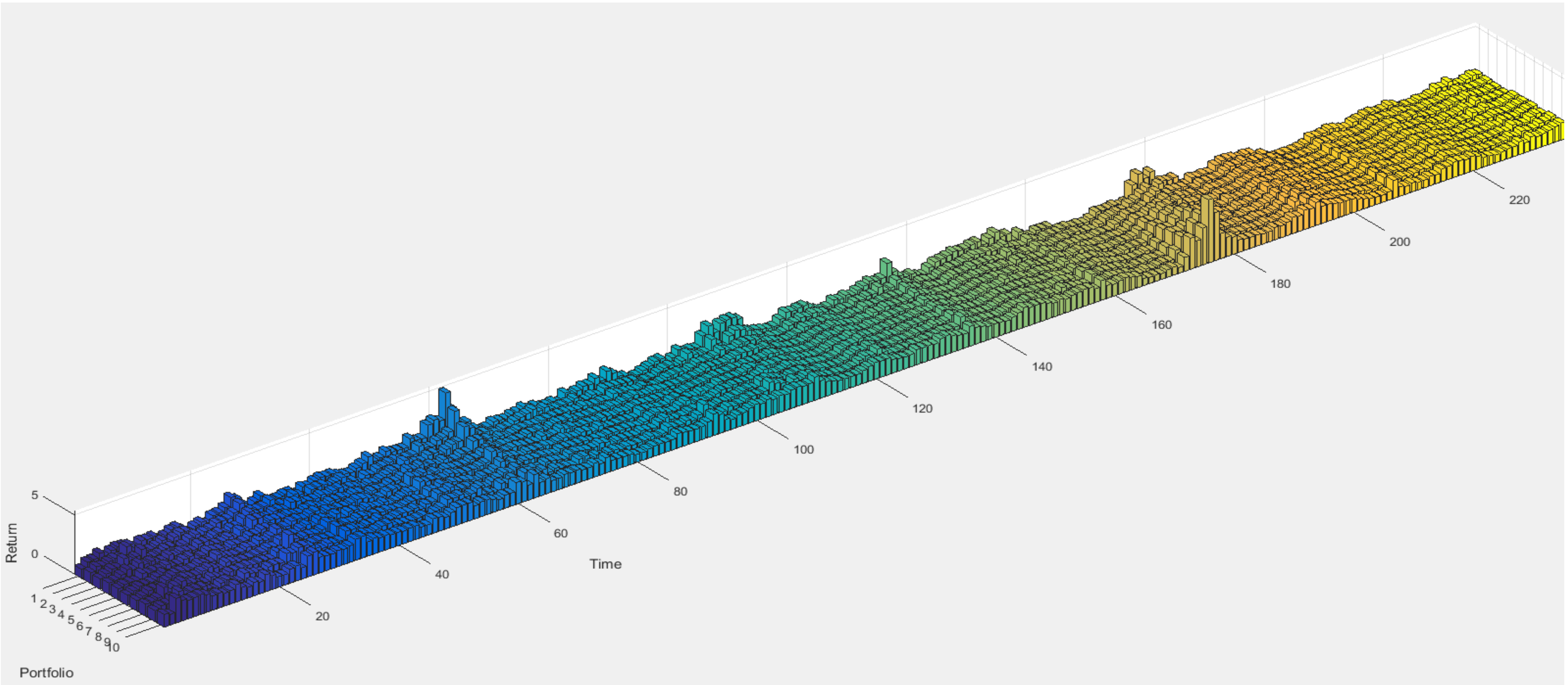


Table 5.13 illustrate the empirical value of the prediction model with backfill bias when estimation period is 9 months. It shows that the prediction model is robust to this test. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. The Buy and bold abnormal return for 6-month holding period are 14%. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative Buy and hold abnormal return. The value of negative Buy and bold abnormal return is -3%。

The Chart 5.13 presents more details on the empirical value of the prediction model with backfill bias data when estimation period is 9 months. Normally, hedge funds in lower liquidity portfolios experience higher performance. Similar to original prediction model, the result between 170th and 174th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between November 2008 and March 2009. The evaluation period of this period is the first 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, the result robust to prediction model with 9-month estimation period for low investor-induced liquidity portfolios.

Table 5.13: Prediction model (9-month estimation period)

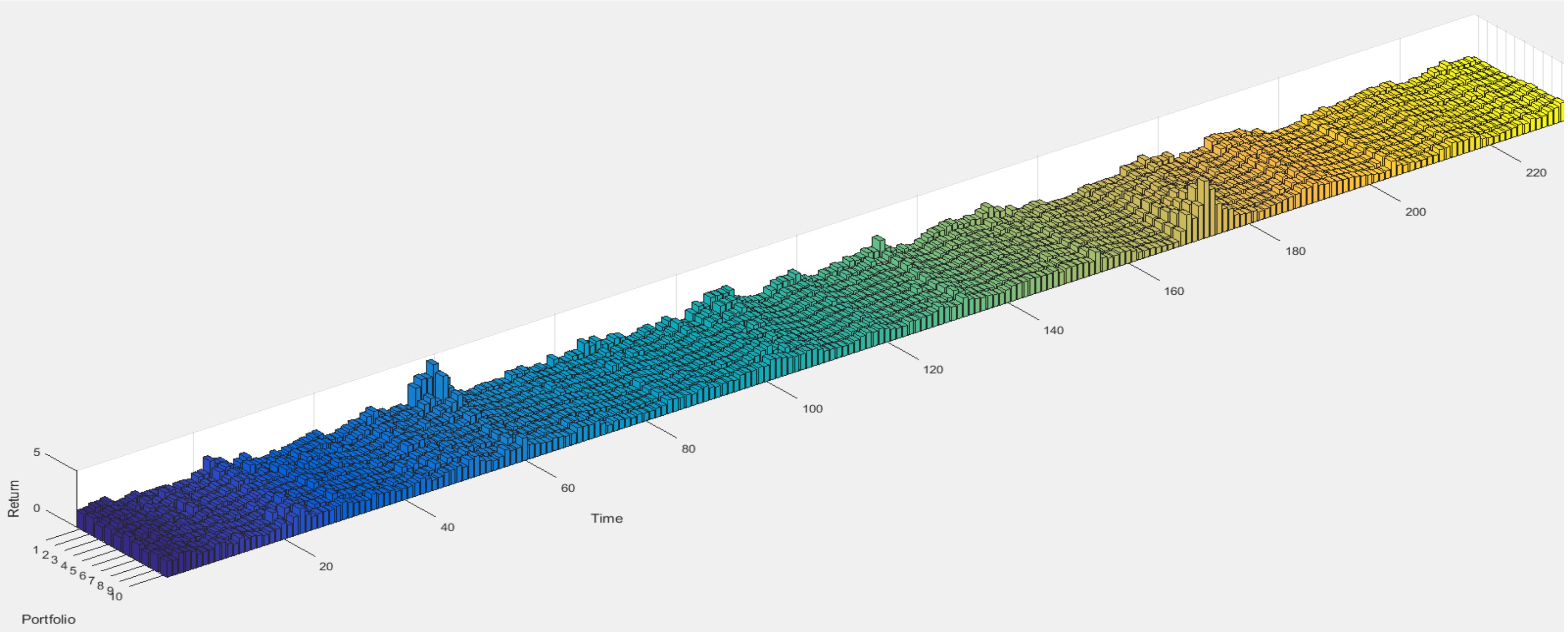
Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from September 1994 to July 2014.

	Portfolio	Return	BHAR	P-value
	1	40%	14%	0.00****
Average return	2	29%	4%	0.02***
	3	26%	0%	0.64
23%	4	26%	1%	0.47
	5	24%	-1%	0.04***
	6	22%	-3%	0.00****
	7	20%	-5%	0.00****
	8	22%	-3%	0.00****
	9	22%	-3%	0.03***
	10	22%	-3%	0.07**

Chart 5.13: Performance of each portfolio (9-month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 9 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate six months' aggregate return for each portfolio. The evaluation period is from September 1994 to July 2014.



It is shown in Table 5.14 that the prediction model is robust to this test on the part of low investor-induced liquidity when estimation period is 12 months. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive Buy and hold abnormal return. The Buy and bold abnormal return for 6-month holding period are 12%. However, Buy and hold abnormal return for a hedge fund in Portfolio 10 with high investor-induced liquidity is not different significantly. This evidence support that some of the hedge funds with low performance do not report their performance after the incubation period. It could also reflect the investor-induced liquidity in the less distance past has more explanatory power on fund performance.

The Chart 5.14 presents more details on the empirical value of the prediction model with backfill bias data when estimation period is 12 months. Normally, hedge funds in lower liquidity portfolios experience higher performance. Similar to original prediction model, the result between 167th and 171th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between November 2008 and March 2009. The evaluation period of this period is the first 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, it is robust to prediction model with 12-month estimation period for low investor-induced liquidity portfolios.

Table 5.14: Prediction model (12-month estimation period)

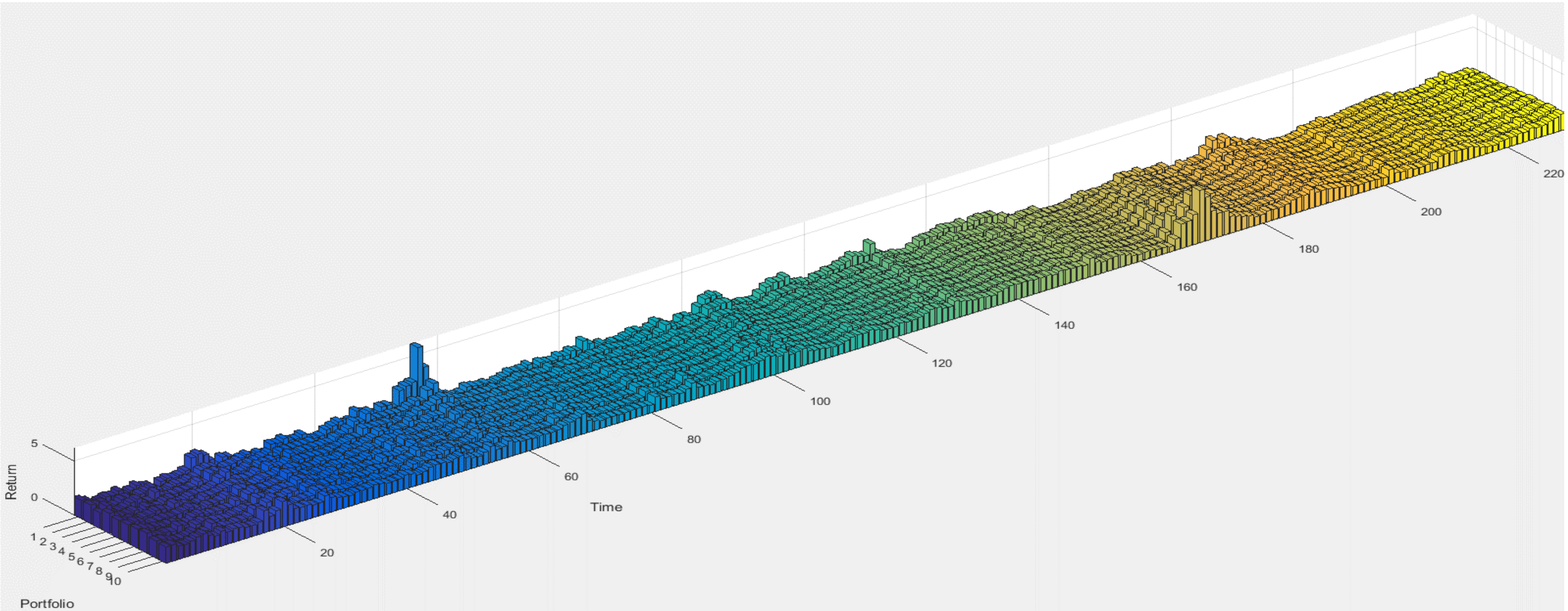
Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 6 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 12 months' forward return. The evaluation period is from December 1994 to July 2014.

	Portfolio	Return	BHAR	P-value
	1	1.37	13%	0.00****
Average return	2	26%	2%	0.17*
	3	25%	1%	0.34
23%	4	23%	-1%	0.09**
	5	22%	-2%	0.01****
	6	23%	-2%	0.04***
	7	20%	-4%	0.00****
	8	21%	-3%	0.01****
	9	22%	-2%	0.22
	10	22%	-2%	0.23

Chart 5.14: Performance of each portfolio (12-month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 12 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is the aggregate six months' aggregate return for each portfolio. The evaluation period is from December 1994 to July 2014.



5.6.3 Robustness test on abnormal return method

There are different methods to estimate abnormal return. This study does robustness test on the prediction model by cumulative abnormal return. Abnormal return in CAR observes the difference between portfolios′ monthly return and market return of all hedge fund. Table 5.15, 5.16 and Table 5.17 illustrate output summary of the CAR with 3, 6, 9 and 12 month estimation period respectively. Chart 5.15, 5.16 and Chart 5.17 show correspond details on the empirical value of the prediction model. It is shown in Table 5.15 that the prediction model robust to CAR method when estimation period is 3 months. A hedge fund in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive CAR. The CAR for 6-month holding period is 7%. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative CAR (-4%).

The Chart 5.15, 5.16, 5.17, 5.18presents more details on the empirical value of the prediction model using CAR method. Normally, hedge funds in lower liquidity portfolios experience higher performance. Similar to original prediction model, the result between 176th and 180th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between November 2008 and March 2009. The evaluation period of this period is the first 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. However, Portfolio 1 performs well during other periods. In total, it is robust to prediction model with 3-month estimation period for low investor-induced liquidity portfolios.

Table 5.15: Prediction model (3-month estimation period)

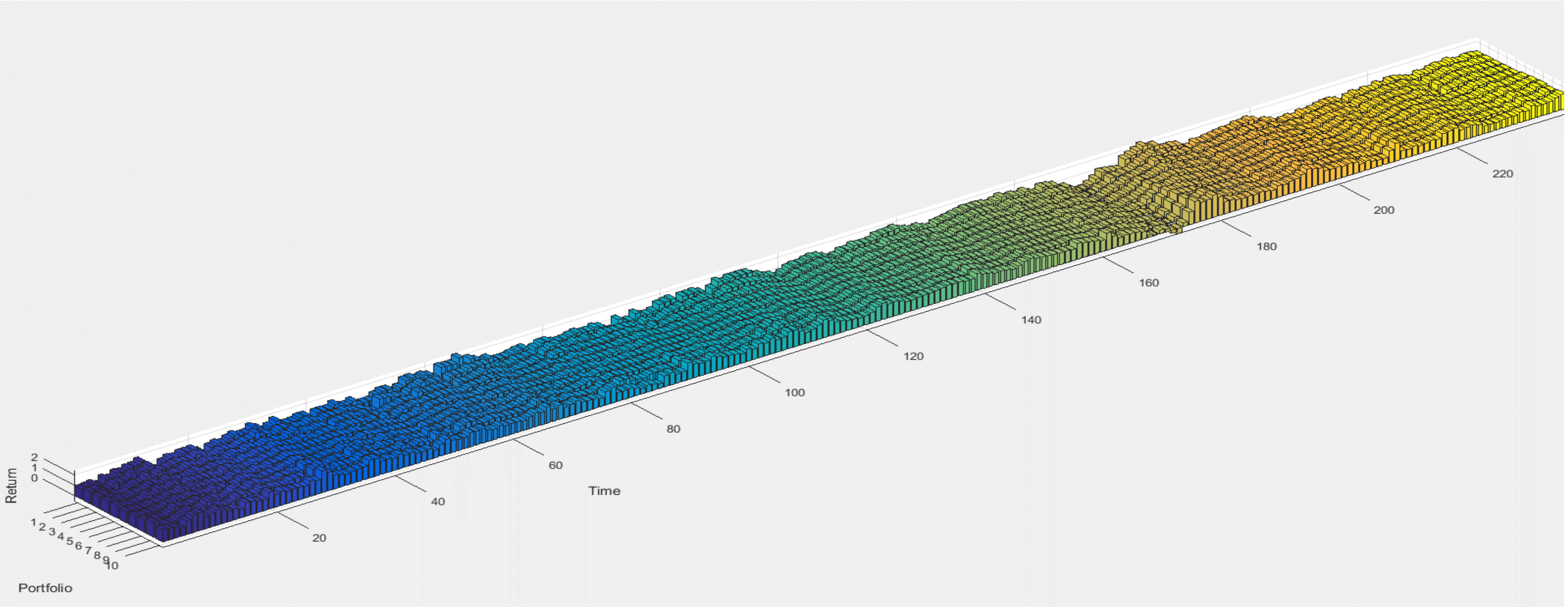
Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 3 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. CAR is Cumulative abnormal return using 6 months' forward return. The evaluation period is from March 1994 to July 2014.

	Portfolio	Return	CAR	P-value
	1	25%	7%	0.00****
Average return	2	23%	4%	0.00****
	3	19%	1%	0.13*
18%	4	18%	0%	0.81
	5	18%	-1%	0.20
	6	17%	-2%	0.00****
	7	16%	-2%	0.00****
	8	16%	-2%	0.01****
	9	16%	-2%	0.04***
	10	14%	-4%	0.00****

Chart 5.15: Performance of each portfolio (3 month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 3 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is six-month Cumulative return for each portfolio. The evaluation period is from April 1994 to July 2014.



It is shown in Table 5.16 that the prediction model robust to CAR method when estimation period is 6 months. hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive CAR. The CAR for 6-month holding period is 10%. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative CAR (-6%).

Table 5.16: Prediction model (6-month estimation period)

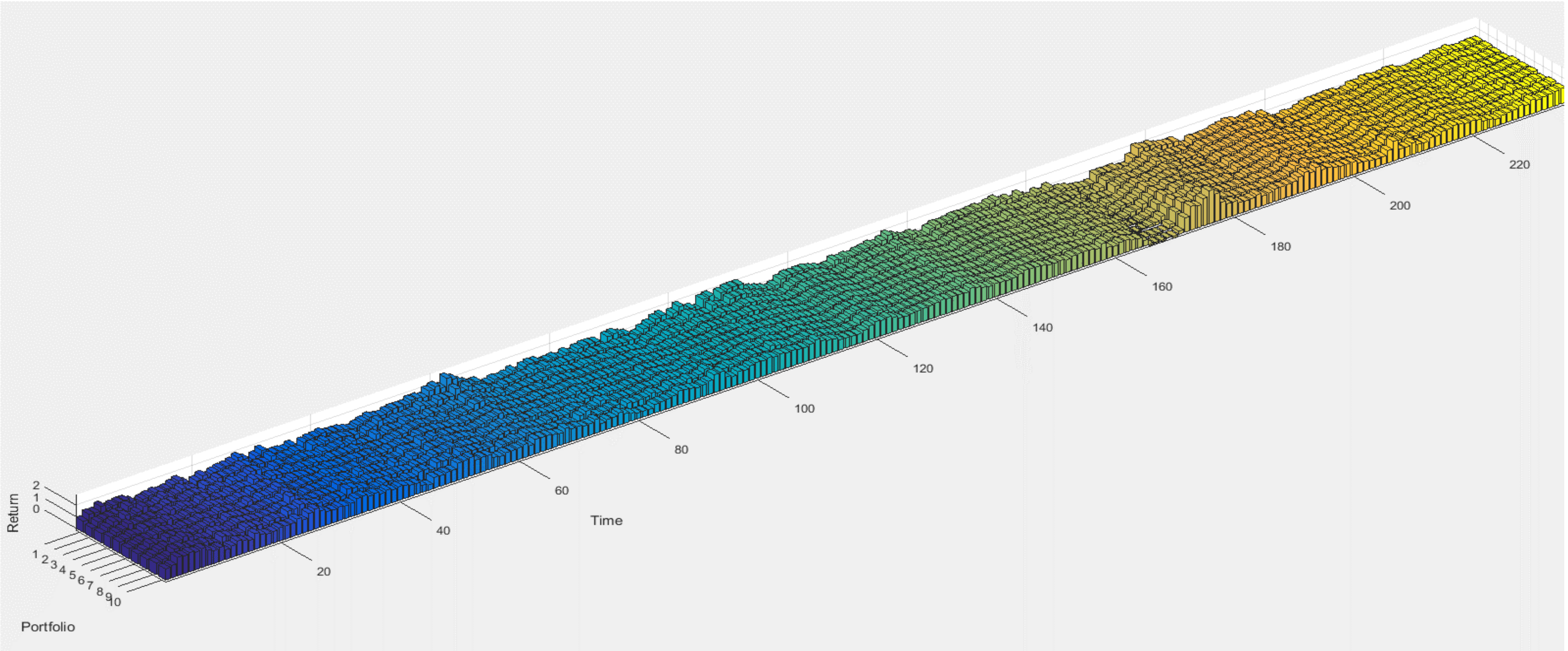
Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 6 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. CAR is Cumulative abnormal return using 6 months' forward return. The evaluation period is from July 1994 to July 2014.

	Portfolio	Return	CAR	P-value
	1	28%	10%	0.00****
Average return	2	23%	5%	0.00****
	3	20%	2%	0.01****
18%	4	19%	1%	0.07**
	5	17%	-1%	0.14*
	6	16%	-2%	0.00****
	7	15%	-3%	0.00****
	8	16%	-3%	0.00****
	9	15%	-3%	0.00****
	10	12%	-6%	0.00****

Chart 5.16: Performance of each portfolio (6 month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 6 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is six-month Cumulative return for each portfolio. The evaluation period is from July 1994 to July 2014.



It is shown in Table 5.17 that the prediction model robust to CAR method when estimation period is 9 months. A hedge fund in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive CAR. The CAR for 6-month holding period is 11%. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative CAR (-6%).

Table 5.17: Prediction model (9-month estimation period)

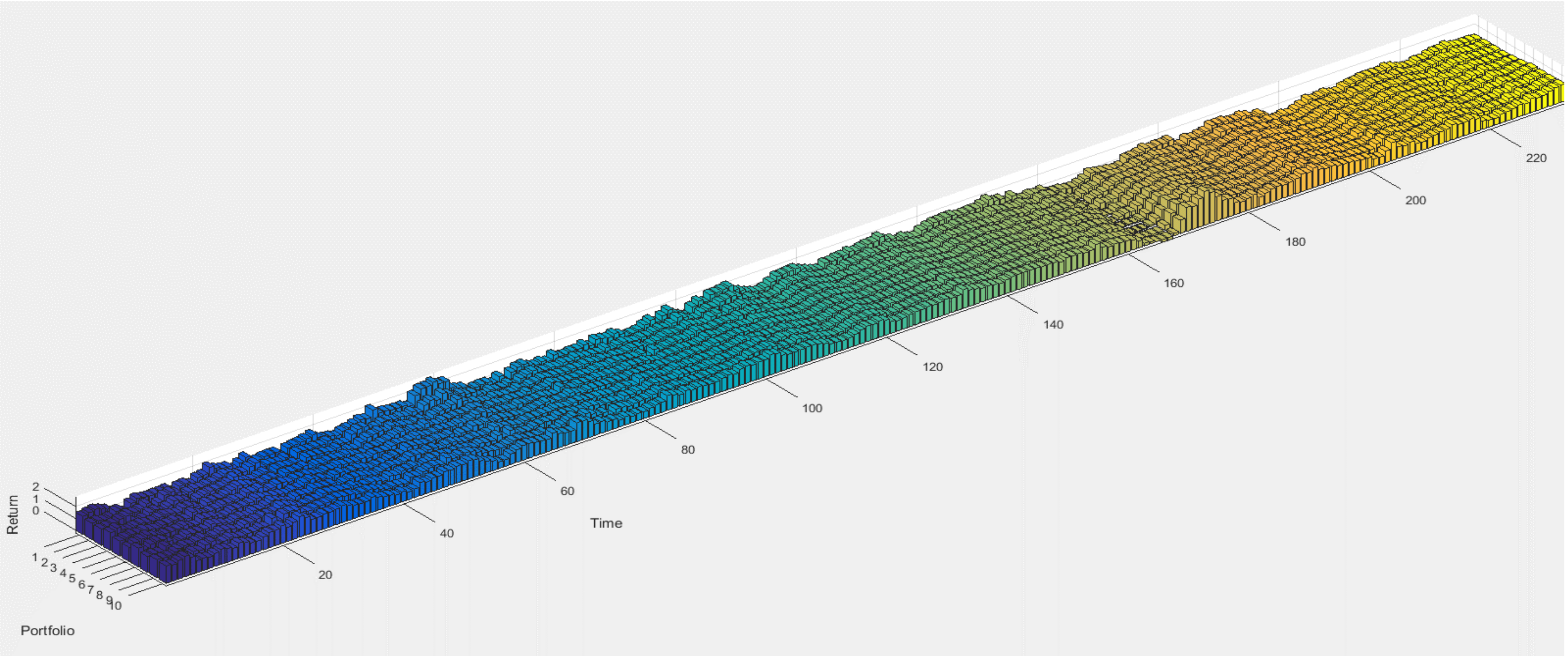
Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. CAR is Cumulative abnormal return using 6 months' forward return. The evaluation period is from September 1994 to July 2014.

	Portfolio	RETURN	CAR	P-value
	1	29%	11%	0.00****
Average return	2	22%	4%	0.00****
	3	19%	1%	0.13*
18%	4	19%	1%	0.14*
	5	18%	0%	0.49
	6	17%	-1%	0.01****
	7	15%	-3%	0.00****
	8	14%	-4%	0.00****
	9	15%	-3%	0.00****
	10	12%	-6%	0.00****

Chart 5.17: Performance of each portfolio (9 month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 9 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is six-month Cumulative return for each portfolio. The evaluation period is from September 1994 to July 2014.



It is shown in Table 5.18 that the prediction model robust to CAR method when estimation period is 12 months. Hedge funds in Portfolio 1 with low investor-induced liquidity present economically and statistically significant positive CAR. The CAR for 6-month holding period is 9%. Hedge funds in Portfolio 10 with high investor-induced liquidity present economically and statistically significant negative CAR (-5%).

Table 5.18: Prediction model (12-month estimation period)

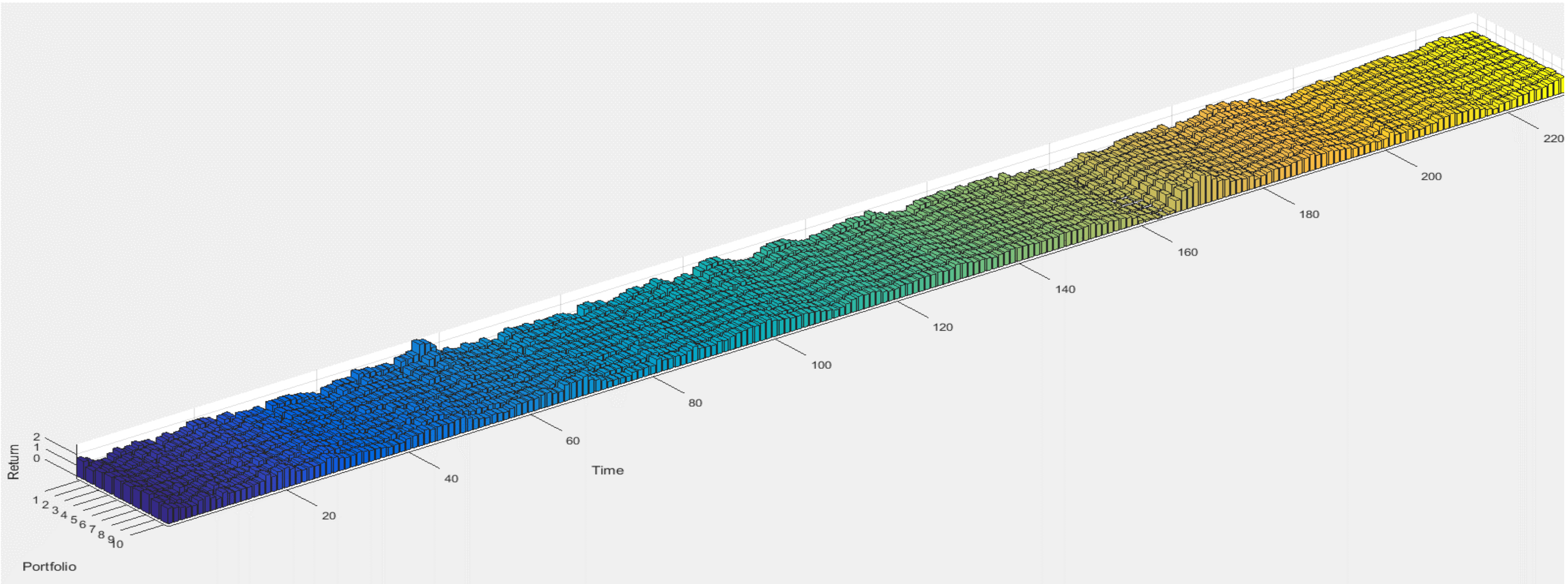
Sorts on investor-induced liquidity

Hedge funds with liquidity terms are sorted every month into deciles based on their investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 12 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. CAR is Cumulative abnormal return using 6 months' forward return. The evaluation period is from December 1994 to July 2014.

	Portfolio	Return	CAR	P-value
	1	27%	9%	0.00
Average return	2	20%	2%	0.04
	3	20%	2%	0.01
23%	4	18%	1%	0.14
	5	17%	0%	0.47
	6	16%	-1%	0.00
	7	15%	-2%	0.00
	8	14%	-3%	0.00
	9	15%	-3%	0.01
	10	13%	-5%	0.00

Chart 5.18: Performance of each portfolio (12 month estimation period)

Hedge funds with liquidity terms are sorted every month into deciles based on their aggregate investor-induced liquidity estimated last month. The aggregate investor-induced liquidity is estimated by equation (5.3) using last 12 months' data, where investor-induced liquidity is estimated by equation (5.2). Return is six-month Cumulative return for each portfolio. The evaluation period is from December 1994 to July 2014.



5.6.4 Summary

Prediction model can allocate portfolios of hedge funds with the significantly high return and low investor-induced liquidity. Moreover, the result robust to different estimation period and evaluation period. The result is not robust to 12-month estimation period and evaluation period on portfolios with high investor-induced liquidity. It indicates that the investor-induced liquidity in the less distance past has more explanatory power on fund performance. This test also robust to CAR methods with different evaluation periods. The most successful method is the original prediction model with 6-month estimation period and 6-month evaluation period. The result also indicates that incubation bias influence performance of hedge fund with high investor-induced liquidity the most significantly. The result from fund performance shows that the fire sale problem is more significant in a recent financial crisis period and it is not significant in a normal period. In total, the prediction model maintained its empirical value and it suggests that investors could take opposite position in the financial crisis period. For long term running, funds with low investor-induced liquidity are able to earn high returns during 1994-2014.

The result consistent with Berk and Green (2004), Chevalier and Ellison, (1997) and Sirri and Tufano (1998) that the high net inflow will ultimately adversely influence the performance of a fund. Using of 20-year testing period together with a lower biased data filtering process, this chapter indicates that the relation between investor-induced liquidity and fund performance is adversely in the hedge fund industry.

5.7 Conclusion

Using data purchased from hedge fund data vendor, this chapter provides a useful tool in order to evaluate hedge fund liquidity risk derived from investor-induced liquidity. The prediction model employs past six-month aggregate investor-induced liquidity for estimation of liquidity risk. Then I form hedge fund portfolios based on liquidity level every month and estimate post ranking performance of each portfolio. Empirical evidence from this chapter suggests that investor-induced liquidity plays an important role in hedge fund returns. Funds with high liquidity risk (low investor-induced liquidity) earn high returns from 1994 to 2014. It suggests that the performance of many hedge funds during 1994-2014 could be driven by investor-induced liquidity. The result from this chapter suggests that the fire sale problem is significant in the financial crisis period. However, in long-term running, fire sale problem does not play a dominant role in hedge fund industry. Hedge funds with low investor-induced liquidity experienced better performance Furthermore, the result robust to several rolling window approaches and CAR method. It indicates that less distance past investor-induced liquidity influence more significantly on hedge fund performance. Interestingly, the model is robust to data include backfill bias to a certain extent.

This Chapter has 3 implications. Firstly, this chapter provides a useful tool to risk management department in order to evaluate hedge fund liquidity risk derived from investors. Secondly, the model from this chapter will allow investors include fund-of-fund manager to estimate the expected performance of a hedge fund before allocation of portfolios and also provide warning signals to investors who have invested in the hedge funds. Last, the governance of hedge fund regulation could take investor-induced liquidity into consideration. The difficulty of find out quality data of hedge fund is well recognized both within industry and academia. It is important to make information public in hedge fund industry. Moreover, take liquidity risk management into consideration, a large amount of investment inflow to individual hedge fund could bring the heavy burden of hedge fund performance. A Large amount of investment outflow from individual hedge fund could cause fire sale problem when market liquidity is tight.

Chapter 6: Combined model analysis

6.1 Introduction

Previous Chapters analysis of hedge fund performance focus on the predictive ability of survival risk or liquidity on hedge fund performance. Chapter 4 identifies a multi-component filter system to identify the real failure of hedge funds. Using of Cox proportional hazard model, chapter 4 identified a specific failure filtering system. The Cox proportional hazard model examined a range of covariates suspected to be significant to hedge fund failure risk including fund size, return, leverage and minimum investment. The estimated coefficients provided quantitative information for the causal factors of hedge fund failure. Hedge funds with low failure risk experienced high performance in following period. Empirical evidence from chapter 5 suggests that investor-induced liquidity plays an important role in hedge fund performance. Funds with high liquidity risk (low investor-induced liquidity) experienced a high performance from 1994 to 2014. It suggests that the performance of hedge funds during 1994-2014 could be driven by both survival risk and investor-induced liquidity.

Based on previous analysis, this chapter investigates the combined predictive ability of survival risk and liquidity risk on hedge fund performance. Determinants of hedge fund performance include investor-induced liquidity, size, past performance, leverage used and minimum investment. This chapter assumes that the fund with low failure risk and high outflow who can provide better liquidity condition of their underlying assets could have a better post-performance. The model with two dimensions could perform better than a single test on survival risk and investor-induced liquidity. Hypothesis 1 is that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form a portfolio that performs better than the model with a single dimension. Hypothesis 2 is that we can extract hedge funds with high investor-induced liquidity from low failure risk group in order to reduce fire sale problem for low failure risk hedge funds. Hypothesis 3 is that we can extract hedge funds with low failure risk from high investor-induced liquidity group in order to decrease the failure risk of hedge funds in low liquidity risk groups. On one hand, we can extract hedge funds with high investor-induced liquidity from low failure risk group in order to reduce fire sale problem for low failure risk hedge funds in the financial crisis period. On the other hand, we can extract hedge funds with low failure risk from high investor-induced liquidity group in order to increase return for hedge funds with low liquidity risk.

In this chapter, Section 6.2 I provide analysis of determinants that influenced hedge fund performance. Section 6.3 describes the development of hypothesis for this study. Section 6.4 explains data and method in this study. Section 6.5 presents the empirical results. Section 6.6 provides Robustness checks and Section 6.7 concludes this chapter.

6.2 Determinants of hedge fund performance

This section analysis determinant that could determinant hedge fund performance. Hedge fund failure risk and liquidity risk are the main determinants of hedge fund performance. The set of covariates which influence hedge fund failure risk includes size, return measures, leverage and minimum investment. Table 6.1 illustrates the expected relationship between determinants and hedge fund performance:

Table 6.1: Expected relationship between covariates and hedge fund performance

Table 6.1 lists the covariates intended for use in this Chapter. The column labeled expected relation indicates the expected relationship with fund performance. The presence of an asterisk "*" denotes that the covariate is represented as a dummy variable.

Determinants	Covariate	Expected Relation
Liquidity risk	Investor induced liquidity	Positive
	Fund size	
	Mean of Return	
	Return on t	
	Average return from t-2 to t	
Failure risk	Variance of return	Negative
	Kurtosis of return	
	Skewness of return	
	Leverage*	
	Minimum investment	

6.2.1 Liquidity risk

The impact of investment flow in the hedge fund industry could be different. Sadka (2006) report that hedge funds experienced positive investor-induced liquidity performs better than hedge funds with negative investor-induced liquidity. The result is same in one and three month's lag. Teo (2011) and Sadka (2006) report that liquidity shock from investor redemption could cause significant fire sale problem that hedge fund has to short their asset with low price in the market because of tight market liquidity. The performance of hedge fund could bias more serious together with the problem of smooth-reported return. Hedge fund manager could report the high price of their return on low liquid asset and the redemption from investor could drag the price down to lower than market value. Ding, Shawky and Tian (2009) also indicate that hedge fund with conservative strategy in coping with liquidity shock often performs worse than a fund with aggressive strategy in coping with liquidity shock. Ding, Shawky and Tian (2009) report that hedge fund experienced high investor-induced liquidity in the last month performs higher than hedge funds with low investor-induced liquidity 1 month forward from 1994 to 2005. On one hand, the time period of this research did not include recent financial crisis period. Sadka (2010) indicate that liquidity risk could conversely effect on hedge fund performance during financial crises period. On the other hand, hedge fund managers could hold an illiquid asset in order to smoothly present their performance. Moreover, the setting of redemption gate of hedge fund could help them to more smoothly presenting their return. Using of 1 month past performance to test 1 or 3 months forward return could not investigate the real effect of investor-induced liquidity. In addition, with increasing of hedge fund size and fund flows, the influence of investor-induced liquidity could close to the mutual fund. Take the characteristic of hedge fund management into consideration, it is important to test the impact of investment flow to hedge fund performance more reasonable. This study would examine on a longer set of past investor-induced liquidity and forward returns in order to test if the decrease of investor-induced capital flow to hedge fund had a negative impact on hedge fund performance from 1994 to 2014.

Using of market-wide liquidity measurement (Pastor and Stambaugh, 2003). Teo (2011) documents that hedge fund managers with less strict share restrictions are more likely to take a high liquidity risk. The liquidity restrictions are not often considered as liquidity risk exposure that hedge fund manager could take. Hedge funds with lockup period perform better than those without lockup period could due to the effect of fund size. Ding, Shawky and Tian (2009) report that large fund is more likely to provide strict redemption gate for their investors. Furthermore, previous studies report the positive relation between fund size and the funds' asset portfolio performance (Liang, 2000; Ding, Shawky and Tian, 2009). The results show that small hedge fund presents higher entire return. However, hedge funds with large assets size present higher risk-adjust return. Large funds hold the more illiquid asset and embrace lower burden of systematic and idiosyncratic risk than small funds. Sadka (2010) also reported that redemption gate that hedge fund managers set for their investors are not significantly related to their return and the result robust to commonly used characteristics in hedge fund analysis. As the result, this thesis is going to investigate hedge fund liquidity based on cash withdraw from investors directly rather than taking share restrictions as the main characteristic for the estimation of hedge fund liquidity.

Empirical finding in Chapter 5 indicates that prediction model can allocate a portfolio of hedge fund portfolio with the significantly high return and low investor-induced liquidity. Moreover, the result robust to different estimation period and evaluation period. The result is not robust to 12-month estimation period and evaluation period on portfolios with high investor-induced liquidity. It indicates that the investor-induced liquidity in the less distance past has more explanatory power on fund performance. This test also robust to CAR methods with different evaluation periods. The most successful method is the original prediction model with 6-month estimation period and 6-month evaluation period. The result also indicates that incubation bias influence performance of hedge fund with high investor-induced liquidity the most significantly. The result from fund performance shows that the fire sale problem is more significant in the recent financial crisis period and it is not significant in a normal period. In total, the prediction model maintained its empirical value and it suggests that investors could take opposite position in the financial crisis period. For long term running, funds with low investor-induced liquidity earn high returns during 1994-2014.

The result consistent with Berk and Green (2004) Chevalier and Ellison, (1997); Sirri and Tufano (1998) that the high net inflow will ultimately adversely influence the performance of a fund. Using of 20-year testing period together with a lower biased data filtering process, this chapter indicates that the relation between investor-induced liquidity and fund performance are both adversely in mutual fund and hedge fund.

6.2.2 Failure risk

Fund size is based on the sample mean of the total net asset (TNA) over the lifetime of the estimation period. This information is reported on a monthly basis for every fund after the sampling process. United States dollars is selected as common currency because the majority of the hedge funds reported in it. Using exchange rate on July 31st, 2014, this study converts total net assets to US dollars in order to place meaningful comparison. Consistent with the extant literature, this study takes the natural logarithm of TNA in United State dollars. It is expected that funds with larger size could withstand the great change of return. Fund size is supposed to negatively relate to failure risk because funds with insufficient size present higher attrition rate (Amin and Kat, 2003). Amin and Kat (2003) documented that funds lack of capital is hard to perform managerial expectations and bear the burden of fixed cost. This opinion is supported by study employing the proportional hazards model (Gregoriou, 2002; Baba and Goko, 2006) and the research using the probit regression analysis (Baquero, Horst and Verbeek, 2005; Liang, 2000; Malkiel and Saha, 2005).

On the other hand, Ammann and Moerth (2005) argue that large funds perform worse than small funds because an investment fund has to diversify away with the growing of fund size. It makes large funds' return more stable and moves closer towards a market portfolio as a poorer performance. On contrary, smaller funds have more flexible and dynamic investment strategies. Large funds present better stability and smaller funds show higher return, the overall effect of fund size on failure risk must be determined empirically.

Fund returns are reported on a monthly basis and net of all fees. It is difficult to calculate returns after fees accurately because incentive fee structure is complex together with hurdle rate, high water marks and different calculation periods. Incentive fee increases with a higher return on investment. For example, incentive fees are 5% when the return higher than hurdle rate and it increases to 10% when the return over 5% higher than hurdle rate. Moreover, Hedge funds calculate their incentive fees annually, semi-annually or even quarterly and it also changes the length of time to reset high water mark. Typically, fees are assessed on an annual basis and allocate estimated fee charges to monthly returns. Using of monthly returns net of fees, this study composes six of return based measures that are mean of return, return on t-1, the average return from t-2 to t, the variance of return, the skewness of return and kurtosis of return.

Mean of return is calculated as the average monthly return over the life of the fund in the estimation period. It is expected that funds with low returns present a higher risk of failure. Funds with negative returns will experience a decreasing of fund TNA. Moreover, negative returns could cause a lower expectation of incentive fee and it could further influence propensity for the fund manager to close down the fund. In addition, Baba and Goko (2006) reported that capital outflow from poor performing funds to funds with good performance. Many of previous research (Baba and Goko, 2006; Baquero, Horst and Verbeek, 2005; Brown, Goetzmann and Park, 2001; Gregoriou, 2002; Liang, 2000; Malkiel and Saha, 2005) find strong evidence to support that fund return is negatively related to the risk of failure. Morover, Amin and Kat (2001) document that average return in the last 12 month of dead funds are negative or do not differ significantly from zero. Baba and Goko (2006) document significant result using of average monthly return both on the latest 3 months and latest month. This indicates that performance in the less distance past is of more importance. It is consistent with Rouah (2005), Liang and Park (2008) and Malkil and Saha (2005) that contemporary measures of mean return have more explanatory power on fund failure than mean returns over the life of the fund.

The variance of return is the sample variance of monthly return over the lifetime of the estimation period. On one hand, increasing of variance increases the probability of higher return. On the other hand, high variance increases the risk of low return. A plethora of previous researchers including Brown, Goetzmann and Ibbotson (1999), Brown Goetzmann and Park (2001), Gregoriou (2002), Malkiel and Saha (2005) all provide evidence to suggest that negative effects of downside risk outweigh the gains from upside risk. As the result, the variance is expected to positively relate to fund failure. Gregoriou and Duffy (2006) reported that most of the hedge fund returns experienced negative skewness and high kurtosis. Liang and Park (2008) also reported that 43.4% of the hedge funds returns reject the null hypothesis of normality at 5%

significance level by using of Jarque-Bera test of normality. Therefore, tests only use variance could underestimate the tail risk of hedge funds. According to investors' utility function, investors will prefer high mean and skewness and low variance and kurtosis. It is expected that funds with high kurtosis and low skewness will have a higher risk of failure.

The use of leverage is an option to hedge fund managers. Funds with leverage could magnify their return and help managers to control the volatility of returns. Simultaneously, using of leverage could cause high fees and even fail to serve creditors. Gregoriou (2002) document that funds employing leverage matter for failure risk. Leveraged funds are expected to have higher failure risk as it embraces greater return volatilities. Baba and Goko (2006) documents that fund with high leverage shows no significant difference compare to lower-leveraged funds. Fang and Hsieh (1997), Gregoriou (2002) and Liang (2000) document that leverage can contribute to the extreme effect on hedge fund performance and length of duration. Hedge fund managers can change amount or margin rates of leverage over time. Moreover, non-debt instruments include derivatives can provide leverage to hedge funds. However, TASS database only provides whether the fund use leverage. Therefore, leverage is treated as a dummy variable in this study: 0 if the fund does not use leverage and 1 otherwise.

Minimum investment in TASS database is the threshold for new investors entering into the fund. A Certain level of minimum initial investment can impact fund liquidity in two ways and matters to fund duration time. Firstly, funds with high minimum investment are likely to reject a big amount of small-scale investors. It indicates that stability of investment in funds is weaker and consequently a lower duration. Secondly, high minimum investment allows redemption from single investor influence constancy of fund size. Funds with high minimum investment are expected to have high failure risk. TASS database provides minimum investment in a different currency. Using exchange rate on July 31st, 2014, this study converts total net assets to US dollars in order to place meaningful comparison.

6.3 Development of Hypothesis

The previous chapters provide evidence of predictability of survival risk and liquidity risk individually. Both survival risk and liquidity risk have significant explanatory power on hedge fund post performance. This chapter investigates the combined predictive ability of survival risk and liquidity risk on hedge fund performance. Determinants of hedge fund performance include investor-induced liquidity, size, past performance, leverage used and minimum investment. This chapter assumes that the fund with low failure risk and high outflow who can provide better liquidity condition of their underlying assets could have a better post-performance. The model with two dimensions could perform better than a single test on survival risk and investor-induced liquidity. Hypothesis 1 is that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form the best portfolio that performs better than the model with a single dimension. Hypothesis 2 is that we can extract hedge funds with high investor-induced liquidity from low failure risk group in order to reduce fire sale problem for low failure risk hedge funds. Simultaneously, extract portfolio could perform better than average level. Hypothesis 3 is that we can extract hedge funds with low failure risk from high investor-induced liquidity group in order to decrease the failure risk of hedge funds in low liquidity risk groups and the extracted portfolio performs better than average value. On one hand, we can extract hedge funds with high investor-induced liquidity from low failure risk group in order to reduce fire sale problem for low failure risk hedge funds in the financial crisis period. On the other hand, we can extract hedge funds with low failure risk from high investor-induced liquidity group in order to increase return for hedge funds with low liquidity risk.

6.4 Data

6.4.1 Data description

The hedge fund has no regular obligation to publish their information to the official governing body and they are forbidden from raising funds publicly. However, fund managers are self-selected to disclose information to private data vendors. The data vendors provide information to existing and indirect potential investors. Kat and Brooks (2002) point out that the data from these providers are not independently verified. Although data vendor tends to perform regular report, the information provided are unaudited. As discussed in Chapter 2, previous studies indicate that TASS database could fit for this thesis because more of dead funds are collected according to previous studies. Therefore, using of TASS database could cause lower self-selection bias. Moreover, the use of monthly return improve the accuracy of variance measure of risk and TASS database could provide better information that could reduce survivorship and backfill bias to a certain extent. In addition, the TASS database collects relatively more observations than other databases.

This chapter estimates hedge fund survival risk and liquidity risk using monthly reported return and total net asset in the TASS database. The database provides monthly returns, total net assets and characters include minimum investment, leverage, management fee and a performance fee. Similar to Chapter 4 and 5, This chapter collect data from January 1994 to July 2014 in this chapter. Using of data before 1994 could cause survivorship bias because TASS started collecting data in 1994 that the hedge funds died before 1994 are not included in the database. Importantly, the sampling time period covered Asian crisis in 1997, Russian crises in 1998, the collapse of sub-prime mortgage crisis in the United States in 2007 and the following credit crunch. The original database contains 14031 of hedge funds in this period, of which 6505 are live funds and 7526 are liquidated funds. Table 3.1 illustrates the characteristic data in the database for active funds, liquidated funds and all funds. The minimum investment is the average requirement that the hedge fund asks for initial investment from their investors. Minimum investment of active fund is about 2 times higher than liquidated funds. Redemption frequency signifies the average times per year that hedge funds redeem their assets. Fund using leverage refers to the percentage of funds which use debt to leverage their capital. Similarly, domiciled in the U.S. is the percentage that hedge funds registered in the United States.

Hedge funds often operate a period before providing information to data vendors. Funds with successful history will report their performance to the database and funds with bad performance tend not to report. Furthermore, reported data of hedge funds often include performance before the time it listed on the database. The backfilled performance can be much better than hedge fund actual returns. In order to reduce this incubation bias, I delete first 12 months' return for each hedge fund. Previous studies indicate that incubation bias significantly influences the estimation of hedge fund performance (Baba and Goko, 2006; Malkiel and Saha, 2005).

Table 3.2 presents the main time series data considered in this Chapter. The average duration of the live fund is about half a year longer than dead funds. Total Net Assets (TNA) of the fund represent the total funds under management for a net of fees and expenses on average in each group. Total net asset between active funds and liquidated funds are not significantly different. The time series data for four return moments shows that active funds experience a higher mean of return than liquidated funds. According to the risk aversion theory, investments with high first and third moments and low second and fourth moments are more preferred. Active funds experienced a higher mean of return and lower kurtosis than liquidated funds. However, active fund experienced higher variance than liquidated funds and skewness of active fund is lower than that of liquidated funds. The descriptive statistics do not show clear support of this theory.

6.4.2 Sampling process

Before proceeding to an empirical analysis, it is necessary to identify an appropriate sample of funds in order to estimate the Cox proportional hazard model proposed by this chapter. The available information on hedge fund is insufficient because hedge fund manager reports their data voluntarily. This section describes the step by step filtering process to rule out funds without sufficient information. The sampling process is same as it is in Chapter 3. Table 6.2 provide sample size after sampling process.

Table 6.2: sampling process

Table 6.2 shows the variation on a number of observations step by step after sampling process. The number of funds who reported their redemption frequency and fees information is limited so that I decide to delete these two covariates from the vector.

	Total	Active	Liquidated
Total number of hedge funds	14031	6505	7526
Minimum investment reported	13817	6405	7412
Monthly return reported	6510	2713	3797
TNA reported	6294	2846	3448
Redemption frequency reported	4487	1704	2783
Fee reported	593	-	-

6.5 Methodology

6.5.1 Research aim

Based on chapter 4 and chapter 5, this chapter combines both failure risk and liquidity risk into a unified prediction model that is capable of constructing practically investable portfolios of hedge funds based on their particular characteristic. Survival risk analysis aims to detect the relationship between factors of individuals and their life length until they meet a specific event. Investor induced liquidity analysis aims to detect liquidity risk of the hedge fund.

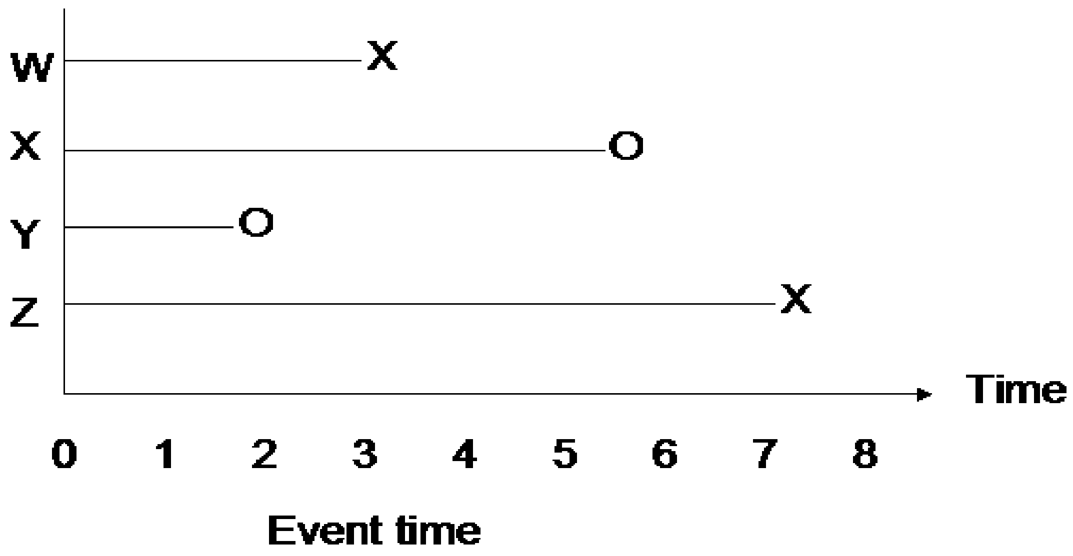
Chapter 4 provide evidence that hedge funds in lower failure risk group outperform other groups significantly. The result robust to a different set of Cox proportional hazard model, alternative identification of funds' failure and alternative abnormal return estimation methods. Empirical evidence from chapter 5 indicates that the high net inflow will ultimately adversely influence the performance of a hedge fund and hedge fund after high net outflow experienced higher performance in the hedge fund market. The fund face with high outflow could also have more probability to be liquidated or dead. However, the hedge fund could provide a better liquidity of their underlying assets if a fund has high outflow with a low failure risk. Based on the empirical result from chapter 4 and 5, this chapter assumes that the fund with low failure risk and high outflow who can provide better liquidity of their underlying assets could have a better post-performance.

6.5.2 Timescale

The time scale measures the units of time that are taken into the estimation. The time series data of return and total net asset in this thesis are monthly reported. Therefore, it is necessary to match the definition of time scale with the resolution of data. The original of time is the first time to run the model where t=0. Typically, there are two ways to define the origin time. The first way measure the origin time as the life length that time 0 is defined as the fund established month and it is called “event time” method (Chart6.1).

Chart 6.1: Event time method

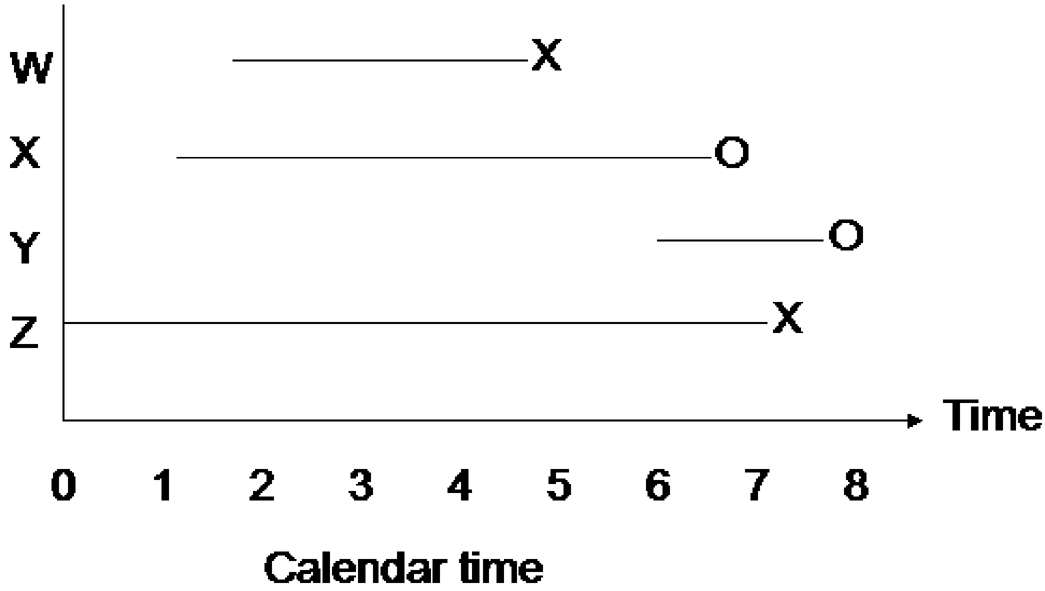
Chart 6.1 presents samples of W, X, Y, Z are measured in event time method. Each of the samples enters the study at time 0. The duration of the time indicates the life length of the sample. "X" symbolizes the sample is a failure and "O" symbolizes the sample stop reporting for other reasons.



The second way defines the origin time as calendar month that the first sample is observed in the dataset. For example, the origin time would be set in January 1994 if the dataset starts in this month (t=0). As a result, t=1 in February 1994, t=2 in March 1994 and so on. It is also called "calendar month" model. As is shown in Chart 6.2

Chart 6.2: Calendar time

Chart 6.2 presents samples of W, X, Y, Z are measured in Calendar time method. Samples enter the study at a different time. The duration of the time indicates the life length of the sample. “X” symbolizes the sample is a failure and “O” symbolizes the sample stop reporting for other reasons.



On one hand, when samples are arranged in the Calendar time model, both of calendar effect and duration effect are included into the hazard model. As the result, other time-varying covariates and economic indicators that are specific in time are comparatively pointless in the model. Furthermore, this model cannot test the effect of duration on failure alone. Survival risk analysis aims to forecast future performance outside the estimation sample that the calendar effects included in the model are unexpected. The calendar time model allows forecast only within the time period modeled because it is inevitably specific to the time period of the observations. Therefore, the event time model is more appropriate for the aims of survival risk analysis. On the other hand, the estimation of liquidity terms aims to observe funds’ flow based on same market liquidity condition. The calendar time model allows forecast in the same calendar time that investor-induced liquidity of hedge fund under the same market condition. As the result, the calendar time model is more appropriate for the aims of liquidity analysis.

6.5.3 Model construction

Duration model and discrete-time model are two kinds of hazard models that are broadly applied to estimate longitudinal data. Extant studies mainly use duration models, although both kinds of model are similar in a statistical sense. Using of duration models can capture a non-monotonic relationship between the probability of fund failure and duration. Discrete-time hazard model such as logit model. For example, based on an assumption that fund failure monotonically increases or decrease with funds' duration time if it is included as an explanatory variable. Moreover, it is better to execute right-censoring problem and time-dependent covariates by using of duration models. This study uses the Cox proportional hazard model which is a semi-parametric duration model.

For liquidity risk, this chapter focus on the aspect of investor directly induced liquidity. Existing literature indicates that redemption shocks from investors could lead to a price change in the short term for the holding asset of hedge funds who embrace excessive market liquidity risk (Gromb and Vayanos, 2002; Campbell, Grossman, and Wang, 1993 and Morris and Shin, 2004). Furthermore, the effect of fire sales becomes more significant when market liquidity and fund liquidity are both tight (Teo, 2011). Subsequently, the tight market liquidity could amplify the decreasing of hedge fund return. This Chapter is going to construct a model to forecast a longer period hedge fund performance based on investor-induced liquidity. To investigate the effects of liquidity under the same market condition, I follow the measure that Ding, Shawky and Tian (2009) estimate investor-induced liquidity. This approach can capture liquidity pressures that hedge fund managers face with investors under same market liquidity condition. Furthermore, this approach estimated investor-induced liquidity present significant relationship with the subsequent reaction of hedge fund managers (Ding, Shawky and Tian, 2009). It indicates that this aspect of liquidity is most likely to influence hedge fund performance.

The main hypothesis in this chapter is hedge fund managers embrace a lower investor-induced liquidity will carry out better performance. In contrast, managers experiencing higher investor-induced liquidity will have lower performance. It is consistent with

Sadka (2010) and Teo (2011) that hedge funds embrace high liquidity risk could perform better. Furthermore, high net investment flow could scale in active portfolio management, it could subsequently cause adversely impact on hedge fund future performance. For example, hedge funds with high net investment flows could cause dilution when its direction correlates to the following return and further reduce the hedge fund performance. In this research, survival risk and liquidity risk are construct into a two dimension model. The two dimensions are considered as individual factor of filtering process. Hedge funds meet the corresponding conditions are

6.5.4 Empirical value of combined prediction model

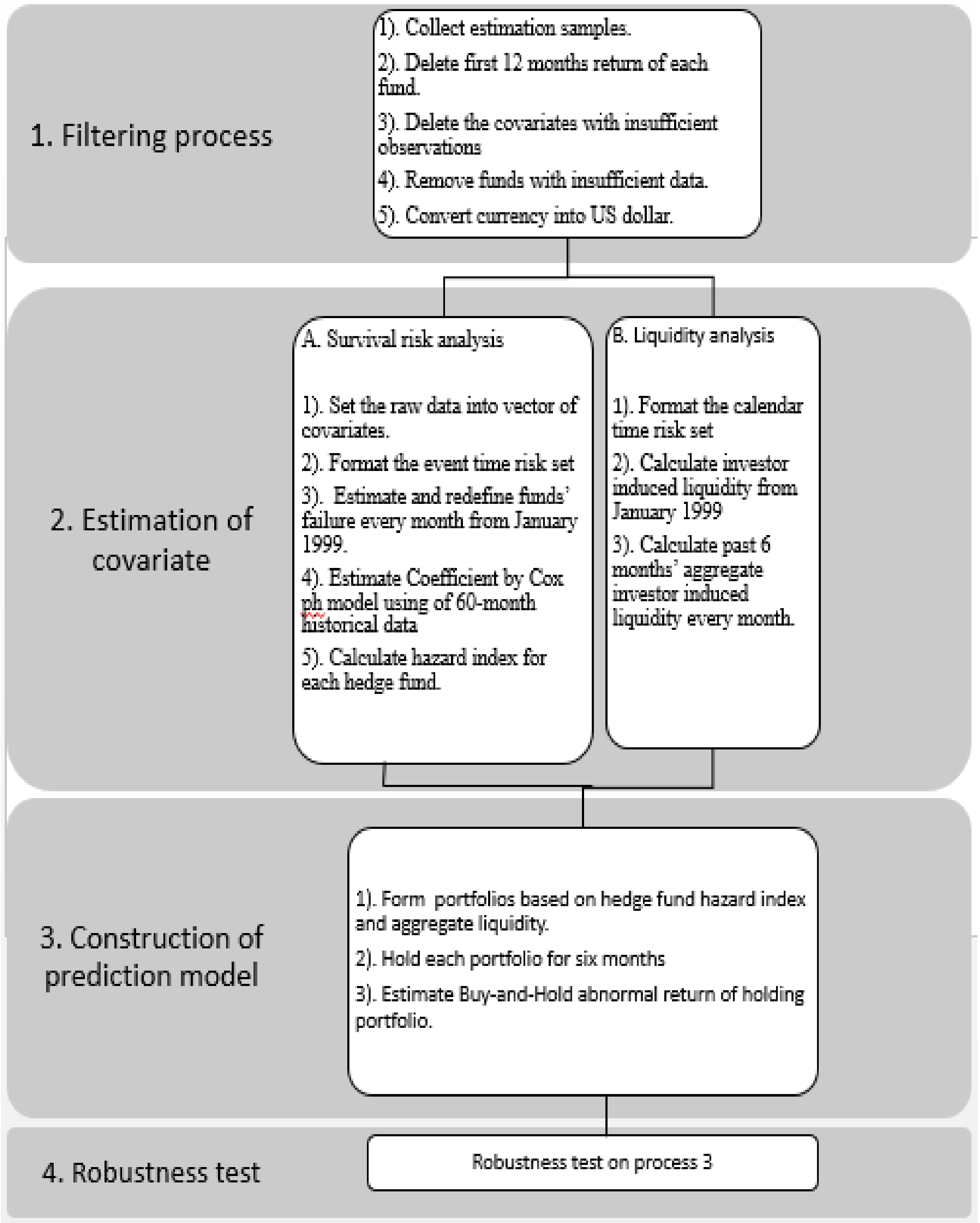
This study employs the abnormal return appetites of hedge funds that grant a favorable interest to their investors. To gauge the practical significance of both failure and liquidity risk measure, I investigate the investment value based on selecting hedge funds with low failure risk and high outflow. Every month starting from January 1999, I estimate the hedge fund net investment flow for each fund using the past 9-month estimation period data and set 10 deciles of liquidity level based on their aggregate net investment flow. Simultaneously, I estimate the hazard index for each fund using the past 60-month estimation period data and then set 10 deciles of survival risk level based on their hazard index. Following that, I form a hundred portfolios based on hedge fund survival risk and liquidity level. Hedge funds in each of portfolio belong to a certain 10 percentile of liquidity level and survival risk level. These portfolios are held subsequently for six months' holding period. This process is repeated every month until December of 2013. All of the funds' returns are included in the evaluation of portfolio return if the fund stops reporting over the holding period. This yields a time series of returns for varying levels of liquidity and failure risk from 1999 to 2013. Furthermore, I follow the Buy-and-Hold abnormal return approach used in Barber and Lyon (1997) to test if the return is statistically significant to the market return. Buy-and-Hold abnormal return could be more practical to assess abnormal return for the sake of this study. The BHAR method observes the difference between holding period return of sample funds and holding period return of the market return of all hedge funds.

The Buy-and-Hold abnormal return supposed to estimate investors experience directly. Furthermore, each of portfolio could contain a big number of hedge funds. Using of 10 percentile on both liquidity and survival risk could produce big numbers of hedge funds in each portfolio. As the minimum initial investment could limit the number of holding hedge funds, this chapter takes further steps to narrow down the set of portfolios in robustness test. To be more specific, this study tests the hedge funds in the top 20 percentile of liquidity and survival risk and sort portfolio with 5 percentile of liquidity and survival risk. There is an alternative test of hedge funds that are in the top 15 percentile of liquidity and survival risk with portfolios that are in 3 percentile of liquidity and survival risk.

6.5.5 Summary of Research Process

The prediction model of this chapter involves Section 6.3 (Data analysis) Section 6.4 (Research method). This section provides a concise summary of the steps in order to clarify the prediction model. As is shown in Chart 6.3, the first process is the set of the filtering process. Subsequently, Hazard index and investor-induced liquidity are estimated individually in process 2. Section A provides integrally ordered estimation in survival risk analysis and section B provide the investor-induced liquidity. After that, 100 investment portfolios are formed every month in Process 3. I form the portfolios based on hedge fund survival risk and liquidity level. Hedge funds in each of portfolio belong to a certain 10 percentile of liquidity level and survival risk level. Then Buy-and-Hold abnormal return for each of the 100 investment portfolios is estimated. Finally, process 4 does the robustness test.

Chart 6.3: Summary of research process



6.6 Empirical findings

6.6.1 Drivers of fund failure

The first outcome of the research procedure is the result of new identification of fund failure. It is discussed in Chapter 4 that it is important to identify the liquidated funds that are not liquidated because of poor performance. Table 6.3 illustrates the number of live funds and failure funds before and after the new identification of fund failure. As reported in the third column, the average amount of failure funds after new identification of fund failure is 111 lower than the original database. It indicates that there are 111 of liquidated hedge funds are not liquidated due to poor performance in the estimation period. Using of ten years estimation period there is more liquidated hedge funds are identified as non-failure. It is because there are more hedge funds reporting their performance in the longer estimation period. As the result, more of hedge funds are able to be estimated as non-failure.

Table 6.3: Original liquidated funds and new identification of fund failure

Hedge funds with sufficient data terms are estimated every 6 months by new fund's failure identification. A live fund is a number of funds that are not failures. The estimation period for the 5-year test is 60 months' data. The evaluation period is from January 2004 to January 2014. Using of a new identification of fund's failure, an average number of live funds is 111 higher than the original database.

	5 years test		Original database	
Date	Live fund	Failed fund	Live fund	Dead fund
01/2004	7418	6613	7384	6647
07/2004	7515	6516	7475	6556
01/2005	7622	6409	7580	6451
07/2005	7696	6335	7645	6386
01/2006	7791	6240	7735	6296
07/2006	7861	6170	7791	6240
01/2007	7919	6112	7831	6200
07/2007	7919	6112	7823	6208
01/2008	8002	6029	7878	6153
07/2008	8015	6016	7857	6174
01/2009	7992	6039	7825	6206
07/2009	7925	6106	7760	6271
01/2010	7797	6234	7642	6389
07/2010	7746	6285	7602	6429
01/2011	7659	6372	7517	6514
07/2011	7590	6441	7459	6572
01/2012	7442	6589	7289	6742
07/2012	7304	6727	7165	6866
01/2013	7166	6865	7046	6985
07/2013	6964	7067	6838	7193
01/2014	6818	7213	6694	7337
Mean	7627	6404	7516	6515

Table 6.4 shows the output of the Cox's proportional hazard model using cross-sectional data. Firstly, the estimation results in Table 6.4 show that an average of coefficient on the Mean of TNA, Mean of return, Average return in last 3 months, Variance of return, Average return in last 3 months, Variance, Kurtosis of return, Skewness of return, leverage used and minimum investment are constant with expected directions. Secondly, the strength of covariates fluctuated over time and some of the covariates even change their directions of relationship with failure over time. The magnitude of hedge fund failure effect could change due to market condition. For example, mean of return in bull market could not as important as it is in the bear market. Because most of the hedge funds could earn a remarkable return in a bull market, however, it could be more important to keep good performance in a bear market. The relation between covariates and failure rates also could change. Covariates like variance and leverage for example, extant research point out that fund with high risk presents both high risks of death and high probability to perform better than others (Brown, Goetzmann and Park, 2001). Therefore, which side overwhelms the other could change due to market condition.

It is discussed in Chapter 4 that less distance past data influence more significantly on fund failure. However, using of longer distance data, the Cox proportional hazard model could estimate covariates with a more significant result. As is shown in Table 6.4, a majority of standard deviation decreased from a test using 5 years data to using 10 years data (Mean of TNA, Mean of Return, Return of t-1, Average return in last 3 months, Kurtosis of return, Skewness of return, Leverage used and Minimum investment). Therefore, this study uses 10 years' historical data to do a robustness test of the prediction model.

Table 6.4: Cox Proportional Hazard Analysis

Hedge funds with sufficient data terms are modeled by Cox proportional hazard model every 6 months. The Hazard is the average of the Beta estimated by the Cox proportional hazard model during the estimation period. The P-value is an average of P-value estimated by the Cox proportional hazard model during the estimation period. The estimation period for the 5-year test is 60 months' data. The evaluation period is from January 1999 to January 2014.The estimation period for the 10 years test is 120 months' data. The evaluation period is from January 2004 to January 2014. Using of longer distance data, the Cox proportional hazard model could estimate covariates with a more significant result.

	5 years test		10 years test	
Covariates	Coe	Std	Coe	Std
Mean of TNA	-0.31	0.32	-0.40	0.21
Mean of Return	-13.56	26.99	-17.83	25.90
Return of t-1	1.32	4.15	0.25	3.66
Average return in last 3 months	-3.91	16.50	-2.90	5.54
Variance	0.84	3.20	1.04	3.31
kurtosis of return	0.35	0.50	0.41	0.31
skewness of return	-0.80	1.91	-0.05	1.69
leverage used	2.53	6.25	0.54	4.11
Minimum investment	0.05	0.21	0.02	0.11

6.6.2 Empirical value of prediction model

To test the effect of both failure risk and investor-induced liquidity on fund performance, I employ the portfolio based approach and use Buy and hold abnormal return method to test if survival risk and investor-induced liquidity influence fund's post-performance. Every month starting from January 1999, I estimate the hazard index for each hedge fund using past 60 months' estimation period and then sort hedge funds by different survival risk levels. Simultaneously, I sort hedge funds based on their past aggregate investor-induced liquidity by using of 9-months' rolling window. The observations are arranged according to Survival risk and investor-induced liquidity with ten levels (10% each arranging from low to high). There are 100 portfolios of hedge funds are produced by using of 10 percentile on both dimensions. Then I calculate buy and hold abnormal return for each portfolio six months forward. The portfolios with equal risk level are extracted in Table 6.5, for example, 0-10% survival risk and 0-10% investor-induced liquidity. The Buy and hold abnormal return reveals corresponding differences between return in the hedge fund market and return on portfolios sorted by investor-induced liquidity and failure risk. Mean represent an average number of hedge funds in extracted portfolio.

Hedge funds in Portfolio 1 with low investor-induced liquidity and low failure risk present economically and statistically significant positive Buy and hold abnormal return (34%). It indicates that the holding of the portfolio with lowest investor-induced liquidity and lowest failure risk delivers economically significant return higher than average return in the hedge fund market in the post-ranking periods and it is at 0.005% significance level. The result supports the hypothesis 1 that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that perform better than the model with a single dimension. Top portfolio of hedge funds in the first level of each dimension (lowest 10% of failure risk and investor-induced liquidity) present over 2 times of BHAR compare to the top portfolio of hedge funds in single dimensions. In addition, mean of fund quantity for extracted portfolio is not equal. It is shown in table 6.5 that the quantity of hedge fund in the top portfolio is much more than other extracted portfolios. Take minimum investment into consideration, holding of the whole top portfolio could cost even double amount of minimum investment to other portfolios. In this chapter, I will analyze the performance of smaller partitions in section 6.8 for robustness test. Interestingly, portfolio 10 with a higher failure risk do not present a significantly lower return in the hedge fund market. It is similar to the single dimension prediction model based on Cox proportional hazard model. However, Sharpe ratio of bot portfolio is the lowest of all portfolios (1.1). Hedge funds with higher failure risk and investor-induced liquidity increase their risk significantly. The performance of prediction model with two dimensions is more closed to the performance of prediction model based on Cox proportional hazard model. It suggests that the failure risk of a hedge fund has more explanatory power than investor-induced liquidity on the hedge fund performance.

Table 6.5: Prediction model (equal risk level)

Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with equal liquidity and failure risk level is extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent an average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value	Sharpe ratio
	0-10% S ; 0-10% L	58%	21.46	34%	0.00****	2.9
Average return	10%-20% S ; 10%-20% L	29%	12.64	5%	0.08**	2.8
	20%-30% S ; 20%-30% L	22%	11.07	-2%	0.52	2.6
24%	30%-40% S ; 30%-40% L	15%	123%	-9%	0.00****	2.2
	40%-50% S ; 40%-50% L	14%	10.81	-10%	0.00****	2.3
	50%-60% S ; 50%-60% L	16%	10.78	-8%	0.00****	2.4
	60%-70% S ; 60%-70% L	12%	10.96	-12%	0.00****	2.5
	70%-80% S ; 70%-80% L	13%	10.58	-11%	0.00****	2.8
	80%-90% S ; 80%-90% L	9%	9.68	-15%	0.00****	2.2
	90%-100%S;90%-100%L	16%	10.91	-8%	0.19	1.1

Chart 6.4 presents more details on the empirical value of the extracted portfolios. The aggregated half year return reveals actual return on each extracted portfolio with equal risk level on both liquidity and survival risk. Normally, hedge funds in portfolios with lower liquidity and failure risk level present higher performance. The result between 120th and 124th shows that portfolio with more investor-induced liquidity and failure risk experienced higher return. That is the portfolio performance between December 2008 and April 2009. The evaluation period of these tests are 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk and failure risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. It is consistent with the fire sale story (Teo, 2011). However, Portfolio 1 performs well during other periods. In total, the prediction model maintained its empirical value and the result suggests that the opposite position should be take in the financial crisis period. More importantly, it is possible to reduce fire sale problem by using two dimensions in the model. On one hand, we can extract hedge funds with high investor-induced liquidity from low failure risk group in order to reduce fire sale problem for low failure risk hedge funds in financial crisis period (H2). On the other hand, we can extract hedge funds with low failure risk from high investor-induced liquidity group in order to increase return for hedge funds with low liquidity risk (H3).

Chart 6.5 presents the average value of six month's buy and hold abnormal returns of 100 portfolios in the prediction model. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high). As can be seen from Chart 6.5, hedge funds with low investor-induced liquidity and failure risk experienced relatively better BHAR than the hedge funds with high investor-induced liquidity and failure risk. The result supports the hypothesis 1 that using a two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that perform better than the model with a single dimension. Interestingly, the BHAR presents a damped oscillation like figure for hedge funds in 0-10% failure risk level from low investor-induced liquidity to high investor-induced liquidity. The BHAR oscillates gradually decreasing and closed to industry return. It supports hypothesis 2 that we can extract hedge funds with high investor-induced liquidity from the low failure risk hedge fund group in order to reduce fire sale problem for low failure risk hedge funds. However, there is no clear evidence for hypothesis 3 that we can extract hedge funds with lows failure risk from high investor-induced liquidity group in order to decrease failure risk for hedge funds in low liquidity risk groups.

Chart 6.4: Performance of extracted portfolio (equal risk level)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with equal liquidity and failure risk level is extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The evaluation period is from January 1999 to January 2014.

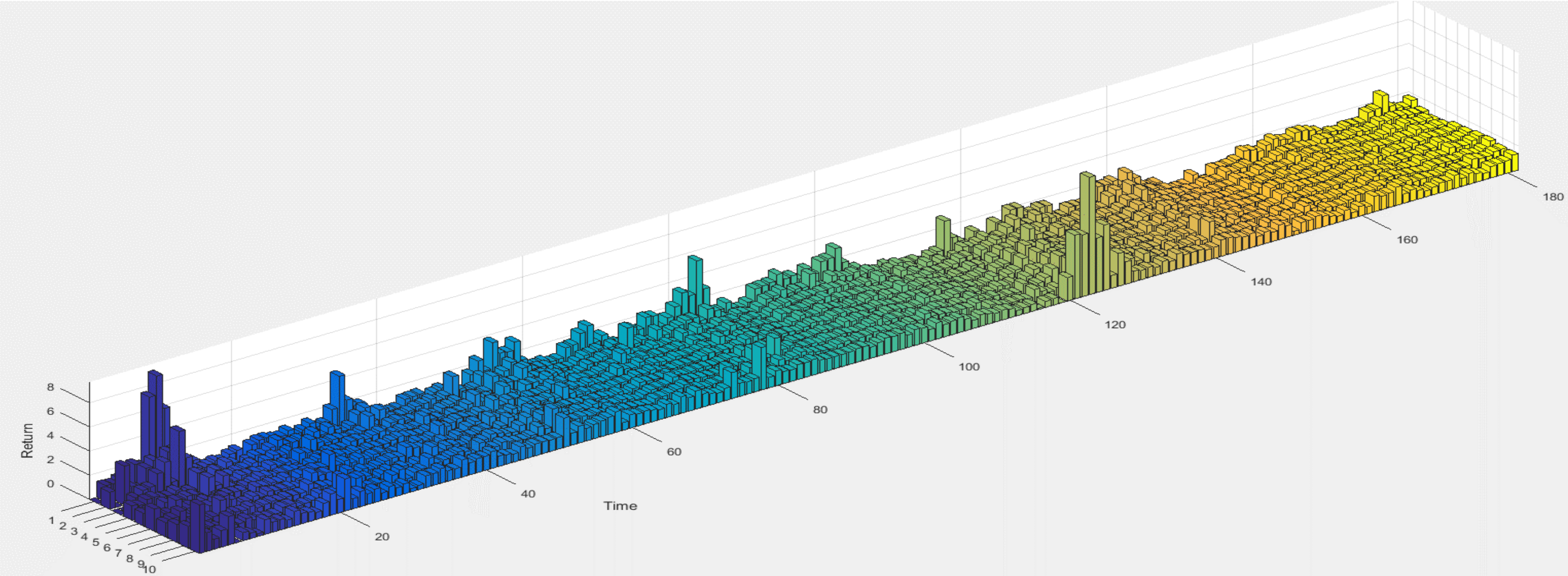
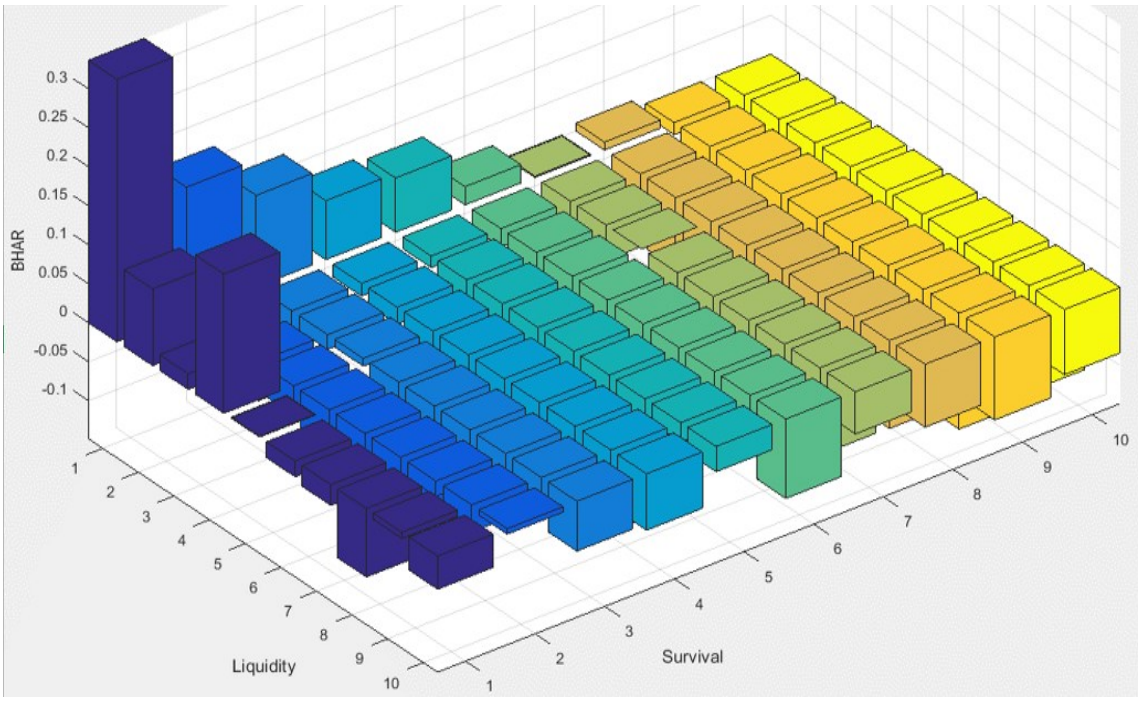


Chart 6.5: Prediction model (10percentile)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high). The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.



The portfolios with 0-10% failure risk level are extracted in Table 6.6. Hedge funds in lower investor-induced liquidity group performs relatively better than high investor-induced liquidity group and top 4 portfolios perform higher than average level. It supports the hypothesis 1 that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that perform better than the model with single dimension on failure risk. Hedge funds in Portfolio 10 with high investor-induced liquidity and low failure risk performs not significantly different with 0. It indicates that the holding of the portfolio with high investor-induced liquidity and lowest failure risk delivers similar performance in the hedge fund market in the post-ranking periods. The result supports the hypothesis 2 that we can extract hedge funds with high investor-induced liquidity from low failure risk group in order to reduce fire sale problem for low failure risk hedge funds. The Sharpe ratio of portfolios in Table 6.6 are all lower than Sharp ratio of top portfolio in Table 4.5 (3.8). It indicates that holding of all low failure risk hedge funds could bring a better risk adjusted return. In addition, mean of fund quantity for extracted portfolio is not equal. It is shown in table 6.6 that the quantity of hedge fund in the top portfolio is much more than other extracted portfolios. Take minimum investment into consideration, holding of the whole top portfolio could cost even double amount of minimum investment to other portfolios.

Table 6.6: Prediction model (0-10% failure risk level)

Sorts on failure risk and investor-induced liquidity

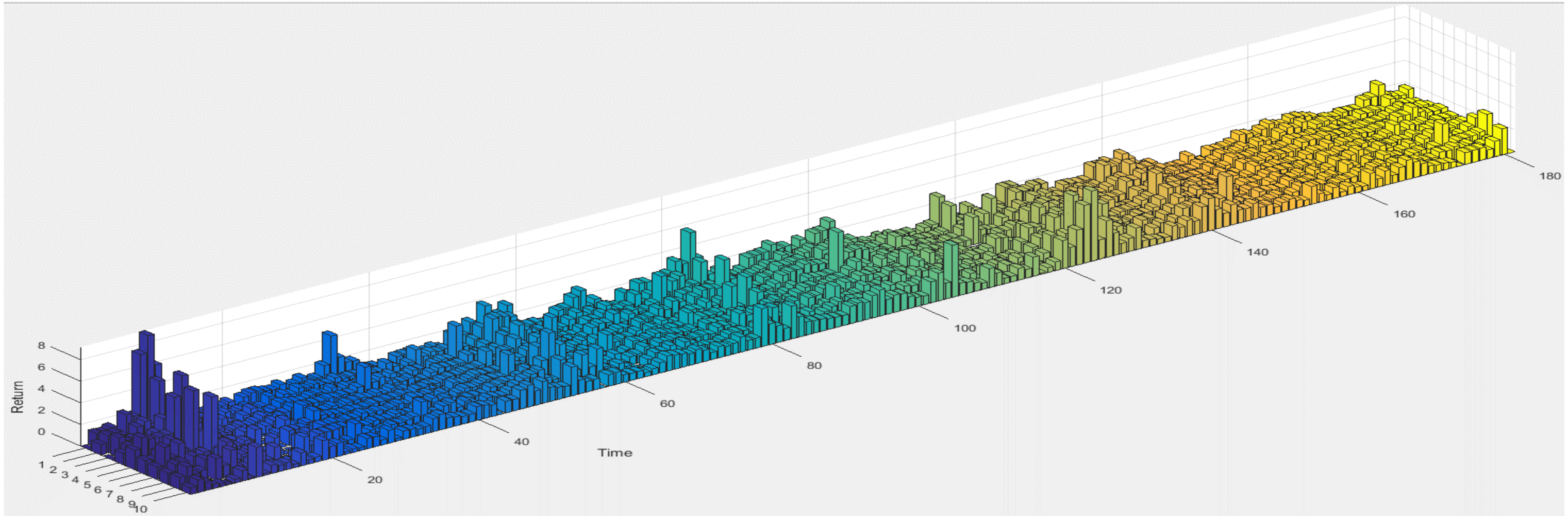
Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with 0-10% failure risk level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value	Sharpe ratio
	0-10% S ; 0-10% L	58%	21.46	34%	0.00****	2.9
Average return	0%-10% S ; 10%-20% L	34%	12.43	10%	0.02***	2.2
	0%-10% S ; 20%-30% L	26%	9.41	2%	0.62	2.4
24%	0%-10% S ; 30%-40% L	42%	52.30	18%	0.00****	2.3
	0%-10% S ; 40%-50% L	24%	8.07	0%	0.98	2.3
	0%-10% S ; 50%-60% L	22%	7.36	-2%	0.63	2.2
	0%-10% S ; 60%-70% L	21%	7.23	-3%	0.43	2.1
	0%-10% S ; 70%-80% L	15%	7.03	-9%	0.02***	2.0
	0%-10% S ; 80%-90% L	23%	7.78	-1%	0.85	2.7
	0%-10% S ; 90%-100%L	20%	9.09	-4%	0.43	2.6

Chart 6.6 presents more details on the empirical value of the extracted portfolios. The aggregated half year return reveals actual return on each extracted portfolio with 0-10% failure risk level. Normally, hedge funds in lower liquidity portfolios present higher performance. The result between 121th and 124th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between January 2009 and April 2009. The evaluation period of these tests are 4 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 with low liquidity risk perform high during this period. It is consistent with the fire sale story (Teo, 2011). However, Portfolio 1 performs well during other periods. In total, the prediction model maintained its empirical value and the result suggests that the opposite position should be take in the financial crisis period. The result supported hypothesis 2 that extracting hedge funds with low liquidity risk in the low failure risk hedge fund group can reduce fire sale problem and it present strong effect in the financial crisis period.

Chart 6.6: Performance of extracted portfolio (0-10 failure risk)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with 0-10% failure risk level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The evaluation period is from January 1999 to January 2014.



The portfolios with 0-10% investor-induced liquidity level are extracted in Table 6.7. Hedge funds in lower failure risk group perform relatively better than high failure risk group and top 5 portfolios perform higher than average level. It supports the hypothesis 1 that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that performs better than the model with single dimension on investor-induced liquidity. The Sharpe ratio of portfolios in Table 6.7 are all lower than Sharp ratio of top portfolio in Table 5.4 (3.7). It indicates that holding of all low investor induced liquidity group could bring a better risk adjusted return. In addition, mean of fund quantity for extracted portfolio is not equal. It is shown in table 6.7 that the quantity of hedge fund in the top portfolio is much more than other extracted portfolios. Take minimum investment into consideration, holding of the whole top portfolio could cost even double amount of minimum investment to other portfolios. In addition, the performance of hedge funds from low failure risk level to high failure risk level declined stable and it is more stable than the performance of hedge funds from low investor-induced liquidity level to high investor-induced liquidity level (Table 6.6). It suggests that the failure risk of a hedge fund has more explanatory than investor-induced liquidity on the hedge fund performance.

Chart 6.7 presents more details on the empirical value of the extracted portfolios. The aggregated half year return reveals actual return on each extracted portfolio with 0-10% liquidity risk level. Normally, hedge funds in low failure risk portfolios present high performance. The result supported hypothesis 1 that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that performs better than the model with a single dimension. The result between 121th and 124th shows that portfolio with high failure risk did not experience higher return in portfolios of hedge funds with low investor-induced liquidity. It suggests that the hedge funds with low investor-induced liquidity perform badly regardless of failure risk. It is consistent with Teo (2011) that the effect of fire sales influence hedge funds' performance when market liquidity and fund liquidity are both tight.

Table 6.7: Prediction model (0-10% liquidity level)

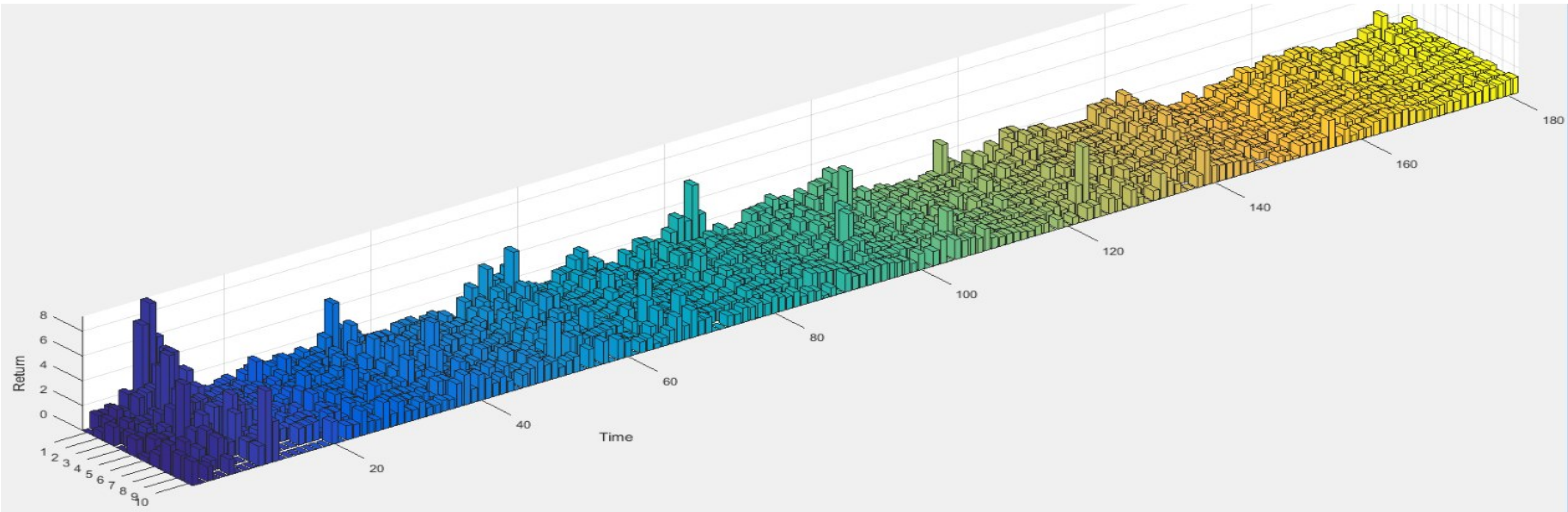
Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with first 0-10% liquidity level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent an average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value	Sharpe ratio
	0-10% S ; 0-10% L	58%	21.46	34%	0.00****	3.1
Average return	10%-20% S ; 0%-10% L	40%	13.32	16%	0.00****	3.3
	20%-30% S ; 0%-10% L	32%	10.38	12%	0.01***	3.4
24%	30%-40% S ; 0%-10% L	31%	8.87	8%	0.09**	2.7
	40%-50% S ; 0%-10% L	31%	8.24	7%	0.07**	2.8
	50%-60% S ; 0%-10% L	26%	7.55	2%	0.59	2.9
	60%-70% S ; 0%-10% L	24%	7.11	0%	0.97	2.7
	70%-80% S ; 0%-10% L	25%	6.46	1%	0.76	2
	80%-90% S ; 0%-10% L	22%	5.82	-2%	0.69	2.5
	90%-100% S ; 0%-10%L	18%	4.12	-6%	0.27	2.8

Chart 6.7: Performance of each portfolio (0%-10% investor-induced liquidity)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with the first 0-10% liquidity level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate nine months' aggregate return for each portfolio. The evaluation period is from June 1999 to June 2014.



The portfolios with 90-100% investor-induced liquidity level are extracted in Table 6.8. Hedge funds in Portfolio 1 with high investor-induced liquidity and low failure risk performs not significantly different with average level (over 40% significant level). It indicates that the holding of the portfolio with the highest investor-induced liquidity and the lowest failure risk delivers similar performance in the hedge fund market in the post-ranking periods. The performance of portfolios shows less order from low failure risk group to high failure risk group. However, the top portfolio present highest risk adjusted return. The result supports the hypothesis 3 that we can extract hedge funds with low failure risk from high investor-induced liquidity group in order to decrease failure risk of hedge funds in low liquidity risk groups. It would provide a portfolio with lowest failure risk and liquidity risk and the performance is not significantly different with industry return.

Integrating result in Table 6.5, Table 6.6, Table 6.7, Table 6.8 and Table 6.9, mean of fund quantity for extracted portfolio is not equal. More specifically, the top portfolio in the prediction model (0-10% failure risk and investor-induced liquidity level) contains a large number of hedge fund (21.98). The mean of fund quantity of top portfolio is 1.5 to 5 times to the number of other portfolios. This result consistent with Teo (2011) that hedge funds embrace high liquidity risk experienced good performance. More interestingly, the number of hedge funds in lowest failure risk level distributed more in low investor-induced liquidity level (Table 6.6) and the number of hedge funds in highest failure risk level distributed more in high investor-induced liquidity level (Table 6.9). For the lowest failure risk group, there is more number of hedge fund embrace low investor-induced liquidity for high performance and the possible fire sale problem could not cause more risk of fund failure. For the highest failure risk group, there is more number of hedge fund attracting high investment for low liquidity risk. It could help them to decrease fire sale problem, especially in the financial crisis period. As the result, this group of hedge fund could reverse the significance of negative BHAR (-0.08% at 20% significant level).

Chart 6.8 presents more details on the empirical value of the portfolios with 90-100% investor-induced liquidity level. The aggregated half year return reveals actual return on each extracted portfolio with 90-100% investor-induced liquidity level. The result between 121th and 125th shows that the hedge funds embracing a different level of failure risk have similar performance. That is the portfolio performance between January 2009 and May 2009. The evaluation period of these times is 5 tests after the collapse of Lehman Brothers on September 15, 2008. The result supports the hypothesis 3 that we can extract hedge funds with lower failure risk from high investor-induced liquidity group in order to decrease failure risk of hedge funds with low liquidity risk (funds with low fire sale problem) in the financial crisis period.

Table 6.8: Prediction model (90%-100% liquidity level)

Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with last 90-100% liquidity level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value	Sharpe ratio
	0-10% S ; 90-100% L	20%	9.09	-4%	0.43	2.6
Average return	10%-20% S ; 90%-100% L	23%	8.16	-1%	0.92	1.7
	20%-30% S ; 90%-100% L	18%	8.57	-6%	0.06**	1.9
24%	30%-40% S ; 90%-100% L	17%	8.69	-7%	0.06**	1.8
	40%-50% S ; 90%-100% L	21%	8.95	-3%	0.43	1.2
	50%-60% S ; 90%-100% L	14%	9.48	-10%	0.05**	1.6
	60%-70% S ; 90%-100% L	19%	9.84	-5%	0.20	1.6
	70%-80% S ; 90%-100% L	16%	10.12	-8%	0.03***	1.7
	80%-90% S ; 90%-100% L	13%	10.74	-11%	0.00****	1.9
	90%-100%S;90%-100%L	18%	0.19	-8%	0.19	1.1

Chart 6.8: Performance of each portfolio (90-100% investor-induced liquidity)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with the last 90%-100% liquidity level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate nine months' aggregate return for each portfolio. The evaluation period is from June 1999 to June 2014.

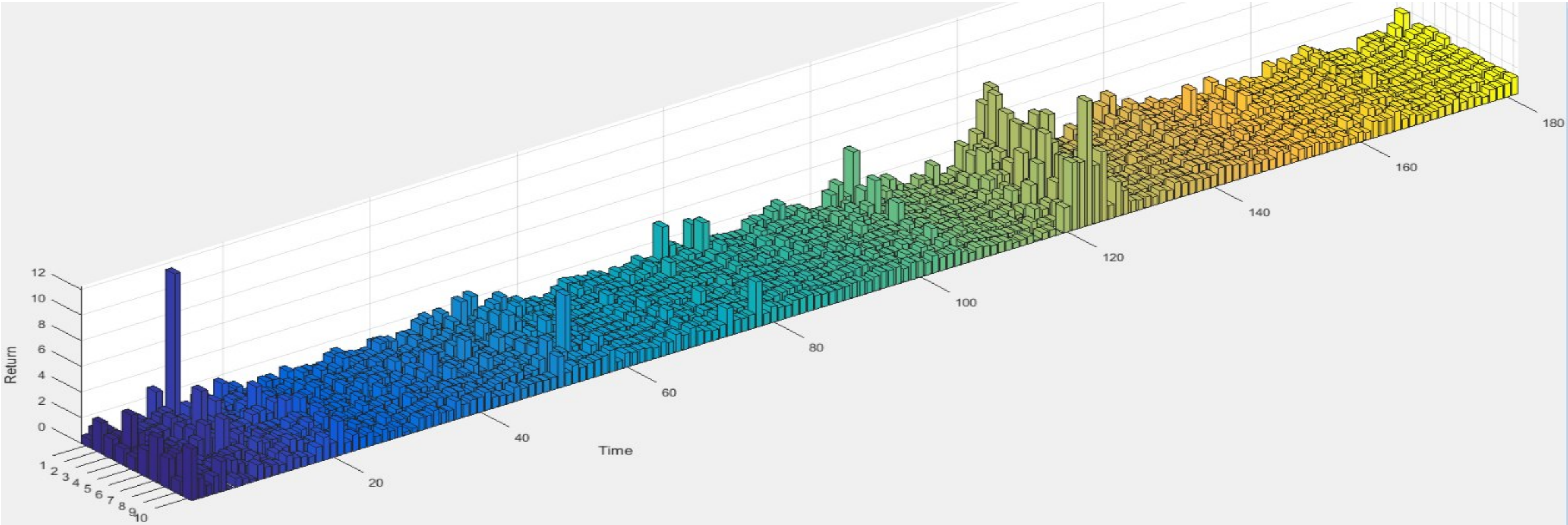


Table 6.9: Prediction model (90%-100% failure risk level)

Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with last 90-100% failure risk level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value	Sharpe ratio
	90-100% S ; 0-10% L	18%	4.12	-6%	0.27	2.8
Average return	90%-100% S ; 10%-20% L	16%	8.16	-8%	0.05***	3
	90%-100% S ; 20%-30% L	13%	8.57	-11%	0.00****	3.2
24%	90%-100% S ; 30%-40% L	15%	8.69	-9%	0.00****	3.2
	90%-100% S ; 40%-50% L	16%	8.95	-8%	0.00****	3.5
	90%-100% S ; 50%-60% L	14%	9.48	-10%	0.00****	3.1
	90%-100% S ; 60%-70% L	9%	9.84	-15%	0.00****	3.3
	90%-100% S ; 70%-80% L	18%	10.12	-6%	0.00****	3.1
	90%-100% S ; 80%-90% L	10%	10.74	-14%	0.00****	2
	90%-100%S; 90%-100%L	16%	10.91	-8%	0.19	1.1

6.7 Robustness test

6.7.1 Robustness test on different set of partitions

Empirical analysis suggests that mean of fund quantity of extracted portfolio is not equal in many cases. Take minimum investment into consideration, holding of the whole top portfolio could cost even double amount of minimum investment to other portfolios. Therefore, it is necessary to do robustness test on the performance of a different set of partitions. In the first step, observations are arranged according to survival risk and investor-induced liquidity with 2 levels (15% each arranging from 0 to 30%). There are 4 portfolios of hedge funds are produced by using of 15 percentile on both dimensions. In the second step, observations are arranged according to survival risk and investor-induced liquidity with 2 levels (30% each arranging from 0 to 60%). There are 4 portfolios of hedge funds are produced by using of 30 percentile on both dimensions. Then I calculate buy and hold abnormal return on each portfolio six months forward. The Buy and hold abnormal return reveals corresponding differences between the return of the hedge fund market and the return of portfolios sorted by investor-induced liquidity and failure risk level. Mean of fund quantity/ portfolios represent average number of hedge funds in extracted portfolio.

It is shown in Table 6.9 that the result robust to wide range of partitions. Hedge funds in portfolios with the lowest investor-induced liquidity and lowest failure risk present economically and statistically significant positive Buy and hold abnormal return. The portfolio with top 15% of failure risk and investor-induced liquidity experienced 26% of buy and hold abnormal return. The portfolio with top 30% of failure risk and investor-induced liquidity experienced 11% of buy and hold abnormal return. The results are all at 0.5% significance level. The top portfolios present higher BHAR than other portfolios. However, using of a wider range of partitions, the difference of the mean of fund quantity per portfolio between top portfolios and other portfolios are not decreased (about 1.5 times of other portfolios).

Table 6.9: Prediction model (wider range of partitions)

Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with different levels (15% and 30% each arranging from low to high respectively). The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value
	0-15% S ; 0-15% L	50%	47	26%	0.00****
Average return	0%-15% S ; 15%-30% L	26%	29	2%	0.44
	15%-30% S ; 0%-15% L	32%	32	8%	0.01***
24%	15%-30% S ; 15%-30% L	20%	32	-4%	0.08**
	0%-30% S ; 0%-30% L	1.35	140	11%	0.00****
	0%-30% S ; 30%-60% L	19%	104	-5%	0.00****
	30%-60% S ; 0%-30% L	24%	106	-0%	0.95
	30%-60% S ; 30%60% L	16%	116	-8%	0.00****

Mean of the quantity of hedge funds in the outperform portfolio is much more than other portfolios. The performance of this group of hedge fund could be less influenced by liquidity condition or survival risk as they could consider less of tightening investment environment. It is necessary to do robustness test for this group of hedge funds with smaller partitions. In the first step, observations are arranged according to survival risk and investor-induced liquidity with 3 levels (5% each arranging from 0 to 15%). There are 9 portfolios of hedge funds are produced by using of 5 percentile on both dimensions. In the second step, observations are arranged according to survival risk and investor-induced liquidity with 5 levels (3% each arranging from 0 to 15%). There are 25 portfolios of hedge funds are produced by using of 3 percentile on both dimensions. Then I calculate buy and hold abnormal return on each portfolio six months forward. The Buy and hold abnormal return reveals corresponding differences between the return of the hedge fund market and the return of portfolios sorted by investor-induced liquidity and failure risk level. Mean of fund quantity/ portfolios represent average number of hedge funds in extracted portfolio.

It is shown in Table 6.10 and Table 6.11 that the result robust to a narrow range of partitions. Hedge funds in portfolios with the lowest investor-induced liquidity and lowest failure risk present economically and statistically significant positive Buy and hold abnormal return. The portfolio with top 5% of failure risk and investor-induced liquidity experienced 51% of buy and hold abnormal return. The portfolio with top 3% of failure risk and investor-induced liquidity experienced 53% of buy and hold abnormal return. The results are all at 0.5% significance level. The top portfolios present higher BHAR than other portfolios. However, using of a wider range of partitions, the difference of the mean of fund quantity per portfolio between top portfolios and other portfolios are not decreased (about 1.5 times of other portfolios.

Table 6.10: Prediction model (5% risk level)

Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with 3 levels (5% each arranging from 0% to 15%) The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value
	0-5% S ; 0-5% L	75%	8.17	51%	0.00****
Averag e return	0%-5% S ; 5%-10% L	50%	4.14	26%	0.07**
	0%-5% S ; 10%-15% L	34%	3.08	10%	0.12*
24%	5%-10% S ; 0%-5% L	53%	4.87	29%	0.01***
	5%-10% S ; 5%-10% L	.38%	4.28	14%	0.01***
	5%-10% S ; 10%-15% L	35%	3.60	11%	0.07**
	10%-15% S ; 0%-5% L	39%	3.23	15%	0.03***
	10%-15% S ; 5%-10% L	49%	3.59	25%	0.01***
	10%-15% S ; 10%-15%L	35%	3.54	11%	0.08**

Table 6.11: Prediction model (3% risk level)

Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with 5 levels (3% each arranging from 0% to 15%) The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return.

	Portfolio	Return	Mean	BHAR	P-value
	0-3% S ; 0-3% L	77%	3.78	53%	0.01***
Average return	3%-6% S ; 3%-6% L	48%	2.01	24%	0.01***
	6%-9% S ; 6%-9% L	40%	1.55	16%	0.07**
24%	9%-12% S ; 9%-12% L	33%	1.17	9%	0.20
	12%-15% S ; 12%-15% L	29%	1.3	5%	0.60
	0%-3% S ; 3%-6% L	71%	2.15	47%	0.00****
	0%-3% S ; 6%-9% L	51%	1.33	27%	0.06**
	0%-3% S ; 9%-12% L	31%	1.16	7%	0.45
	0%-3% S ; 12%-15% L	47%	0.93	23%	0.05***
	3%-6% S ; 0%-3% L	70%	2.64	46%	0.00****
	6%-9% S ; 0%-3% L	69%	2.60	45%	0.00****
	9%-12% S ; 0%-3% L	34%	1.22	10%	0.30
	12%-15% S ; 0%-3% L	35%	1.12	11%	0.44

Chart 6.9 presents the average buy and hold abnormal returns of robustness test on 5% risk level. The observations are arranged according to liquidity and failure risk with 3 levels (5% each arranging from 0 to 15%). Chart 6.10 presents the average buy and hold abnormal returns of robustness test on 3% risk level. The observations are arranged according to liquidity and failure risk with 5 levels (3% each arranging from 0 to 15%). As can be seen from Chart 6.9 and Chart 6.10 that hedge funds with low investor-induced liquidity and failure risk experienced relatively better BHAR than the hedge funds with high investor-induced liquidity and failure risk. The result is robust to narrow range of partitions. Using of model with two dimentions, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that performs better than the model with a single dimension.

Chart 6.9: Prediction model (5% risk level)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with 3 levels (5% each arranging from 0% to 15%) The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.

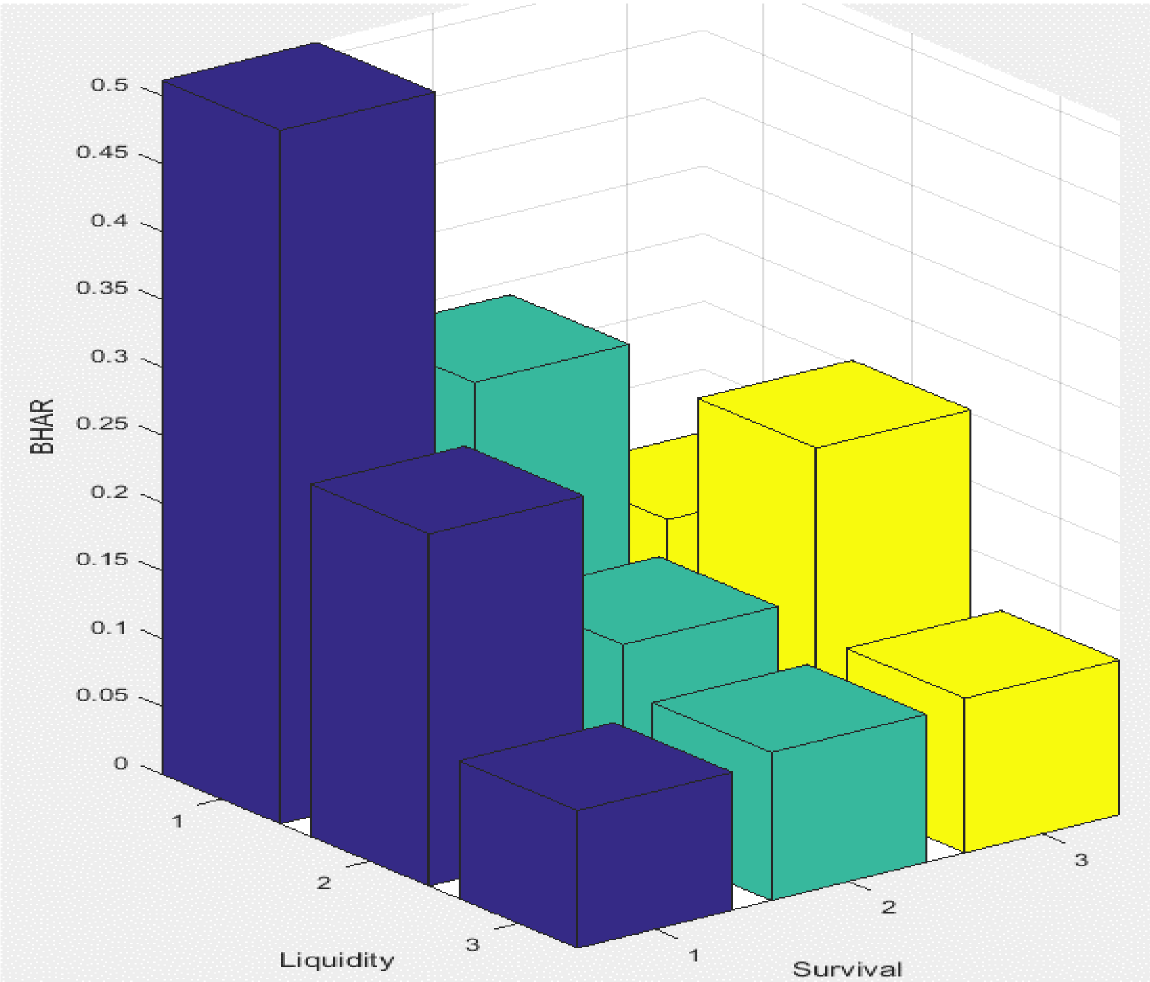
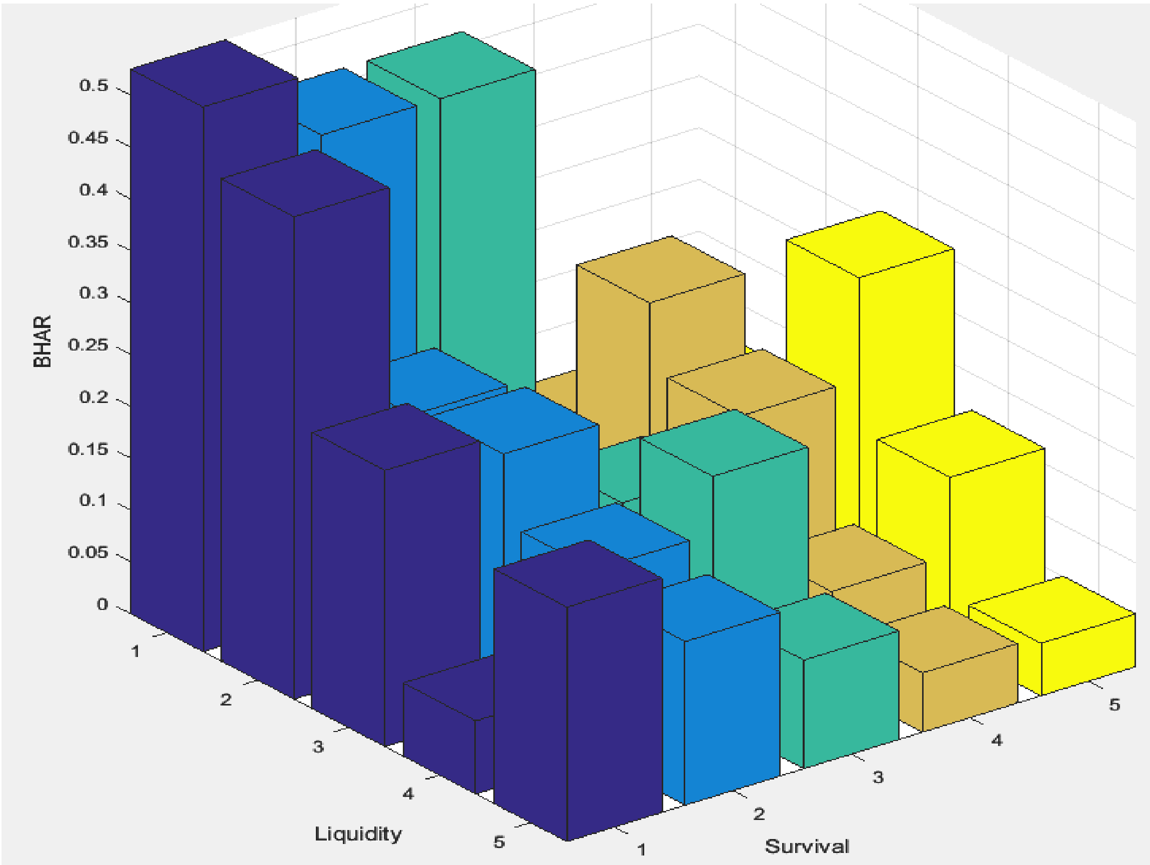


Chart6.10: Prediction model (3% risk level)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with 5 levels (3% each arranging from 0% to 15%) The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.



6.7.2 Robustness test on different estimation period

The previous section indicates that less distance past data influence more significantly on fund failure. However, using of longer distance data, the Cox proportional hazard model could estimate covariates with a more significant result. Therefore, it is necessary to do robustness test on a different length of historical data. This section does robustness test on 10 years historical data for robustness test. Every month starting from January 2004, I estimate the hazard index for each hedge fund using past 120 months' estimation period and then sort hedge funds by different survival risk levels. Simultaneously, I sort hedge funds based on their past aggregate investor-induced liquidity by using of 9-months' rolling window. The observations are arranged according to Survival risk and investor-induced liquidity with ten levels (10% each arranging from low to high). There are 100 portfolios of hedge funds are produced by using of 10 percentile on both dimensions. Then I calculate buy and hold abnormal return for each portfolio six months forward. The portfolios with equal risk level are extracted in Table 6.12. For example, 0-10% survival risk and 0-10% investor-induced liquidity. The Buy and hold abnormal return reveals corresponding differences between return in the hedge fund market and return on portfolios sorted by investor-induced liquidity and failure risk. Mean of fund quantity/ portfolios represent average number of hedge funds in extracted portfolio.

Table 6.12 shows that the result is robust to 10 years historical estimation period. Hedge funds in Portfolio 1 with low investor-induced liquidity and low failure risk present economically and statistically significant positive Buy and hold abnormal return. The portfolio with top 10% of failure risk and investor-induced liquidity experienced 26% of buy and hold abnormal return and it is at 0.5% significance level. It indicates that the holding of the portfolio with lowest investor-induced liquidity and lowest failure risk delivers economically significant return higher than average return in the hedge fund market in the post-ranking periods. It is similar to original prediction model that portfolio 10 with a higher failure risk do not present a significantly lower return in the hedge fund market. It could because hedge funds with higher failure risk or investor-induced liquidity have higher probability of getting extremely high returns in the financial crisis period. The performance of prediction model with two dimensions is more closed to the performance of prediction model based on Cox proportional hazard model.

Table 6.12: Prediction model (10-year estimation period)

Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with equal risk level is extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 2004 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value
	0-10% S ; 0-10% L	50%	25.98	26%	0.00****
Average return	10%-20% S ; 10%-20% L	27%	15.44	3%	0.40
	20%-30% S ; 20%-30% L	18%	14.13	-6%	0.09**
24%	30%-40% S ; 30%-40% L	20%	13.1	-4%	0.09**
	40%-50% S ; 40%-50% L	18%	13.57	-6%	0.00****
	50%-60% S ; 50%-60% L	16%	12.34	-8%	0.00****
	60%-70% S ; 60%-70% L	12%	13.64	-12%	0.00****
	70%-80% S ; 70%-80% L	18%	12.19	-6%	0.04***
	80%-90% S ; 80%-90% L	11%	11.45	−13%	0.00****
	90%-100%S;90%-100%L	19%	13.1	-0%	0.96

Chart 6.11 presents more details on the empirical value of the extracted portfolios. The aggregated half year return reveals actual return on each extracted portfolio with equal risk level on both liquidity and survival risk. Normally, hedge funds in portfolios with lower liquidity and failure risk level present higher performance. The result between 60th and 64th shows that portfolio with more investor-induced liquidity and failure risk experienced higher return. That is the portfolio performance between December 2008 and April 2009. The evaluation period of these times is 5 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge funds embracing higher liquidity risk and failure risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 experienced high performance during this period. It is consistent with the fire sale story (Teo, 2011). However, Portfolio 1 performs well during other periods. In total, the result robust to 10-year estimation period in Cox proportional hazard model. The prediction model maintained its empirical value and the result suggests that the opposite position should be take in the financial crisis period.

Chart 6.12 presents the average value of six month's buy and hold abnormal returns of 100 portfolios in the prediction model. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high). As can be seen from Chart 6.5, hedge funds with low investor-induced liquidity and failure risk experienced relatively better BHAR than the hedge funds with high investor-induced liquidity and failure risk. The result robust to 10-year estimation period in Cox proportional hazard model. It supports the hypothesis 1 that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that performs better than the model with a single dimension. Interestingly, the BHAR presents a damped oscillation like figure for hedge funds in 0-10% failure risk level from low investor-induced liquidity to high investor-induced liquidity. The BHAR oscillates gradually decreasing and closed to industry return. It supports hypothesis 2 that we can extract hedge funds with high investor-induced liquidity from the low failure risk hedge fund group in order to reduce fire sale problem for low failure risk hedge funds. However, there is no clear evidence for hypothesis 3 that we can extract hedge funds with lows failure risk from high investor-induced liquidity group in order to decrease failure risk for hedge funds with low liquidity risk.

Chart 6.11: Performance of each portfolio (10-year estimation period)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with equal risk level is extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The evaluation period is from January 2004 to January 2014.

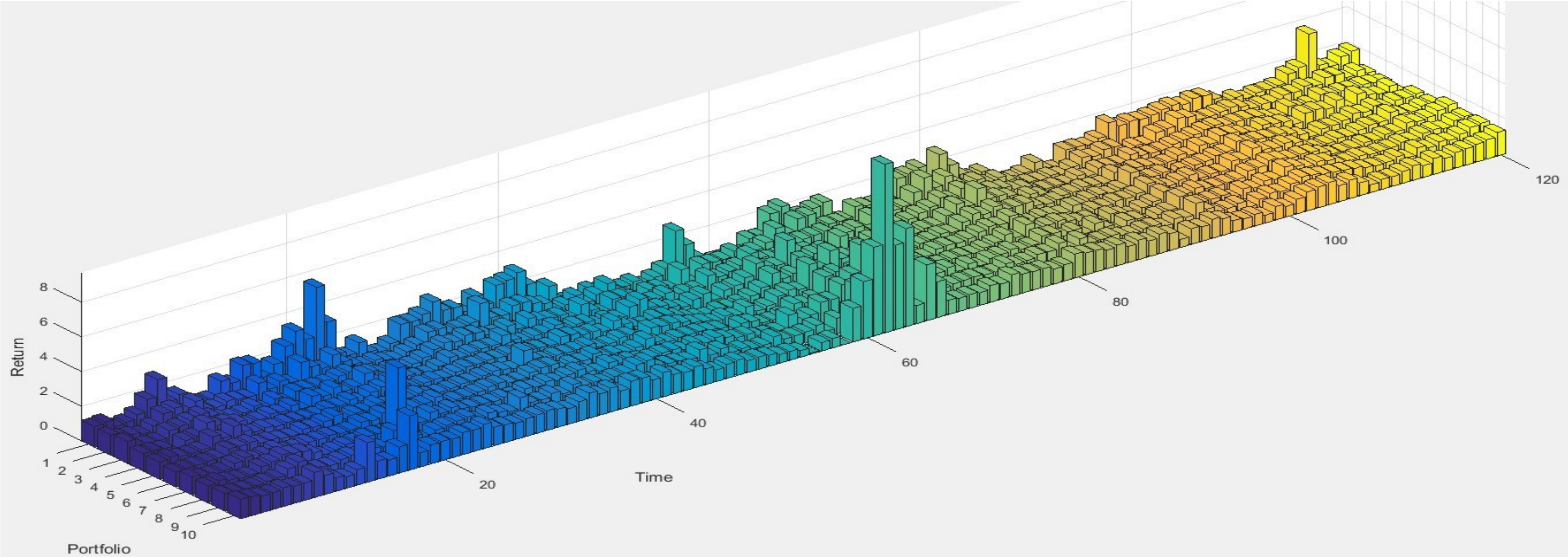
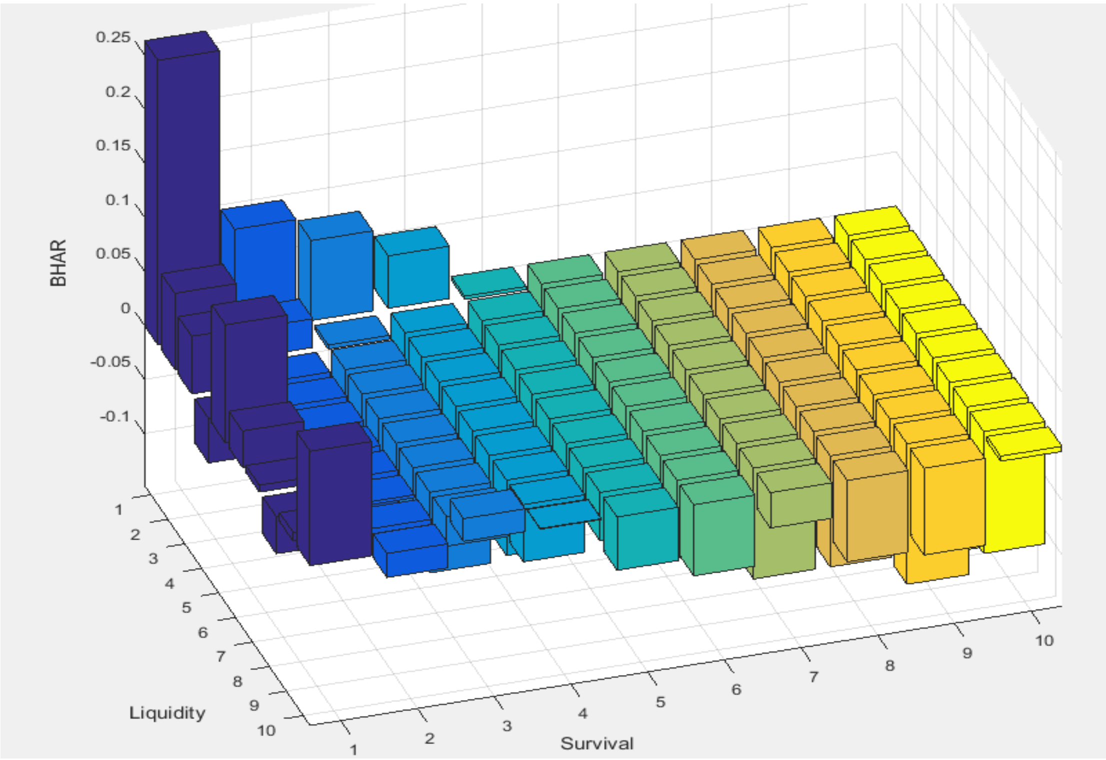


Chart 6.12: Prediction model (10-year estimation period)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high). The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The evaluation period is from January 2004 to January 2014



The portfolios with 0-10% failure risk level are extracted in Table 6.13. The result robust to 10 year estimation period that hedge funds in lower investor-induced liquidity group performs relatively better than high investor-induced liquidity group. It supports the hypothesis 1 that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that performs better than the model with single dimension on failure risk. Hedge funds in Portfolio 10 with high investor-induced liquidity and low failure risk performs significantly different with 0. It indicates that the holding of the portfolio with high investor-induced liquidity and low failure risk outperform hedge fund market in the post-ranking periods. The result supports the hypothesis 2 that we can extract hedge funds with high investor-induced liquidity from low failure risk group in order to reduce fire sale problem for low failure risk hedge funds.

Chart 6.13 presents more details on the empirical value of the extracted portfolios. The result robust to 10-year estimation period. Aggregated half year return reveals actual return on each extracted portfolio with 0-10% failure risk level. Normally, hedge funds in lower liquidity portfolios present higher performance. The result between 61st and 63th shows that portfolio with more investor-induced liquidity experienced higher return. That is the portfolio performance between January 2009 and March 2009. The evaluation period of these times is 3 tests after the collapse of Lehman Brothers on September 15, 2008. The hedge fund,s embracing higher liquidity risk could face with fire sale problem during this period. On the other side, hedge funds in the Portfolio 10 with low liquidity risk perform high during this period. It is consistent with the fire sale story (Teo, 2011). However, Portfolio 1 performs well during other periods. In total, the prediction model maintained its empirical value and the result suggests that the opposite position should be take in the financial crisis period. The result supported hypothesis 2 that extracting hedge funds with low liquidity risk in the low failure risk hedge fund group can reduce fire sale problem and it present strong effect in the financial crisis period.

Table 6.13: Prediction model (10-year estimation period 0-10% failure risk level)

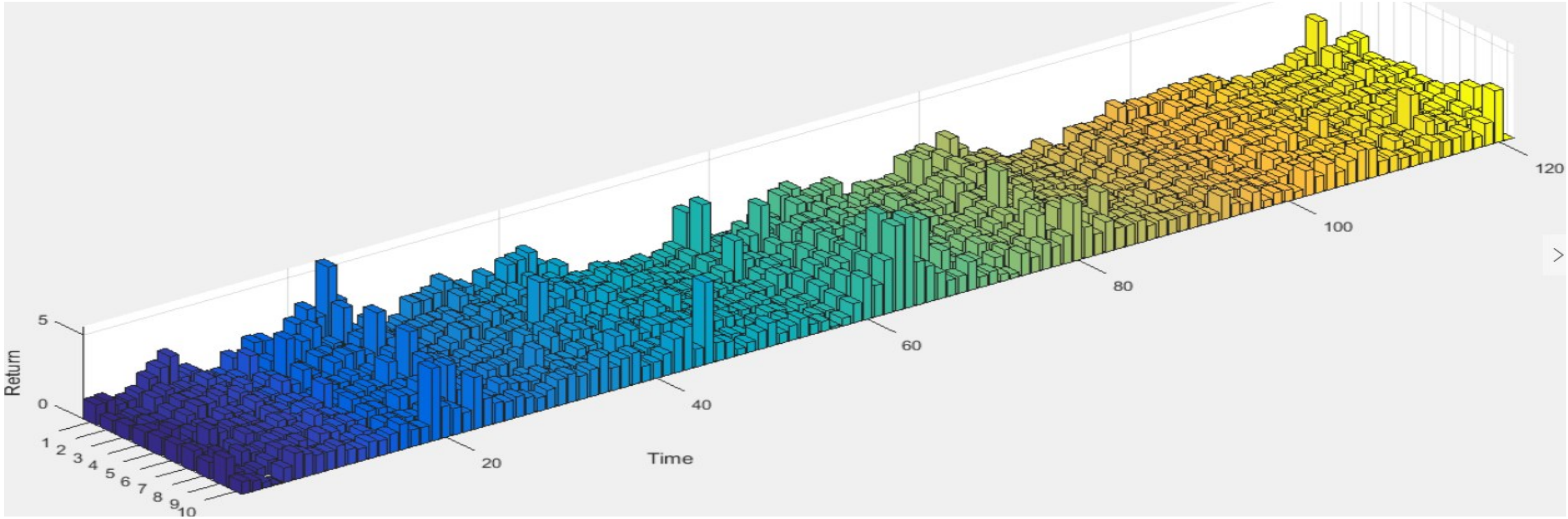
Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with 0-10% failure risk level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 2004 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value
	0-10% S ; 0-10% L	50%	25.98	26%	0.00****
Average return	0%-10% S ; 10%-20% L	31%	14.96	7%	0.15*
	0%-10% S ; 20%-30% L	29%	11.59	5%	0.18
24%	0%-10% S ; 30%-40% L	20%	72.75	-4%	0.16
	0%-10% S ; 40%-50% L	1.35	8.69	11%	0.01***
	0%-10% S ; 50%-60% L	21%	8.68	3%	0.41
	0%-10% S ; 60%-70% L	25%	8.02	1%	0.83
	0%-10% S ; 70%-80% L	21%	9.17	-3%	0.35
	0%-10% S ; 80%-90% L	25%	10.93	1%	0.87
	0%-10% S ; 90%-100%L	1.35	16.46	11%	0.10**

Chart 6.13: Performance of each portfolio (10-year estimation period 0-10% failure risk level)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with 0-10% failure risk level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The evaluation period is from January 2004 to January 2014.



The portfolios with 0-10% investor-induced liquidity level are extracted in Table 6.14. The result robust to 10 year estimation period that hedge funds in lower failure risk group perform relatively better than high failure risk group and top 3 portfolios performs higher than average level. It supports the hypothesis 1 that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that performs better than the model with single dimension on investor-induced liquidity. In addition, mean of fund quantity for extracted portfolio is not equal. It is shown in table 6.7 that the quantity of hedge fund in the top portfolio is much more than other extracted portfolios.

Chart 6.14 presents more details on the empirical value of the extracted portfolios. The result robust to 10-year estimation period. Aggregated half year return reveals actual return on each extracted portfolio with 0-10% liquidity risk level. Normally, hedge funds in low failure risk portfolios present high performance. The result supported hypothesis 1 that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that performs better than the model with a single dimension. The result between 61st and 64th shows that portfolio with high failure risk did not experience higher return in portfolios of hedge funds with low investor-induced liquidity. It suggests that the hedge funds with low investor-induced liquidity perform badly regardless of failure risk. It is consistent with Teo (2011) that the effect of fire sales influence hedge funds' performance when market liquidity and fund liquidity are both tight.

Table 6.14: Prediction model (10-year estimation period 0-10% liquidity level)

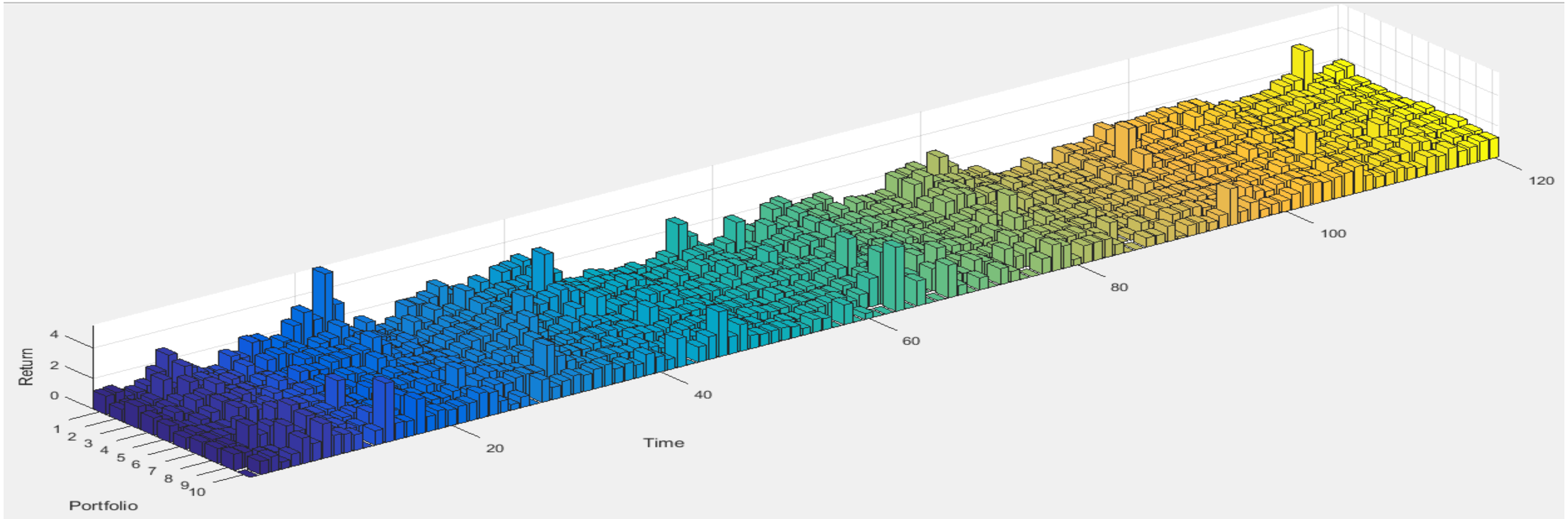
Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with 0-10% liquidity level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 2004 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value
	0-10% S ; 0-10% L	50%	25.98	26%	0.00****
Average return	10%-20% S ; 0%-10% L	34%	13.92	10%	0.02***
	20%-30% S ; 0%-10% L	31%	14.54	7%	0.10**
24%	30%-40% S ; 0%-10% L	19%	14.15	5%	0.23
	40%-50% S ; 0%-10% L	21%	12.35	-3%	0.94
	50%-60% S ; 0%-10% L	20%	9.23	-4%	0.17
	60%-70% S ; 0%-10% L	21%	7.98	-3%	0.43
	70%-80% S ; 0%-10% L	15%	7.52	-9%	0.01***
	80%-90% S ; 0%-10% L	17%	6.71	-7%	0.04***
	90%-100% S ; 0%-10%L	19%	4.51	-5%	0.42

Chart 6.14: Performance of each portfolio (10-year estimation period 0-10% liquidity risk level)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with 0-10% liquidity level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data.   Return is the aggregate nine months' aggregate return for each portfolio. The evaluation period is from June 2004 to June 2014.



The portfolios with 90-100% investor-induced liquidity level are extracted in Table 6.15. The result robust to 10 year estimation period. Hedge funds in Portfolio 1 with high investor-induced liquidity and low failure risk experienced economically and significantly positive BHAR (11% BHAR at 10% significant level). The result supports the hypothesis 3 that we can extract hedge funds with low failure risk from high investor-induced liquidity group in order to decrease failure risk of hedge funds in low liquidity risk groups. Integrating result in Table 6.12, Table 6.13, Table 6.14, Table 6.15 and Table 6.16, mean of fund quantity for extracted portfolio is not equal. More specifically, the top portfolio in the prediction model (0-10% failure risk and investor-induced liquidity level) contains a big number of hedge fund (25.98). The mean of fund quantity of top portfolio is 1.5 to 5 times to the number of other portfolios. This result consistent with Teo (2011) that hedge funds embrace high liquidity risk experienced good performance. More interestingly, the number of hedge funds in lowest failure risk level distributed more in low investor-induced liquidity level (Table 6.12) and the number of hedge funds in highest failure risk level distributed more in high investor-induced liquidity level (Table 6.16). For the lowest failure risk group, there are more number of hedge funds embrace low investor-induced liquidity for high performance and the possible fire sale problem could not cause more risk of fund failure. For the highest failure risk group, there are more number of hedge funds attracting high investment for low liquidity risk. It could help them to decrease fire sale problem especially in the financial crisis period.

Chart 6.15 presents more details on the empirical value of the portfolios with 90-100% investor-induced liquidity level. The result robust to 10-year estimation period. Aggregated half year return reveals actual return on each extracted portfolio with 90-100% investor-induced liquidity level. The result between 61st and 65th shows that the hedge funds embracing a different level of failure risk have similar performance. That is the portfolio performance between January 2009 and May 2009. The evaluation period of these tests are 5 tests after the collapse of Lehman Brothers on September 15, 2008. The result supports the hypothesis 3 that we can extract hedge funds with lower failure risk from high investor-induced liquidity group in order to decrease failure risk of hedge funds with low liquidity risk (funds with low fire sale problem) in the financial crisis period.

Table 6.15: Prediction model (10-year estimation period 90-100% liquidity level)

Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with last 90-100% liquidity level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 2004 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value
	0-10% S ; 90-100% L	35%	16.46	11%	0.10**
Average return	10%-20% S ; 90%-100% L	22%	6.40	-2%	0.64
	20%-30% S ; 90%-100% L	26%	10.86	2%	0.65
24%	30%-40% S ; 90%-100% L	24%	9.59	0%	0.99
	40%-50% S ; 90%-100% L	19%	9.59	-5%	0.21
	50%-60% S ; 90%-100% L	17%	11.27	-7%	0.03***
	60%-70% S ; 90%-100% L	21%	11.36	-3%	0.53
	70%-80% S ; 90%-100% L	16%	12.65	-8%	0.09**
	80%-90% S ; 90%-100% L	16%	13.14	-8%	0.03***
	90%-100%S;90%-100%L	24%	13.1	-0%	0.96

Chart 6.15: Performance of each portfolio (10-year estimation period 90-100% liquidity level)

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with the last 90%-100% liquidity level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate nine months' aggregate return for each portfolio. The evaluation period is from June 2004 to June 2014.

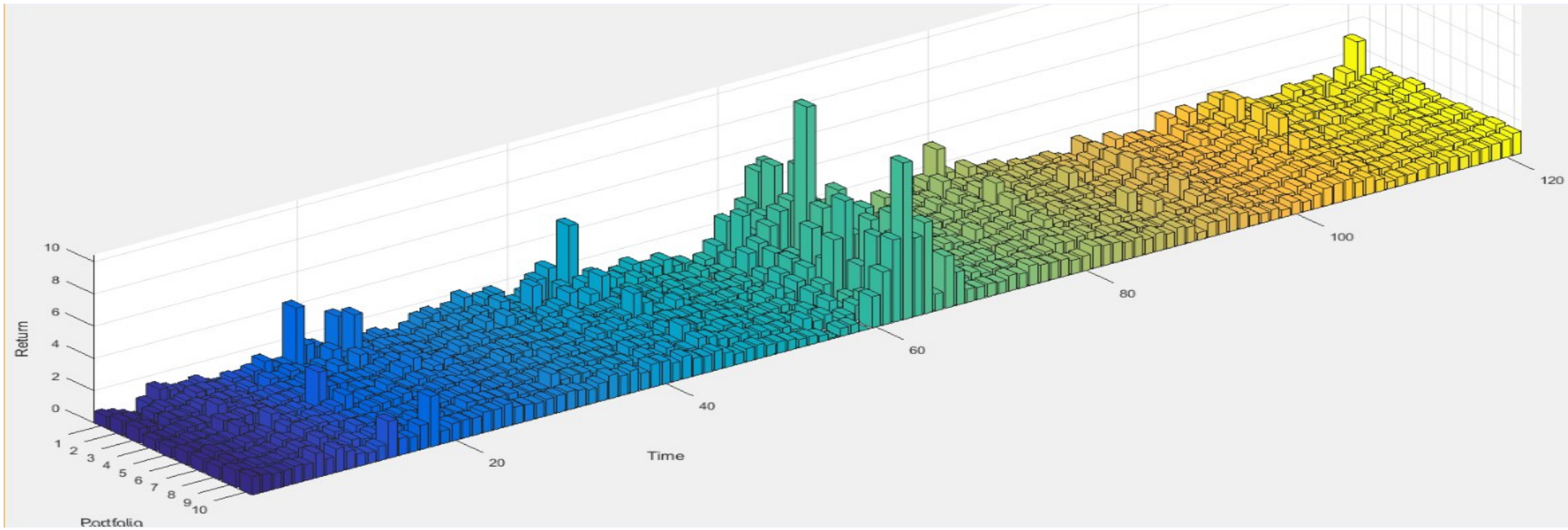


Table 6.16: Prediction model (90%-100% failure risk level)

Sorts on failure risk and investor-induced liquidity

Hedge funds are sorted every month based on their failure risk and investor-induced liquidity estimated last month. The observations are arranged according to liquidity and failure risk with ten levels (10% each arranging from low to high) The portfolios with last 90-100% failure risk level are extracted. The hazard ratio is estimated by equation (4.1), where vector β is estimated by the Cox proportional hazard model using last 60 months' data and z is the vector of covariate for each fund. The identification of real fund failure follows section 6.5.5.The aggregate investor-induced liquidity is estimated by equation (5.3), where investor-induced liquidity is estimated by equation (5.2) using last 9 months' data. Return is the aggregate six months' return for each portfolio. The P-values are derived from standard errors. Mean of fund quantity/Portfolio represent average number of hedge funds in extracted portfolio. BHAR is Buy-and-Hold abnormal return estimated by equation (4.2) using 6 months' forward return. The evaluation period is from January 1999 to January 2014.

	Portfolio	Return	Mean	BHAR	P-value
	90-100% S ; 0-10% L	20%	4.51	-4%	0.42
Average return	90%-100% S ; 10%-20% L	17%	4.65	-7%	0.04***
	90%-100% S ; 20%-30% L	13%	4.80	-11%	0.00****
24%	90%-100% S ; 30%-40% L	15%	5.22	-9%	0.00****
	90%-100% S ; 40%-50% L	13%	5.88	-11%	0.00****
	90%-100% S ; 50%-60% L	15%	7	-9%	0.00****
	90%-100% S ; 60%-70% L	9%	7.63	-15%	0.00****
	90%-100% S ; 70%-80% L	11%	8.6	-13%	0.00****
	90%-100% S ; 80%-90% L	13%	10.54	-11%	0.03***
	90%-100%S;90%-100%L	24%	13.1	-0%	0.96

In this chapter, I also do robustness test on different estimation period for assessing of investor-induced liquidity and different evaluation period for assessing of BHAR. The result robust to 3, 9 and 12 months of different estimation period for assessing of investor-induced liquidity. The result robust to 3, 9 and 12 months of the different evaluation period for assessing of BHAR.

Prediction model can allocate portfolios of hedge funds that embrace low survival risk and liquidity risk with significantly high return. Moreover, the result robust to different estimation period and evaluation period. The result is not robust to 12-month estimation period and evaluation period on portfolios with high investor-induced liquidity. It indicates that the investor-induced liquidity in the less distance past has more explanatory power on fund performance. This test also robust to CAR methods with different evaluation periods. The most successful method is the original prediction model with 6-month estimation period and 6-month evaluation period. The result also indicates that incubation bias influence performance of hedge fund with high investor-induced liquidity the most significantly. The result from fund performance shows that the fire sale problem is more significant in the recent financial crisis period and it is not significant in a normal period. In total, the prediction model maintained its empirical value and it suggests that investors could take opposite position in the financial crisis period. For long term running, funds with low investor-induced liquidity and low survival risk earn high returns during 1994-2014.

The model with two dimensions performs better than a single test on survival risk and investor-induced liquidity. According to empirical result, we accept hypothesis 1 that using two dimension model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. It could form portfolios that perform better than the model with a single dimension. We also accept hypothesis 2 that we can extract hedge funds with high investor-induced liquidity from low failure risk group in order to reduce fire sale problem for low failure risk hedge funds. The extracted portfolio performs better than average value. The result also accepts the hypothesis 3 that we can extract outperform hedge funds with low failure risk from high investor-induced liquidity group in order to decrease the failure risk of hedge funds in low liquidity risk groups. As the result, on one hand, we can extract hedge funds with high investor-induced liquidity from low failure risk group in order to reduce fire sale problem for low failure risk hedge funds in the financial crisis period. On the other hand, we can extract hedge funds with low failure risk from high investor-induced liquidity group in order to increase return for hedge funds with low liquidity risk and failure risk.

6.8 Conclusion

This Chapter investigates predictability of hedge fund performance by combined prediction model. Using data purchased from hedge fund data vendor, this chapter provides a useful tool for hedge fund performance analysis. Based on previous 2 Chapters, both survival risk and liquidity risk are employed into the combined model. The prediction model can allocate portfolios of hedge funds with relatively low survival risk and investor-induced liquidity. The optimized portfolio experienced significant high performance. The model with two dimensions performs better than a single test on survival risk and investor-induced liquidity. On one hand, we can extract hedge funds with high investor-induced liquidity from low failure risk group in order to reduce fire sale problem for low failure risk hedge funds in the financial crisis period. On the other hand, we can extract hedge funds with low failure risk from high investor-induced liquidity group in order to increase return for hedge funds with low liquidity risk. The result also indicates that incubation bias influence performance of hedge fund with high investor-induced liquidity the most significantly. The result from fund performance shows that the fire sale problem is more significant in recent financial crisis period than normal period. It suggests that investors could take opposite position in the financial crisis period. For long term running, funds with low investor-induced liquidity and low survival risk earn high returns during 1994-2014.

This Chapter has 3 implications. Firstly, this chapter provides a useful tool to risk management department in order to evaluate hedge fund liquidity risk and survival risk together. Secondly, the combined prediction model from this chapter will allow investors include fund-of-fund manager to estimate the performance of hedge fund before allocation of the portfolio and it also provides warning signals to investors who have invested in a hedge fund. Last, the governance of hedge fund regulation could take both failure risk and liquidity risk into consideration. The difficulty of find out quality data of hedge fund is well recognized both within industry and academia. It is important to make information public in hedge fund industry. Moreover, take liquidity risk management into consideration, a large amount of investment inflow to individual hedge fund could bring a heavy burden of hedge fund performance. A large amount of investment outflow from individual hedge fund could cause fire sale problem when market liquidity is tight.

Chapter 7: Conclusion

7.1 Summary of research findings

Chapter 4 estimated the predictability of hedge fund performance by using a semi-parametric procedure. Firstly, it estimated causal factors that influence hedge fund failure risk. Using a Cox proportional hazard model, Chapter 4 estimated the characteristics that could influence hedge fund failure risk. TNA, leverage, minimum investment, return, average return in the past three months, variance, kurtosis and skewness of return, are the main characteristics that influence hedge fund failure risk. This thesis expects that fund size, mean of return, return on the last three months and skewness of return are negatively related to hedge fund failure risk. Large sized hedge funds could withstand a great change in returns, while hedge funds with insufficient size present a higher attrition rate. Moreover, hedge funds with a lack of capital find it hard to meet managerial expectations and bear the burden of fixed costs. It is expected that funds with low returns present a higher risk of failure. Funds with negative returns will experience a decrease of fund TNA. Moreover, negative returns could cause a lower expectation of the incentive fee and could further influence the propensity for the fund manager to close down the fund. Moreover, performance in the more recent past is of greater importance. Contemporary measures of mean returns have more explanatory power on fund failure than mean returns over the life of the fund. On the other hand, I expect leverage, minimum initial investment, and variance and kurtosis of return to be positively related to hedge fund failure risk. Funds with leverage could magnify their returns and help managers to control the volatility of returns. Simultaneously, using leverage could cause high fees and even fail to serve creditors. Funds with high minimum investment are likely to reject a large number of small-scale investors. This indicates that the stability of investment in funds is weaker and consequently of lower duration. Furthermore, high minimum investment allows redemption from a single investor to heavily influence the fund size. The increase of variance increases the probability of higher returns and the risk of low returns, however, the negative effects of downside risk outweigh the gains from upside risk. According to investors' utility function, investors will prefer high mean and skewness and low variance and kurtosis. It is expected that funds with high kurtosis and low skewness will have a high risk of failure.

Empirical findings suggest that hedge fund monthly returns are predictable. The results are robust to the different estimation period (10-year estimation period), and failure identification (alternative failure identifications and no filter on fund failure). The results are also robust to CAR method on abnormal return test. Chapter 4 confirms the previous studies on hedge fund survival risk analysis. The results further suggest that hedge funds with low failure risk outperform hedge funds embracing high failure risk. Remarkably, this chapter also provides identification of fund failure. The identification of fund failure can extract funds that are liquidated because of poor performance. Empirical evidence suggests that fund failure predicts hedge fund performance better than fund liquidation. The influence of failure risk and hedge fund returns is stable to a certain extent and it is helpful to investigate interactions between the risk of hedge funds and their performance practically.

Chapter 5 estimates the predictability of hedge fund performance by using liquidity risk. I employ investor-induced liquidity as the estimation of hedge fund liquidity. I expect that investor-induced liquidity will negatively influence hedge fund performance in the long term. The results are robust for different evaluation periods (3, 9 and 12 months' evaluation periods) and estimation periods (3, 9 and 12 months' evaluation periods). The results are also robust for non-filtering processes on backfill bias and different abnormal return measurement (CAR method). The result supports a stream of previous empirical reports that state a high net inflow of hedge funds shows a negative effect on performance in the long term. The results suggest that hedge fund liquidity risk derived from investors is an important factor of hedge fund performance analysis for the risk management department. The results also confirm that investor-induced liquidity in the more recent past has more explanatory power regarding its post-performance. Moreover, incubation bias could influence the predictability of hedge fund performance significantly. Taking liquidity risk management into consideration, large amounts of investment inflow to individual hedge funds could place a heavy burden on hedge fund performance. Large amounts of investment outflow from individual hedge funds could cause fire sale problems when market liquidity is tight. The results from fund performance show that the fire sale problem was more significant in the recent financial crisis period and high investment inflow influence is more significant in normal periods.

Chapter 6 investigates the predictability of hedge fund performance by using a combined prediction model. I expect that hedge funds with both low survival risk and low liquidity risk will experience significant high post-performance. Firstly, I expect that by using a two dimensional model, we can extract hedge funds with both low investor-induced liquidity and low failure risk. The model could form a portfolio that performs better than the model with a single dimension. Secondly, I expect that we can extract hedge funds with high investor-induced liquidity from the low failure risk group in order to reduce fire sale problems for low failure risk hedge funds. Lastly, I expect that we can extract hedge funds with low failure risk from high investor-induced liquidity groups, in order to decrease the failure risk of hedge funds in low liquidity risk groups. The results indicate that a combined prediction model exhibits more detail and performs better than using a prediction model with a single dimension. By using a combined prediction model, we can extract hedge funds with low investor-induced liquidity and failure risk with a significantly high performance in the hedge fund industry. The combined prediction model also enables us to extract hedge funds with low liquidity risk from low failure risk groups, which is helpful in reducing fire sale risk during financial crisis periods. Empirical results also indicate that the combined prediction model enables us to extract outperforming hedge funds with low failure risk from high investor-induced liquidity groups in order to decrease the failure risk of hedge funds in low liquidity risk groups. As a result, on the one hand, we can extract hedge funds with high investor-induced liquidity from low failure risk group. in order to reduce the fire sale problem for low failure risk hedge funds during a financial crisis period. On the other hand, we can extract hedge funds with low failure risk from high investor-induced liquidity groups in order to increase return for hedge funds with low liquidity risk and failure risk. The result also indicates that incubation bias influences the predictability of hedge fund performance. Moreover, more recent data influence the predictability of hedge fund performance more significantly. On the other hand, long term past data can bring more significant results in the estimation of covariates in a Cox proportional hazard model.

7.2 Implications of the research

This thesis documents the predictability of hedge fund performance by using survival risk analysis and liquidity risk analysis. On the one hand, forecasting models based on survival risk or liquidity risk analysis present high performance. On the other hand, prediction model combined survival risk analysis and liquidity risk provides more detail on hedge fund performance analysis. I read this result as evidence that the prediction of hedge fund performance is about presenting the structure of hedge fund returns, survival risk and liquidity risk. Fitting curves of a scatter plot could not present hedge fund performance sufficiently. This thesis is relevant to both researchers and practitioners in exploring a tangible analysis of hedge fund performance.

The prediction model of survival risk and liquidity risk analysis provides fundamental reactions between hedge fund characteristics, survival risk and performance. The results will allow investors to estimate the expected performance of a hedge fund before the allocation of portfolios and also provide warning signals to investors who have invested in a hedge fund. Furthermore, a model capable of predicting the risk of funds failure and estimating their performance will be invaluable to the broad set of stakeholders far beyond that of direct investors and creditors of hedge funds.

The results also provide warning signals regarding the governance of hedge funds. The governance of hedge funds could take information from this thesis. The difficulty of identifying the quality of hedge fund data is well recognized both within industry and academia. It is important to make detailed information public regularly using qualified data vendors. Furthermore, liquidity risk management plays an important role in the hedge fund industry. Large amounts of investment inflow to individual hedge funds could be a heavy burden on hedge fund performance and large amounts of investment outflow from individual hedge funds could cause fire sale problems when market liquidity is tight.

7.3 Limitations of research and areas for future study

The biggest issue stems from the raw information that is available in the TASS database. This study shows that estimation of hedge fund managers could be more accurate in the testing of fund liquidity and survival risk. However, the TASS database does not provide information on hedge fund managers. For an estimation of survival risk, the work of Bares, Gibson and Gyger (2001) is an example of estimation of hedge fund managers. This study shows the benefit of classifying new funds with existing managers that could have similar performance. For the estimation of liquidity, some hedge fund managers could launch new funds after the good performance of old funds. The new funds could be considered as the same fund and could present a more accurate estimation of fund flows and investor-induced liquidity. Furthermore, TASS provides all hedge funds' performance before they are listed on the database. There is not a specific time when hedge funds start to attract outside investors. As a result, it is hard to convert hedge fund minimum investment into dollars on a particular date. This study uses the exchange rate on July 31st, 2014 to estimate minimum investment and fund size.

Another concern is that the high net investment flow could scale in active portfolio management, which could subsequently cause an adverse impact on hedge fund future performance. Moreover, in terms of the redemption gate that hedge fund managers grant to investors, withdrawal of capital often forewarns hedge fund managers. The influence of fund flow could exist before the actual fund flow. Consequently, the timing strategy produced by this thesis could reduce the investors' return, which the hedge fund manager should consider, i.e. they keep the investment inflow in cash or invest it. Furthermore, this study only employ TASS database that is available in this research. There are other data vendors provide hedge fund information include FRM, Morning star and CSFB. With more comprehensive data, the result could be more precise. But it is hard to overturn the result that hedge fund with low failure risk perform better than average value.

Future research based on this thesis could explore several areas. Survival risk and failure risk analysis could be employed in other financial industries which present complicated characteristics or high attrition rates. In the hedge fund industry, this thesis employs investor-induced liquidity as a measure of liquidity risk. Other measures of liquidity risk or systematic risk could also perform well in the prediction of hedge fund performance. The regulation of hedge funds could change and, with more data, future analysis of hedge funds could be more precise.

References

Acharya, V.V., and Pedersen, L.H., 2005. Asset pricing with liquidity risk. *Journal of Financial Economics*. 77(2), pp. 375-410.

Ackermann, C., McEnally, R., and Ravenscraft, D., 1999. The Performance of Hedge Funds: Risk, Return and Incentives. *Journal of Finance*. 54(3) (June), pp. 833-874.

Adrian, T. "Measuring Risk in the Hedge Fund Sector." Current Issues in Economics and Finance, 13(2007), Federal Reserve Bank of New York, pp. 1-7.

Agarwal, V., and Naik, N.Y., 2000a. Multi-Period Performance Persistence Analysis of Hedge Funds. *Journal of Financial and Quantitative Analysis* .35, pp. 327-342.

Agarwal, V., and Naik, N.Y., 2000b. Performance Evaluation of Hedge funds with Optional-based and Buy-and-Hold Strategies. Working thesis.

Agarwal, V., and Naik., N.Y., 2004. Risks and portfolio decisions involving hedge funds. Technical Report, London Business School.

Agarwal, V., Naveen D., and Naik. N.Y., 2007, Role of managerial incentives and discretion in hedge fund performance, Unpublished Working Thesis, London Business School.

Amihud, Y., and Mendelson, H., 1986. Asset pricing and the bid-ask spread. *Journal of Financial Economics*. 17, pp. 223-249.

Amin, G., and Kat, H., 2003. Stocks, Bonds and Hedge Funds. *Journal of Portfolio Management*. 29(4), pp. 113-120.

Ammann, M., and Moerth, P., 2005. Impact of fund size on hedge fund performance, *Journal of Asset Management*, 6(3), pp. 219-238.

Aragon, G, 2007. Share restrictions and asset pricing: Evidence from the hedge fund industry. *Journal of Financial Economic*. 83(1), pp. 33-58.

Aragon, G.O., and Strahan, P.E., 2012. Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy. *Journal of Financial Economics.*103(3), pp. 570-587.

Asness, C., Krail, R. and Liew J., 2001. Do Hedge Funds Hedge? *The Journal of Portfolio Management.* 28, pp. 6-19.

Baba, N., and Goko. H., 2006. Survival Analysis of Hedge funds. *Bank of Japan*. Working thesis.

Bali, T. G., Brown, S. J., and Caglayan, M. O., 2011. Do hedge funds' exposures to risk factors predict their future returns? *Journal of Financial Economics.* 101(1), pp.36-68.

Bali, T. G., Brown, S. J., and Caglayan, M. O., October 2012. Systematic risk and the cross section of hedge fund returns. *Journal of Financial Economics.* 106(1). pp. 114-131

Baquero, G., Horst, J., and Verbeek, M., 2005. Survival, Look-Ahead Bias, and Persistence in Hedge Fund Performance. *Journal of Financial and Quantitative Analysis*. 40(3), pp. 493-517.

Barber, B.M., and Lyon, J.D., 1997. Detecting Long-Run Abnormal Stock Returns: The

Empirical Power and Specification of Test Statistics. *Journal of Financial Economics,* 43, pp. 341-372.

Bares, P., Gibson, R., and Gyger, S., 2001. Style Consistency and Survival Probability in the Hedge Funds Industry. *EFA 2001 Barcelona Meetings; EFMA 2001 Lugano Meetings*. Available at SSRN: http://ssrn.com/abstract=273737.

Berk, J., and Green. R., 2004. Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy*. 112(6), pp. 1269-1295.

Bhargava, R., Bose, A., and Dubofsky, D., 1998. Exploiting International Stock Market Correlations with Open-End International Mutual Funds. *Journal of Business, Finance and Accounting.* 25, pp. 765-773.

Bianchi, R., and Drew, R., 2010. Hedge fund regulation and systemic risk. *Griffith Law Review*. 19(1), pp. 6-29. Griffith University, Department of Accounting, Finance and Economics.

Bianchi, R., Drew, M., and Wijeratne, T.R., 2010. Systemic risk, the TED spread and hedge fund returns. Working thesis.

Bollen, P. B., and Whaley, R. E., 2009. Hedge fund Risk Dynamics: Implications for performance Appraisal. Journal of Finance. 64(2), pp. 985-1035.

Boudoukh, J., Richardson, M., Subrahmanyam, M., and Whitelaw, R., 2002. Stale Prices and Strategies for Trading Mutual Funds. *Financial Analysts Journal.* 58, pp. 53-71.

Boyson, N., 2002. How Are Hedge Fund Manager Characteristics Related to Performance, Volatility and Survival. Ohio State University. Working Thesis.

Brav, A., Jiang, W., Partnoy, F., and Thomas, R., 2008. Hedge Fund Activism, Corporate Governance, and firm performance. *The Journal of Finance,* 63(4), pp. 1729-1775.

Brennan, M.J., and Subrahmanyam, A., 1996. Market microstructure and asset pricing: on the compensation for illiquidity in stock returns. *Journal of Financial Economics*. 41, pp. 441-464.

Brown, S.J., and Goetzmann, W.N., 2003. Hedge Funds with Style, *Journal of Portfolio Management,* 29(2).

Brown, S.J., Goetzmann, W.N., and Ibbotson, R.G., 1999. Offshore Hedge Funds: Survival and Performance 1989-95. *Journal of Business.* 72 (January), pp . 91-117.

Brown, S.J., Goetzmann, W.N., and Park. J., 2001. Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry. *The Journal of Finance.* 56(5) (Oct), pp. 1869-1886.

Brown, S.J., Goetzmann, W.N., and Ross, S.A., 1995. Survival. *Journal of Finance.* 50, pp. 853-873.

Campbell, J.Y., Grossman, S.J., and Wang, J., 1993. Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics.* 108. pp. 905-939.

Capocci, D., and Hubner, G., 2004. Analysis of hedge fund performance. Journal of Empirical Finance. 11(1), pp. 55-89.

Chalmers, J., and Kadlec, G.B., 1998. An empirical examination of the amortized spread. *Journal of Financial Economics*. 48, pp. 159-188.

Chalmers, J., Edelen, R., and Kadlec, G., 2001. On the Perils of Security Pricing by Financial

Intermediaries: The Wildcard Option in Transacting Mutual-Fund Shares. *Journal of Finance.* 56, pp. 2209-2236.

Chandar, N., and Bricker, R., 2002. Incentives, Discretion, and Asset Valuation in Closed-End Mutual Funds. *Journal of Accounting Research.* 40, pp. 1037-1070.

Chapman, Luke., 2007. Flying Blind: Identifying financial distress in hedge funds. Unpublished Honours Thesis. Faculty of Economics and Business. The University of Sydney.

Chevalier, J., and Ellison, G., 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy.* 144, pp. 389-432.

Dimson, E., 1979. Risk Measurement When Shares Are Subject to Infrequent Trading. *Journal of Financial Economics*. 7, pp. 197-226.

Ding, B., Getmansky, M., Liang, B., and Wermers, R., 2007. Investor flows and share restrictions in the hedge fund industry. Working thesis, University at Albany-SUNY.

Ding, B., Shawky, H.A., and Tian, J., 2009. Liquidity shocks, size and the relate performance of hedge fund strategies. *Journal of Banking and Finance*. 33(5). pp. 883-891.

Edelman, D., Hsieh, D., and Naik, N., 2012. Funds of hedge funds: performance, risk and capital formation 2005 to 2010. *Financial Markets and Portfolio Management.* 26(1), pp. 87-108.

Edwards, F. R., Caglayan, M. O., 2001. Hedge fund performance and manager skill. *Journal of Future Markets.* 21(11), pp. 1003-1028.

Eleswarapu, V.R., 1997. Cost of transacting and expected returns in the NASDAQ market. *Journal of Finance*. 52, pp. 2113-2127.

Fisher, J., Gatzlaff, D., Geltner, D., and Haurin, D., 2003. Controlling for the Impact of Variable Liquidity in Commercial Real Estate Price Indices. *Real Estate Economics.* 31, pp. 269-303.

Fisher, J., Geltner, D., and Webb. R., 1994. Value Indices of Commercial Real Estate: A Comparison of Index Construction Methods. *Journal of Real Estate Finance and Economics.* 9, pp. 137-164.

Friesen, G.C., and Sapp., T.R.A., 2007. Mutual fund flows and investor returns: An empirical examination of fund investor timing ability. *Journal of Banking and Finance*. 31(9), pp. 2796-2816.

Fung, W., and Hsieh, D., 1997a. Empirical characteristics of dynamic trading strategies: The case of hedge funds. *Review of Financial Studies.* 10 (Summer), pp. 275-302.

Fung, W., and Hsieh, D., 1997b. The Information Content of Performance Track Records: Investment style and Survivorship Bias in historical Returns of Commodity Trading Advisers. *The Journal of Portfolio Management.* 24, pp. 30-41

Fung, W., and Hsieh, D.A., 1998. Performance Characteristics of Hedge Funds and CTA Funds: Natural versus Spurious Biases. Unpublished Manuscript, Duke University.

Fung, W. and Hsieh, D.A., 1999. A Primer on Hedge Funds. *Journal of Empirical Finance.* 6, pp. 309-331.

Fung, W., and Hsieh D.A., 2000a. The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. *Review of Financial Studies.* 14(2), pp. 313-341.

Fung, W., and Hsieh D.A., 2000b. Measuring the market impact of hedge funds, *Journal of Empirical Finance*. 7, pp. 1-36.

Fung, W., Hsieh, D., Naik, N., Ramadorai, T., 2008. Hedge funds: Performance, risk, and capital formation. *Journal of Finance.* 63, pp. 1777-1803.

Goetzmann, W., Ivkovic, Z., and Rouwenhorst, G., 1999. Day Trading International Mutual Funds: Evidence and Policy Solutions. *Journal of Financial and Quantitative Analysis.* 36, pp. 287-309.

Greene, J., and Hodges, C., 2002. The Dilution Impact of Daily Fund Flows on Open-End Mutual Funds, *Journal of Financial Economics* 65, pp. 131-158.

Gregoriou, G.N., 2002. Hedge fund survival lifetimes. *Journal of Asset Management.* 3(3), pp. 237-252.

Gregoriou, G.N., and Duffy, N.E., 2006, Hedge funds: A summary of the literature, *Pensions: An International Journal*. 12(1), pp. 26-44

Gromb, D., and Vayanos, D., 2002. Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics*. 66, pp. 361-407

Gruber, M., 1996. Another puzzle: the growth in actively managed mutual funds. *Journal of Finance.* 51, pp. 783-810.

Gyourko, J., and Keim, D., 1992. What Does the Stock Market Tell Us About Real Estate Returns. *AREUEA Journal.* 20, pp. 457-486.

Kat, H.M., and Brooks, C., 2002. The Statistical Properties of Hedge Fund Index Returns and Their Implications for Investors, *Journal of Alternative Investments*, 5(2), pp. 26-44.

Kat, H. M., and Menexe, F., 2003. Persistence in hedge fund performance: the true value of he track record. (Academic's corner). *Journal of Alternative investments.* 5(4), pp. 66-67.

Keifer, N.M., 1988. Economic Duration Data and Hazard Functions. *Journal of Economic Literature*, 26(2), pp. 646-679.

Kosowski, R., Naik, N. Y., and Teo, M., 2007. Do hedge funds deliver alpha? A Bayesian and bootstrap analysis. *Journal of Financial Economics*. 84(1), pp. 229-264.

Liang, B., 1999. On the Performance of Hedge Funds. *Financial Analysts Journal.* 55, pp. 72-85.

Liang, B., 2000. Hedge Funds: The Living and the Dead. *Journal of Financial and Quantitative Analysis.* 35(3) (September), pp. 309-326.

Liang, B., and Park, H., 2010. Predicting Hedge Fund Failure: A Comparison of Risk Measures. *Journal of Financial and Quantitative Analysis.*45(1), pp. 199-222.

Lee, D., Lwi, S., and Phoon, K.F., 2004. An Equitable Structure for Hedge Fund Incentive Fees, *The Journal of Investing*, 13(3), pp. 31-43.

Malkiel, B.G., and Saha, A., 2005. Hedge Funds: Risk and Return. *Financial Analysts Journal*. 61, pp. 81-88.

Minamihashi, N., and Wakamori, N., 2014. How would hedge fund regulation affect investor behavior? Implications for Systemic Risk. Free University of Berlin, Humboldt University of

Berlin, University of Bonn, University of Mannheim, University of Munich.

Mitchell, M., Pedersen, L.H., and Pulvino, T., 2007. Slow moving capital. *American Economic Review (Thesis and Proceedings)*. 97, pp. 215-220.

Morris, S., and Shin, H.S., 2004. Liquidity black holes. *Review of Finance.* 8, pp. 1-18.

Morton, D.P., Popova, E., and Popova, I., 2006. Efficient fund of hedge funds construction under downside risk measures. *Journal of Banking & Finance.* 30, pp. 503-518.

Nicholas J.G., 1999. Investing in hedge funds. Bloomberg Press.

Park, J., 2008. Conditions for Survival: Changing Risk and the Performance of Hedge Fund Managers and CTAs. Yale School of Management. Working Thesis.

Pulvino, T., 1998. Do asset fire sales exist? An empirical investigation of commercial aircraft transactions. *Journal of Finance*, 53, pp. 939-978.

Ross, S. and Zisler, R. 1991. Risk and Return in Real Estate, *Journal of Real Estate Finance and Economics*. 4, pp. 175-190.

Rouah, F., 2005. Competing Risks for Hedge Fund Survival. Working Thesis, McGill University.

Sadka, R., 2006. Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics*. 80(2), pp. 309-349.

Sadka, R., 2010. Liquidity risk and the cross-section of hedge-fund returns. Journal of Financial Economics. 98(1), pp. 54-71.

Savona, R., February 2014. Risk and beta anatomy in the hedge fund industry. The European Journal of Finance. 20(1), pp. 1-32.

Schaub, N., and Schmid, M., 2013. Hedge fund liquidity and performance: Evidence from the financial crisis. Journal of Banking & Finance. 37 (3), pp. 671.

Scholes, M., and Williams, J., 1977. Estimating Betas from Nonsynchronous Data. *Journal of Financial Economics.* 5, pp. 309-328.

Schwert, G., 1977. Stock Exchange Seats as Capital Assets. *Journal of Financial Economics.* 4, pp. 51-78.

Scott, Robert C., and Horvath, P. A., 1980. On the Direction of Preference for Moments of Higher Order than the standard deviation. *Journal of Finance.* 35(4) (September), pp. 915-919.

Siegmann, A., and Lucas, A., 2002. Explaining hedge fund investment styles by loss aversion, Technical Report, Tinbergen Institute Discussion Thesis.

Sirri, E.R., and Tufano. P., 1998. Costly Search and Mutual Fund Flows. *Journal of Finance*. 53(5), pp. 1589-1622.

Slavutskaya, Anna., 2013. Short-term hedge fund performance. *Journal of Banking and Finance.*37(11), pp. 4404-4431.

Sun, Z., Wang, A., and Zheng, L., 2012. The road less traveled: strategy distinctiveness and hedge fund performance. *The Review of Financial Studies.* 25(1), pp. 96-143.

Teo, M., 2011. The liquidity risk of liquid hedge funds. *Journal of Financial Economics.* 100, pp. 24-44.

Ter Horst, J.R., Nijman T., and Verbeek, M., 2001. Eliminating Look-Ahead Bias in Evaluating Persistence in Mutual Fund Performance. *Journal of Empirical Finance.* 8, pp. 345-373.

Titman, S., and Tiu, C., 2011. Do the best hedge funds hedge? The Review of Financial Studies. 24 (1), pp. 123-168.

Zheng, L., 1999. Is money smart? A study of mutual fund investors' fund selection ability. *Journal of Finance.* 54, pp. 901-933.