University of Sussex

An empirical analysis of controlled risk and investment performance using risk measures:

A study of risk controlled environment

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Submitted for the degree of Doctor of Philosophy

University of Sussex

2013

Declaration

I hereby declare that this thesis has not been and will not be submitted in whole or in part to another University for the award of any other degree.

Signature:

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UNIVERSITY OF SUSSEX

HAIDAR HAIDAR, SUBMITTED FOR DOCTOR OF PHILOSOPHY

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Abstract

In this thesis, I study the performance behaviour of hedge funds and mutual funds. I study a basket of various risk statistics that are widely used to measure the fluctuation of asset prices. Those risk statistics are used to rank the performance of the assets. The linear dependence relation of these risk measures in ranking assets is investigated and the set of risk measures is reduced by excluding risk measures that produce linearly dependent ranking vectors to other risk measures. The ranks within each of the selected remaining risk statistics are standardised and then linearly transformed into a new set of linearly independent factors where principal component analysis is carried out as a variable reduction technique to remove the noise while preserve the main variation of the original data. The transformed factors are sorted in descending order according to their contribution to the variation of the original data. The factor loadings of the first two principal components PC1 and PC2 are reviewed and interpreted as styles (PC1 as consistency and PC2 as aggression). The universe of a set of hedge funds is classified according to these styles as BL=(low

consistency, low aggression), BR=(high consistency, low aggression), TL=(low consistency, high aggression) and TR=(high consistency, high aggression). I examine the performance behaviour of the four different classified classes whereby this classification method provides an indication on returns and management styles of hedge funds. A three-factor prediction model for asset returns is introduced by regressing 12 weeks' forward rank of return on the historical ranks of risk statistics. The first few principal components, which explain the main variation of information captured by risk statistics, are used in the prediction model. The robustness of the model is tested by applying the model to the following 12-week period using the set of independent factors. An investment strategy is constructed based on the prediction model using the set of independent factors. I discover high evidence of predictability and I test for out-of-sample forecasting performance. I then examine the use of subsets of risk statistics from the basket rather than using the set of all risk statistics. I further study the use of the so-called $\frac{\sigma^2}{\mu}$ risk measure in predicting the market "turning point" of performance of a portfolio of hedge funds. Risk measure quantity $\frac{\sigma^2}{\mu}$ replaces the traditional variance σ^2 in the Black-Scholes option valuation formula when it is evaluated for hedge funds.

Acknowledgements

This work would have never been done without the care and mercy of God and the help and support of the community around me. I would like to express my deepest thanks and gratitude to my supervisor Dr. Qi Tang for his supervision, patience, support and advice, and providing the friendly atmosphere I had during my PhD time. Tang has helped me to gain a professional academic and industrial experience during the time of my PhD, which helped me to start my career. A special thanks goes to Dr. Anotida madzvamuse for his help, support and discussions since I came to Sussex University in 2007. Prof. James Hirshfield has supported me thankfully and I am thankful to all faculty members of Maths department. I also thank Xiaobo Wang the useful discussions we had while she was an MSc student in 2010. I thank my colleagues and friends, in particular: Christof, Erin, Francisco Carreras, Konstantinos, Maan, Marwan and Waewta. I should not forget to thank Tom Armour from IT department and Rai Robertson at Kings road university accommodation. I am grateful to Louise Winter and Juan Moreno for their help while they worked in the school office. My lovely flatmate Christophe, deserves a big thank for the atmosphere he gave me when we lived together. I am also grateful to Mr. Bernard Minsky for the industrial discussions we had. I should not forget my lecturers at Kuwait University who helped and supported me to continue my higher studies at Sussex University. I would like to thank my grandparents for the hospitality they gave me during my stay in the UK. Also, I would like to thank my examiners Dr. Bertram During and Prof. Qiwei Yao for their valuable comments and suggestions. Finally, but most important, I would like to thank my father, mother, brother and two sisters for their care and support. My brother, Ahmad, has always advised me through my life. Chapter two was funded by International Asset Management (IAM).

Contents

List of Tables

List of Figures

1 Introduction

1.1 Introduction to investment opportunities

A dollar investment at the beginning of 1960 in S&P500 with a buy-and-hold strategy would have grown up to $\$5.5$ at the end of 1990 (Becker and Seshadri, 2003). However, buy-and-hold strategy performed poorly during bear markets and financial crises (Fernandez-Rodriguez et al., 2000). The risk controlled environment of mutual funds and hedge funds was an attractive alternative for investors who prefer to avoid such a poor performance. Investors tend to invest in mutual funds as an easy way to diversify their portfolios and gain from professional managements, while keep low transaction fees. Hedge funds have their own way of thinking and investment strategies and aim to gain an absolute return during all market conditions, whether the market is a stable bull market or not. Hedge funds are attractive for high net worth investors because they diversify risk away from traditional asset classes to avoid the incurred losses when the market crashes. Hedge funds have the right to make extensive use of derivatives and short selling to hedge against the market risk (Stulz, 2007). Hedge funds are open to investors who meet minimum wealth requirements, while mutual funds are open for the general public. Hedge funds are limited in the number of investors they take, which helps to keep the management fees low. Some hedge funds stop accepting new investors to avoid large volume trading, which may expose the investment strategy that they use. Hedge fund Investors pay management fees for the high skills and strategies that hedge fund managers apply to the fund to increase the return and reduce the risk. Those fees are normally a combination of small management fees of about 1% of the total assets' value plus performance fees of higher percentages, while mutual funds are regulated under the federal law and they can charge limited fees that do not include any performance fees. Since mutual funds are regulated, they are not generally allowed to do short selling or to make extensive use of derivatives (Koski and Pontiff, 1999). Performance fees are normally on long term performance to prevent managers form taking risk by investing in short term out-performance investments. Mutual funds usually receive a fixed percentage fee. The risk controlled environment of mutual funds and hedge funds has grown fast in the last decades. According to Hedge Fund Research Inc, hedge funds industry was estimated in 2013 at more than $ 2.4 trillion, while ICI Factbook has reported that assets managed under mutual funds have exceeded $ 13 trillion in the US in 2012. Note that investors can sell their stocks when the market is open, while for mutual funds, investors can only sell their funds at the end of the trading day. Investors in hedge funds need two months' notice period to withdraw the money from the funds. There are no restrictions on buying. For this reason, I constructed my mathematical models based on 12-week window for mutual funds but on 12-month window for hedge funds. In this section, I will provide a simple example to define the most used terms in my thesis, 'risk' and 'return'. Assume two identical investment opportunities 'A' and 'B', each with only two expected final outcomes after a fixed time T. Either the wealth will increase by 10% with a probability of $\frac{1}{2}$ or it stays as it was initially with the remaining probability of $\frac{1}{2}$. In such a case, rational investors have no investment preference if all investment factors are matched. Take another example when there is only one difference between the two investments such that the probability of the event of a 10% increase on wealth when taking investment opportunity 'A' has raised to $\frac{3}{4}$, resulting in a probability of $\frac{1}{4}$ for the wealth to stay as it was initially when taking investment 'A'. Leave investment 'B' as it was described initially with equal probabilities of $\frac{1}{2}$. Given the choice between the two investment opportunities, investors prefer investment 'A', which has a higher certainty of an increase in wealth than the certainty of investment ‘B’.

Investors measure the success of an investment by the expected change in wealth resulted by that investment. Measuring the change in wealth over time is presented by the percentage change in wealth value after time T due to an investment and that percentage change is known as the ‘return’. When an investment has a historical record of returns, potential investors analyse and assess the past historical performance of the investment, and expect, to a degree, a similar stable performance for the near future. Investors consider all present available information about future events that have an effect on the investment environment. However, Future events are not certain and therefore there is a risk that actual events do not match with our expectations. Investment decisions are made based on the expected return and the risk associated with the uncertain environment of the investment. ‘Risk’ is basically the uncertainty of having the wealth increased or decreased by an expected return. Risk has been very important in modern financial studies (e.g. Markowitz, 1952; Sharpe, 1964). It is involved in investment processes and has played an important role in portfolio analysis. Modern risk measures try to capture more information about the investment. Let us discuss a basic example that illustrates the reason why the risk is associated with the expected return with a positive relation between them.

In this section, I will provide a practical example to define the most used terms in my thesis, ‘risk’ and ‘return’. Assume two identical investment opportunities ‘A’ & ‘B’ each with only two expected final outcomes after a fixed time T. Either the wealth will increase by 10% with a probability of $\frac{1}{2}$ or it stays as it was initially with the remaining probability of $\frac{1}{2}$. In such a case, investors have no investment preference if all investment factors are matched. Take another example when there is only one difference between the two investments such that the probability of the event of a 10% increase on wealth when taking investment opportunity 'A' has raised to $\frac{3}{4}$, resulting in a probability of $\frac{1}{4}$ for the wealth to stay as it was initially when taking investment 'A'. Leaving investment 'B' as it was described initially with equal probabilities of $\frac{1}{2}$. Giving the choice between the two investment opportunities, investors prefer investment 'A' which has a higher certainty of an increase in wealth than the certainty of investment 'B'. Investors began to measure the expected events and their effect on the change of wealth. Measuring the wealth over time is presented by the percentage change in wealth value after time T due to an investment and that percentage change is known as the 'return'. Investors started to look at the past historical performance of an investment and expect, to a degree, a similar stable performance for the near future. They take into account all available information about the future events that have an effect on the investment environment. Future events are not certain and therefore there is a risk that events do not match with the expectations. Investment decisions are all made based on the expected return and the risk associated with the investment. 'Risk' is basically the uncertainty of having the wealth increased or decreased by an expected return.

1.2 Introduction to risk and uncertainty

The main widely used risk measure for the instability and uncertainty of return over time is the variation over the expected return, which is the variance. There have been many discussions in recent years as to why standard deviation is not an appropriate measure of risk (Keating and Shadwick, 2002; Ghaoui et al., 2003). These observations are backed up by real financial data testing (Better and Glover, 2006). Newer risk measures such as Value at Risk (Linsmeier and Pearson, 1996), Expected Tail Loss (Acerbi and Tasche, 2002), Omega ratio (Shadwick and Keating, 2002) and Maximum DrawDown (Chekhlov et al.,

2005) are discussed and mathematically defined along with the variance in Chapter2. This still does not solve the problem of uncertainty, because risk measures are based on available information and may not reflect the performance over the future. Measuring risk via risk measures introduces the uncertainty of the value of the risk measure itself (uncertainty of uncertainty). Later in Chapter 2, I briefly discuss and present some popular risk measures (risk statistics). Sharpe (1964) has classified the risk into systematic risk and non-systematic risk. The systematic risk is the risk associated with the whole market such as world events and this type of risk cannot be avoided. The non-systematic risk is the risk that can be eliminated by diversification. So there is always a degree of risk that cannot be removed and there is no zero risk investment. The interest rates of the financial instruments issued by the US Federal Reserve are used as a proxy for the risk-free interest rates throughout this thesis. The main widely used risk measure for the instability and uncertainty of return over time is the variation over the expected return, which is the variance. The variance will be introduced and mathematically defined in Chapter 2.

Investments with high risk tend to result in a high positive return but sometimes also in high negative return. In this thesis, I test, using historical information, the existence of a linear relation between mutual fund performance and the past information given by applying risk measures to a set of mutual funds. I also study the asset managed style of hedge funds by looking at risk measures. I will extract information related to expected returns and management styles by combining information from the market, risk-free interest rates, and historical risk performances of assets. As a part of the development of the financial system over decades, people introduced the idea of measuring risk and exchanging it with return. Insurance and reinsurance contracts are examples of how people can reduce their risk, but should also give some of their return. People who don't want to establish and manage their own businesses with a considerable risk of failure, which could lead to a bankruptcy and reduction in wealth, tend to exchange risk with return.

Before people consider any investment opportunity, they look at the circumstances that may affect the investment. The negative effects on the investment is what people refer to as risk and which prevents people from taking some investment opportunities. Risk and return are key factors for comparing investment opportunities, as the risk measures the possibility of a negative return (loss). The risk of launching a new business is relatively high because of the high uncertainty of increasing the wealth after a certain time. A successful business with historical record and stable performance will more likely obtain a similar performance in the near future. Therefore, Investing in such businesses is less exposed to the risk of the business failing. Based on historical performance information, a successful business is seen to have more consistency in the near future and is associated to less risk in comparison to the risk of starting a new business. People investing in a successful business should expect a smaller return than what the founders of the business had when they established their business. You will not earn a return on investing a dollar in Microsoft nowadays as much as Bill Gates has earned, per dollar invested, when he founded Microsoft.

Public investors therefore can have investment opportunities with less expected return but also with less risk of losing their money. The current price of a stock still depends on the future performance of the business even though the past performance is considered as an indicator of the stability of returns of the business. People have different preferences toward the degree of acceptable risk and thus some people do not accept the fact that there is still a considerable degree of risk associated with their wealth. They look for a way to increase their wealth but with more certainty of receiving a positive return even with lower values. They expect a “risk-free” investment, which is in fact risky but to a very low degree. Those type of risk-averse investors, who look for low risk investments, deposit their money in banks for some promised small future payments at the end of certain periods. There is still uncertainty if banks keep the money safe and will be able to return the money to investors plus an expected return known as interest. Banks do not do us favours and keep our money for free, but they use our money to make profit. In order for banks not to reduce their capital when paying interests to their clients, they loan the money out to companies as bonds/loans, to individual investors as personal loans and to public as mortgages. Banks charge interests for giving loans and mortgages more than the interest they pay to investors who deposit their money in banks. The difference between the two rates is taken by the bank as a profit. Note that banks earn from other services as well such as giving financial advice, offering insurance policies, exchanging currencies and managing investment funds. Banks, by using the deposited money to make profit, they expose the deposited money to risk, as borrowers may not be able to pay their loans back on the agreed times. This was not the purpose of the risk-averse investors to keep their money safe in banks.

Other types of investors believe that the uncertainty can be controlled and reduced to a degree but it requires high skills which they don’t possess. Therefore, they invest their money in mutual funds and hedge funds. This introduces a new type of risk associated with the new investment environment as investors put their money in someone’s hands. Readers can take Bernard Madoff (2008) and Long Term Investment Management LTCM (1998) as two real examples where the money was not in safe hands. Investment funds invest in bonds, stocks, cash and commodities. Funds charge some fees for the service they provide and the investment skills they have. In this environment, the risk is reduced to a degree, lower than stocks but higher than depositing the money in banks. Investors should then expect a return between what is expected from banks deposit interest rates and what is expected from stocks.

In order to control the risk of fund management introduced by investing in funds, investors can consider funds of hedge funds. This environment is called ‘risk controlled square’ environment. In such an environment, investors expect to earn less money than what they expect by investing directly in hedge funds, but in return, they expect less risk. Nevertheless, an additional risk is introduced in the ‘risk controlled square’ environment, since we have more people who deal our money. Hedge funds and funds of hedge funds publish their portfolios’ records on a monthly basis and they require a notice for investors to withdraw their money. This can be explained by the time it takes funds to evaluate their investments in a ‘risk controlled square’ environment. I can therefore say that risk can be reduced but can never be completely eliminated.

1.3 Literature Review

Principal Component Analysis (PCA) is a statistical variable reduction technique that linearly transforms a set of variables by rotation where the images of the transformation are new uncorrelated factors. Initially proposed by Pearson (1901), it was developed by Hotelling (1933) (see textbooks Dunteman, 1989; Jolliffe, 2002). PCA applications vary between signal networks, gene expression (e.g. Yeung and Ruzzo, 2001; Raychaudhuri et al., 2000), image compression; face recognition and modern Geography (e.g. Daultrey, 1976). PCA has been also applied to study bond returns (Litterman and Scheinkman, 1991). The method of classifying funds into classes and observe their performances has been previously looked at by Brown and Goetzmann (2003) using generalized style classifications by comparing returns data to index portfolios and corresponding loading factors. Further studies have been carried out in Gibson and Gyger (2007). In Chapter 3, I carry Principal Components Analysis as a variable reduction technique to remove the noise while preserve the main variation of my original data.

Ben-Dor and Xu (2012) discusses the issue of consistency from various management points of view. I argue a similar issue from quantitative analysis point of view for not a single fund, but rather a portfolio of hedge funds. In Dewaele et al. (2011), the authors use a different classification method to categorize funds of hedge funds; however they did not give a very clear indication on how their classes behave in terms of long term return performance. In Chapter 4, I study the asset management style of hedge funds by looking at risk measures. I extract information related to expected returns and management styles by combining information from the market, risk-free interest rates, and historical risk performances of assets.

Many statistical models have been developed to construct an investment strategy based on the prediction of future returns of different asset classes. The main models are based on identifying risk factors and constructing factor regression models. However, it has been widely argued that most of those models are based on assumptions that are not realistic and the choice of factors has been an argument (Jagannathan and Wang, 1996; Fama and French, 1993). Sharpe (1964) introduced the Capital Asset Price Model (CAPM) as the main single-factor regression model to explain security returns. Sharpe assumed that security returns depend on one risk factor, which is the sensitivity to the market excess returns over risk-free rate. Fama and French (1993) expanded the CAPM and identified three risk factors to explain stock returns. Carhart (1997) then introduced a four factor model. Femma and French, and Carhart showed that when using empirical results, the factor introduced by Sharpe has little information about stock returns and that more factors should be included in the model. However, the mechanism of how to choose the risk factors was not explained enough, and of whether the chosen risk factors are consistent over time. Goyal and Welch (2004) claimed that not a single regression prediction model would have helped a real-world investor. Bossaerts and Hillion (1999) argued that the prediction models had no out-of-sample forecasting performance. Paye and Timmermann (2006) explained that the return forecasting models had a very weak out-of-sample predictability. Campbell and Thompson (2007) disagree with Goyal and Welch and show that many predictive models can beat the historical average returns but the out-of-sample forecasting performance is still small. The purpose of Chapter 5 is to establish a dynamic prediction method, based on risk performance measures for mutual funds that explain the main variation of returns. The robustness of the model is tested out-of-sample to illustrate the results. Sharpe (1966), and Fama and French (2008) ranked mutual funds to test the persistence of fund's performance. Fama and French suggested that the persistence of fund's performance based on post-ranking is temporary and of little use to investors. It was not questionable whether the persistence of mutual funds performance exist, but rather how strong it is.

Financial derivatives are financial instruments that are written as contracts and their values depend on some underlying assets (bonds, stocks, commodities, currencies, etc) and so they are named derivatives. A financial option, which is a financial derivative, is a contract between two parties for exchanging risk with return and it gives one party, the holder of the option, the right but not the obligation to exercise the option under certain conditions on or at any time until a prescribed date known as maturity T. Black and Scholes (1973) and Merton (1973) have priced options based on securities that follow a

Geometric Brownian motion with constant drift and volatility. Heston (1993) has priced options based on securities with stochastic volatilities that follow Ornstein-Uhlenbeck process to overcome the assumption of a constant volatility in the Black-Scholes model. The Black-Scholes formula does not depend on the drift μ, but only on the variance σ^2, which measures the total variation of the movement over the drift, but it does not take into account whether the variation is positive or negative. In Chapter 6, I introduce a new risk measure, which depends on the volatility and the drift, for hedge funds to replace the traditional variance measure.

In this thesis, I analyse historical performances of some asset classes in order to reduce the reducible non-systematic risk based on some mathematical models. The thesis is organised as follows. In Section 1.4, I present the data used in my thesis. Chapter 2 briefly introduces risk measures that are used in my thesis and looks at the amount of linear dependency among the rank statistics. In Chapter 3, I describe how Principal Components Analysis is applied to the dataset. Chapter 4 is dedicated to the study of management styles of hedge funds and consequences on fund performance over 12-month periods. In Chapter 5, I build and study the persistence of a three factor prediction model for mutual funds returns over 12-week periods. I further study in Chapter 6 the use of the so-called $\frac{\sigma^2}{\mu}$ risk measure in predicting the market "turning point" of performance of a portfolio of hedge funds.

1.4 Data

International Asset Management (IAM) is a fund of hedge funds based in London. IAM researches the hedge fund market and builds portfolios of hedge funds for its clients. The mutual funds data and hedge fund data are downloaded from the IAM proprietary database of investment funds. Hedge fund and fund of hedge fund performance is collated from a variety of sources including HFR, EurekaHedge, Altvest, Bloomberg and proprietary sources. **Note:** Transaction costs, and both capital and corporate taxes are not taken into consideration in this thesis. I focus more on the relative performance of constructed portfolios and make a performance comparison within the investment universe.

1.4.1 Data used in Chapter 4

A set of hedge funds is used as the subject of Chapter 4. I first obtain date of 14173 live and dead hedge funds that reported for at least a 24-month period during the January 2003 to December 2011 period in the International Asset Management (IAM) database. For any 24-month period (12-month for historical statistic computation and 12-month for future return computation) under investigation, I deal with a subset of funds that has reported for the entire period. Therefore, the number of hedge funds analysed in a period varies between 4835 and 5638. A set of 108 monthly returns from January 2003 to December 2011 are used in the calculations. A rolling window of 12 consecutive months is used to compute the risk statistics at each time step. A new time series of 97 periods is generated for each of the risk statistics, where each is calculated over 12 weeks.

1.4.2 Data used in Chapter 5

In this section, I describe the data that are used in Chapter 5, and the source and the structure of the data. A set of 1132 mutual funds is the subject of my investigation in Chapter 5. A time series of 756 weekly adjusted close prices of Tuesdays from August 19, 1997 to February 7, 2012 is used in the calculations. Those prices are used to calculate 755 weekly returns for each fund. A new time series of 755 consecutive weekly returns is used in the calculations and the weekly return of the j-th fund at week t is denoted by $r_{j,t}$

for $t = 1, 2, \ldots, 755$. I have investigated a set of 24-week periods such that any given 24-week period under investigation consists of first a 12-week sub-period for computation of historical risk statistics and second a 12-week sub-period for computation of future returns. Therefore, I construct 732 24-week periods with the first 12-week sub-period within each 24-period under consideration is used to calculate the risk values that are generated for each of the 15 risk statistics. At any given 24-week period, the number of mutual funds used is the subset of the 1132 funds that reported to the database for that 24-week period under consideration. Therefore, for any 24-weeks' period under investigation, I use the subset of funds that were reported for the period. I denote the number of Mutual funds under investigation at each time point t by N_t. The number of Mutual funds analysed in the 24-week periods period varies between 70 and 1130. My 24-week periods under consideration reorganised as follows: weeks 1-12 are used to predict the rank of return over weeks 13-24, weeks 2-13 to predict the rank of return over weeks 14-25 and so on until the last 24-week period, in which risk statistics calculated using data from weeks 732-743 are used to predict the rank of return over weeks 744-755. Within each of the 732 24-week periods under consideration, I use the historical risk statistics calculated for the first 12 weeks (calculated using weekly returns data in these 12 weeks) to predict the forward rank of return for the second half (the following 12 weeks) of the 24-week period. The statistics are listed and defined in Section 2.1 along with identification numbers. A new time series of 732 risk values is generated for each of the 15 risk statistics for which each point in the series is the value of the risk measure calculated over 12 weeks. Similar calculations are performed for each 12-week sub-periods to compute 12 weeks' compounded returns, $R_{j,t}$, for each fund labeled with j. This gives a new time series of 732 compounded returns, each of the compounded returns is calculated over 12 consecutive weeks that are used as the second 12 weeks within my 24-week periods under consideration. $R_{j,t}$ is computed as follows.

$$\text{12 weeks' compounded Return}(R_{j,t}) = \left(\prod_{k=t-11}^{t} (1 + r_{j,k}) \right) - 1 \quad \forall t \in \{24, 25, \ldots, 755\}. \tag{1.1}$$

The funds are ranked within each statistic from the best to the worst performance according to the sign of the statistic, which represents the natural preference for investors, as shown in Section 2.1. This set of ranked statistics is referred to as Rank-Statistics, RS, in the rest of this thesis, where $RS_{k,j,t}$ is the rank of the j-th fund according to the k-th risk statistic calculated over the period of week $t - 11$ to week t. The risk statistics are standardised and made comparable by looking at their Rank-Statistics rather than their values. Similarly the compounded 12-week returns are ranked in a descending order such that the fund ranked first represents the fund with the highest return over the 12-week sub-period and the ranks of returns are denoted by RR. Returns, r_t, are transformed into Rank-Statistics, $RS_{k,t}$, for each fund by calculating the 12-week's trailing risk statistics for each of the 732 sub-periods of 12-week length and then the 15 risk scores are replaced by their ranks according to the preference signs. A positive (negative) sign means the higher (lower) the measure of the function the better the investor's expectations. The example in Table 1 illustrates: 1) how seven funds are ranked for a risk statistic with negative preference sign with the lowest score ranked one and the highest score ranked seven; and 2) how the funds are ranked for a risk statistic with positive preference with the highest score ranked one and the lowest score ranked seven.

Data	**Sign**	**Order**	Funds						
Statistics			-0.12	0.27	0.14	0.02	-0.20	-0.13	0.05
RS	-	Ascending	3	7	6	4	1	2	5
	+	Descending	5	1	2	4	7	6	3

Table 1: An example on how to compute Rank-Statistics

1.4.3 Data used in Chapter 6

IAM provided me with anonymised hedge fund returns data dated from November 1999 to June 2011, which covers the summer of 2008 when volatility of the financial markets shot up. The number of available funds from the database are 16, 27, 38, 62, and 229 in periods Jan/96-Dec/98, Nov/99-Dec/01, Feb/01-Apr/04, Jun/03-Nov/05, and Jan/05-Jun/11, respectively. Note that for the S&P 500 investors can sell the stocks immediately while for hedge funds I allow two months notice period to withdraw the money from the funds. There are no restrictions on buying.

The source and type of the data that are used in this thesis are listed in Table 2. The tested period and the number of available observations are listed on the table for each set of data. A set of 108 monthly returns for hedge funds is used in Chapter 4 with the Libor USD 1 month used as a proxy for risk-free interest rates and the MSCI world index is used as a benchmark in the calculations. In Chapter 5, 756 weekly prices are used for mutual funds with the interest rates of three months U.S. government instruments, with 3 months constant maturity, used as a proxy for risk-free interest rates. S&P500 is used as a benchmark for the calculations in Chapter 5. In Chapter 6, the number of observations varies over each tested sub-period as explained earlier in this Chapter. Interest rates are not used in Chapter 6.

Chapter	Data	Type	# Observations	From	To
4	Hedge Funds (HF)	monthly returns	14173	January 2003	December 2011
Time Periods	Rolling Window	Tested Sub-Periods	Benchmark	Risk-Free Rate	Source
108	12 months	97	MSCI world	Libor USD 1 Mnth	IAM
Chapter	Data	Type	# Observations	From	To
5	Mutual Funds	weekly prices	1133	August 19, 1997	February 7, 2012
Time Periods	Rolling Window	Tested Sub-Periods	Benchmark	Risk-Free Rate	Source
756	24 weeks	732	S&P500	H15_TCMNOM_M3	Bloomberg
Chapter	Data	Type	# Observations	From	To
6	Hedge Funds (HF)	monthly returns	$\in (16, 229)$	January 1996	June 2011
Time Periods	Rolling Window	Tested Sub-Periods	Benchmark	Risk-Free Rate	Source
	12 months				IAM

Table 2: Data summary

2 Risk Measures

2.1 Introduction to Risk Measures

In this chapter, I describe and define 17 commonly used risk measures with some given examples. The first 15 risk measures (Alpha α (Jensen, 1986), Beta β (Sharpe, 1966), Trend Correlation, Maximum DrawDown (MDD) (Chekhlov et al., 2005), Volatility σ, Downside Deviation (DD), Sortino Ratio (Sortino and Van Der Meer, 1991), Sharpe Ratio (Sharpe, 1966 and Sharpe, 1998), Up Capture, Down Capture, Positive Excessive Return (+ve), Negative Excessive Return (-ve), Calmar Ratio (Young, 1991), Omega ratio, Ω, (Shadwick and Keating, 2002), and Winning runs) are used in the rest of the thesis but not Value at Risk (VaR) (Linsmeier and Pearson, 1996) and Expected Tail Loss (ETL) (Acerbi and Tasche, 2002). The Calculations of VaR and ETL based on historical observations need considerable number of observations (returns) to give accurate estimates. I deal with 12 weekly returns and 12 monthly returns as for mutual funds and hedge funds calculations, respectively. I could overcome this by fitting a distribution to the data but this will incur some assumptions. It is also worth to define them for the interest of the readers and I will also discuss the technical reasons why I exclude them. The risk measures are listed in table 3 with their identification numbers and preference signs. **Note:** The below examples and patterns are based on the tested periods and they do not reflect any overall relation between risk measures and the return.

Identification #	Measure	Sign
1	Alpha	+
2	Beta	-
3	Trend Correlation	+
4	Maximum Drawdown	-
5	Volatility	-
6	Downside Deviation	-
7	Sortino Ratio	+
8	Sharpe Ratio	+
9	Up Capture	+
10	Down Capture	-
11	Excessive return +ve	+
12	Excessive return -ve	+
13	Calmar Ratio	+
14	Omega Ratio	+
15	Winning Runs	+
16	Value at Risk	-
17	Expected Tail Loss	-

Table 3: Relation with performance

2.1.1 Alpha α

Risk measures, Alpha and Beta, result from regressing the excess return over risk-free interest rate, $(r_i - f_i)$, against the market excess returns over risk-free interest rate, $(m_i - f_i)$. Readers can refer to Table 2, for the market benchmark, m, and the proxy for risk-free interest rates, f, used in the calculations. Alpha is the intercept of the regression in (2.2) and is used as an over-performance measure of funds adjusted for market risk.

$$\alpha = \overline{(r - f)} - \beta \times \overline{(m - f)}, \tag{2.2}$$

where $\overline{(r - f)} = \dfrac{1}{n}\sum_{i=1}^{n}(r_i - f_i)$, which is the average of the excess return over risk-free interest rate, $r_i - f_i$. The average is performed over the number of observations, n, in the time period under consideration. In this thesis, I define $\overline{x}$, for any quantity x, to be the average of all n observations of x in a given time period. β is defined in the next subsection.

2.1.2 Beta β

Sharpe (1964) has introduced Beta risk measure as a unique risk factor to explain returns. Beta, which is the slope of the regression in (2.2), is the covariation between the returns of the fund and the returns of the market and it represents the sensitivity of the fund price movements to changes in the market. Beta is defined in (2.3). Figure 1 illustrates the existence of a positive relation (funds with higher returns tend to have higher values of beta and alpha) between the 12-week return, and both Alpa and Beta risk measures calculated over the 12-week period ended on July 5, 2005, for a set of mutual funds.

$$\widehat{\beta} = \frac{\sum_{i=1}^{n} \left[(r_i - f_i) - (\overline{r - f})\right] \times \left[(m_i - f_i) - (\overline{m - f})\right]}{\sum_{i=1}^{n} \left[(m_i - f_i) - (\overline{m - f})\right]^2}. \tag{2.3}$$

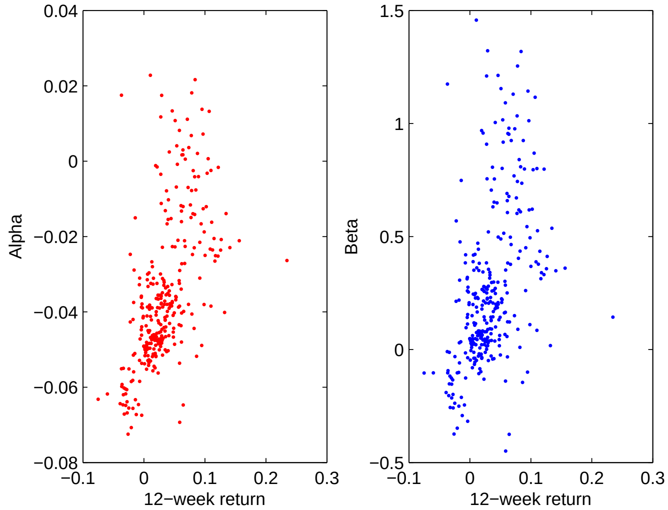

Figure 1: Alpha & Beta vs. 12-week return calculated over the 12-week period

2.1.3 Trend Correlation

Trend correlation is a risk measure that has the value and the sign of the standard statistical correlation when the market return is positive but with an opposite sign of the standard statistical correlation when the market return is negative. Positive Trend Correlation comes either from a positive correlation with the market when the market return is positive or from a negative correlation with the market when the market return is negative. Trend Correlation is defined in (2.4). Figure 2 illustrates a positive relation between the return and the Trend Correlation in the scenario of a positive market return (left graph) as well as the scenario of a negative market return(right graph).

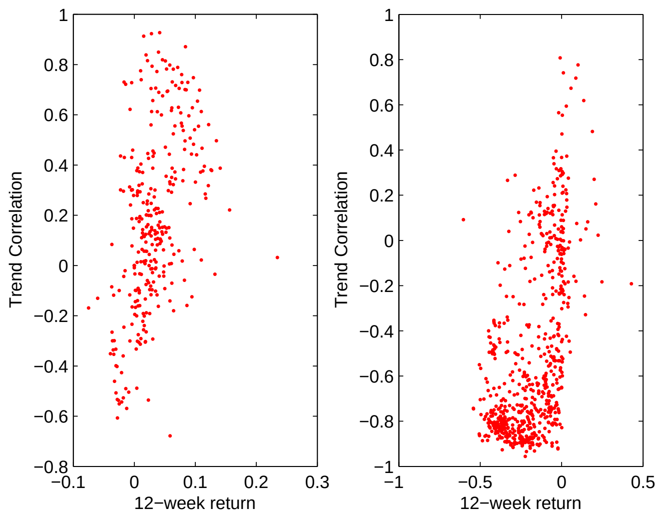

Figure 2: Trend Correlation vs. 12-week return of a set of mutual funds as on July 5, 2005 (Left) and October 21, 2008 (Right)

$$\text{Trend Correlation} = (-1)^k \times \frac{\sum_{i=1}^{n}(r_i - \overline{r}) \times (m_i - \overline{m})}{\sqrt{\sum_{i=1}^{n}(r_i - \overline{r})^2} \times \sqrt{\sum_{i=1}^{n}(m_i - \overline{m})^2}}, \tag{2.4}$$

where

$$k = \begin{cases} 0 & \text{if } \sum_{i=1}^{n} m_i \geq 0. \\ 1 & \text{if } \sum_{i=1}^{n} m_i < 0. \end{cases}$$

2.1.4 Maximum DrawDown (MDD)

Definition: Maximum DrawDown is the maximum loss (in percent) incurred over a given period for a buy-and-hold investor. Maximum DrawDown is defined in (2.5).

$$MDD = \max_{i,j} \frac{S_{i\in(0,T)} - S_{j\in(i,T)}}{S_i}, \ S_t \text{ is the asset price at time } t \in (0,T). \tag{2.5}$$

Example: $MDD = 32\%$ tells us that a maximum loss of 32% could happen if an investor has bought the security at peak and sold it at bottom that is the worst scenario in the holding period.

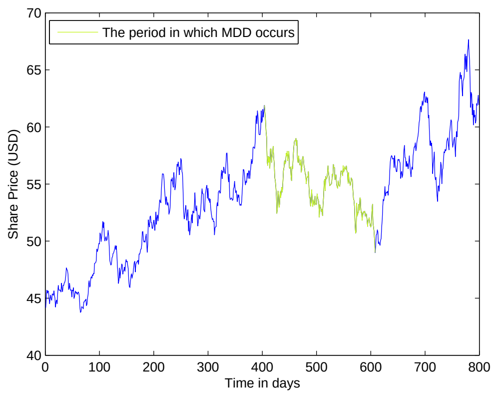

Figure 3: Maximum DrawDown for BP calculated over the period October 04, 2004 to December 04, 2007

2.1.5 Volatility σ

The most widely used risk measure for the instability and uncertainty of returns over time is the variation around the expected return and is measured by the variance and the standard deviation, which is the square root of the variance. I denote the standard deviation in my thesis by Volatility. It is known in finance for its role in pricing financial options using the Black-Scholes model. As we will see in Chapter 6, it is not a valid risk measure for all types of financial securities. Volatility is defined in (2.6).

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (r_i - \overline{r})^2}{n-1}}. \tag{2.6}$$

2.1.6 Downside Deviation (DD)

Downside Deviation is similar to the volatility in that both measure the variation of returns over the mean. The only difference between them is that the Downside Deviation measures the deviation of the negative returns from the expected return and it does not count any positive return when measuring the risk. Downside Deviation is defined in (2.7). The values of Volatility and Downside Deviation get closer when we have negative returns as we can see in Figure 4, which shows an example when high variance captures negative returns and funds with high volatility had low return with a negative relation between volatility and returns. While in Figure 5, high variances result from high return values with small values for the downside deviation.

$$DD = \sqrt{\frac{\sum_{i=1}^{n}(L_i)^2 \times 12}{n-1}}, \quad L_i = \min(r_i, 0). \tag{2.7}$$

2.1.7 Sortino Ratio

Sortino Ratio is a performance measure that is defined as the amount of excess returns over risk-free interest rate per unit of risk that is measured by Downside Deviation.

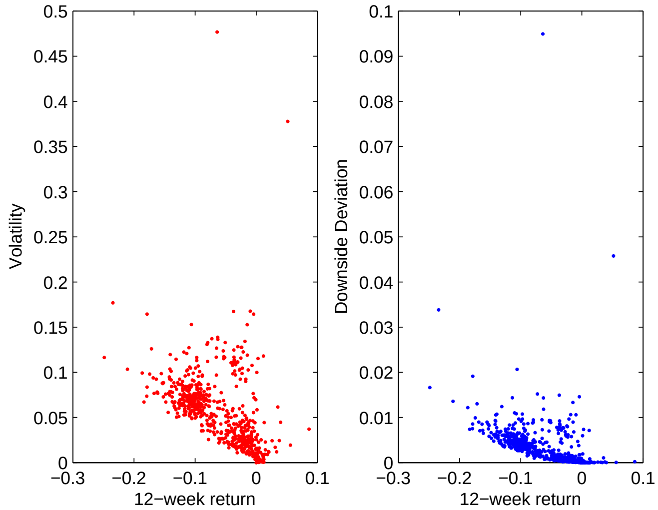

Figure 4: Volatility and Downside Deviation vs. 12-week return of a set of mutual funds as on July 29, 2008

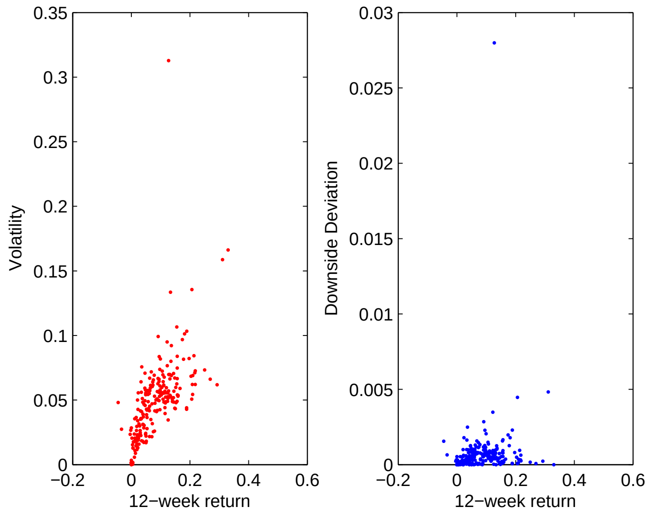

Figure 5: Volatility and Downside Deviation vs. 12-week return of a set of mutual funds as on July 8, 2003

Sortino Ratio is defined in (2.9).

$$\text{Sortino Ratio} = \frac{\left(\prod_{i=1}^{n}(1+r_i)\right)^{12/n} - \left(\prod_{i=1}^{n}(1+f_i)\right)^{12/n}}{DD} \tag{2.8}$$

$$= \frac{\text{Annualised excess returns over risk-free rate}}{\text{Downside Deviation}}, \tag{2.9}$$

where n is the period under consideration.

Example: A fund with a Sortino Ratio of 10% scores a 10% annualised excess return over risk-free interest rate for every unit of Downside Deviation risk incurred.

2.1.8 Sharpe Ratio

Sharpe ratio is the most common risk-adjusted performance measure that is defined as the amount of excess returns over risk-free interest rate per unit of volatility. Sharpe Ratio is defined in (2.11). Sharpe Ratio values that are larger than one are considered as good values.

$$\text{Sharpe Ratio} = \frac{\left(\prod_{i=1}^{n}(1+r_i)\right)^{12/n} - \left(\prod_{i=1}^{n}(1+f_i)\right)^{12/n}}{\sigma} \tag{2.10}$$

$$= \frac{\text{Annualised excess returns over risk-free rate}}{\text{Annualised Volatility calculated over the same period}}, \tag{2.11}$$

where n is the period under consideration.

Example: A fund with a Sharpe Ratio of 10% scores a 10% annualised excess returns over risk-free interest rate for every 1 unit of Volatility incurred.

2.1.9 Up Capture

Up Capture is a performance measure that measures the relative performance of the security to the performance of the market only when the market has positive returns and it does not count any returns when the market has negative returns. Up Capture is defined in (2.12).

$$\text{Up Capture} = \frac{\prod_{i=1}^{n}(1+U_i)-1}{\prod_{i=1}^{n}\big(1+\max(m_i,0)\big)-1}, \quad U_i = \begin{cases} r_i & \text{if } m_i \geq 0. \\ 0 & \text{if } m_i < 0. \end{cases} \tag{2.12}$$

2.1.10 Down Capture

Down Capture is a performance measure that measures the relative performance of the security to the performance of the market only when the market has negative returns and it does not count any returns when the market has positive returns. Down Capture is defined in (2.13). Figure 6 shows how Up Capture has positive relation with returns while Down Capture has negative relation with returns.

$$\text{Down Capture} = \frac{\prod_{i=1}^{n}(1+L_i)-1}{\prod_{i=1}^{n}\big(1+\min(m_i,0)\big)-1}, \quad L_i = \begin{cases} r_i & \text{if } m_i < 0. \\ 0 & \text{if } m_i \geq 0. \end{cases} \tag{2.13}$$

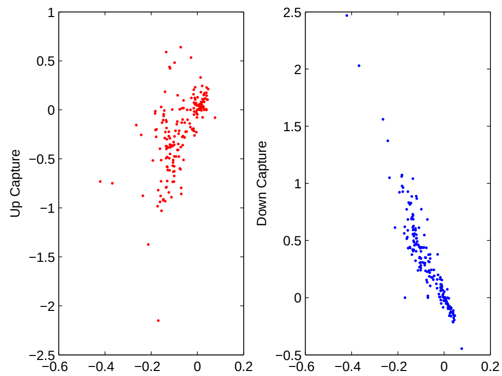

Figure 6: Up Capture (left) and Down Capture (right) vs. 12-week return of a set of mutual funds as on September 4, 2001

2.1.11 Positive Excessive Return (+ve)

Positive Excessive Return measures the amount of excess return over the market return when the market has positive return. Excessive Return (+ve) is defined in (2.14).

$$\text{Excessive return (+ve)} = \prod_{i=1}^{n}(1+U_i) - \prod_{i=1}^{n}\big(1+\max(m_i,0)\big). \tag{2.14}$$

2.1.12 Negative Excessive Return (-ve)

Negative Excessive Return measures the amount of excess return over the market return when the market has negative returns. Excessive Return (+ve) is defined in (2.15). Figure7 shows an example when risk measures, Excessive Return (+ve) and Excessive Return (-ve), each had positive relation with 12-week return on the period ended September 4, 2001.

$$\text{Excessive return (-ve)} = \prod_{i=1}^{n}(1+L_i) - \prod_{i=1}^{n}\big(1+\min(m_i,0)\big). \tag{2.15}$$

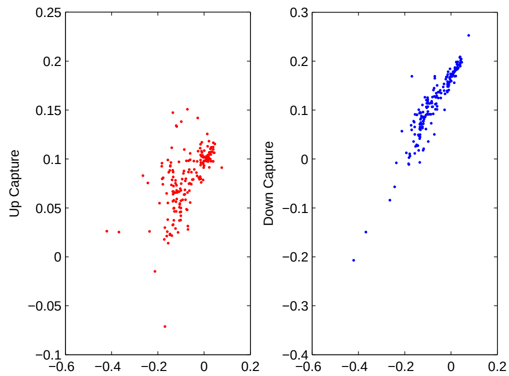

Figure 7: Excessive Return (+ve) (left) and Excessive Return (-ve) (right) vs. 12-week return of a set of mutual funds as on September 4, 2001

2.1.13 Calmar Ratio

Calmar ratio is a performance measure mainly used in the hedge funds industry and it is the ratio of return to the Maximum Drawdown and is normally calculated over three years. In my thesis, I calculate Calmar ratio over the period of time that is under consideration, which is 12 weeks for mutual funds and 12 months for hedge funds. Calmar Ratio is defined in (2.17).

$$\text{Calmar Ratio} = \frac{\left(\prod_{i=1}^{n}(1+r_i)\right)^{12/n} - 1}{MDD} \tag{2.16}$$

$$= \frac{\text{Annualised return}}{\text{Maximum Drawdown}} \tag{2.17}$$

2.1.14 Omega Ω

Definition: Omega risk measure is the ratio of expected (probability weighted) gains above a threshold to the expected (probability weighted) losses below the same threshold. Omega ratio Ω is defined in (2.18) and it represents the ratio of Area ‘B’ to Area ‘A’ in Figure 8. Bacmann and Scholz (2003) argue that the evaluation of an investment with the Omega ratio should be considered for thresholds between 0% and the risk-free rate, and therefore 0 is used in my thesis as a threshold τ.

$$\Omega(\tau) = \frac{\displaystyle\int_{\tau}^{\infty} [1 - F(x)]\,\mathrm{d}x}{\displaystyle\int_{-\infty}^{\tau} F(x)\,\mathrm{d}x}, \tag{2.18}$$

$$= \frac{\text{Expected (probability weighted) gains above the threshold } \tau}{\text{Expected (probability weighted) losses below the threshold } \tau}$$

$F(x)$ is the cumulative distribution function of returns and 0 is used as a threshold τ .

Example: $\Omega(0.02) = 2.5$ tells us that the expected return exceeding 2% is 2.5 times the expected return less than 2% i.e. $\Omega(0.02) = \dfrac{E(r|r > 0.02) - 0.02}{0.02 - E(r|r < 0.02)} = \dfrac{\text{Potential Gain}}{\text{Potential Loss}}$.

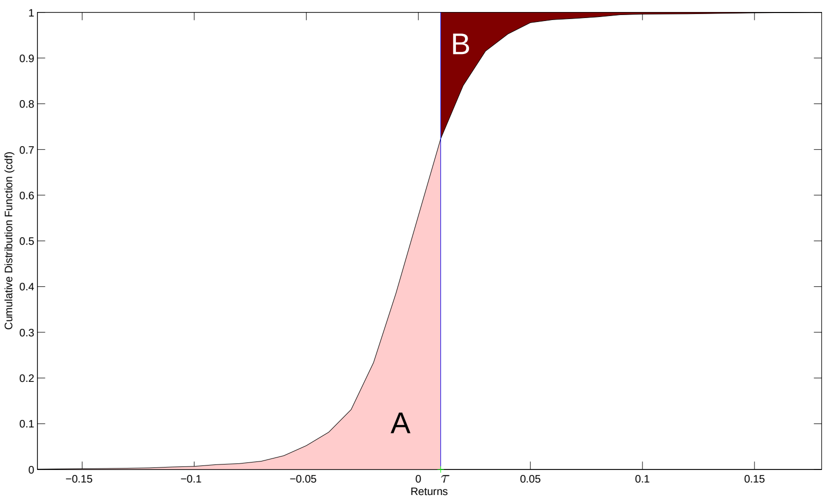

Figure 8: Expected (probability weighted) gain and loss areas

2.1.15 Winning runs

Winning runs is a performance measure that is used in games as well as in finance and it is defined in (2.19).

$$\text{Winning Runs} = \frac{\sum_{i=1}^{n-1} A_{i,i+1}}{n-1}, \tag{2.19}$$

where

$$A_{i,i+1} = \begin{cases} 1 & \text{if } r_i \text{ and } r_{i+1} > 0. \\ -1 & \text{if } r_i \text{ and } r_{i+1} < 0. \\ 0 & \text{otherwise}. \end{cases}$$

2.1.16 Value at Risk (VaR)

Definition: VaR_α is the minimum amount of money that is at risk when the investment is at the worst $\alpha\%$ scenarios. A mathematical definition of VaR is given in (2.20).

$$VaR_\alpha(S) = -\text{sup}\{x : \mathbf{P}[S < x] \leq \alpha\}, \tag{2.20}$$

where S is the investment value that is considered to be a random variable.

Example: If $VaR_{5\%} = 400$ with daily data used in the calculations, then there is a worst case scenario with a 5% probability of loosing at least 400 in the next day.

Hendricks (1996) argues that Value at Risk calculated over short periods of time of 50 days is unstable, while it is more stable if it is calculated over long periods of 500 and 1250 days. Since I am calculating risk measures over 12 consecutive weeks, the VaR will be based, in most cases, on one observation if calculated using a large $(1-\alpha)\%$ confidence level. I therefore exclude VaR from further studies in this thesis.

2.1.17 Expected Tail Loss (ETL)

Definition: Expected Tail Loss is known as the Conditional Value at Risk ($CVaR_\alpha$), which is defined as the expected loss given that the loss is beyond the VaR_α of the investments. A mathematical definition of CVaR is given in (2.21).

$$CVaR_\alpha(S) = -\mathsf{E}[S|S \leq -VaR_\alpha(S)], \tag{2.21}$$

where S is the investment value that is considered to be a random variable.

Example: $CVaR_{3\%} = 200000$ with monthly data used in the calculations means that the expected loss next month is 200000, given that the loss is known to be greater than or equal to the Value at Risk based on the worse 3% scenarios.

Note that CVaR is excluded from further studies in this thesis for the same reasons that VaR is excluded.

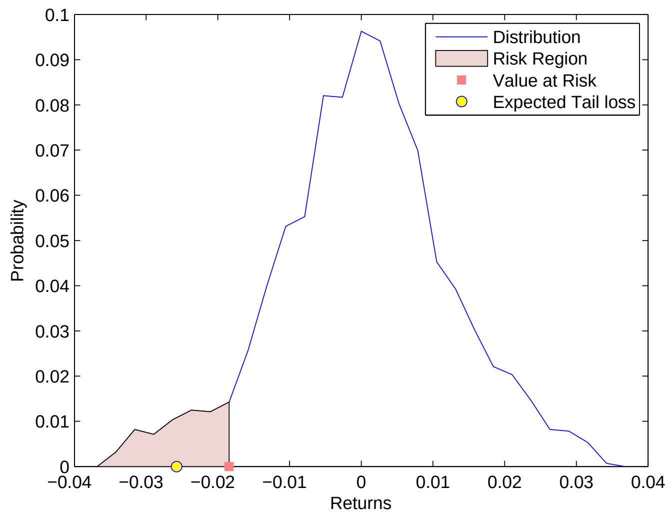

Figure 9: VaR & CVaR

2.2 Rank Correlation

Risk statistics are functions of returns and they measure different aspects of risk, which allows comparing investments according to their risk level. I replace risk values by the ranks to standardise different risk measures and to eliminate the effect of outliers on my prediction model. The statistics are therefore given equal weights when they are ranked. The main disadvantage of using the ranks is that the magnitude is lost and that extreme risk values have small effect on the model. The effect of the market is neglected as well and it is limited to the order of the ranks. We get standardised ranked vectors whether the market is moving up or down. Kendall (1938) has introduced the rank correlation and it is used when comparing two ranked vectors. Each vector of length N has a mean of $\frac{N(N+1)}{2}$ and therefore when computing the standard correlation between two ranked vectors of the same length, there will be some loss in information for the observations with middle ranks about the mean. I therefore use the rank correlation, which is similar to the standard statistical correlation in that both have values between -1 and 1, but the rank correlation takes care of the order of the ranks rather than dealing with the ranks as values.

Consider a sequence of N integers and let $B(i)$ be the i-th element in the sequence. Then for every $i \in \{1, 2, \ldots, N-1\}$, I count the number of $B(j)$'s that are greater than $B(i)$, $\forall j \in \{i+1, i+2, \ldots, N\}$. The counted number for each $B(i)$ is denoted by $C(i)$. The rank correlation, τ, is then defined as

$$\tau = \frac{4S - N(N-1)}{N(N-1)}, \tag{2.22}$$

where $S = \sum_{i=1}^{N-1} C(i)$.

An example is given below on how to compute the rank correlation between two vectors of length $N = 10$. Let

$$A = \{6, 3, 7, 8, 5, 1, 2, 4, 9, 10\}, \tag{2.23}$$

$$B = \{6, 2, 1, 7, 8, 3, 4, 5, 10, 9\}. \tag{2.24}$$

In order to compute the rank correlation, I need to rearrange the vectors such that one of the vectors, say A, has an objective ascending values and rearrange the other vector B to correspond to the initial ranks in A. This gives

$$A = \{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}, \tag{2.25}$$

$$B = \{3, 4, 2, 5, 8, 6, 1, 7, 10, 9\}. \tag{2.26}$$

Then for $B(i), i = \{1, 2, \ldots, N - 1\}$, I count $C(i)$ as defined previously to get the following

$$\{7, 6, 6, 5, 2, 3, 3, 2, 0\}. \tag{2.27}$$

The first element in (2.27), $C(1)$, has come from having seven integers to the right of $B(1) = 3$ in (2.26) that are greater than three. Then $S = 34$ is the sum of integers in (2.27). Define $\Sigma = 2S - \frac{N(N-1)}{2} = 23$, then the rank correlation is computed as $\tau = \frac{2\Sigma}{N(N-1)} = 0.511$. Note that if $A = B$, then $\Sigma = 1 + 2 + \cdots + N - 1 = \frac{N(N-1)}{2}$ and this gives a rank correlation of $+1$. While if B was in a reverse order of A, then $S = 0$, $\Sigma = -\frac{N(N-1)}{2}$ and the rank of correlation is -1.

2.3 Testing the Independence of the Rank-Statistics

Risk measures are provided under different mathematical contexts. They could produce Rank-Statistics that are linearly dependent (it is worth noting that Rank-Statistics vectors could be very different from the risk value vectors). In order to carry out regression analysis, linearly dependent vectors should be excluded. Therefore I need to investigate the dependence issue between the Rank-Statistics vectors I constructed for the 15 risk measures at each 12-week sub-period. In this section, I apply the test on the set of mutual fund described in Table 2. A similar statistical test is performed separately for the set of hedge funds used in Chapter 4. I look at the rank correlations described in the previous section, as absolute values and compute the average of the reported correlations over the whole sub-periods. In Table 4, I highlight the pairs that are highly correlated with correlation of more than 70% in average. Beyond pair-wise correlation, I was still concerned that some of the statistics might be linearly dependent upon a combination of several other statistics —that is, one rank vector (say obtained by using Calmar Ratio as risk measure) is statistically expressed as a linear combination of two other ranks vectors (e.g. obtained by using Downside Deviation and Sharpe Ratio). Therefore, I devise a test of the Rank-Statistics across all the time periods to identify highly dependent subsets within the set of Rank-Statistics that persist throughout the test period.

The method of investigating the dependence among the Rank-Statistics across all linear combinations using regression analysis is described below in five steps:

1. The statistics are computed using the definitions in Section 2.1 over rolling 12 weeks sub-periods (the first 12-week sub-period of the 732 24-week periods under consideration) as described in Section 1.4.

2. The Rank-Statistics are computed according to the investor's natural preference in

Section 2.1 to produce 15 vectors of length N_t for each rolling 12 week sub-period.

3. During each sub-period, I regress all the possible combinations of the Rank-Statistics vectors starting with pairs, then triples and so forth.

   a) I identify the first combination where the coefficient of determination, R^2, is at least 95%. R^2 is a statistical measure of the goodness of a linear model and has values between 0 and 1, with $R^2 = 1$ indicates a perfect linear model.

   b) I remove the regressand from the set of Rank-Statistics being tested for that sub-period and record each statistic, regressor or regressand, being involved in the regression.

   c) I restart step 3 of the test using the remaining Rank-Statistics at the tested sub-period.

   d) I continue the regression test for that sub-period until all the possible combinations have been considered or all the Rank-Statistics are eliminated. In other words, no combination of the remaining Rank-Statistics can result in a regression with R^2 of 95% or more.

   e) I score 1 for each statistic that has been recorded in at least one regression for which R^2 is at least 95% for that sub-period.

4. I then move to the next 12-week sub-period and repeat the same procedure until I complete the 732 sub-periods.

5. All the instances of a Rank-Statistic featuring in a regression with an R^2 of at least 95% as a regressor or regressand are counted and plotted as a relative frequency histogram in Figure 10. The chart shows that there are nine Rank-Statistics which

feature in regressions with high R^2 statistics in more than 95% of the tested sub-periods. This support my intuition that some of the Rank-Statistics can be eliminated without information related to the performance.

I study the components of each combination that passed the test at each sub-period and summarize the results based on the set of mutual funds that has been used:

1. The most dependent Rank-Statistics were 9, 10, 11 and 12, and they produced two pairs of highly correlated Rank-Statistics 9 and 11, and Rank-Statistics 10 and 12 across all periods. This result is not surprising because of the definitions of statistics 9 and 11, and 10 and 12.

2. Rank-Statistics 7 and 8 occurred more frequently as correlated than the rest of the Rank-Statistics. This is explained as both statistics have the same numerator on their mathematical definitions and both have denominators with negative preference signs.

3. Rank-Statistics 4, 5, 6, 7 and 8 were highly dependent and appeared in most periods as pairs, triples, or a combination of Rank-Statistics.

4. Rank-Statistics 1 and 2 appeared together very often with a combination of Rank-Statistics 11 and 12.

5. Rank-Statistics 2 appeared either with Rank-Statistics 3 as a pair or with a combination of other Rank-Statistics.

6. Rank-Statistics 6 appeared with the pair of Rank-Statistics 4 and 8 very often.

7. Rank-Statistic 13 appeared in combination with Rank-Statistics 11 and 12, or with Rank-Statistics 6 and 8.

Some of the pair-wise relations can be seen from their definitions, but since we have some linear relations between more than two statistics at a given period, the linear dependency test was necessary. This, together with correlation analysis, and by looking at the nature of the definitions of the risk statistics, I consider that the information contained within Rank-Statistics 2, 5, 6, 8, 11 and 12 can be generated from the remaining Rank-Statistics and therefore I exclude them from subsequent studies. The dependent test is repeated among the remaining nine Rank-Statistics. The resulting Figure 10 clearly shows that the co-linearity between Rank-Statistics is very significantly reduced.

Statistics	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	**83**	64	35	48	39	51	49	67	42	66	42	17	17	18
2		**71**	43	50	46	48	49	53	56	52	57	19	14	16
3			26	27	27	27	27	44	47	44	47	16	13	15
4				66	**82**	56	62	23	47	23	48	40	25	16
5					**77**	**83**	**95**	39	39	38	40	22	17	15
6						66	**73**	27	46	26	47	32	21	15
7							**86**	48	34	47	35	20	19	19
8								42	37	41	38	21	17	15
9									27	**99**	27	28	27	25
10										26	**99**	35	25	20
11											27	28	28	25
12												35	25	20
13													63	40
14														49

Table 4: The average of the rank correlations between the Rank-Statistics calculated over 732 tested 24-week periods

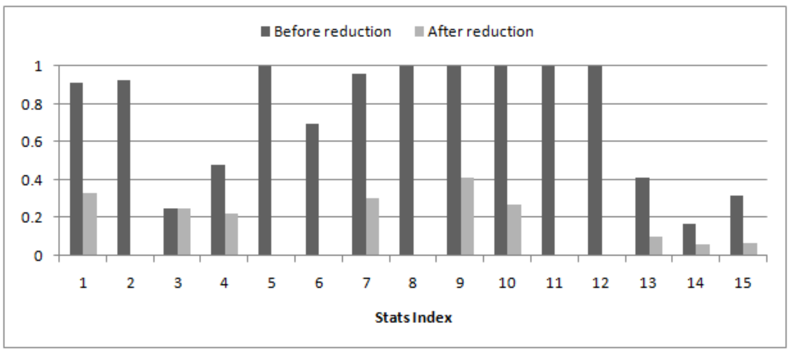

Figure 10: Relative frequency distribution of 15 Rank-Statistics: $R^2 \geq 95\%$

3 Principal Components Analysis

3.1 Introduction

Principal Component Analysis is a statistical variable reduction technique that linearly transforms a set of variables to a new uncorrelated factors. Each new factor is a linear combination of the original variables. The complete set of new factors preserve as much variation as the original variables presented. The factors are sorted in a descending order according to the amount of variation explained in their variances and generally the first few principal components explain most of the variation indicating that the effective dimensionality of the original set of variables is considerably less than the total number of variables. The remaining components are associated with eigenvalues of the covariance matrix that are close to zero and have little explanatory power. Including all 15 Rank-Statistics would have resulted in very small and possibly zero eigenvalues that do not explain any additional variation in the data and therefore I only used the remaining nine Rank-Statistics before PCA is applied.

3.2 Applications

I choose to apply PCA to my dataset to reduce the dimensionality of the problem whilst producing uncorrelated factors. The covariance matrix of the original set of Rank-Statistics expresses the variability and covariability of the dataset. The information which is preserved after the transformation is represented in the variances of the uncorrelated factors. PCA, which is a singular value decomposition (SVD) problem, extracts orthogonal factors in descending order of importance as measured by the factor variance. The factors are a rotation of the original Rank-Statistics centred on zero; and the complete set of nine principal components explains all the variation observed in the original dataset. Each factor is therefore a linear combination of the nine centred Rank-Statistics. Generally, I have found that the first two or three factors explained most of the variation whilst the rest of the factors tend to capture noise as can be seen later. Therefore by selecting the first two or three factors and using those in my model building process, I capture the essence of the original dataset with a much smaller set of uncorrelated variables. For simplicity in this subsection, I ignore the time index t of $RS_{k,j,t}$ and N_t, and refer to the Rank-Statistics RS by a $9 \times N_t$ matrix where each row of RS corresponds to a Rank-Statistic, and similarly I refer to the principal component factors by a $9 \times N_t$ matrix F whose rows are the transformed factors. The nine Rank-Statistics are centralised such that each has a zero mean by subtracting the mean of the sample from each of the observations. In most applications of PCA the data are normalised by scaling the variables according to their standard deviations. However, this is not necessary with Rank-Statistics as all my variables have the same standard deviation because each Rank-Statistic consists of the unique ranks between 1 and N_t.

The Rank-Statistics are linearly transformed at each time step by a transformation matrix $V_{9\times9}$, with $V^{-1} = V^T$, to be the matrix whose columns are the orthonormal eigenvectors of $Cov\left(RS_{9\times N} - \overline{RS}_{9\times N}\right) = Cov\left(\widehat{RS}_{9\times N}\right)$, where $\widehat{RS} = RS - \overline{RS}$ and all elements of the mean matrix $\overline{RS}$ are identical and equal to

$$\frac{1}{N}\sum_{j=1}^{N} j = \frac{N+1}{2}.$$

The columns, which are the eigenvectors of the covariance matrix, are sorted in a descending order, according to the value of the corresponding eigenvalue. I then get

$$F_{9\times N} = V_{9\times 9}\left(RS_{9\times N} - \overline{RS}_{9\times N}\right) = V_{9\times 9}\left(\widehat{RS}_{9\times N}\right) \text{ with the diagonal covariance matrix} \tag{3.28}$$

$$Cov(F) = \frac{1}{N-1} F \times F^T = V \times Cov(\widehat{RS}) \times V^T = \begin{bmatrix} \lambda_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \lambda_9 \end{bmatrix}, \tag{3.29}$$

where the diagonal entries, $\lambda_1 \geq \lambda_2 \ldots \geq \lambda_9$, are the eigenvalues of the covariance matrix.

4 Quantitative Insight into Management of Hedge Funds and Consequences on Fund Performance

4.1 Introduction

Many statistical models have been developed to predict future returns of different asset classes over the last four decades. Sharpe (1992) applies style analysis to mutual funds and argues that mutual funds can be classified by limited asset classes. Fung and Hsieh (1997) find that hedge fund returns are classified differently from mutual funds. Fung et al. (2008) has classified funds of hedge funds into two classes according to performance measures. Das (2003) used a clustering method to classify hedge funds.In this respect, I develop a slightly different idea in Chapter 4. Instead of looking at predictions, I classify hedge funds using risk measures of historical data. I expect that in a risk controlled environment (hedge funds and investment funds) and risk control squared environment (funds of hedge funds), the risk classification is good enough to reflect management quality through quantitative description of consistency and aggression in management styles. The consistency and aggression classifications are introduced and discussed in Section . It is well known that the investment community has various opinions regarding the quality of risk measures. Issues of consistency and usefulness are constantly under discussion and the use of one particular risk measure may not reflect all aspects of an asset. In Chapter 4, I combine nine popular and standard risk and performance measures: (1) Annualised Return, (2) Annualised Alpha, (3) Annualised Volatility, (4) Trend Correlation, (5) Maximum Drawdown, (6) Sortino Ratio, (7) Up Capture, (8) Down Capture, (9) Winning Runs; and apply them to historical returns of hedge funds. I then produce a ranking of each asset according to each statistic calculated among all other assets used in the test. In addition, I determine the ranking order (ascending or descending in terms of risk values) according to the natural preference of a rational investor (that is, a balanced way of increasing returns and decreasing risk). When using a basket of statistics all based on returns, it seems likely that there will be a considerable degree of co-dependence as evidenced by the correlation between the ranks of the statistics. For this reason I restrict myself to nine risk measures against a much larger set of readily available risk measures. Subsequently I compute the principal components of these ranking vectors. Because of the significant proportion of the total variance of the original ranking vectors explained by the principal components, I concentrate on the first and second principal components, denoted as PC1 and PC2, respectively. By inspecting the factor loadings, I infer that PC1 represents the consistency of the hedge funds and PC2 represents the aggression of the hedge funds. I note that if PC is a principal component, any scaling of PC, $\alpha \times$PC, is also a principal component, for any given non-zero constant α. I note that any principal component may be replaced by its mirror image without impacting the overall mathematical results (the mirror image principal component will have the same variance and will be uncorrelated with all the other principal components). Therefore, I have chosen factor loadings such that increasing factor score corresponds to increasing the strength of the style inferred. I use 12 month returns for each rolling year period of historical data to produce a matrix of the risk statistic ranks, with number of columns corresponding to number of hedge funds in the sample and nine rows corresponding to nine risk statistics used. I then produce the principal components of the rankings and plot, for fund i, the point x_i, given by

$$
\begin{aligned}
&x_i = (x_{i1}, x_{i2}) = \\
&\Big((Return_i\ ,\ Alpha_i\ ,\ Volatility_i\ ,\ TrendCorrelation_i\ ,\ MaximumDrawdown_i\ , \\
&\quad SortinoRatio_i\ ,\ UpCapture_i\ ,\ DownCapture_i\ ,\ WinningRuns_i\ ) \bullet PC1, \\
&(\ Return_i\ ,\ Alpha_i\ ,\ Volatility_i\ ,\ TrendCorrelation_i\ ,\ MaximumDrawdown_i\ , \\
&SortinoRatio_i\ ,\ UpCapture_i\ ,\ DownCapture_i\ ,\ WinningRuns_i\ ) \bullet PC2\Big),
\end{aligned} \tag{4.30}
$$

where $risk_i$ is the ranking number of the i-th asset under that risk statistic, the $\bullet$ represents scalar product between two vectors, PC1 and PC2 are the factor loadings calculated for the first two principal components for that window. In Section 4.2, I calculate the required variables to be used in the model, discuss the results and interpret the role of principal components analysis. In Section 4.3, I discuss the classification and consequence on hedge fund performance. In Section 4.4, I investigate the migration rate of hedge funds and draw conclusions that hedge funds are pro-active in investment management, subsequently I make some comments on whether the pro-active nature affects the returns. Section 4.5 is dedicated to discussions relating to the financial crisis of 2008 and subsequent European turbulence. Finally, Section 4.6 provides an overall conclusion. The preparation of Chapter 4 has relied heavily on the joint work of Dambrauskaite et al. (2012).

4.2 PC1 Consistency and PC2 Aggression

As previously stated in Section 4.1, I interpret PC1 as a reflection of consistency and

PC2 as aggression. In Tables 5 and 6, I summarise the factor loadings for PC1 and PC2 over time. It is important to note that with the + and - sign classification of the statistics obtained in Section 2.1, the rational investor preferences have been respected. Hence, for the first factor, PC1, I see that all median or mean coefficients are positive, but the trend correlation has a negative small weight and, annualised volatility and up capture have the next smallest weights. As these factors represent exploiting trending or bull markets and the other factors representing performance in all types of environments and avoiding poor performance, it seems reasonable to define PC1 as a measure of consistency. For the second factor, PC2, as the median or mean weights for annualised volatility, trend correlation, drawdown and down capture are negative or near zero, while positive for the other factors and the greatest weight attached to up capture, PC2 appears to reflect aggression. First, I place more stress on median weights because the definitions of the BL=(low consistency, low aggression), BR=(high consistency, low aggression), TL=(low consistency, high aggression) and TR=(high consistency, high aggression) classes, refer to the number of funds placed into the category. Second, the effect on long-term performance may tell a different story from the consistency and aggression I observe which leads me to reveal an interesting management style of hedge funds collectively.

Statistics	Mean	Median	Standard Deviation
Annualised Return (%)	40.02	40.06	5.32
Annualised Volatility (%)	10.82	15.24	15.71
Annualised Alpha (%)	37.31	42.45	11.22
Trend Correlation (%)	6.37	-0.32	17.96
Maximum DrawDown (%)	30.50	33.65	12.07
Annualised Sortino Ratio (%)	43.42	44.59	4.13
Up Capture (%)	15.16	16.83	19.01
Down Capture (%)	30.98	34.38	13.95
Winning Runs (%)	37.16	39.01	6.14

Table 5: mean, median and standard deviation of cross-sectional, time series factor loadings for PC1

Statistics	Mean	Median	Standard Deviation
Annualised Return (%)	9.60	14.16	27.43
Annualised Volatility (%)	-3.10	-28.94	46.29
Annualised Alpha (%)	15.53	13.37	25.29
Trend Correlation (%)	2.28	-5.83	31.30
Maximum DrawDown (%)	3.10	-9.91	34.72
Annualised Sortino Ratio (%)	13.83	14.30	13.67
Up Capture (%)	16.16	51.41	47.41
Down Capture (%)	-0.92	-7.68	29.01
Winning Runs (%)	11.12	6.68	13.29

Table 6: mean, median and standard deviation of cross-sectional, time series factor loadings for PC2

4.3 Classification of hedge funds and performance evaluation

For a given 12-month period, I evaluate using (4.30), for each of the existing hedge funds (the precise number varies as per my explanation in Section 1.4) the points and plot these points on the (PC1, PC2) plane (Figure 11).

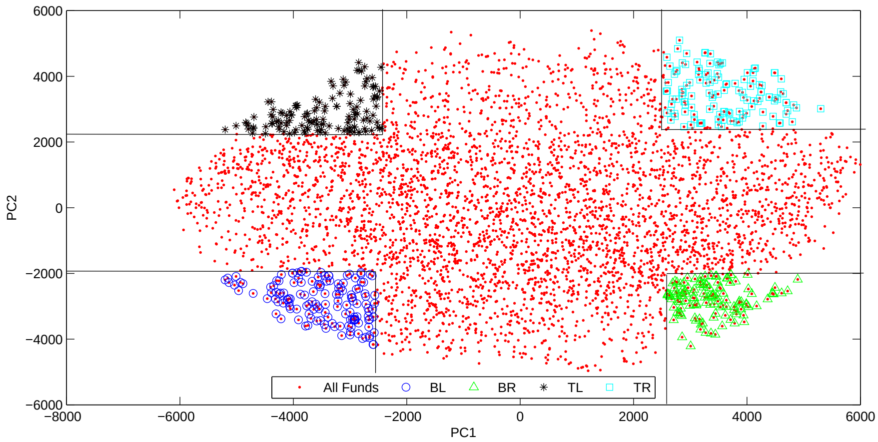

Figure 11: Hedge funds classification using PC1 as consistency and PC2 as aggression

Each dot represents a point x_i corresponding to the i-th hedge fund. I draw a square from the bottom-left of the plane and push it to include 2.5% of the total points, and define all hedge funds falling in this region to form the BL class. Note I use 2.5% because I aim to retain approximately 100 to 150 funds in each class. Correspondingly, BR class is the bottom-right, TR class is the top-right and TL class is the top-left (see Figure 11 for self-evident explanations).

After classification, I am going to compare class average returns against the index of hedge funds. In the universe of hedge funds, the index of hedge funds can be regarded as risk-free return as hedge funds aim for absolute returns. In this section, I mainly observe the excessive alpha returns and make corresponding remarks on management styles (for definition of alpha returns in the particular context of hedge funds, readers can refer to Philipp et al., 2009).

For the funds in the BL class, I calculate the forward 12-month return and corresponding investment value of each dollar invested using equal weights on its constituents and the corresponding return is recorded at the end of the time period concerned. I repeat this at the end of every month to obtain a returns table together with the corresponding ending month and then calculate the average 12 of them as the yearly return. For example, to obtain the return for January 2004-December 2004, I average the returns in January 2004, February 2004, . . . , December 2004, then record the annual return January 2004-December 2004 at December 2004. I carry out similar computations for BR, TL and TR classes and plot these against the Index of hedge funds (called Market in the graphs) and the results are shown in Figure 12. I note that BL class has scored positive return in most periods including the financial crisis 2008-2009, but did not benefit from the market jump in late 2009 and early 2010. BL returns therefore had a high median comparing with other classes. BR class has performed best during late 2009 and early 2010, but then performed worst in late 2010 and in 2011. This explains why BR scored the highest standard deviation among other classes. High aggression classes, TR and TL, performed badly during the 2008-2009 financial crises with returns as low as -40%. I note that BL class has scored positive return in most periods including the financial crisis 2008-2009, but did not benefit from the market jump in late 2009 and early 2010. BL returns therefore had a high median comparing with other classes. BR class has performed best during late 2009 and early 2010, but then performed worst in late 2010 and in 2011. This explains why BR scored the highest standard deviation among other classes. High aggression classes, TR and TL, performed badly during the 2008-2009 financial crises with returns as low as -40%.

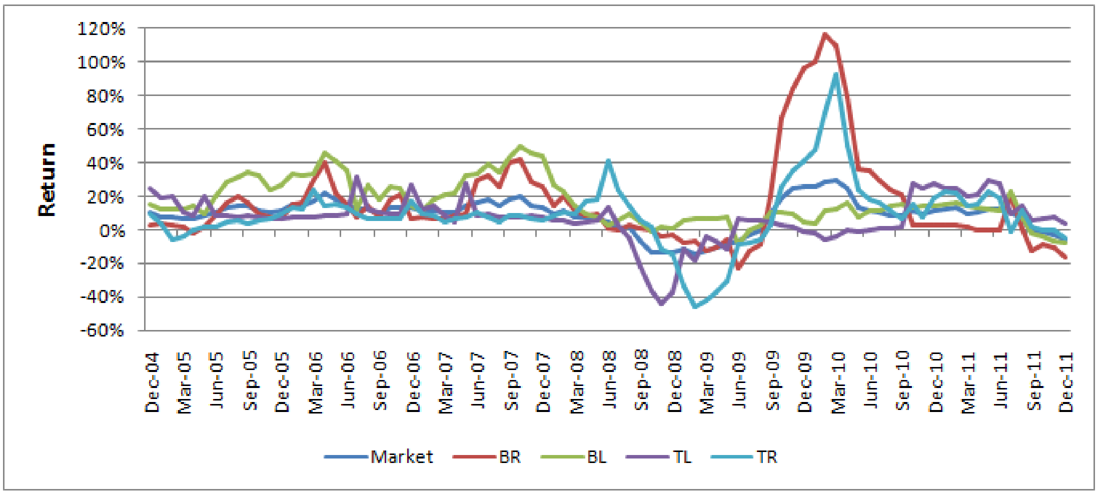

Figure 12: Average 12 months returns of the four classes against the index of hedge funds

	Mean (%)	**Median (%)**	**Standard Deviation (%)**
Market	8.97	10.66	9.86
BR	15.87	7.82	27.38
BL	16.61	13.80	13.23
TL	6.68	7.57	13.55
TR	9.34	8.05	19.89

Table 7: Statistics for Figure 12

From Table 7, it is clear that both BL and BR classes have considerable advantage over TL and TR classes. According to the definition, the BL and BR classes are defined to be “less aggressive” than TL and TR classes in my frame work. I can conclude that during this particular period, aggression (as measured by PC2 component) is less helpful to gain longer term wealth accumulation. The PC1 by contrast, seems to be more relevant to long term wealth accumulation. In Figure 13, the accumulated portfolio asset values appear to more precise.

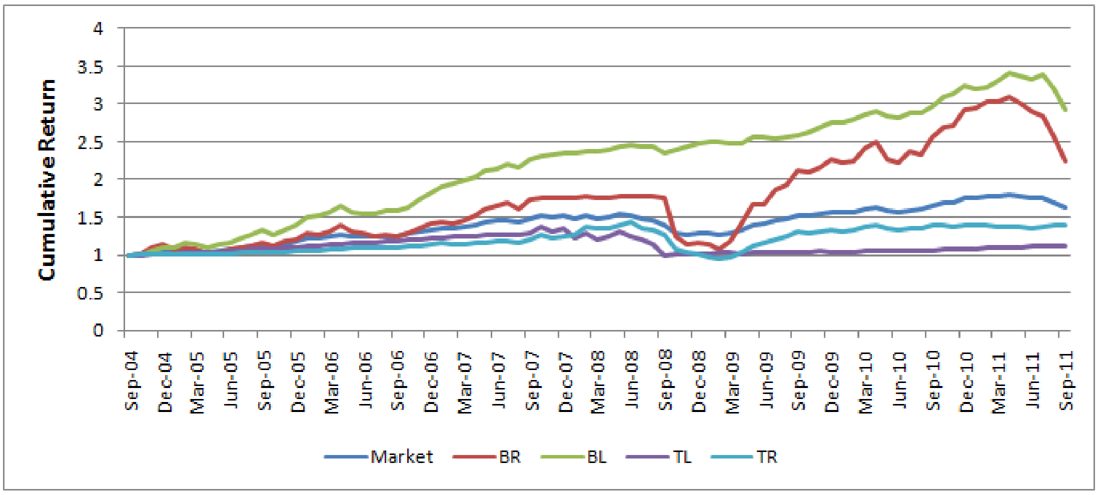

Figure 13: Portfolio Asset Values

If I look at the portfolio asset values in Figure 13, the BL class has performed significantly better and BR slightly outperformed the market while TL and TR classes underperformed most of the time.

The advantage of BL class against BR class is clear during the depth of the crisis, BL class outperforms BR class dramatically, and although the subsequent recovery is not as strong, BL class still maintains its advantage. There is a clear indication that with rigorous risk control, the hedge funds in the BL class present better opportunities for the longer term investors. In order to obtain a closer look at the effect of financial crisis, I divide the time interval into various sub-periods (Figures 14-23).

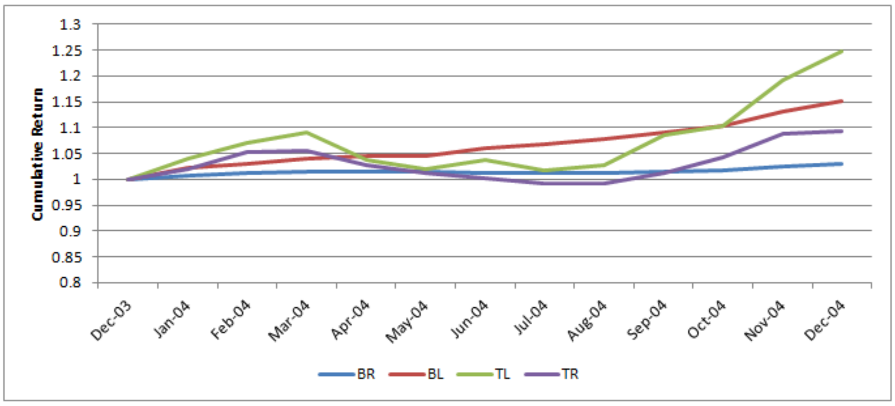

Figure 14: December 2003 to December 2004 asset accumulation

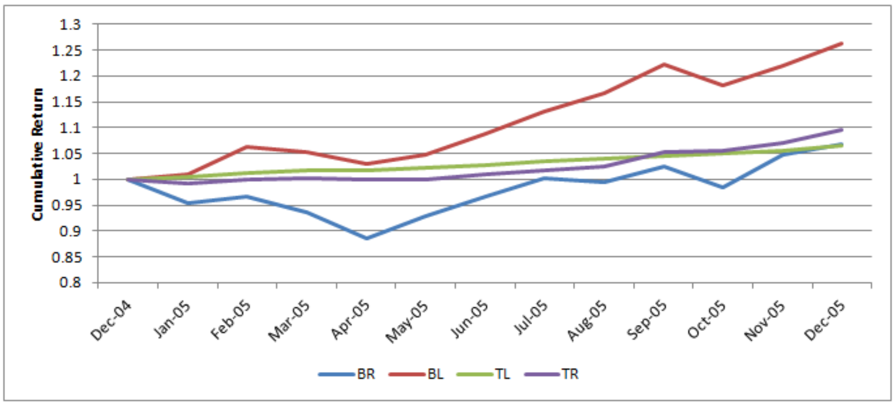

Figure 15: December 2004 to December 2005 asset accumulation

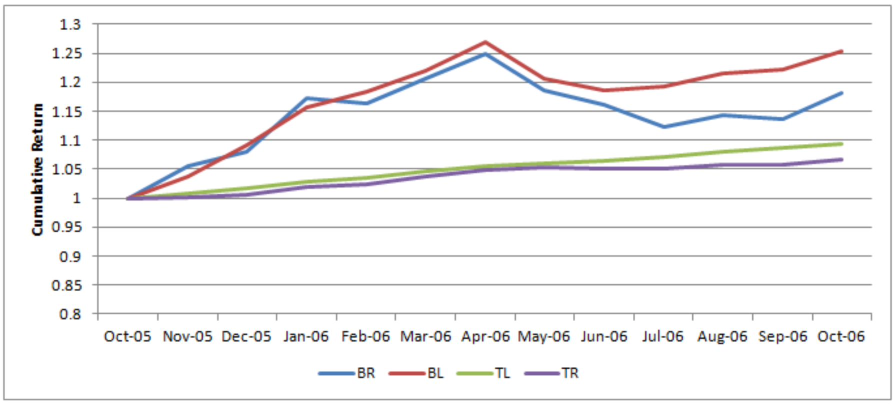

Figure 16: October 2005 to October 2006 asset accumulation

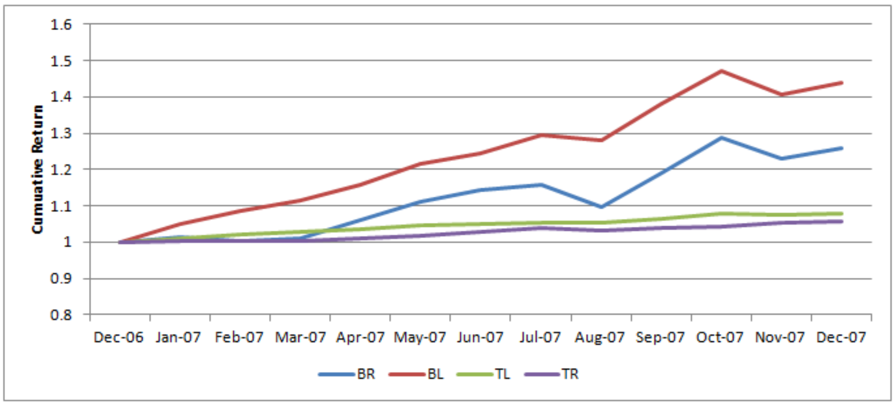

Figure 17: December 2006 to December 2007 asset accumulation

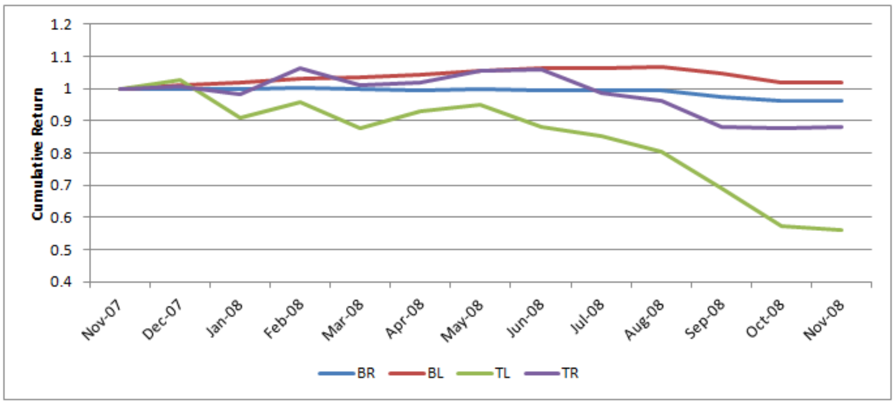

Figure 18: 2007 to November 2008 asset accumulation

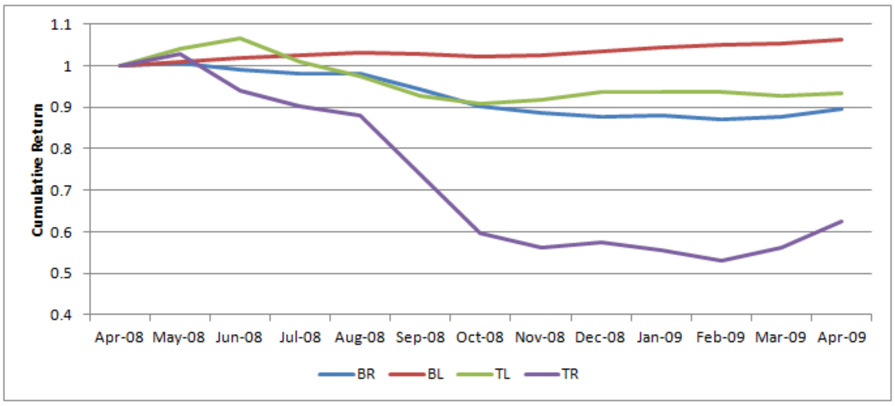

Figure 19: April 2008 to April 2009 asset accumulation.

Note: Just before the bottom of the financial crisis, the BR class underperforms BL class by more than 10%, while BL maintains stability.

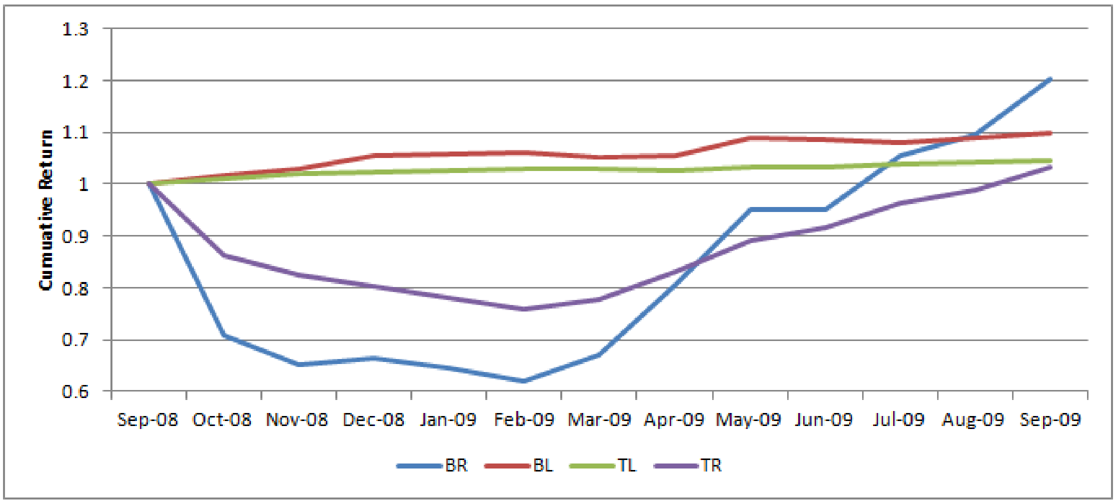

Figure 20: September 2008 to September 2009 asset accumulation

Note: This is the bottom behaviour, the centre is placed at March 2009, when the stock market bottomed, BR class is the most exhilarating class while others maintain relative stability, BL class is by far the best asset class.

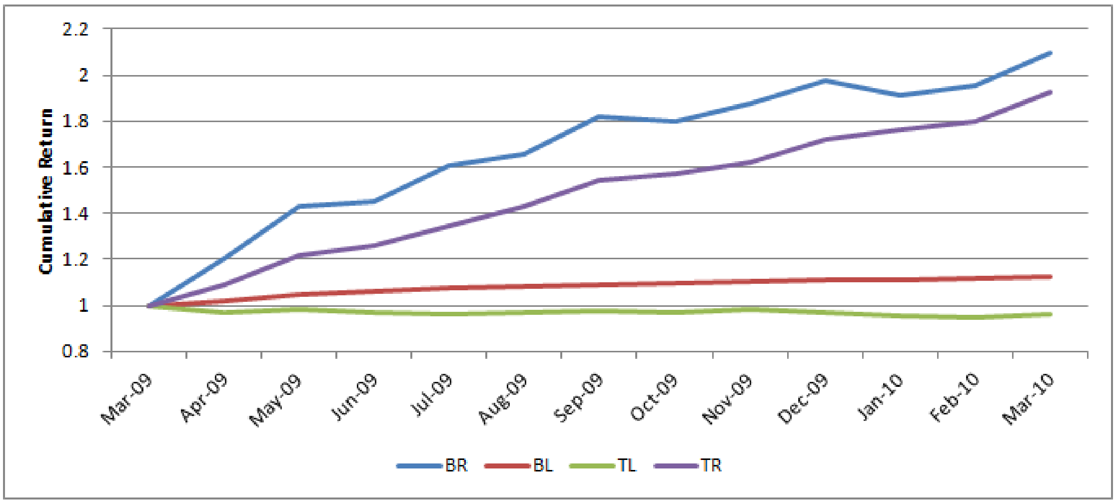

Figure 21: March 2009 to March 2010 asset accumulation

Note: In the recovery phase, since BR class tanked the most beforehand, its recovery has also been exciting.

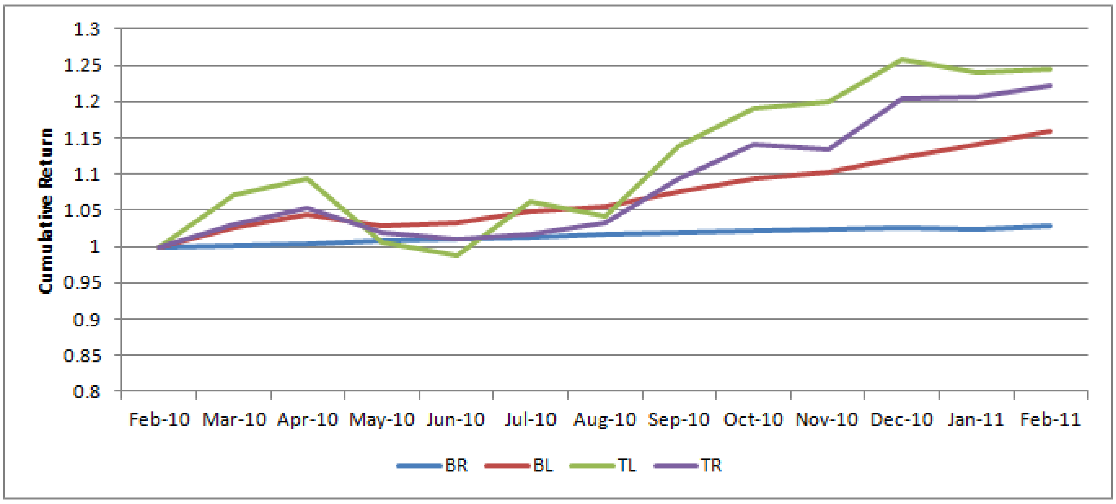

Figure 22: February 2010 to February 2011 asset accumulation

Note: After the initial recovery, TL class forms the best asset class, in response to its much earlier pre-crisis under-performance of 2008-2009.

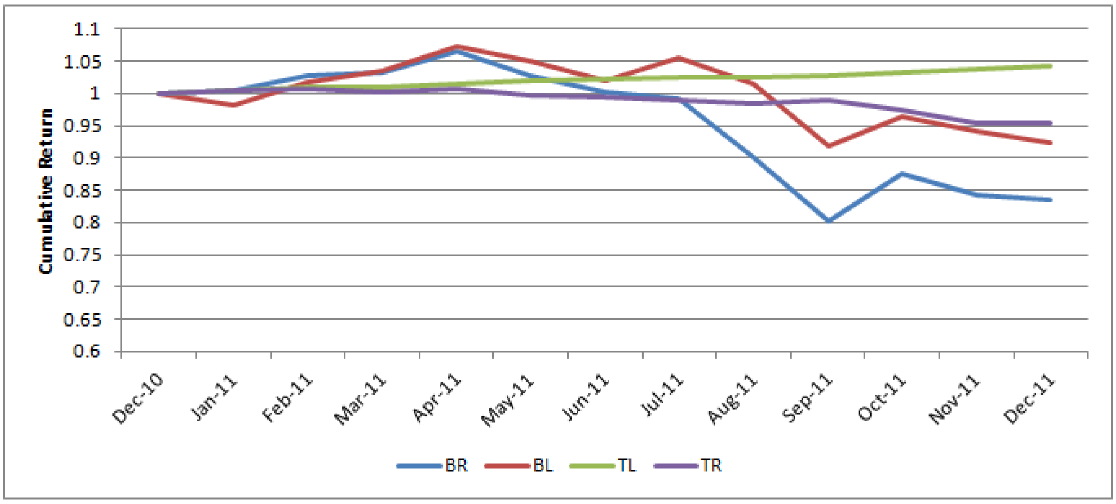

Figure 23: December 2010 to December 2011 asset accumulation

Note: After the initial recovery, TL class forms the best asset class, in response to its much earlier pre-crisis under-performance of 2008-2009.

I observe that

1. The TL class, which according to my definition, has strong aggression and weak consistency, demonstrates some bright spots in 2004 and 2010-2011, but is one of the worst asset classes in pre-crisis 2008-2009. During the 2008-2009 financial crisis, I can easily conclude that the TL class suffered early asset value fall and is very late to recover. The consolation is that this “long-term” reaction to the crisis is not very dramatic in terms of percentage performance.

2. The TR class has mostly been an under-dog despite having strong consistency and strong aggression according to my definition.

3. The BL class, which is very weak in both consistency and aggression by my definition, behaved remarkably well.

4. The BR class performed poorly in the pre-2008 crisis and recovered very strongly in the recovery market after March 2009, again performed very poorly in the secondary European crisis during 2010 and 2011. Although it corresponds to low aggression and high consistency according to my definition, it is actually very aggressive and quick to respond to events.

From the remarks made in (1) to (4), I notice that if I apply quantitative risk analysis concepts to hedge funds, a hedge fund that scores highly on both principal components, PC1 and PC2, in one year seems to have poorest returns in the immediate year after. The opposite regarding a hedge fund that scores low on PC1 and PC2 in one year seems to have better returns in the immediate year after. It prompts me to make an investigation in the following section and reveal an interesting insight into the management mentality of hedge funds as a group from a pure quantitative point of view.

4.4 The 'Pro-Active' nature of hedge funds

I follow the same discussions as in the previous section, but I now look at another piece of information: on a time rolling basis, whereby I calculate the risk measures using one year data, e.g. 2007, then I classify them into BL, BR, TL, TR, and remainder. I look at the percentage number of funds within each class that remained in the same class in the immediate following year, e.g. 2008 (see Table 8 for all percentages). I compare the average return of BL, BR, TL and TR against (1) the average returns of those hedge funds which remained in the same class (2) the average returns of those hedge funds which did not remain in the same class. Figures 24-27 depict returns and show that

1. The overall BR, BL, TL, TR class average returns are almost the same as the corresponding "out" class average returns, suggesting that most of the funds "pro-actively" move out of their existing situation. In many periods, all existing funds in TL and BR classes moved out and this can be seen by the discontinuous red lines in Figures 24-27 when no fund stayed in. Therefore, hedge funds seem to be actively managing portfolios.

2. The hedge funds in BR, TR classes are better off to move out of their existing position as those staying in are the under-performing ones. This implies that if historical data dictates that a fund is "consistent", then change is needed.

3. The TL class is a 'mixed bag'. During most of the time periods, staying in the class proved to be a better strategy suggesting that if the fund's historical data indicates that it is aggressive but not consistent, then staying in the same class during the turbulent times of 2008-2009 crisis and the subsequent European crisis is a better

option. The fact that hedge funds are locked into gated or suspended investments in 2008 witnessed many funds recover in the bull market run of after the market bottom in March 2009.

4. For the BL class staying in is the best option since it is the best performing class.

Finally, I note an alternative argument: the seemingly high rate of hedge funds moving out of their existing class may be caused by the underlying holdings of hedge funds, which cannot be independently verified here. Future investigation is needed to clarify this possibility.

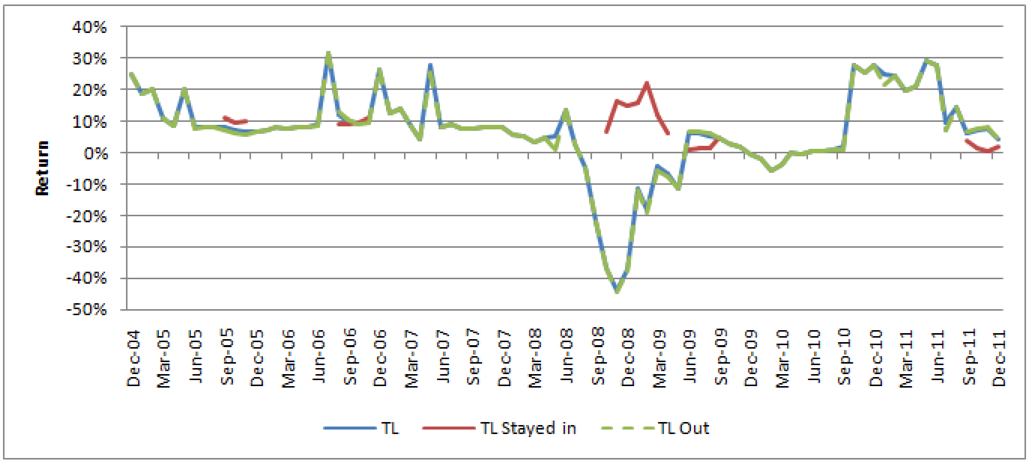

Figure 24: Migration performance analysis for TL class

4.5 Application to Financial Crisis 2008-2009

In this section, I look at the number of funds reporting, the changes in management styles and the asset returns of the classified classes.

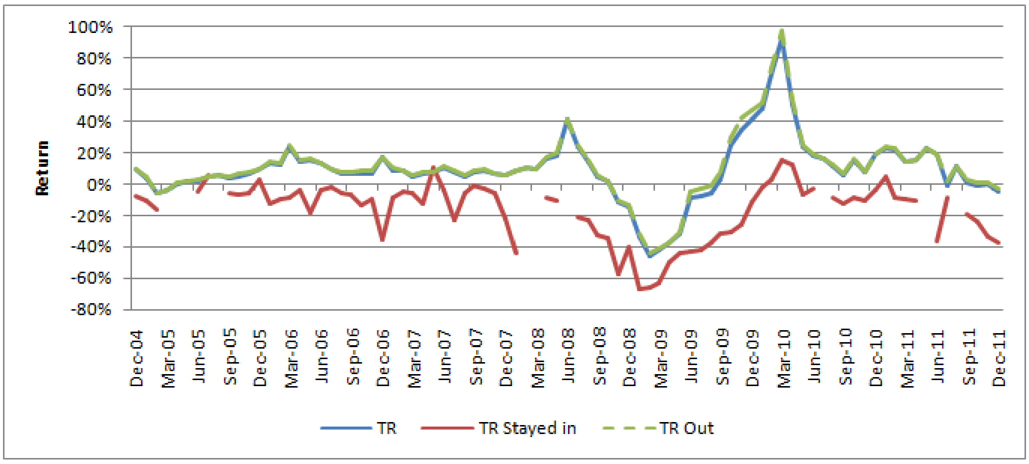

Figure 25: Migration performance analysis for TR class

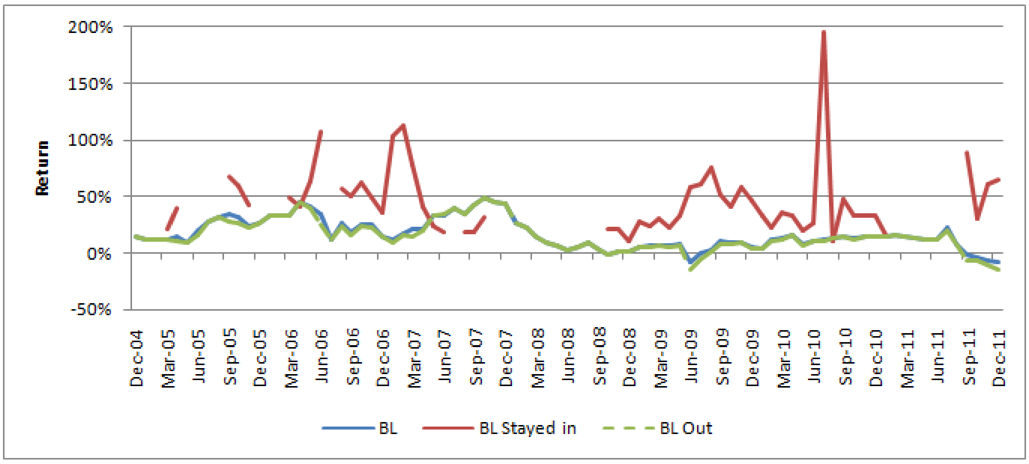

Figure 26: Migration performance analysis for BL class

4.5.1 The total number of funds in existence for reporting

The number of funds declined significantly from the peak of mid-2008 and it appears that the hedge funds industry has been going into a gradual decline since 2008.

4.5.2 The change in “staying in class” mentality

Figures 24-27 illustrate the migrations rates in the four classes. Immediately after the Lehman bankruptcy in September 2008 a significant proportion of hedge funds and hedge

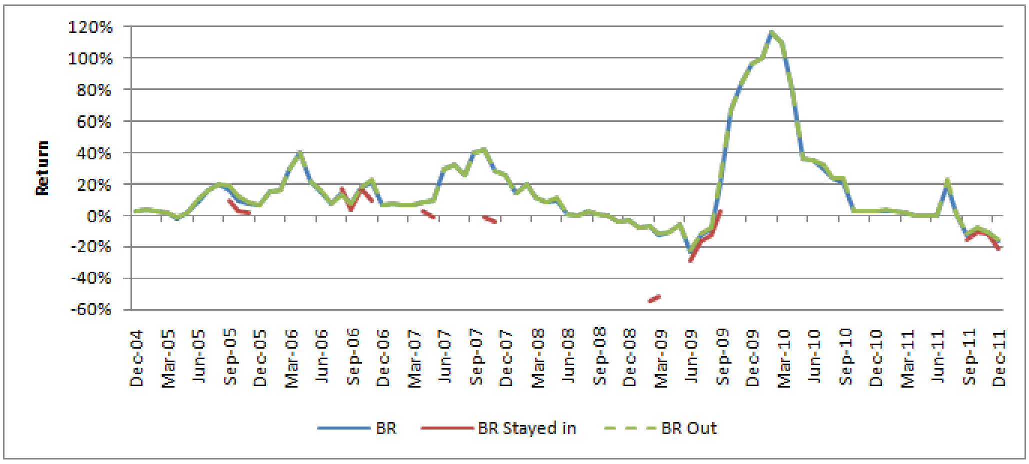

Figure 27: Migration performance analysis for BR class

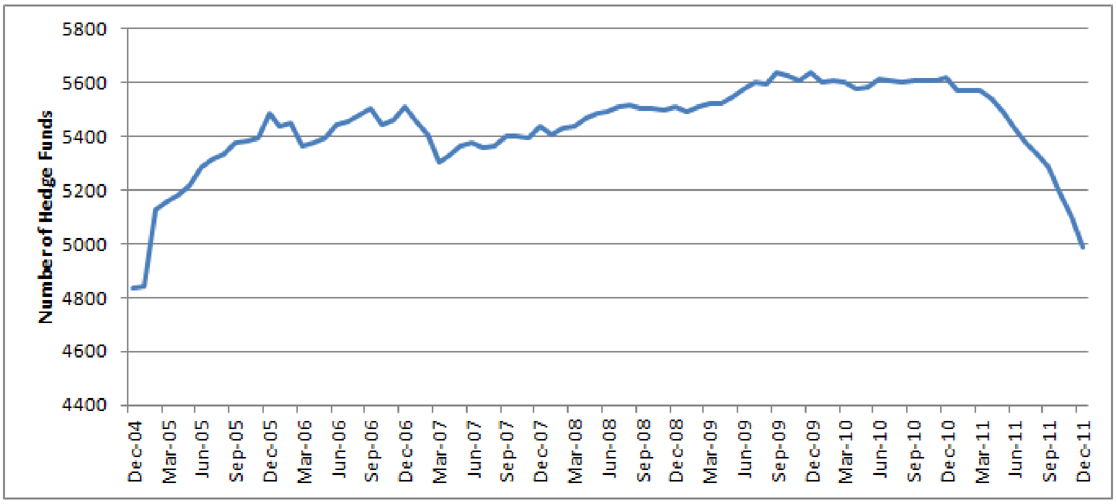

Figure 28: Number of funds reporting

funds experienced very high redemption rates which they are unable to meet. As a consequence the funds and hedge funds gated or suspended redemptions for at least 12 months. This meant that the hedge funds are unable to manage their portfolios actively. Many of the hedge funds that have suspended redemptions are able to participate in the bull market rally since 2009. Shortly before the market bottoming out in March 2009, the rate of migration between the classes has decreased significantly. This might not have been caused by deliberate actions of hedge funds, but might have been the results of market turbulence causing hedge funds and hedge funds to suspend redemptions and, consequently, finding it much more difficult to trade in and out of the positions.

4.6 Conclusion

In the risk control squared environment of hedge funds, it is interesting to observe the pro-active management activities in changing the risk profiles of themselves, most of the times to replicate better results of the past. I believe the idea of classification is of great help in the risk controlled and risk control squared environments. My belief is that I can work out a precise rating system using this idea for the fund industry. This will be the aim of my future work. From my observation, it is clear that PC1 has a much stronger impact on long-term performances; PC2 by contrast, should be kept at a relatively low level for long-term performance purposes but could present fantastic investment opportunities in the short term recovery phase.

A final interesting remark is that the BL class boasts an excessive return of between 2%-3% per annum over the period of investigation. If I apply the same analysis to hedge funds, the excessive return of the BL class is well over 10% per annum.

Date	BR	BL	TL	TR	Date	BR	BL	TL	TR	Date	BR	BL	TL	TR
Dec-04	0%	0%	0%	4%	May-07	1%	1%	11%	1%	Oct-09	0%	4%	0%	7%
Jan-05	0%	1%	0%	3%	Jun-07	0%	2%	0%	5%	Nov-09	0%	1%	0%	10%
Feb-05	0%	0%	0%	2%	Jul-07	0%	0%	0%	2%	Dec-09	0%	2%	0%	10%
Mar-05	0%	1%	0%	0%	Aug-07	0%	1%	0%	3%	Jan-10	0%	2%	0%	7%
Apr-05	18%	11%	16%	5%	Sep-07	0%	1%	0%	4%	Feb-10	0%	2%	0%	5%
May-05	0%	0%	0%	0%	Oct-07	2%	1%	0%	4%	Mar-10	0%	2%	0%	6%
Jun-05	18%	12%	26%	10%	Nov-07	1%	0%	0%	4%	Apr-10	0%	4%	0%	5%
Jul-05	0%	0%	0%	1%	Dec-07	0%	0%	0%	2%	May-10	0%	6%	0%	3%
Aug-05	0%	0%	0%	0%	Jan-08	0%	0%	0%	1%	Jun-10	0%	6%	0%	4%
Sep-05	26%	14%	23%	10%	Feb-08	0%	0%	0%	0%	Jul-10	6%	1%	2%	0%
Oct-05	24%	16%	28%	13%	Mar-08	0%	0%	0%	0%	Aug-10	0%	1%	0%	5%
Nov-05	14%	10%	26%	9%	Apr-08	0%	0%	0%	1%	Sep-10	11%	2%	6%	3%
Dec-05	0%	0%	0%	1%	May-08	7%	15%	8%	6%	Oct-10	0%	1%	0%	2%
Jan-06	0%	2%	0%	4%	Jun-08	0%	0%	0%	0%	Nov-10	0%	1%	0%	1%
Feb-06	0%	0%	0%	3%	Jul-08	0%	0%	0%	2%	Dec-10	0%	1%	0%	1%
Mar-06	0%	2%	0%	4%	Aug-08	0%	0%	0%	2%	Jan-11	12%	14%	13%	4%
Apr-06	0%	1%	0%	3%	Sep-08	0%	0%	0%	1%	Feb-11	0%	0%	0%	1%
May-06	0%	4%	0%	3%	Oct-08	0%	2%	1%	1%	Mar-11	0%	0%	0%	1%
Jun-06	20%	12%	21%	3%	Nov-08	0%	4%	1%	2%	Apr-11	0%	0%	0%	1%
Jul-06	0%	0%	0%	1%	Dec-08	0%	1%	1%	2%	May-11	0%	0%	0%	0%
Aug-06	7%	6%	21%	7%	Jan-09	0%	3%	1%	5%	Jun-11	0%	0%	0%	1%
Sep-06	4%	8%	27%	7%	Feb-09	1%	8%	2%	7%	Jul-11	12%	6%	52%	22%
Oct-06	13%	5%	24%	8%	Mar-09	2%	2%	8%	5%	Aug-11	0%	0%	0%	0%
Nov-06	17%	11%	27%	7%	Apr-09	0%	5%	8%	3%	Sep-11	35%	5%	19%	6%
Dec-06	0%	1%	0%	1%	May-09	0%	4%	0%	2%	Oct-11	24%	6%	9%	5%
Jan-07	0%	2%	0%	6%	Jun-09	21%	8%	10%	9%	Nov-11	23%	5%	6%	3%
Feb-07	0%	2%	0%	4%	Jul-09	25%	8%	14%	12%	Dec-11	26%	8%	7%	5%
Mar-07	0%	10%	0%	7%	Aug-09	19%	2%	15%	12%					
Apr-07	1%	7%	0%	7%	Sep-09	21%	4%	14%	11%					

Table 8: Percentage of funds stayed in the same style in the following Year

5 Risk Measures and Investment Performance Prediction

5.1 Introduction

In this chapter, I introduce a dynamic three-factor regression model to explain mutual funds' returns. The model reserves the main variation of a basket of risk measures. Each factor of the three factors is a linear combination of the larger set of risk measures in the basket for which the factor introduced by Sharpe, β, is included. I introduce a dynamic selection mechanism to the three factors in my model to explain the returns based on larger set of variables. The persistence of my model is tested by applying the coefficient built using an investigated period to the following 12-week period to predict the rank of returns.

I rank the funds according to their predicted returns based on our risk factors, and then group the funds into subsets to illustrate the model for relative returns. In my research, I have found clear evidence, based on prediction of the ranks of mutual fund returns, that an asset allocation strategy can over-perform the market out-of-sample during a long term bull market. My approach is to use historical return data of mutual funds to extract risk information as measured by popular risk statistics. I then rank the funds, within each risk statistic, according to the usual perception of low/high risk. I derive a classification method that is based on these historical information to divide them into distinctive groups based on their expected future ranks of returns (that is, using regression, I predict future returns ranking using past risk ranking data). I define a mechanical approach using a combination of commonly used risk statistics that aim to outperform in a bull market. In the case of an ultimate bull market over the past 8 years, I was able to beat the index on a significant scale. I also observe that if a strong bear market arrives, my strategy does underperform the market, but the losses incurred are more than recovered in the subsequent rally within the data set I have. The existence of the underperformance periods agrees with the findings of Fama and French (2008).

In this study, I have used 15 popular risk statistics where the return plays an important role in the calculations. Each risk statistics is used to calculate the risk values based on the historical weekly returns of the assets on a 12-week period of time. I look at the relative measure of the statistics by considering the rank of the asset according to each statistic calculated among all other assets used in the test. I rank the assets using numbers 1, 2, . . . , N, where number 1 indicates the fund that has the preferred risk value and so on. Modern portfolio theory (Markowitz, 1952) assumes that given two assets that have the same risk, investors will prefer the asset with higher return. The choice of a preferred risk value is set according to investor's natural preference. E.g. if the investor's natural preference is a low risk value, as in the case of standard deviation of returns, the fund ranked first represents the fund with the smallest standard deviation. The example from the other side is Sharpe Ratio, where investor's natural preference is larger values, so the fund ranked first represents the fund with largest Sharpe Ratio. In Chapter 5 I only work with the ranks of the statistics rather than the actual quantities.

After getting 15 vectors of rank values for a 12-week period, I investigate the co-dependence of these vectors using rank correlation (see Section 2.2) between the ranks of the statistics. The dependence information among the 15 risk statistics is investigated for every 12 consecutive weeks available within the tested period. The statistical dependence test is performed separately in Section 2.3 and statistics that are extremely highly correlated with at least one of the other statistics are removed. The set of 15 risk statistics is reduced by removing six risk measures whose rank statistics are linearly dependent on the rank statistics generated by the other nine risk statistics. The nine remaining risk statistics are then standardised and linearly transformed, using a variable reduction technique, into a new set of nine uncorrelated factors (components) that explain the variation within the original data. The transformed factors are then ordered by their explanatory power. A subset of the factors (principal components), with the greatest contribution to the overall variation within the dataset, is used to establish an investment strategy based on the prediction of the rank of asset returns using a linear regression model. The estimated parameters from the regression are linearly transformed back into coefficients on the original ranks of the risk statistics. I use the obtained coefficients to construct a prediction model for the forward rank of 12-week returns. For each prediction period I create a set of ten disjoint portfolios each of which contains 10% of the available assets by segmenting the mutual funds universe into deciles according to the predicted rank of asset returns. The prediction groups are formed with the funds that have their predicted ranking falling into the ten different sub-categories from the highest predicted returns ranking to the lowest predicted returns ranking. The return of each established portfolio is analysed and compared with the fund universe, which is an equally weighted portfolio of all available assets at the time.

Chapter 5 is organised as follows. In Section 5.2, I introduce and illustrate the prediction model, used to form the investment strategy. Section 5.3 discusses the prediction performance of the model. Section 5.4 discusses the persistence of the model over 12-week period and gives some real-world applications of the prediction performance of the model. Section 5.5 shows that empirically reducing the number of risk measures from the originally proposed set of 15 risk measures results in improvements in the performance

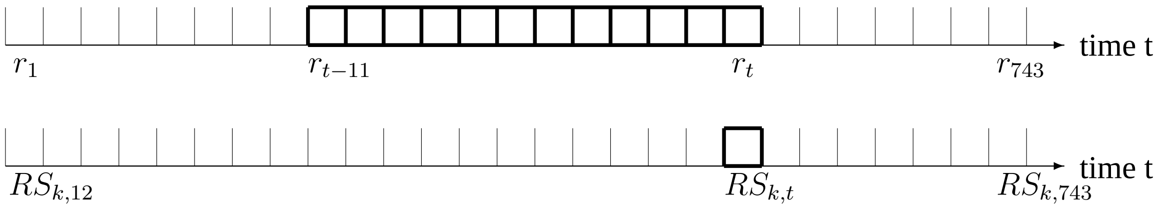

Figure 29: The timeline shows how each Rank-Statistic is calculated using 12 consecutive weekly returns

of my investment strategy and that not all risk measures should be included in the model. The preparation of Chapter 5 has relied heavily on the joint work of Haidar et al. (2012) and has resulted in the working paper.

5.2 Prediction model

Figure 29 shows how the returns, r_t, are transformed into Rank-Statistics, $RS_{k,t}$, for each fund by calculating the 12 weeks' trailing risk statistics for each of the 732 sub-periods and then replace the risk score by the rank according to the preference sign. I then test for the linear dependent information between the Rank-Statistic vectors RS.

Recall that the Rank-Statistics are denoted by $RS_{k,t}$ where each row of RS corresponds to a Rank-Statistic at time t, and that the new transformed factors are denoted by $F_{k,t}$. The corresponding eigenvalue of each factor directly measures the explanatory power of the factor relative to the complete variation of the original dataset. The eigenvalue analysis in Figure 30 shows that the first three components explained the vast majority of the variation in the Rank-Statistics dataset, with an average of 88% of the variation of the original variables. Since my objective is to select the factors that made the greatest contribution to the variation in the Rank-Statistics, PCA suited my objective very well. As a cross-validation, I regressed the rank of return against the complete set of principal components lagged by 12 weeks and I denoted the frequency of factors that had statistically significant coefficients with a p-value of less than 1%, as shown in Figure 31. The first three factors scored the highest frequency. The selected factors were those corresponding to the largest eigenvalues. Therefore, I eliminate the subsequent factors, which had less explanatory power from the dataset. This gives a reduction in the dimensionality of the dataset and the model was then constructed using only the first three factors. The estimated model can be restated in terms of the original nine variables using the factor loadings calculated within the PCA.

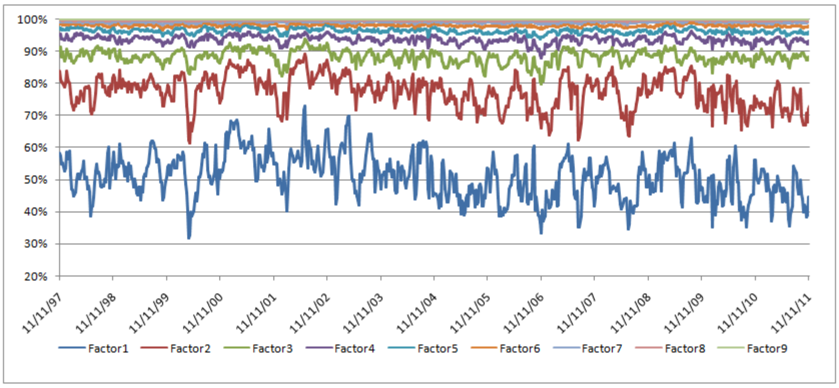

Figure 30: The cumulative explanatory power of the principal components

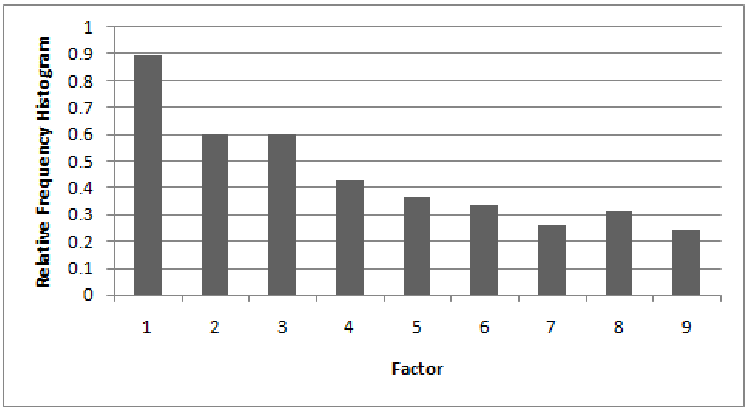

Figure 31: Frequency of statistically significant coefficient across time interval

Having reduced the number of factors to consider, I then estimate the prediction model

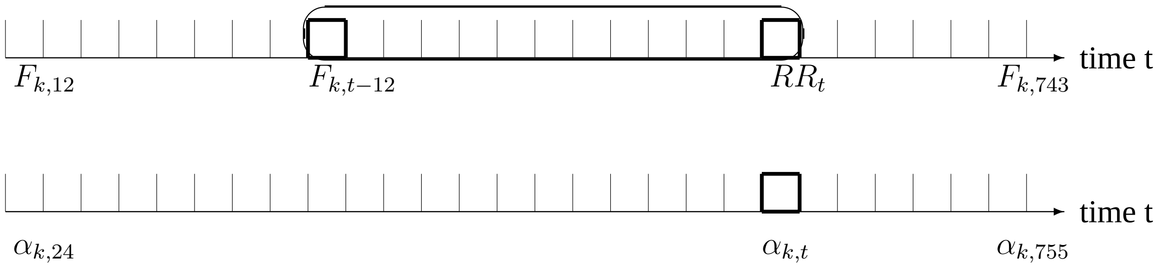

Figure 32: The timeline shows how the model coefficients $\alpha_{k,t}$ are calculated by regressing the rank of return against the first three PCA factors lagged by 12 weeks

using a multiple linear regression of the ranks of return, $RR_{j,t}$, as defined in (1.1), against the reduced set of PCA factors lagged by 12 weeks as illustrated in Figure 32. I then transform back each of the three PC factors to its linear combination of the Rank-Statistics and transform weights to the resultant regression to give a set of coefficients for the nine Rank-Statistics underlying the PC. The prediction test is conducted sequentially for each period. Below I describe how to use the regression analysis to produce rank of return predictions using historical principle components generated from historical Rank-Statistics.

PCA-based prediction model

The three-factor linear regression model can be mathematically written as

$$RR_{j,t} = \alpha_{0,t} + \alpha_{1,t}\, F_{1,j,t-12} + \alpha_{2,t}\, F_{2,j,t-12} + \alpha_{3,t}\, F_{3,j,t-12} + \epsilon_{j,t}, \tag{5.31}$$
$$\forall j \in (1, 2, \ldots, N_t),\ \forall t \in (24, 25, \ldots, 755),$$

where $\epsilon_{j,t}$ represents the noise, N_t is the number of funds that are under investigation at time t, and

$$F_{i,j,t} = \sum_{k=1}^{9} \gamma_{k,i,t}\, \widehat{RS}_{k,j,t}. \tag{5.32}$$

That is

$$RR_{j,t} = \sum_{k=1}^{9} \beta_{k,t} \ \widehat{RS}_{k,j,t-12} + \epsilon_{j,t}, \tag{5.33}$$

where

- $RR_{j,t}$ is the rank of return of the j-th fund at time period t as in (1.1).
- $F_{i,j,t}$ is the score for the j-th fund on the i-th principal component estimated using Rank-Statistics at period t.
- $RS_{k,j,t}$ is the Rank-Statistic k of the j-th fund at time t.
- $\gamma_{k,i,t}$ is the principal component loadings. $\forall k, i \in (1, 2, \ldots, 9)$, $\forall t \in (12, 13, \ldots, 743)$.
- $\beta_{k,t} = \sum_{i=1}^{3} (\alpha_{i,t} \times \gamma_{k,i,t-12})$.
- The constant term α_0 does not affect the order of the ranks and therefore it is set to zero and is removed from the model.
- $\epsilon_{j,t}$ is a random variable that is normally distributed with an expected value of zero and an unknown variance.

Lets denote the sum of squared prediction errors at time t by,

$$ERR_t = \sum_{j=1}^{N_t} (RR_{j,t} - \alpha_1 \ F_{1,j,t-12} - \alpha_2 \ F_{2,j,t-12} - \alpha_3 \ F_{3,j,t-12})^2. \tag{5.34}$$

Recall that each regressor is a linear combination of the nine standardised Rank-Statistics and from equations (5.32) and (3.28), I take the expectation of F_j as follows,

$$E\left[F_{i,j,t}\right] = \sum_{k=1}^{9} \gamma_{k,i,t} \ E\left[\widehat{RS}_{k,j,t}\right] = 0. \tag{5.35}$$

Recall equation (3.29),

$$Cov\left(\vec{F_l}, \vec{F_m}\right) = \frac{1}{N_t}\sum_{j=1}^{N_t}(F_{l,j,t-12}\ F_{m,j,t-12}) = 0,\ \ \forall t \text{ when } l \neq m. \tag{5.36}$$

ERR_t is then minimised over α_k for $l = 1, 2, 3$, to fit the coefficients that minimise the sum of squared prediction errors. Therefore,

$$\frac{\partial ERR}{\partial \alpha_k} = \sum_{j=1}^{N_t}\left(-2\ F_{k,j,t-12}\left(RR_{j,t} - \sum_{m=1}^{3}\alpha_m\ F_{m,j,t-12}\right)\right) \tag{5.37}$$

$$= -2\sum_{j=1}^{N_t}\Big(\ F_{k,j,t-12}\ RR_{j,t} - \alpha_k\ F_{k,j,t-12}\ F_{k,j,t-12}\Big) \tag{5.38}$$

$$= 0.$$

This results in

$$\alpha_{k,t} = \frac{\displaystyle\sum_{i=1}^{N_t} F_{k,i,t-12}\ RR_{i,t}}{\displaystyle\sum_{i=1}^{N_t}\left(F_{k,i,t-12}\right)^2}. \tag{5.39}$$

This is indeed a minimum point since

$$\frac{\partial^2 ERR}{\partial \alpha_k^2} = \ 2\sum_{j=1}^{N_t}(F_{k,j,t-12})^2 > 0. \tag{5.40}$$

The coefficient of determination R^2 of the regression model in (5.31) has an average value of 41% over the 732 tested 12-week periods with values varies between 0% and 84%. 63 periods out of the 732 tested 12-week periods scored an R^2 of less than 10%, this may suggest that the basket of 15 risk measures could be expanded to include more risk factors with a different nature such as accounting ratios.

5.3 The out-of-sample predictability of the model

The performance of the model is tested by applying the model obtained at each tested 24-week period (12-week period for Rank-Statistics $RS_{k,j,t-12}$ followed by 12-week period for rank of return $RR_{j,t}$) to the 12-week Rank-Statistics $RS_{k,j,t}$ to predict the forward 12-week rank of return $RR_{j,t+12}$, which is the expected rank of return over the 12-week period $[t+1, t+12]$. I denote the predicted rank of return for the j-th fund over the 12-week period $[t-11, t]$ by $PR_{j,t}$ while the actual rank of return was previously denoted by $RR_{j,t}$. There is a number of studies on the persistence of mutual funds performance (Bolen and Busse 2004; Huij and Verbeek 2007). However, in this paper, we test the persistence of the performance of the model rather than the funds performance since we have dynamic coefficients for the model. We test for a persistency over 12-week period that matches with the tested period of Bolen and Busse (2004). This with (5.31) give the following formula for the predicted rank of return

$$PR_{j,t+12} = \alpha_{1,t}\, F_{1,j,t} + \alpha_{2,t}\, F_{2,j,t} + \alpha_{3,t}\, F_{3,j,t} + \epsilon_{j,t}, \tag{5.41}$$

where $\alpha_{l,t}$ was given in (5.39).

The predicted rank of returns, PR_t, is a vector that is a linear combination of the first three principal components lagged by 12 weeks. Since the elements of PR are centred on zero, I therefore rank PR in the same way that I ranked RR previously, so that it is comparable to RR. The rank correlation was then computed between RR and PR as a predictive performance indicator of the model. I use the rank correlation rather than the coefficient of determinations in order to count the negative correlations that give negative returns. The indicator of the prediction model is shown in Figure 33 along with R^2 from the regression model used to calculate the coefficients (Note that I used 720 periods instead of 732 because the the actual returns of the last 12 weeks were unknown at the time of the computations). The chart shows that the correlation persisted for periods of several months in some years like 2010. However, there were periods when the correlation was highly negative and the model underperformed, but as an overall long-term investment strategy, the model outperformed the market.

As described in Section 5.2, betas were obtained by regressing each 12-week rank of return against the first three principal components lagged by 12 weeks (returns of weeks 13-24 vs. components of weeks 1-12, weeks 14-25 vs. weeks 2-13, . . . , weeks 744-755 vs. weeks 732-743). Figure 34 shows how the estimated model was tested out-of-sample by using data not included in the estimation process to predict the following 12 forward weeks' rank of return as shown in (5.41).

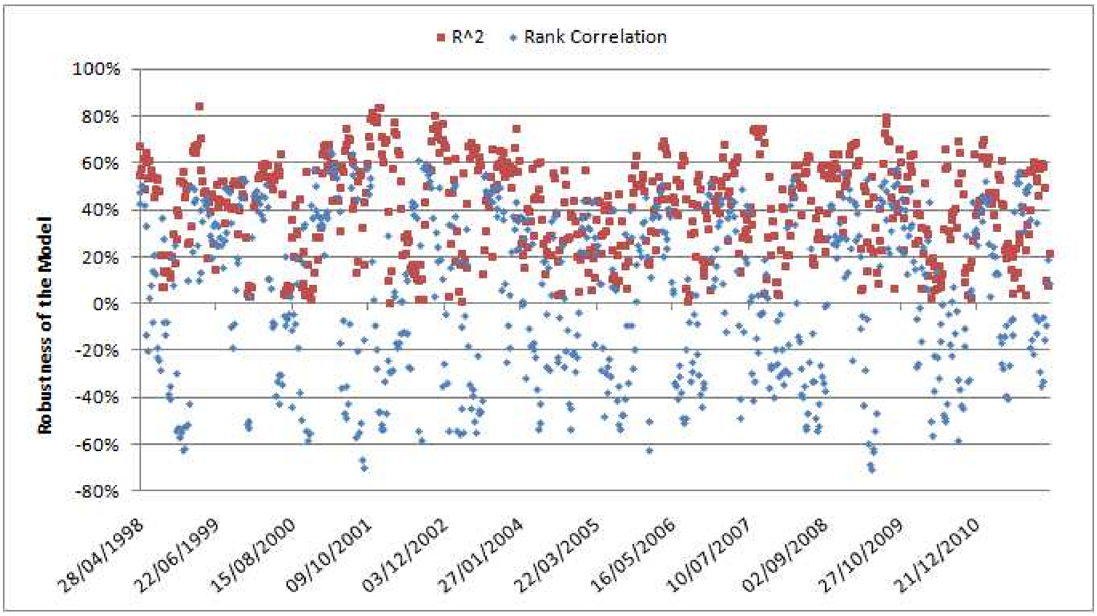

Figure 33: Prediction indicators for the model, R^2 and rank correlation, over time

I have further illustrated the quality of the model in Figure 35 by showing an example of the actual ranked returns vs. the predicted ranked returns. The actual ranked returns

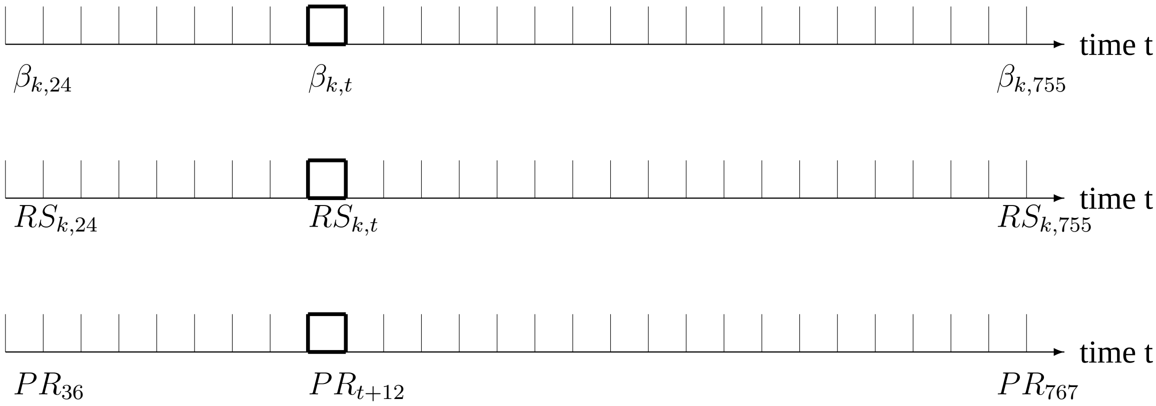

Figure 34: The timeline shows how the constructed model is used to calculate the predicted rank of return, PR_t, for the next 12-week period.

are calculated over the 12-week period from 08-Jun-2011 to 30-Aug-2011, while the predicted ranked returns are calculated using Rank-Statistics calculated over the 12-week period from 16-Mar-2011 to 07-Jun-2011 based on the coefficients estimated over the 24-week from 22-Dec-2010 to 07-Jun-2011. In the example shown in Figure 35, there was a swarm of points around the line of perfect prediction with a rank correlation score of 40% in the mentioned period.

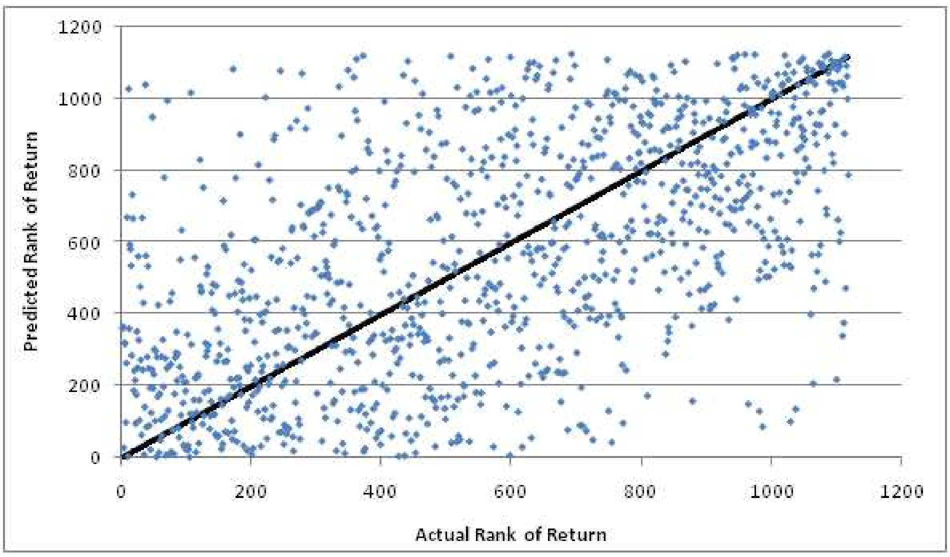

Figure 35: Actual Ranks vs. Predicted Ranks (30-Aug-2011)

5.4 Performance test and investment strategy

As indicated from the results of testing the predictability of ranked returns, the method seems likely to yield an effective investment strategy for the tested data. my next step is to determine an investment strategy to exploit this information. My approach is to divide the funds into ten groups according to their descending order of predicted rank of returns. I then construct ten disjoint portfolios that each represented 10% of the funds in my sample. “First decile portfolio”, representing the first decile of predicted funds (with funds scored top 10% of predicted return ranks), while the “second decile portfolio”, representing the second decile of funds and so forth. The portfolio asset allocation is determined at each time step to reflect the dynamic nature of the prediction model. As the prediction period is 12 weeks ahead, I construct an algorithmic trading test where I rank the returns using data from week $t-12$ to week $t-1$, purchase each portfolio at the beginning of week t and sell at the end of week $t+11$. The process is repeated every week and the 12 weeks realised return is measured at every week from week 36 to week 395. The average and the volatility of the 12-week actual returns are calculated over the 720 sub-periods for each of the ten “decile portfolios”. The results shown in Table 9 clearly indicate that the portfolio returns are correlated with the portfolio prediction order.

Portfolio	1st decile	2nd decile	3rd decile	4th decile	5th decile
Average	1.36	1.12	1.02	0.87	0.72
Standard Deviation	6.60	5.69	5.47	5.19	5.60
Portfolio	6th decile	7th decile	8th decile	9th decile	10th decile
Average	0.58	0.22	0.02	0.09	0.17
Standard Deviation	5.65	6.12	6.37	6.65	7.66

Table 9: 12-week returns and volatility for the decile portfolios

In Figure 36, I show the frequency with which each portfolio falls into each decile of observed performance. The charts show that "decile portfolio" strategy with rebalancing each period had a high predictive frequency such that the modal value for each portfolio was the same as its predicted decile. The second most frequent outcome was a reversal of the order of portfolio returns such that the "first decile portfolio" produced the "weakest portfolio returns" and so forth. This suggests that there were times when an opposite strategy might be beneficial.

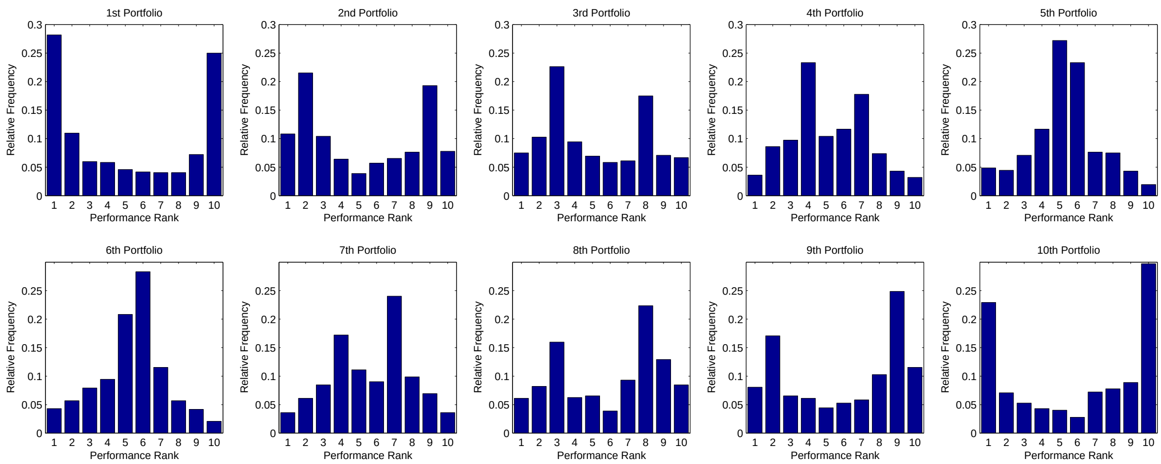

Figure 36: Comparison of the return performance of the ten decile portfolios (each subfigure shows the relative frequency of the rank of the decile portfolio among the other portfolios).

I have compared the performance of the "first decile portfolio" to that of my universe by creating an equally weighted portfolio of all funds at each time period, which I refer to as the "ETF Index". Omega risk measure was defined in Section2.1.14 as the ratio of expected (probability weighted) gains above a threshold to the expected (probability weighted) losses below the same threshold. I calculate Omega ratio as a performance measure for the ten constructed portfolios (see Table 10 for details). The results demonstrate that the "1st decile portfolio" has performed best in respect to producing gains relative to accepting losses and that the "last decile portfolio" ("10th decile portfolio") has performed the worst. This shows how the prediction model has discriminated between the better and worse performing funds.

Portfolio	1st decile	2nd decile	3rd decile	4th decile	5th decile	6th decile
Omega ratio	2.1291	1.9531	1.8767	1.7816	1.6797	1.4559
Portfolio	7th decile	8th decile	9th decile	10th decile	ETF Index	
Omega ratio	1.1926	1.1380	0.9064	0.9026	1.4520	

Table 10: Omega ratio for the ten disjoint constructed portfolios and ETF Index

Figure 37 shows the distribution of "first decile portfolio" and "last decile portfolio" performance compared with that of the "ETF Index" portfolio. The chart and Omega ratio of the distributions show that "1st decile portfolio" has performed best in respect to producing gains relative to accepting losses and that "last decile portfolio" has performed worse than the "ETF Index" with lower Omega ratio. This chart shows how the prediction model has discriminated between the better and worse performing funds. Figure 37 shows the distribution of "first decile portfolio" and "last decile portfolio" performance compared with that of the "ETF Index" portfolio. The chart and Omega ratio of the distributions show that "1st decile portfolio" has performed best in respect to producing gains relative to accepting losses and that "last decile portfolio" has performed worse than the "ETF Index" with lower Omega ratio. This chart shows how the prediction model has discriminated between the better and worse performing funds.

In Figure 38, I show the results obtained when I simulate the performance of the strategy of selecting the "decile portfolios" and rebalancing them according to the model predictions every 12 weeks starting on 3-Feb-1998 and calculating cumulative performance.

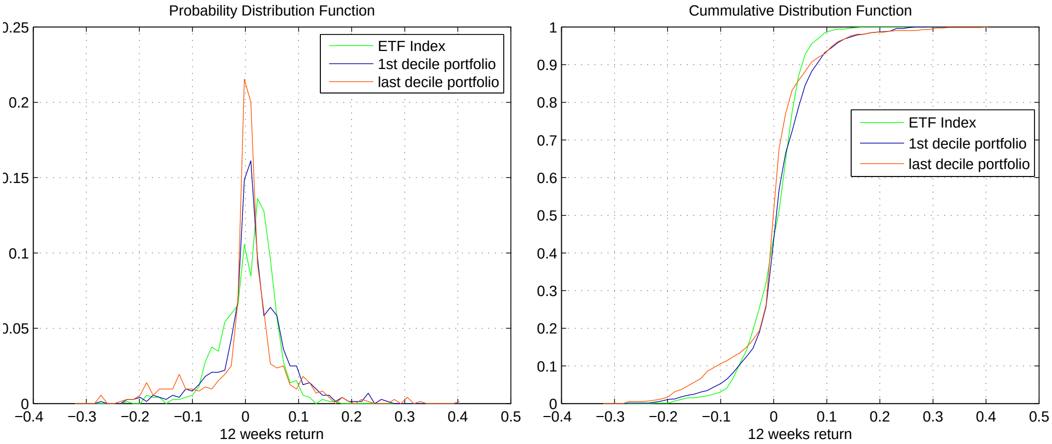

Figure 37: Probability distribution function and cumulative distribution function of first and last decile portfolios vs. ETF Index

60 disjoint 12-week investment periods are performed (out of the 720 12-week periods) since each portfolio had a life time of 12 consecutive weeks. Each of the portfolios was rebalanced every 12 weeks. My starting point in 1998 coincided with a period of negative rank correlations between the actual and the predicted ranks of returns, and therefore the weakness of performance in the first year was not unexpected. The following year, I saw a high rank correlation.

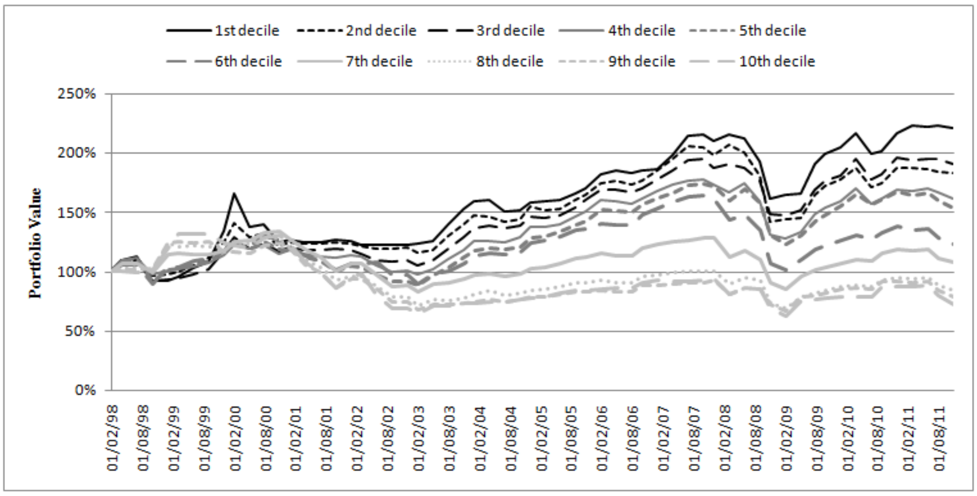

Figure 38: Mutual Funds: performance of the ten decile portfolios established on 3-Feb-1998

The first row of Table 11 show the results obtained in Figure 38. Generally speaking, I encountered bad investment periods when I faced a bear market and good investment periods when I had a bull market. Although the 12-week performance of the strategy was strongest for the periods when the predictions of the ranks were strongest, the strategy provided an attractive return over the whole time interval. Separate numerical tests in Table 11 show that the outperformance phenomenon is independent from the starting time chosen over long bull market. The model had predictive performance over the whole period as the ranking of the performance observed at the end of the time interval matched that of the “decile portfolios”.

Investment Date	decile Portfolios	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
	Holding weeks										
03/02/1998	60	2.21	1.82	1.90	1.61	1.53	1.23	1.08	0.83	0.78	0.71
10/03/1998	60	1.64	1.69	1.31	1.28	1.48	1.37	1.10	0.97	0.88	1.32
21/04/1998	60	2.68	2.02	2.13	1.72	1.28	1.37	1.17	0.77	0.74	0.72
11/08/1998	58	1.65	1.31	1.39	1.40	1.39	1.52	0.91	1.12	1.09	1.10
06/10/1998	58	3.46	2.60	2.75	2.20	1.67	1.40	1.18	0.80	0.79	0.73
23/03/1999	56	3.28	2.51	2.68	2.00	1.51	1.21	0.96	0.64	0.60	0.57
22/06/1999	54	2.15	1.74	1.94	1.55	1.45	1.13	0.94	0.68	0.63	0.54
23/05/2000	50	1.61	1.43	1.60	1.36	1.28	1.00	0.85	0.68	0.68	0.60
08/05/2001	46	1.54	1.42	1.28	1.11	1.25	1.07	0.99	1.09	0.97	0.87

Table 11: Cumulative value of one money unit investment for the ten decile portfolios using various starting dates.

5.5 Are some of the statistics better than others in this study? empirical observations

I have included a set of nine statistics, with moderate to low correlation between the pairs, and have used the first three principal components to predict the rank of return. I then investigate whether I should include all nine statistics in the prediction model, or include only a subset of the nine statistics. In Figures 39 and 40, I plot the coefficients $\beta_{k,t}$ of the prediction model, obtained at each period of investigation, for each of the nine statistics that are involved in the model. I look at the absolute value of the coefficient to determine its absolute effect on the prediction and the result shows that Maximum DrawDown scored the highest in 48.4% of the weeks, followed by Sortino ratio which scored 17.5% of the tested 12-week periods. This suggests that the previous two statistics play important role in the prediction.

Do the first factors reduce the error? Assume that linear regression assumptions hold. The variance of the coefficients $\alpha_{l,t}$ is then estimated as:

$$\text{Var}(\alpha_{l,t}) = \frac{\sigma^2}{SST_l(1 - R_l^2)}, \tag{5.42}$$

where

- $\alpha_{l,t}$ is the estimated coefficient of $F_{l,t-12}$ in (5.31).

- σ^2 is the estimated variance of errors with $N_t - k - 1 = N_t - 4$ degrees of freedom

$$\sigma^2 = \frac{\sum_{i=1}^{N_t} \left(RR_{i,t} - \hat{RR}_{i,t} \right)^2}{N_t - 4}, \tag{5.43}$$

  where $k = 3$ is the number of factors in the model.

- SST_l is the sum of squared total sample variation in F_l

$$SST_l = \sum_{i=1}^{N_t} \left(F_{l,i,t} - \bar{F}_{l,t} \right)^2$$

- R_l^2 is the coefficient of determination obtained from a regression of F_l on all other independent variables $F_j,\ j \neq l$. It picks up any multicollinearity between the explanatory variables.

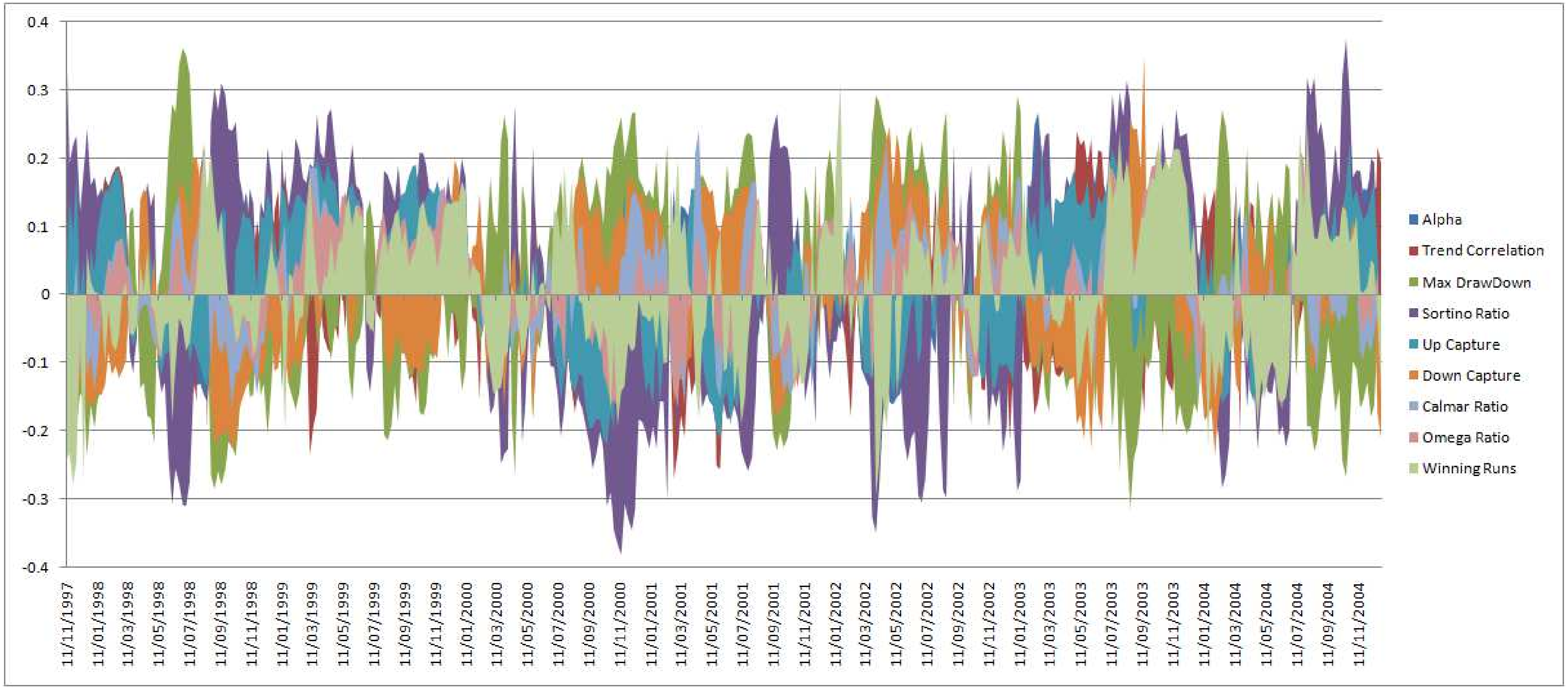

Figure 39: Coefficients $\beta_{k,t}$ of the prediction model over 1997-2004

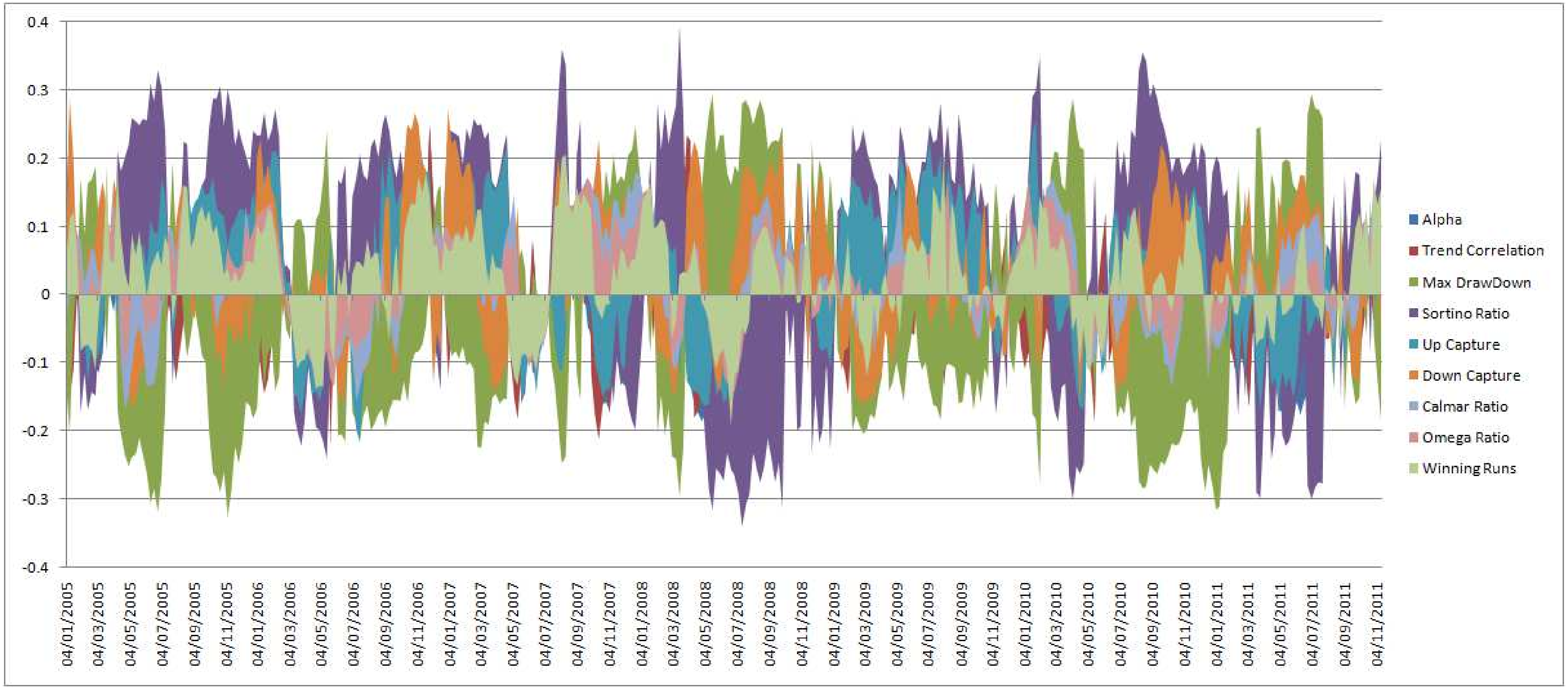

Figure 40: Coefficients $\beta_{k,t}$ of the prediction model over 2005-2011

R_l^2 is zero in this model because F_l and F_m $(l \neq m)$ are eigenvectors and therefore they are linearly independent, i.e.

$$\sum_{i=1}^{N_t} (F_{l,i,t}\ F_{m,i,t}) = 0, \qquad\qquad \forall t \text{ when } l \neq m. \tag{5.44}$$

This implies that the coefficients of the regression, between F_l and all F_m, are zero and that the coefficient of determination is therefore zero. This can also be implied when using the same terminology used in deriving (5.39). This gives:

$$\text{Var}(\alpha_{l,t}) = \frac{\sigma^2}{SST_l}. \tag{5.45}$$

Therefore, $\text{Var}(\alpha_{l,t})$ has a negative relation with SST_l. Recall equation (3.29) that the variation of $F_{m,t}$ is greater than the variation of F_l when $m < l$. This gives $\text{Var}(\alpha_{m,t}) < \text{Var}(\alpha_{l,t})$ when $m < l$ as shown in Figure 41 where the variance of each coefficient is plotted against the tested time period. This is another reason why only the first three principal components, with the highest variations, are used in the model. The variances have dropped down after the first few years since the number of mutual funds with valid data under investigations has increased dramatically in those years (see Figure 42 for detailed number of available funds at each period).

Having the Rank-Statistics to be independent does not mean that they all are good predictor variables. I suspect that not all the risk statistics should be included, so I test all combinations of the available statistics starting with all nine statistics $(C_9^9 = \binom{9}{9} = 1), 8, 7, \ldots,$ and three statistics $(C_9^3 = \binom{9}{3} = 84)$; and calculate the principal components of the Rank-Statistics. I use the first three factors produced by transforming the chosen statistics using principal components to build my prediction model. I test the return

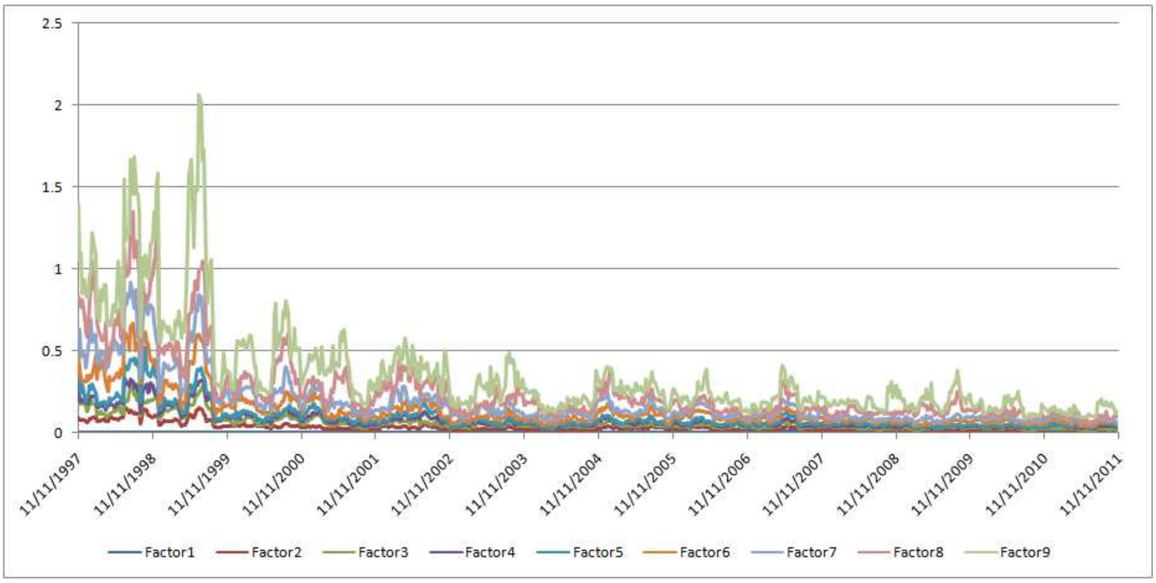

Figure 41: The error of coefficients $\alpha_{l,t}$ of the predictors over tested periods

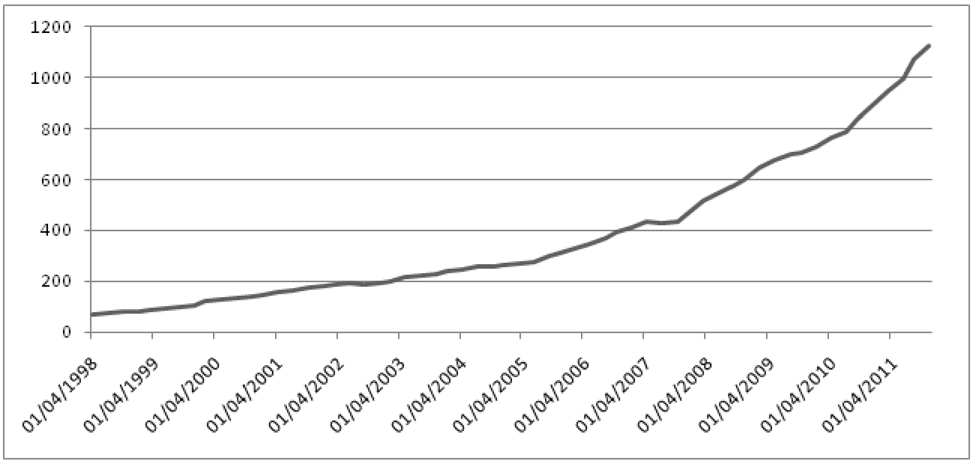

Figure 42: The number of tested mutual funds at each time period

performance for each model represented by its statistics. I then look at the “first decile portfolio”, which is of my interests. I then take the average of the 12-week returns of the portfolios over the available 360 investment periods, similar to what was done in Table 9. The results are shown as gray circles on Figure 43.

I have repeated the test again for all combinations of statistics but without transforming the available statistics into principal components, assuming that the 12-week rank of return was a linear model of some Rank-Statistics lagged by 12 weeks. I have taken all statistics in each combination rather than the first three principal component factors. I then look at the "first decile portfolio" and plot the results as dots on Figure 43 alongside the results of corresponding portfolios established using the first three principal component factors.

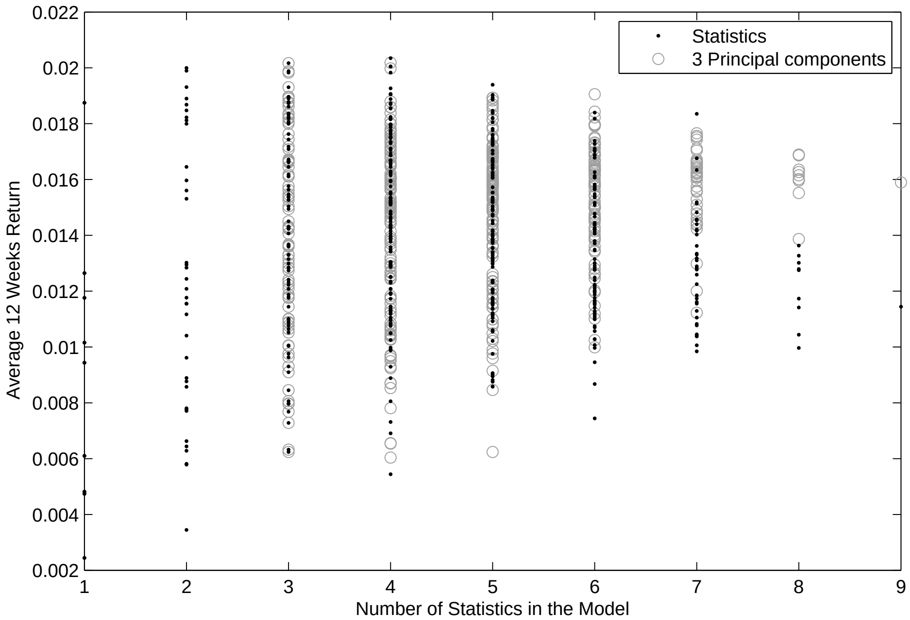

Figure 43: Models performance based on statistics combinations

Figure 43 shows that using the principal components would have improved the performance of the investment strategy. These produced considerably better results than dealing with the whole basket of statistics (see the cases of eight and nine statistics). This is seen by the way the principal component results (the graycircles) registered greater returns, on average for the "first decile portfolio", than the portfolios based on regressing the original nine Rank-Statistics. Thus, I believe that I could achieve better portfolio performance by reducing the number of predictor statistics.

I look at the combinations of statistics by considering the performance of the constructed "first decile portfolio" based on the chosen statistics. I notice that statistics with orders 1 (Alpha), 3 (Maximum DrawDown) and 6 (Down Capture) of the nine statistics included in the principal component analysis did not perform well, in terms of the performance of the “first decile portfolio”. It is therefore more sensible not to include them in the model.

5.6 Conclusion

In this chapter, I have shown that a basket of risk statistics could be used to build a predictive model of performance ranks for mutual funds. By using the ranking of the statistic across the set of funds, my approach standardises the statistics so that they can be compared and combined. However, if I use too many statistics, it is likely to produce more linearly dependent ranking vectors, which can limit the out-of-sample predictive capability of the proposed model. I deal with this by first eliminating obviously highly correlated variables from the dataset of ranked statistics and then use principal components analysis as a variable reduction tool that preserve the salient information held within my dataset. The coefficients of the constructed three-factor model depend on the tested time and I confirm that the results shown are consistent within my data set and that they are independent of the starting point chosen, which coincides mainly with a bull market including severe market downturns and recoveries.

Further work on the applicability of this approach could consider:

1. whether it is applicable to other types of funds and assets;
2. whether the rolling window used is the most appropriate;
3. whether the principal component factors are consistent over time;
4. whether the principal component factors have an intuitive interpretation;

5. whether good investment periods for the strategy can be determined and whether I can avoid investing in periods when the model underperforms;

6. which statistics to consider and to include in the basket and in the prediction model.

Consideration can also be given to whether the predictability, which was found with the mutual fund dataset, is related to the skill and style involved in fund management rather than the fundamental attributes of the assets traded by the fund. This behavioural aspect of performance can be the reason why the approach yielded a predictive model when other approaches looking at market traded assets and securities have been less successful.

6 A Risk Measure for S-shaped Assets in Option Valuation and in Prediction of Investment Performance

6.1 Introduction

In technology development, it is known that the S-curve descriptor is widely used in describing the evolution of technology projects (Nieto et al., 1998) and in government R&D investment. The curves that are non-decreasing over time are called S-curves. My study is about the valuation of assets whose price changes follow the pattern of an S-shaped asset. That is, the asset price either goes up or stays unchanged at each time interval. Hedge funds seek “geared, absolute return,” and their performance is usually measured against zero (or in some cases, against the risk-free interest rate). Hence, at every report time window, the fund is expected to have a positive return (or in some cases, better than the risk-free interest rate). Consequently, in the case of hedge funds, negative returns are regarded as highly undesirable.

In the normal times, the negative returns are very rare, but during financial crises, I notice that the number of negative returns is more pronounced. Hedge funds aim to gain an absolute return over time and they use risky financial instruments to hedge against the market. I look for an indicator for financial crisis that capture the periods when high risk in hedge fund industry gives negative returns. Hence, I anticipate that modelling hedge funds using the concept of S-shaped assets during stable times may indicate the approach of financial crises.

I am out to demonstrate, in Chapter 6, using the three most recent financial crises as examples, that hedge funds performance gives signs of financial crises before they take place with some clear measurable indicators. I follow the standard binomial formulation to establish the value of call/put options for S-shaped assets. Under appropriate assumptions, I further derive the approximate Black-Scholes (BS) European option pricing formula. It is interesting to note that in the involvement of the variance of the asset returns σ^2 in the BS formulae is replaced by $\frac{\sigma^2}{\mu}$ (variance of asset returns)/(expected return). And using $\frac{\sigma^2}{\mu}$ risk measure, I further examine how hedge funds (as a group) anticipate the arrival of financial crises.

In the mathematical derivation, formal asymptotic analysis methods are used. An additional assumption to those in the standard Black-Scholes model is assumed to hold that the quantity of $\frac{\sigma^2}{\mu}$ is small compared to one. Theoretically, this can be justified in S-shaped assets when the increase in the asset value is in one direction and is reasonably uniform. In this case, it is easy to demonstrate that $\sigma^2 \propto \mu^2$. Practically, this is justified by the hedge funds return data provided by International Asset Management (IAM) in non-financial-crisis periods.

In this chapter, I argue that $\frac{\sigma^2}{\mu}$ is a new kind of risk measure or a new starting point to search for a new class of risk functions. Some of the interesting behaviours it exhibits give it a new dimension in assessing absolute return assets.

I have discovered that for IAM selected quality hedge funds, if I use Monte-Carlo methods to generate portfolio weights between 0 and 1 and plot the corresponding $\left(\frac{\sigma^2}{\mu}, \mu\right)$ points, when the performance deteriorate, the shape of the cluster of points of $\left(\frac{\sigma^2}{\mu}, \mu\right)$ begin to change shape dramatically with ample warning in advance —note that withdrawals from hedge funds usually face a three-month notice period or even temporary suspension in bad times; hence warnings in advance are particularly important. I point out that my prediction method is for hedge funds only and cannot be readily applied to other investment vehicles where absolute return is not the primary investment objective.

I also apply the same technique to draw similar conclusions for the 1998 and 2001 financial crises. Due to the fact that there are not as many hedge funds during those historical periods, I use all the hedge funds available in the IAM database at the time and I need to be aware that these are not the same data pool in each case.

Chapter 6 is organised as follows: Section 6.2 outlines the basic assumptions needed. Section 6.3 uses standard binomial option price formula to formulate the option valuation formula. Section 6.4 includes the Black-Scholes type formula. Section 6.5 uses historical hedge fund return data to reveal how the quantity $\frac{\sigma^2}{\mu}$ tells the âĂİtrend changeâĂİ of a portfolio of hedge funds. Section 6.6 summarizes and discusses the results we obtained. The preparation of Chapter 6 has relied heavily on the joint work of Tang et al. (2012) and has resulted in the published work.

6.2 Assumptions

I adopt the standard binomial formulation in my discussion. Assuming that

1. μ is the expected unit time period return and is assumed to be known throught the investment period,
2. The volatility of the security is σ,
3. S_γ is the price of the security at $t = \gamma$ and it follows a geometric Brownian motion with a constant drift μ and constant volatility σ,
4. $S_{\Delta t}$ is assumed to be a random variable which either takes the value $S_0 u$ ($u > 1$ which is the up movement) with probability p, or stays at the value S_0 with probability $1 - p$.

Hence, I have

$$\mathrm{E}(S_{\Delta t}) = pS_0 u + (1 - p)S_0, \tag{6.46}$$

$$\mathrm{Var}(S_{\Delta t}) = S_0^2 p(1-p)(u-1)^2. \tag{6.47}$$

Let μ be the expected unit time period return, σ be the one time period risk of the asset. Given that S_t follows a geometric Brownian motion, I have

$$\mathrm{E}\left(\frac{S_{\Delta t} - S_0}{S_0}\right) \approx \mu \Delta t => \mathrm{E}(S_{\Delta t}) \approx S_0(1 + \mu\Delta t),$$

$$\mathrm{Var}\left(\frac{S_{\Delta t} - S_0}{S_0}\right) \approx \sigma^2 \Delta t => \mathrm{Var}(S_{\Delta t}) \approx S_0^2 \sigma^2 \Delta t,$$

which gives

$$\begin{cases} pS_0 u + (1-p)S_0 \approx S_0(1+\mu\Delta t), \\ S_0^2 p(1-p)(u-1)^2 \approx S_0^2 \sigma^2 \Delta t. \end{cases} \tag{6.48}$$

Asymptotically (when Δt is small), I can regard the above as equalities. Solving for u, I obtain

$$u = 1 + \frac{\sigma^2}{\mu} + \mu\Delta t. \tag{6.49}$$

I can also obtain the following relationships:

$$\begin{cases} \mu\Delta t = p(u-1), \\ \sigma^2 \Delta t = p(1-p)(u-1)^2, \\ \frac{\sigma^2}{\mu} = (1-p)(u-1). \end{cases} \tag{6.50}$$

These relationships imply that there is at least one variable which can be set freely. I have to make the following assumptions to further my discussions:

Assumption: In my scenario where asset prices can only go up or stay stationary, I assume that the variance σ^2 based on daily returns of the asset is a small quantity compared to μ.

Justification: μ is the expected unit time period return, it is usually a constant of a few percentage point. In my case where asset prices can only go up or stay stationary, the daily increase rate of the asset cannot exceed μ. Since σ^2 is the average of (daily return - average return)^2, hence I can justify that, under usual circumstances where there is no high volatility in the underlying asset prices, I should expect $\sigma^2 \leq c\mu^2 \ll \mu$, hence, when Δt is regarded as a small quantity,

$$(u-1)^2 = (\frac{\sigma^2}{\mu} + \mu\Delta t)^2 \ll u - 1 = \frac{\sigma^2}{\mu} + \mu\Delta t. \tag{6.51}$$

This relation cannot be directly implied from (6.50).

6.3 Binomial formula

6.3.1 Put Option

In addition to the price movement patterns assumed in the previous section, I add the following assumptions:

1. Short selling permitted.
2. Any fraction of the security is permitted to be traded, no trading transaction cost occur and no dividends are paid.
3. No arbitrage opportunities exist. Wilmott et al. (1995) explain this assumption as "there is no risk-free opportunity to make an instantaneous profit".

Denote by P_0 the value of the put option on this security at t_0, and by P_+ (P_-) the corresponding option values at $t = t_0 + \Delta t$ if the underlying prices goes up (stays the same):

$$P_0 = P(S_0, t_0),\ P_+ = P(S_0 u, t_0 + \Delta t),\ P_- = P(S_0, t_0 + \Delta t),$$

where the payoff of the put option is $P_T = \max(E - S(T), 0)$, and E is the exercise price of the option.

Now consider a portfolio consisting of one put option, and a short position of a quantity Ξ to be specified later. I establish the value of the portfolio at $t_0 + \Delta t$:

1. If the price has stayed, the portfolio has value $P_- - \Xi S_0$.

2. If the price has moved up, the portfolio has value $P_+ - \Xi S_0 u$.

I choose Ξ so that the portfolio has the same value in both cases:

$$P_- - \Xi S_0 = P_+ - \Xi S_0 u, \Rightarrow \Xi = \frac{P_- - P_+}{S_0(1-u)}. \tag{6.1}$$

I now have, using standard non-arbitrage theory,

Proposition 6.1 *: By the principle of non-arbitrage, I have*

$$P_0 - \Xi S_0 = exp(-r\Delta t)(P_- - \Xi S_0), \tag{6.2}$$

where r is the risk-free interest rate. Substituting (6.1) into (6.2) and rearranging, I get

$$\begin{cases} P_0 = \Xi S_0 + (P_- - \Xi S_0)exp(-r\Delta t) = \frac{P_- - P_+}{1-u} + \frac{P_+ - P_- u}{1-u} e^{-r\Delta t}, \\ P_T = \textit{max}(E - S(T), 0). \end{cases} \tag{6.3}$$

The proof is to use standard arbitrage arguments and it is omitted in this thesis. Readers can refer to Haidar (2007) for the complete proof.

6.3.2 Call Option

Proposition 6.2 *: Similarly, let C be the value of the call option, using same notations, I have*

$$\begin{cases} C_0 = \Xi S_0 + (C_- - \Xi S_0)exp(-r\Delta t) = \frac{C_- - C_+}{1-u} + \frac{C_+ - C_- u}{1-u} e^{-r\Delta t}, \\ C_T = \textit{max}(S(T) - E, 0). \end{cases} \tag{6.4}$$

where r is the risk-free interest rate.

6.4 Derivation

Following the assumption in (6.51), under normal circumstances, I can regard $O((u-1)^2)$ as small quantity, hence following the ideas developed in Wilmott et al. (1995), to get

$$\frac{\partial P}{\partial S}(S_0,t_0)S_0 r + \frac{1}{2}\frac{\partial^2 P}{\partial S^2}(S_0,t_0)rS_0^2\frac{\sigma^2}{\mu} - P(S_0,t_0)r + \frac{\partial P}{\partial t}(S_0,t_0) = 0.$$

Proposition 6.3 *: Under my assumptions, the put option value for my up-only asset is determined by*

$$\frac{\partial P}{\partial t} + rS\frac{\partial P}{\partial S} + \frac{1}{2}\frac{r\sigma^2 S^2}{\mu}\frac{\partial^2 P}{\partial S^2} - rP = 0 \textit{ with } P(T) = \textit{max}(E - S(T), 0). \tag{6.1}$$

This formula is also true when r, the risk-free interest rate depends on t (possibly also on S).

6.4.1 Call option

Same assumptions and arguments lead to

Proposition 6.4 *: Under my assumptions, the call option value for my up-only asset is determined by*

$$\frac{\partial C}{\partial t} + rS\frac{\partial C}{\partial S} + \frac{1}{2}\frac{r\sigma^2 S^2}{\mu}\frac{\partial^2 C}{\partial S^2} - rC = 0 \textit{ with } C(T) = \textit{max}(S(T) - E, 0). \tag{6.2}$$

This formula is also true when r, the risk-free interest rate depends on t (possibly also on S).

6.5 Financial crisis 2008-2009

I have established the following important proposition: as far as option value is concerned, under not too volatile market conditions, my S-risk function σ^2/μ is a more suitable measure of risk than the traditional variance in hedge fund investments. Now I demonstrate how this new risk measure can be used to predict the performance trend change of a portfolio of hedge funds.

It is well known that one of the selling points of hedge funds is the absolute return. It is therefore possible to view hedge funds as a kind of S-shaped assets (in real life, this is not true but not too far from true in a rational market – especially when market is calm and $\sigma^2/\mu \ll 1$).

I use Monte-Carlo method to generate random nonnegative portfolio weights $(w_1, w_2, \cdots, w_{60})$ twenty thousand times such that $w_1 + \cdots + w_{60} = 1$. Using 1 year historic data to calculate and plot the graph of $(\sigma^2/\mu, \mu)$. The Figures 44-49 are given at the end of the chapter. Visual observation of more risk associated with less return, confirms the arrival of bad investment periods including the financial crisis in advance. Visual observation does not confirm pattern of distribution of $\left(\sigma^2/\mu, \mu\right)$, so regress σ^2/μ on μ of the samples generated by Monte Carlo methods. The coefficient β of μ generated by the regression $\frac{\sigma^2}{\mu} = \alpha + \beta\mu$ indicates the sensitivity of the S-risk function to the return. A negative β represent higher risk associated with lower return. A β value of -1 represents a unit return loss for one more unit of risk. I suggest that investors should shorten their investing periods and avoid some predicted bad periods when they receive the warning sign (i.e. $\beta < -1$) and wait until the sign recovers. The value of β to depend on the investor's risk tolerance. These tell us that using my S-risk function σ^2/μ, the warning sign would have been clear by Jan-Feb 2008. Taking into decision making time and an average of two months notice period required for withdrawal, investors still would have avoided the disaster for hedge funds performances of the second half of 2008 if they had taken action in by March 2008.

Similar simulation has been applied to 1998 and 2001 financial storms. During these periods, I have less hedge funds available, hence I have chosen ALL funds data that existed during the period (16 funds for 1997-1998, 27 funds available for 2000-2001), I do not make any selections using any criteria. The results show that (see Figures 47-49)

1. For 1998, the warning sign became clear in June 1998 (using 9 months back data, the warning sign appeared in April, but I need further study to confirm if shorter historical data gives many more *false* warnings). The aftermath has seen some strong negative returns from the portfolios of the hedge funds. This again clearly indicated the Russian currency

crisis and the beginning of the end of Long Term Capital Management. The recovery took place in May 1999 when risk and return became positively correlated again.

2. For 2001, the warning sign became clear in Nov 2000. The effect of this down turn is much milder. In fact, the simulated portfolios remained in positive returns, but the "turning point" shape of the (σ^2/μ,μ) graph has been persistent until May 2003. That means, for this considerable period of time, higher risk implies lower return in the hedge fund portfolio. It is interesting that from Nov 2000 to May 2003, although higher return brings lower return, the actual return of my Monte-Carlo portfolios never turned negative. Around June 2003 (shortly before and afterwards), σ^2/μ risk-return graph finally turned the trend to the "normal pattern" where higher risk implies statistical higher returns. The hedge fund industry really flourished around June 2003, many new funds are born and the "good time" has come.

I plot the effect of the S-risk function on investing one unit of money in hedge funds universe index, which represents an equal-weighted exchange-traded fund (ETF) of the existing funds, and in S&P 500 for the period from September 2000 to June 2011. I find that hedge funds have strong ability in defending the financial crisis. So the choice of -1 as a threshold leads to missing many good investing opportunities. I allow less restrictions on the sign and for a comparison I choose a less strict threshold indicator of -4 to extend the investing time periods. I plot the effect of S-risk function using β of -1 and -4 for hedge fund universe in Figure 50 and for S&P 500 in Figure 51. I can further rearrange the regression equation to get $\sigma^2 = \alpha\mu + \beta\mu^2$ that represents a reverse efficient frontier when β is negative as more risk leads to less return. It is also easy to show that $\mu = \frac{-\alpha}{2\beta}$ is a critical point for which the variance has a minimum value when β is negative.

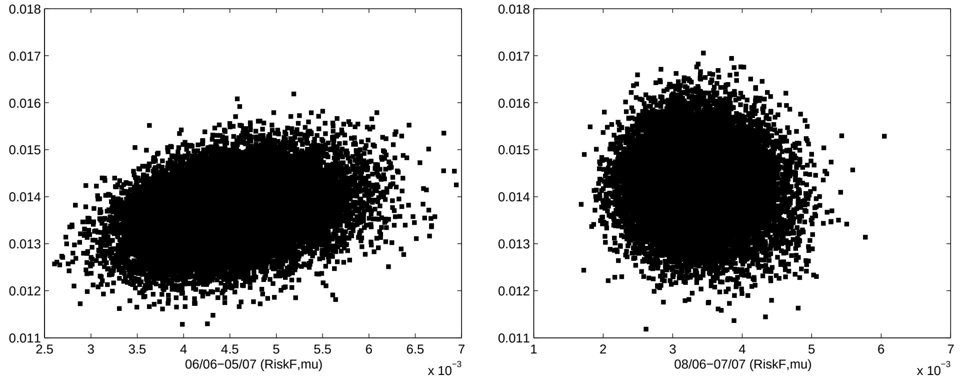

Figure 44: Return against risk function σ^2/μ (the generated portfolios have performed reasonably with a positive relation on the first graph between RiskF=σ^2/μ and mu=μ. Risk-reward seems to be in proportion)

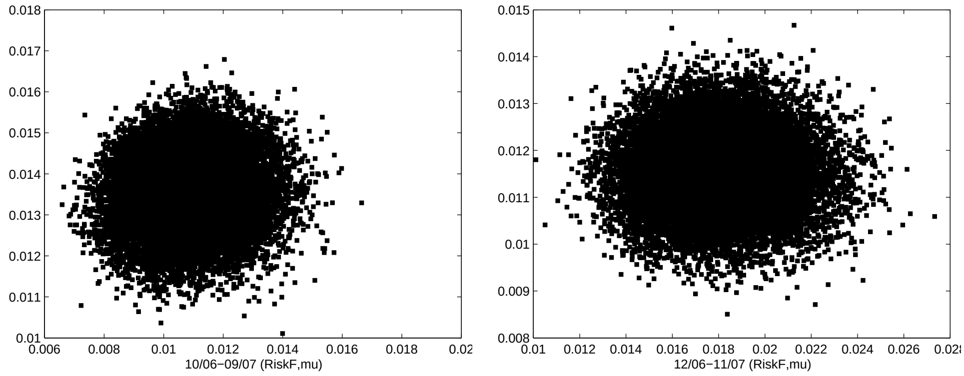

Figure 45: Return against risk function σ^2/μ (The portfolios generated have performed reasonably. However, the second graph begins to show that larger risks may not bring higher returns)

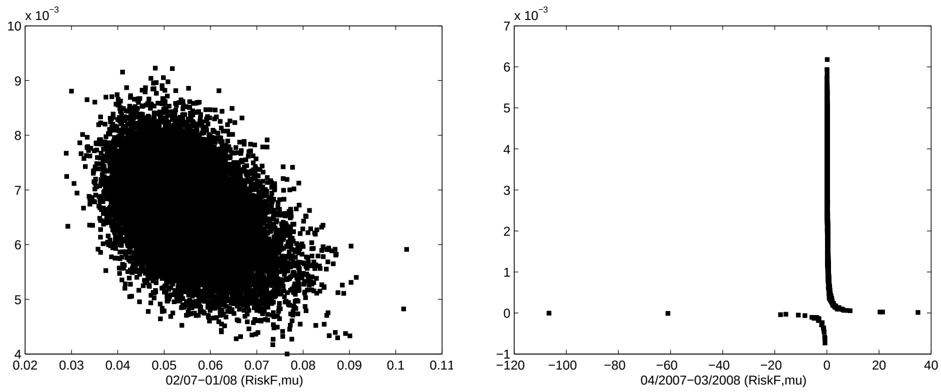

Figure 46: Return against risk function σ^2/μ (The first graph shows the performance deterioration clearly: high risks seem to bring lower returns - bad sign for hedge funds. The second graph shows that the value of the risk measure becomes large and is no longer suitable to be used to measure risk, with a negative relation between RiskF=σ^2/μ and mu=μ)

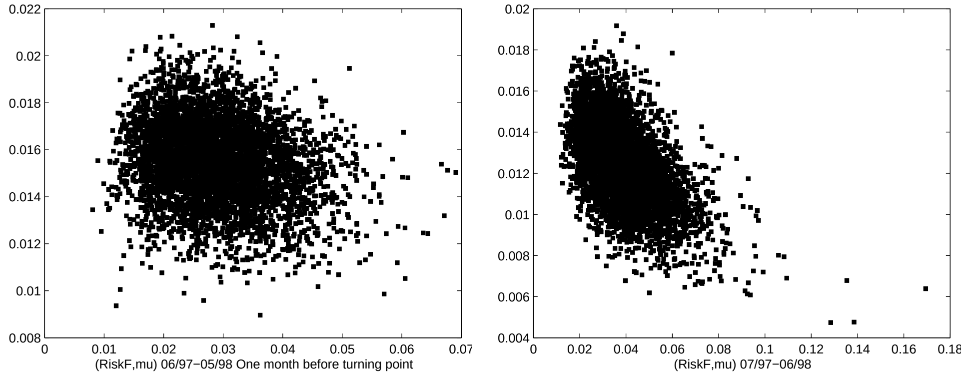

Figure 47: The run up to the 1998 downturn

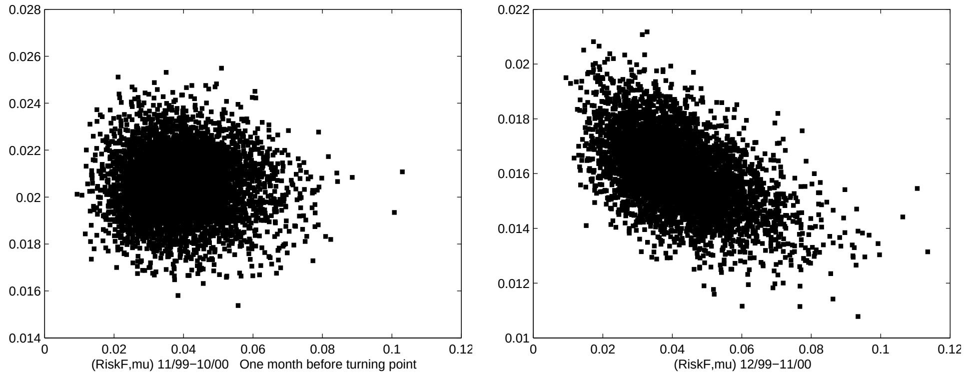

Figure 48: The run up to the 2001 downturn

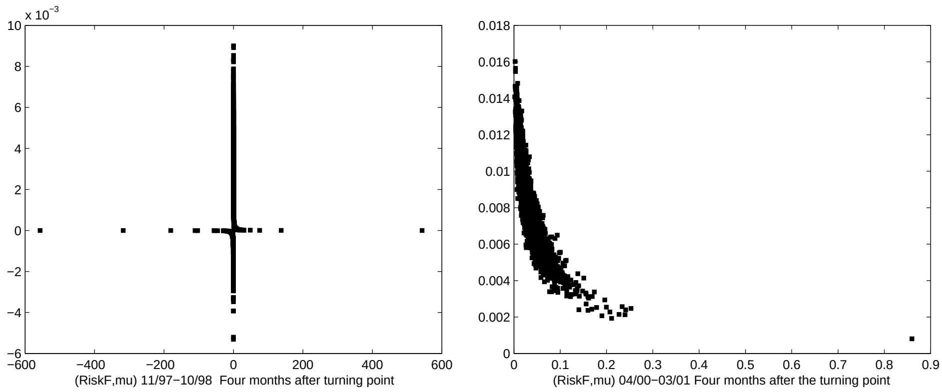

Figure 49: The aftermaths (The 1998 (first graph) downturn “turning point” implied serious negative performance risk. The 2001 (second graph) downturn “turning point” implied more risks, but no significant negative performance risk as a portfolio)

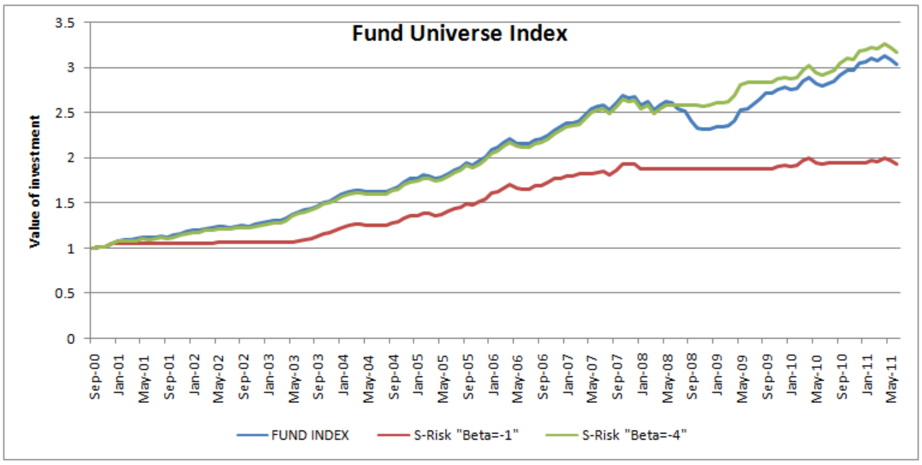

Figure 50: The effect of S-risk function on investing one unit of money in hedge funds

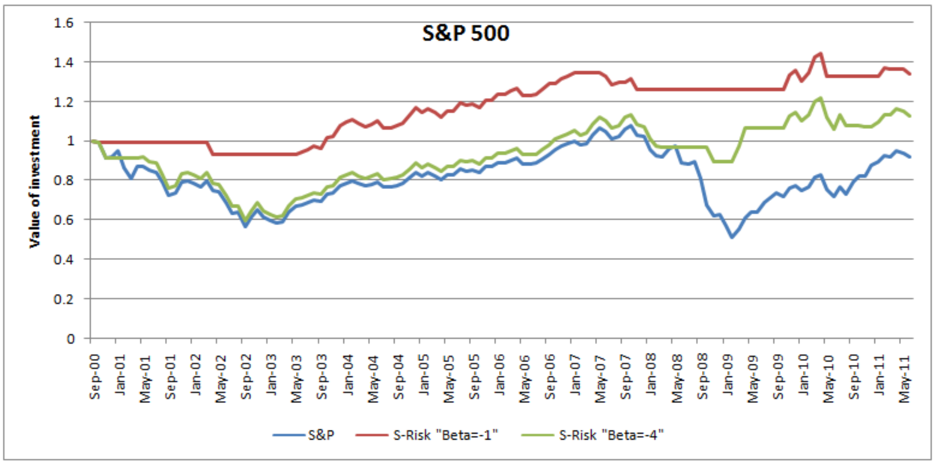

Figure 51: The effect of S-risk function on investing one unit of money in S&P500

6.6 S-risk function application

The case where asset price cannot go down (or cannot go up) can often be used to approximate the cases of technology projects (the widely known S-curve theory) funding assessment and operational loss assessment. In these circumstances, the amount of investment that required to support the project or to cure the cause of loss needs to be evaluated.

The model in this chapter is proposed as a first step in the effort of valuing this kind of assets. The PDE model, with exact solution, is a good approximation of the binomial formulation. Due to the explicit solution formula, the PDE solution can be used in a much wide context much more efficiently. The most meaningful part of discussion here is that I found that the risk measure σ^2/μ is suitable assessment for performances of assets with expected absolute returns. In this particular context, the quantity σ^2/μ replaced the traditional σ^2 in the Black-Scholes option value formula as an indicator of risk of the asset.

My assumptions are more restrictive than those for the standard Black-Scholes equation as I do have to add an empirical type condition that σ^2/μ is small compared to 1. These conditions are usually satisfied when the market conditions are good. I give a theoretical justification/clarification in Section 6.2. In Section 6.5, this is further justified by the hedge funds data before the market turmoil (see the graphs for $(\sigma^2/\mu, \mu)$ during periods 06/06-05/07, 08/06-07/07, 10/06-09/07 and 12/06-11/07). It is clear that as market condition deteriorate in 02/07-01/08 and 04/2007-03/2008, this assumption no longer holds. But correspondingly, the visual trend of funds performances also changes in time to give good warning about the market storm.

Finally, I conclude that by using risk control, investment in hedge funds can be improved by 10% over 2007-2008 financial crisis. By contrast, the investment in S&P can be improved by over 40%. This means that hedge funds as a whole, provides strong risk mitigating abilities when facing financial storms (Figures 50 and 51).

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