University of Cape Town

Master of Commerce in Economics

Analysis of Hedge Funds' Performance in South Africa

June 2013

Author: Cephas Dube

Supervisor: Prof. Haim Abraham*

University of Cape Town

*Acknowledgements:

I would like to thank my thesis supervisor Prof. Haim Abraham for his invaluable help and support as well as insightful guidance throughout the whole thesis process. My wife (Noelline N.) and our boys (Ayanda N. and Mayibongwe L.) inspire me daily to reach new heights.

University of Cape Town

The copyright of this thesis vests in the author. No quotation from it or information derived from it is to be published without full acknowledgement of the source. The thesis is to be used for private study or non-commercial research purposes only.

Published by the University of Cape Town (UCT) in terms of the non-exclusive license granted to UCT by the author.

Abstract

I examine performance of hedge funds in South Africa by aiming to answer four related research questions: 1) Is the market in South Africa as represented by JSE All Share index efficient? 2) Is there persistence in single hedge funds' performance in South Africa? 3) Do hedge fund portfolios formed on the basis of single hedge funds' past average returns rankings display performance persistence? And finally, 4) What are the sources of risks in hedge fund returns? I use an aggregated hedge fund dataset in South Africa, seven different performance persistence test methodologies and perform my analysis across different hedge fund strategies at four different time horizons (monthly, quarterly, semi-annually and annually). I find statistically significant performance persistence of net returns at quarterly, semi-annually and annual time periods in all persistence test methodologies but Hurst exponent[1]. An investor could have utilised a quarterly momentum strategy to gain superior returns during my investigation period. While I find that the JSE All Share Index shows signs of inefficiency the results do not present a robust framework from within which the validity of the efficient market hypothesis can be challenged. Using my own asset-based style (ABS) factors adapted from Fung & Hsieh (2004) I can explain up to 75% of monthly return variations for diversified hedge fund portfolios.

University of Cape Town

[1] See De Souza & Gokcan (2004) for details on Hurst exponent and also discussed in Chapter 4 of this thesis, on Page 53.

Table of Contents

Abstract ii

List of Tables vi

CHAPTER 1 Introduction 1

1.1. Background and Summary of Thesis Hypotheses 1

1.2. Summary of Results 5

1.3. Thesis Outline 6

CHAPTER 2 Literature Review 7

2.1. Performance Persistence-The Model 7

2.2. Traditional Mutual Funds 8

2.3. Hedge Funds 8

2.3.1. Cross-Sectional Regression Test 10

2.3.2. Cross Product Ratio and Chi-Square Test 11

2.3.3. Kolmogorov/Smirnov Test 13

2.3.4. Spearman's Rank Correlation Test and Rank Information Coefficient 14

2.3.5. Other Tests 14

2.4. Duration of Performance Persistence of Hedge Fund Portfolios 15

2.4.1. Winners/Losers Portfolios Strategy 16

2.4.2. Octal Portfolios Strategy 18

2.4.3. Decile Portfolios Strategy 19

2.4.3. Momentum Strategies in Hedge Funds 20

2.5. Efficient Market Hypothesis 21

2.5.1. Causes of Market Inefficiencies 28

2.6. Sources of Risks in Hedge Funds 31

CHAPTER 3 Data Description 35

3.1. Sample Data for Hedge Funds 35

University of Cape Town

3.2. Sample Data for the Risk Factors in Hedge Fund Returns 47
3.3. Sample Data for Efficient Market Hypothesis Test 48
CHAPTER 4 Methodologies 49
4.1. Return Persistence 49
4.1.1. Contingency Table Based Cross Product Ratio Test 50
4.1.2. Chi-Square Test 51
4.1.3. Spearman's Rank Correlation Coefficient Test 52
4.1.4. Cross-Sectional Regression Test 53
4.1.5. Hurst Exponent 53
4.1.6. Binomial Test 54
4.1.7. Kolmogorov/Smirnov Test 55
4.2. Duration of Performance Persistence of Hedge Fund Portfolios 56
4.3. Efficient Market Hypothesis 57
4.4. Sources of Risk in Hedge Funds 60
CHAPTER 5 Results 63
5.1. Results on Hedge Fund Return Persistence 63
5.1.1. CPR and Chi-Square Test Results 63
5.1.2. Cross-Sectional Regression Test Results 66
5.1.3. Spearman's Rank Correlation Test Results 67
5.1.4. Binomial Test Results 68
5.1.5. Hurst Exponent Test Results 70
5.1.6. Kolmogorov-Smirnov Test Results 71
5.2. Summary of Results and Comparative Analysis 75
5.3. Duration of Performance Persistence of Hedge Fund Portfolios' Results 76
5.4 Efficient Market Hypothesis 80
5.5. Sources of Risks in Hedge Fund Returns 82

University of Cape Town

5.6. Limitation of the Research 85

CHAPTER 6 Conclusion 87

6.1. Concluding Remarks.. 87

6.2. Suggestions for Further Research 89

Bibliography 91

Appendix 97

University of Cape Town

List of Tables

Table 1: Funds by Strategy Contained in my Database before Data Cleaning 37

Table 2: Estimation of Attrition Rates for Different Hedge Fund Databases..................................... 40

Table 3: Survivorship Bias in South African Hedge Funds (2007-2011) 41

Table 4: Estimation of Backfill bias in South African Hedge Funds (2007-2011) 45

Table 5: Funds by Strategy after Data Cleaning 47

Table 6-Equity Long Short CPR and Chi-Square Test Results 63

Table 7-All Hedge Funds CPR and Chi-Square Test Results 64

Table 8-Surviving/Living Hedges Funds Only CPR and Chi-Square Test Results 65

Table 9-Cross Sectional Regression at 5% Level 66

Table 10-Spearman's Rank Correlation Test at 5% Level.. 68

Table 11-Binomial Test at 5% Level 69

Table 12-Hurst Exponent Test at 5% Level 71

Table 13-Equity Long Short Kolmogorov-Smirnov Test Results.. 72

Table 14-All Hedge Funds Kolmogorov-Smirnov Test Results 73

Table 15-Surviving/Living Hedge Funds Only Kolmogorov-Smirnov Test Results 74

Table 16-Quarterly Momentum Portfolio Results 76

Table 17-Semi-Annual Momentum Portfolio Results 78

Table 18-Annual Momentum Portfolio Results 79

Table 19-Results of Principal Symbols for the Inequalities... 80

Table 20-Results for the Elements of R. Shiller's Three Variance Inequalities 80

Table 21-Regression of the HFI on Nine Hedge Fund Risk Factors 82

Table 22: Summary of Hedge Fund Strategies.. 97

Table 23: Summary of Measures for Testing Performance Persistence... 98

Table 24: Summary of Methodologies for Testing Performance Persistence 99

University of Cape Town

Table 25: Summary of Advantages and Disadvantages of the Methodologies 100

Table 26-Equity Market Neutral CPR and Chi-Square Test Results 102

Table 27-Fixed Income Arbitrage CPR and Chi-Square Test Results 102

Table 28-Other Hedge Fund Strategies CPR and Chi-Square Test Results 102

Table 29-Cross Sectional Regression at 1% Level 103

Table 30-Spearman's Rank Correlation Test at 1% Level 103

Table 31-Binomial Test at 1% Level 104

Table 32-Hurst Exponent Test at 1% Level 104

Table 33-Equity Market Neutral Kolmogorov-Smirnov Test Results 105

Table 34-Fixed Income Arbitrage Kolmogorov-Smirnov Test Results 105

Table 35-Other Hedge Fund Strategies Kolmogorov-Smirnov Test Results 105

Table 36-Regression of the FoHF on Nine Hedge Fund Risk Factors 106

Table 37-Annual Performance of Hedge Funds Strategies 107

Table 38-Eqautions 108

Table 39-Linking Market Inefficiencies to Hedge Fund Strategies 109

University of Cape Town

CHAPTER 1 Introduction

1.1. Background and Summary of Thesis hypotheses

The industry of hedge funds lacks a common, all-encompassing definition of what a hedge fund is, and even the vast literature on hedge funds does not arrive at any common definition as noted by Connor & Lasarte (2004) and Garbaravicius & Dierick (2005) among others. The characteristics common to hedge funds include use of leverage, broader flexibility in their trading, not required to publicly report their activities, charging performance fees and also being structured as partnerships. Despite their commonalities, hedge funds are not a homogeneous class of investment, and how they actually invest their money differs quite substantially. Traditional investing has always been dominated by mutual funds which are investment vehicles made up of pools of capital collected from many investors for the purpose of investing in securities such as stocks, bonds, money market instruments and similar assets. Hedge funds and mutual funds trade in similar asset classes but differ in their trading strategies and how they are regulated ((see, e.g. Fung & Hsieh 1997), (Liang 2000), (Agarwal & Naik 2004)).

Since hedge funds and mutual funds trade in similar asset classes, one of the prudent ways of defining and understanding hedge funds is to use mutual funds as a benchmark comparison. Hedge funds seek to provide a positive expected return on capital with a minimal exposure to systematic risk, by hedging away exposure to traditional asset classes held in the investment portfolio. This is usually accomplished through short selling which is simply borrowing a security you don't own, selling it, then hoping it declines in value, at which time you can buy it back at a lower price than you paid for it and return the borrowed securities (Goetzman & Ibbotson 1999). While some mutual funds are able to short sell, this is often on very tight regulatory framework compared to hedge funds. Hedge funds therefore enjoy much broader flexibility in their trading and can hold more varied positions in securities, including options

University of Cape Town

and derivatives (Goetzman & Ibbotson 1999). According to Brown & Goetzmann (2001), hedge funds are best defined by their freedom from regulatory controls. Mutual funds have restrictions on the types of securities they can hold, the degree to which the investment portfolios may be concentrated in a single security, the percentage they may hold in any one firm and the amount of leverage they may take. Mutual funds are required by law to offer daily pricing and liquidity to investors and to publicly report their security holdings on a quarterly basis (Goetzman & Ross 2000). These tight regulatory policies are not imposed on hedge funds.

The other distinctive feature of hedge funds is that they are structured to allow almost pure bets on managerial skill. Unlike the traditional mutual funds whose returns are mostly a function of the performance of an asset class, hedge funds returns are almost entirely a function of the manager's skill to identify and capture transitory trading opportunities (Brown et al. 1999). The efficiency of the most of the capital markets makes trading on mispricing a highly specialized skill. Hedge fund managers typically therefore develop focused knowledge of particular markets and securities.

Fixed income funds seek to exploit subtle differences in forward rates implied by current bond prices or differential values arising from liquidity or credit considerations. Derivatives managers use options pricing models to evaluate deviations in the market price of options and convertible bonds from their fundamental values. Relative value funds trade offsetting long and short positions in securities that are close economic substitutes. Quantitative trading funds seek to profit through sophisticated proprietary statistical arbitrage models. Distressed security managers generate value through their expertise on the intricacies of bankruptcy and debt structuring of companies in distress. Mortgage backed security funds provide value through their ability to try and forecast the refinancing behaviour of homeowners and their expertise at evaluating different components of complex mortgage backed securities. Event

University of Cape Town

driven arbitrage managers usually focus on mergers and acquisitions activities (Goetzman & Ross 2000). These different hedge fund investment strategies are summarized in Table 22 in appendix.

Despite the variety of different hedge fund strategies, they all essentially share a common value proposition. All hedge funds seek to exploit temporary mispricing in the value of marketable securities or anticipate various markets' directional trends (Goetzman & Ross 2000). Temporary mispricing in the value of marketable securities means that security markets may temporarily deviate from being in continuous stochastic equilibrium where market prices fail to instantaneously and fully reflect all available information. In turn this creates pockets of market inefficiencies which hedge funds try to successfully exploit. Mutual funds typically employ a long-only buy and hold strategy on standard asset classes and help capture risk premium associated with equity risk, interest rate risk, default risk, etc., but are however not able to capture risk premium associated with dynamic trading strategies or spread based strategies that are used by hedge funds (Agarwal & Naik 2004). While mutual funds are available to the general public and are not limited in the number of investors who can invest in the fund, hedge funds are private pools of investment capital available to accredited investors as defined by the laws of the country in question.

The three major hedge fund strategies in South Africa by assets under management are equity long short, equity market neutral and fixed income arbitrage consisting of at least 75% of industry capital while funds of funds are the largest allocators of capital to the industry. (see, Novare Investment SA Hedge Fund Survey 2011).

The purpose of this thesis is to assess hedge funds' performance in South Africa by researching four different objectives. The **first** objective is to test the hypothesis of whether or not single hedge fund performances display any persistence? The popular adage found in most investment product prospectuses is that past performance is not an indicator of future

University of Cape Town

performance (Eling 2008). However most of the capital allocation by investors to different funds is based on funds' track record, implying an expectation of stable returns over time by investors and that some fund managers will provide superior returns than others (Caponi N et al. 1996). I achieve the objective of testing performance persistence in single hedge funds by using an extensive list of performance persistence test methodologies, developed from my literature review framework to measure whether some fund managers can sustainable achieve superior (or inferior) returns than their peers (competitors).

The **second** objective of the thesis is directly linked to the first one. I perform a specific analysis on the duration of performance persistence of hedge fund portfolios. Using momentum strategies as in Bares et al. (2002)' s work I ascertain whether hedge fund portfolios formed on the basis of hedge funds past average returns rankings display short and long term performance persistence. Understanding the duration and also the patterns in hedge fund portfolios persistence can offer valuable insights regarding the type of strategies that are better suited for hedge funds investors whether these are momentum or contrarian. Since hedge funds seek to exploit temporary mispricing in the value of marketable securities or anticipate various markets' directional trends the **third** objective is to test whether the market in South Africa as represented by JSE All Share index is efficient or not. I achieve the objective of testing market efficiency by using Shiller (1981)'s work where he tests the assertion that share price indices look to be too volatile for the efficient market hypothesis model to hold. If the market is inefficient then hedge fund managers who seek to exploit inefficiencies in the market have expanded opportunity set to show differential skills in delivering absolute returns (Eling 2008).

The above analysis of the first two objectives is however based on hedge fund rankings dependent on a one dimensional performance measure of their past average returns. It does not focus on the multiple sources of risk employed by the hedge fund managers. The **fourth**

University of Cape Town

objective of this thesis is therefore to address this issue by investigating the different sources of risks in hedge funds. Using a hedge fund risk-factor model that tries to mimic the arbitrage pricing theory (APT) model I come up with my own asset-based style (ABS) factors adapted from Fung & Hsieh (2004) work to investigate different sources of risks in hedge funds in South Africa.

1.2. Summary of Results

I used an aggregated hedge fund dataset in South Africa, seven different performance persistence test methodologies and performed my analysis across different hedge fund strategies at four different time horizons (monthly, quarterly, semi-annually and annually). I found statistically significant performance persistence of net returns at quarterly, semi-annually and annual time periods in all persistence test methodologies but Hurst exponent. The seven different performance persistence test methodologies used are Cross product ratio test, Chi-square test, Spearman rank correlation test, Hurst exponent, Cross-sectional regression test, Binomial test and the Kolmogorov-Smirnov test. Performance persistence seemed to be at its peak in quarterly horizons across all different hedge fund investment styles. I examined the duration of hedge fund portfolios performance persistence by ranking managers according to their past realised returns averaged over three to twelve months formation periods. I then formed two portfolios that contained the top performing ten funds and the other that contained the worst performing bottom ten funds. Portfolios were held during periods extending from three to twenty four months. I observed clear indication of short term portfolio performance persistence at three months' and six months' time horizon with different holding periods for the portfolios with top performing funds and the duration of hedge fund portfolios performance persistence seemed stronger at three months' time horizon. I also found a reversal in performance for the worst fund portfolios at longer holding time horizons. Using variance bound test as used in Shiller (1981), an empirical test of the

University of Cape Town

efficient market hypothesis and testing whether the market in South Africa as represented by the JSE All Share Index is efficient or not, I found that Shiller's three main inequalities are clearly violated by the sample statistics suggesting that the South African market showed signs of inefficiency. These results however do not present a robust framework from within which the validity of the efficient market hypothesis can be challenged, as the data set used violate the assumptions underlying the methodology used to test the hypothesis. Lastly I found that I could explain up to 75% of monthly return variations for diversified hedge fund portfolios in South Africa by using a hedge fund risk-factor model that tries to mimic the arbitrage pricing theory (APT) model as used by Fung & Hsieh (2004) in their asset-based style (ABS) factors.

1.3. Thesis Outline

The rest of the thesis is structured as follows: Chapter 2 discusses literature review regarding the work of previous studies about the research questions outlined above. Chapter 3 describes in detail the data that was used to test my research questions. My methodology used to test the hypotheses is presented in Chapter 4. The results are showed and critically analysed in Chapter 5 as well as limitations to the research. Finally Chapter 6 concludes the thesis and presents possible areas for future work.

University of Cape Town

CHAPTER 2 Literature Review

2.1. Performance Persistence-The Model

A common feature in investment products is a disclaimer that past performance is not an indicator of future returns. Nevertheless, most investors allocate capital to different managers on the basis of the managers' track record (Caponi et al. 1996 and Eling 2008). Good performances tend to be rewarded with higher allocation while badly performing managers are replaced. The weight placed upon a track record by investors implies that most of them believe that good and bad performance will persist, meaning that winners will continue to win and losers will continue to lose (Kat & Menexe 2003). The above argument forms the bases of my hypothesis. The model of my research of hedge funds' performance persistence is therefore defined as follows:

"Under the null hypothesis of no performance persistence, no funds are expected to sustainably achieve higher (or lower) returns than their peers within a predetermined time period".

Authors such as Eling (2008), Droms (2006), Brown & Agarwal & Naik (2000a), Hendricks et al. (1993), Chen & Passow (2003) and many others as outlined in my literature review below have tested this hypothesis for mutual funds as well as for hedge funds. These authors use different methodologies to test this hypothesis. Using the methodological framework developed in the literature review which consists of seven different statistical methodologies, I present empirical evidence of performance persistence on the hedge funds in South Africa. These methodologies are the binomial test, contingency table based cross product ratio test, chi-square test, Hurst exponent test, Spearman's rank correlation test, cross sectional regression test and the Kolmogorov/Smirnov test.

University of Cape Town

2.2. Traditional Mutual Funds

An extensive overview of the research into performance persistence in mutual funds is provided by Droms (2006) and concludes that most of the studies show that short term performance persistence is much stronger than long term persistence. He argues that there is less clear evidence on long term performance persistence tests, as compared with the short term performance persistence tests. Research seems to differ on whether performance does persists in the long term, though collectively the balance of the evidence supports much weaker persistence or no persistence at all over longer periods of time. The research papers on this topic are discussed later on in this section under the topic of momentum and reversals, as most of the papers use momentum strategies to test performance persistence.

2.3. Hedge Funds

Hedge fund academic literature on performance persistence comes to widely divergent conclusions. Eling (2008) attributes these differences in the results as due to the use of heterogeneous databases, investigation periods, performance measures and statistical methodologies. Studies have used a wide range of measures to analyse hedge fund performance persistence. These include simple raw and net return, higher moments, correlation and risk adjusted measures. An overview of the different measures analysed in the 25 studies on hedge fund performance persistence are given by Eling (2008) in his analysis. Table 23 in appendix, on page 97 gives Eling's overview that I have updated with other studies.

Among the risk adjusted performance measures are information ratio, alpha, appraisal ratio and Sharpe ratio. The information ratio measures the relationship between manager's ability to generate excess returns (return minus selected benchmark), and the tracking error (standard deviation of the difference between returns of the portfolio and the returns of the benchmark). Jensen (1968) introduced alpha in the context of a single index model as a regression of the market excess return on the fund excess return. The single factor model can be extended into

University of Cape Town

a multi-factor model to try and improve portions of variance explained by the regression, (Eling 2008). One good example is the Fama & French (1993) model which used two additional factors one for size and the other one the ratio of book to market. Some researchers in hedge fund performance have used hedge fund specific style factors such as hedge fund indices along with some common risk factors. Examples are studies by Gibson and Cooper (2004) who use 19 factors, Capocci & Hubner (2004) use 11 factors, both Kosowski et al. (2006) and Koh et al. (2003) use 7 factors. Alpha is the intercept of the regression of several market factors on the hedge fund excess returns while appraisal ratio is the relationship between alpha and the residual standard deviation of the regression. The Sharpe ratio is a measure of the relationship between excess return (return minus the risk free rate) and the standard deviation.

Table 23 in appendix on page 98, shows all the different measures used by Eling (2008) in his research. He concludes that the use of different performance measures is not the reason for the conflicting results found in hedge fund performance persistence literature. The results comparing different measures used to assess hedge fund performance persistence were very similar. Studies have also used different statistical methodologies. Table 24 in appendix on page 99, is adapted from Eling (2008) and reports the statistical methodologies used on hedge fund performance persistence studies updated with binomial test. These studies show that we can distinguish between two-period and multi-period statistical approaches in our examination of hedge fund performance persistence. In the two-period approach, two consecutive time horizons, e.g. months or quarters are compared to each other and in the multi-period case more than two consecutive time horizons are analysed. The two-period approach can be further divided into nonparametric and parametric approaches. The nonparametric frameworks include the contingency table based cross product ratio test, chi-square test, binomial test, Hurst test, Spearman's rank correlation test and the correlation-

University of Cape Town

based rank information coefficient test. The parametric framework is a linear regression. The Kolmogorov/Smirnov test belongs to the multi-period approach. Table 25 is again derived from Eling's work, updated with the binomial test and gives a summary of the advantages and disadvantages of using the different methodologies for testing performance persistence in hedge funds.

The literature review on hedge funds' performance persistence is structured by grouping the methodological framework used in the studies into five different classes. These are a) cross sectional regression test b) cross product ratio and chi-square test c) Kolmogorov/Smirnov test d) rank information coefficient and Spearman's rank correlation test and e) other tests which include Hurst exponent, descriptive comparison of rankings, Bootstrap and Bayesian approach.

2.3.1. Cross-Sectional Regression Test

Brown et al. (1999) investigate performance persistence in hedge funds during the period 1989 and 1995. Their dataset consists of 399 hedge funds taken from US Offshore Funds Directory database and they use the return, alpha and appraisal ratio as performance measures for their analysis. Employing a regression methodology where a fund's performance measure (return, alpha and appraisal ratio) of one time horizon is regressed on the same measurement value of the previous time horizon, they find no evidence of performance persistence at 12 months horizon. Winners follow winners in 1991 to 1992 and also 1992 to 1993 but this pattern reverses in 1993 to 1994 and 1994 to 1995 as losers follow winners. These results are supported by Brown & Goetzmann (2003), Chen & Passow (2003) and Capocci & Hubner (2004), Kat & Menexe (2003) who use the same regression methodology in different investigation periods and find no evidence of performance persistence in the time horizons tested. On the contrary, Boyson & Cooper (2004) analyse 1659 hedge funds from TASS database over the period 1994 to 2000 using alpha as their performance measure and 3

University of Cape Town

months the measurement testing period. They use the regression test and find persistence at quarterly horizons. Amenc et al. (2003) employ the regression methodology in analysing 9 hedge fund indices taken from the CSFB/Tremont indices during the period 1994 to 2000 using monthly return as the performance measure and find persistence at monthly horizon. The work done by Agarwal & Naik (2000a) finds persistence at quarterly intervals with no persistence at semi-annual and yearly horizons. De Souza & Gokcan (2004) use the return, standard deviation and Sharpe ratio as their performance measures and, 24 and 36 months as their time period measures, regression methodology and find no persistence in both time periods with return but persistence with risk. Other studies that find performance persistence using regression method are Harri & Brorsen (2004) at time periods of 1, 2, 3, 6 … to 24 months, Jagannathan et al. (2006) at three year horizon, Agarwal et al. (2007) and Kosowski et al. (2007) at annual horizon.

2.3.2. Cross Product Ratio and Chi-Square Test

The work of Agarwal & Naik (2000a) tests the null hypothesis of no manager skill using both methods above. They analyse 746 hedge funds from HFR database for performance persistence during the period 1982 to 1998, using alpha and appraisal ratio as their performance measures, and test time periods of 3, 6, and 12 months. In their two period framework they construct a contingency table of winners and losers, and define a fund as a winner if its performance is higher than the median performance measure of all funds in a similar strategy over the defined time period in the study, and a loser as the fund with performance lower than the median performance measure of all the funds in a similar strategy. They then use the cross product ratio and the chi-square methodologies to test for persistence. Following the work of Brown et al. (1999) they extend their test to include the regression methodology. They find persistence at quarterly intervals with no persistence at semi-annual and yearly horizons. Again in 2000, Agarwal & Naik (2000b) make use of 167

University of Cape Town

hedge funds selected from the HFR database to test for performance persistence over the period 1995 to 1998. They use the cross product ratio method as described above in their first study and only tested the 3 month time horizon. Their results demonstrate a degree of performance persistence among the sample of 167 hedge funds though it must be noted that losers exhibit more persistence than winners.

In 2001, Edwards & Caglayan (2001), investigate performance persistence over annual and biannual time horizons using non-parametric (cross product ratio) test. They use 1665 hedge funds taken from the MAR database over the period 1990 to 1998, and the results show significant positive and negative persistence for global macro funds, market neutral and funds of funds in both time horizons tested. Kat & Menexe (2003) analyse 324 hedge funds from the TASS database during the period 1994 to 2001 using return, standard deviation, Skewness, kurtosis and correlation as performance measures over a time horizon of 36 months. Using non-parametric (cross product ratio test), they find no evidence of performance persistence at three year horizon with returns, but persistence with higher moments. It must be noted that they find significant level of persistence for funds of hedge funds and emerging market strategies.

In their research Henn & Meier (2004) use EurekaHedge database to analyse 1217 hedge funds for performance persistence in 1994 to 2004. Their study use return as the performance measure and cross product ratio methodology, and find evidence of performance persistence at monthly, quarterly and annual time periods. Using the chi-square test, TASS database and appraisal ratios at 12 months' time horizons to test the above model, Park & Staum (1998) find persistence at yearly horizons. Kouwenberg (2003) investigates 2614 hedge funds taken from Zurich (MAR) over the period 1995 to 2000 using return, alpha and Sharpe ratio as performance measures and a time horizon of 36 months utilising the chi-square test. Though his results are mixed he finds persistence at three year horizon in event driven, global funds

University of Cape Town

and market neutral strategies. Another study by Malkiel & Saha (2005) which involves 2065 hedge funds from the TASS database during the period 1996 to 2003 using return as performance measure, and 12 months' time period find no evidence of performance persistence at annual horizons using the chi square test method. Agarwal et al. (2007) put together CISDM, HFR, MSCI and TASS databases and effectively end up with 7535 hedge funds on which they test persistence over the period 1994 to 2002, using return as their performance measure, chi square methodology, 12 months as their testing measurement period. They find persistence at yearly horizon.

2.3.3. Kolmogorov/Smirnov Test

The work of Agarwal & Naik (2000a) already mentioned above was different in that instead of just testing performance persistence within a two period framework they extended this to a multi-period one. Using the Kolmogorov-Smirnov (K-S) test to improve robustness of results, they find persistence at quarterly intervals with no persistence at semi-annual and yearly horizons. It must be noted that the multi period analysis K-S test shows little persistence in comparison to the other two methods used, cross product ratio and the chi-square test. Asian only hedge funds are analysed by Koh et al. (2003) who combine EurekaHedge and Asia Hedge to come up with a database containing 3810 hedge funds over the period 1999 to 2003. Using time horizons of 1, 2, 3, 6, 9, 12 months and return and alpha as their performance measures they test performance persistence as described in my model with the cross product ratio, chi-square and Kolmogorov-Smirnov methodologies. They find evidence of significant performance persistence at monthly and quarterly horizons, but that the strength of the persistence weakens considerably when the measurement period is lengthened beyond a quarter.

University of Cape Town

2.3.4. Spearman's Rank Correlation Test and Rank Information Coefficient

Using Spearman's rank correlation coefficient test, TASS database and appraisal ratios at 12 months' time horizons to test the above model, Park & Staum (1998) find persistence at yearly horizons. In 2004, Harri & Brorsen (2004) examine persistence in 1209 hedge funds from LaPorte database during the period 1977 to 1998 using return, information ratio, Sharpe ratio and alpha as performance measures over the time periods of 1, 2, 3, 6 … to 24 months. Their analysis use Spearman Rank correlation and regression methodology and find persistence at all horizons. Research done by Herzberg & Mozes (2003), combine the HedgeFund.Net, Altvest and Spring Mountain Capital databases to create a database containing information on approximately 3300 funds over the period 1995 to 2001. They use return, Sharpe ratio, maximum drawdown, standard deviation and correlation as their performance measure in their analysis over a time period of 12 months. The authors use the Rank Information Coefficient (RIC) test, where RICs are calculated on each 31 December between the value of a given performance measure for the prior 36 month period and its value for the subsequent 12-month period. They find no performance persistence at annual horizons with returns while risk shows persistence.

2.3.5. Other Tests

Applying a simple trading strategy where last year's winning hedge fund is used as this year's selection during the period 1988 to 1999, and using alpha as a performance measure and 12 month time horizon on Zurich/LaPorte database, Gregoriou & Rouah (2001) find no significant performance persistence at yearly horizon. The binomial test was introduced by Barès et al. (2003). They analyse 4934 hedge funds from the Financial Risk Management during the period 1992 to 2000 using return and alpha as their performance measures, and time horizon of 1, 3, 6, and 12 months. They choose the benchmark as the median performance of the set of managers present during the entire time horizon so that only two possible outcomes are possible, where either a manager is performing above or below the

University of Cape Town

benchmark. They then count the number of non-overlapping time horizons k_i during which the fund performance dominates the investment strategy median, and then test the null hypothesis with the binomial representation$b(k_i, n_i, p = {}^{1}/_{2}$: the fund performance is equally distributed on each side of the median, where n_i is the total number of time horizons during which fund i is reporting performance. They find persistence over short term horizons of 1 and 3 months but that this rapidly vanishes as the formation or holding period lengthens when using portfolios ranked based on their past average returns.

De Souza & Gokcan (2004) use the return, standard deviation and Sharpe ratio as their performance measures and, 24 and 36 months as their time period measures, Hurst exponent methodology and find no persistence in both time periods with return but persistence with risk. Baquero et al. (2005) analyse 1797 hedge funds from the TASS database over the period 1994 to 2000 using return and alpha as performance measures and 3, 12 and 24 months' time horizons. Employing descriptive comparison of rankings among the hedge funds as their methodology, they find performance persistence at quarterly and annual horizons but not on bi-annual horizons.

Kosowski et al. (2007) use the same databases as Agarwal et al. (2007) and come up with 9338 hedge funds on which they investigate persistence over a much longer period ranging from 1990 to 2002 using alpha as performance measure, and 12 months as testing measurement period. While they use regression as one of their methods they also turn to more sophisticated modern methodologies involving bootstrap and Bayesian approaches. Their conclusion is that there is evidence of performance persistence at annual horizon.

2.4. Duration of Performance Persistence of Hedge Fund Portfolios

A lot of attention has been dedicated to the topic of momentum in the stock market and not much so in hedge funds. This is because hedge funds are not required by law to publicly disclose their activities making it difficult to obtain reliable data for such research purposes.

University of Cape Town

The objective of this section is to examine the duration of the performance persistence of hedge fund portfolios. As a corollary, I wish to examine if their positive short term performance persistence is followed by reversal over longer investment horizon. I report some results about the predictability of stock returns since a possible explanation of those patterns at the level of hedge funds could be related to the presence of momentum or reversal effects in the stock market.

First I discuss the literature review for the momentum strategies in mutual funds as these give the foundation of the momentum strategies in hedge funds. I divide the mutual fund literature review according to the momentum strategies that the researchers use to test momentum. I come up with three groups of strategies namely, Winners/Losers Portfolios strategy, Octal Portfolios strategy and Decile Portfolios strategy. One of the reasons why the researchers come up with different results is because they use these different strategies and also different databases, performance measurements and testing measurement periods.

University of Cape Town

2.4.1. Winners/Losers Portfolios Strategy

Jegadeesh & Titman (1993) find that momentum strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly will generate significant positive returns over time horizons of 3 to 12 months during the period 1965 to 1989 for US stocks. They discover that this pattern diminishes over longer holding periods. The same authors in 2001 extended the same study and conclude that momentum strategies have remained profitable until 1998 (Jegadeesh & Titman 2001). In a similar study Rouwenhorst (1998), analysing stocks of European countries over the period 1978 to 1995 comes to same conclusion as that of the above researchers.

In their study, Goetzmann & Ibbotson (1994) use a sample of 276 US and international equity funds to study performance persistence in the period 1976 to 1988. They examine growth funds over a number of two year periods. The authors then group the growth funds into winners (funds with returns above the median) and losers (funds with returns below the median) according to their two year returns, and analyse their performance measured by their alphas over the next two year period. They repeat the same procedure for the three year period and conclude that winners and losers are likely to repeat even when performance is adjusted for relative risk. Their conclusion is that past returns and relative rankings are useful in predicting future returns and rankings. They also contend that this appears to be true for raw returns and Jensen risk-adjusted alpha measures.

Malkiel (1995) uses a dataset that is free of survivorship bias consisting of all diversified US equity funds that were in existence during the period 1971 to 1991. He starts with 210 funds in 1971 and ends up with 684 funds during the investigation period. He tests for performance persistence of alpha and further tests the strategies of investing in the previous year's winners. Malkiel finds that there is considerable performance persistence during the 1970s period where winners following winners occurred much more often that a win followed by a loss. This relationship is however not significant during the 1980s. Again he finds that losers following losers are highly likely.

From the strategies of investing in the previous year's winners, Malkiel finds these to be effective in producing excess returns during the first decade of 1971 to 1980, but the strategy failed to produce excess returns in the next decade. Droms (2006) notes that Malkiel's results show that either the presence of performance persistence or the lack of performance persistence is likely to vary across time periods. In their paper Droms & Walker (2001a) argue that the difference in results between the 1970s and 1980s is related to the small-stock effect in that small market capitalization stocks outperformed the S&P 500 during the 1971-1980, but underperformed the S&P during 1981-1990. They conclude that significant results in the 1970s are likely due to the persistence of superior performance by mutual funds holding small cap stocks. Droms (2006) also points out that these results support the position

University of Cape Town

that persistence should be measured within investment styles subcategories instead of relative to a general benchmark.

A much longer period of investigation covering a 40 year period that stretches from January 1961 to June 2000 is used by Jan & Hung (2004). Their sample consists of returns on a total of 3316 mutual funds which are free of survivorship bias. They follow Carhart (1997)'s model and conclude that mutual funds with short and long run performance usually have strong subsequent year performance and that investors can benefit from choosing mutual funds on this basis of short and long run performance.

2.4.2. Octal Portfolios Strategy

The study by Hendricks et al. (1993) use a sample of 165 funds to analyse mutual fund performance persistence based on net quarterly returns over the period 1974 to 1988. Firstly, they compute the serial correlation in the individual factor loading of present returns on lagged ones. Their results prove statistically significant positive performance persistence on a quarterly basis with the strongest evidence for a one year time horizon. Using net returns, they come up with eight rank portfolios based on performance meaning that the highest ranked portfolio contained one-eighth of the sample with the highest returns and the lowest ranked portfolio contained one-eighth of the sample with the lowest returns. They observe that the mean excess return and the Sharpe Ratio increase monotonically with the octal ranks. This is commonly referred to as a "hot hands" effect in the literature. They further find that portfolios of recent poor performers do significantly worse than standard benchmarks and portfolios of recent top performers do better, although this was not significant.

Brown & Goetzmann (1995) analyse performance persistence in all US mutual funds using annual returns over the period 1976 to 1988. Starting with annual returns in 1976, they rank all mutual funds in eight different equal size groups (1 being the worst and 8 being the best). They then computed the annual rate of return on each group of these mutual funds for 1977.

University of Cape Town

Using 1977 returns, they again created a new set of groups as they did in 1976 and calculated the rate of return on each group for 1978. This was repeated for each year in 1977 to 1988. Their results revealed that the top two groups had a substantially better performance than the rest. They also find strong relative performers where persistence is most pronounced among the best and worst funds. They conclude that there is clear evidence of relative performance persistence and that historical data can be used to beat the peers. They find weaker evidence that historical information can be used to earn returns in excess of benchmarks and that these dependent on the period of analysis.

2.4.3. Decile Portfolios Strategy

In their paper Elton et al. (1996) test for performance persistence using a sample of 188 mutual funds that is free of survivorship bias during the period 1977 to 1993.Using Jensen's alpha as a measure of risk adjusted performance, they come up with decile portfolios and exclude funds where their model has a low explanatory power which they defined as R^2 being below 0.8. This they argue is to avoid misrepresentation of the results. Their analysis shows that one year alphas provide information about future performance, and that portfolios based on past performance had a tendency to significantly outperform equally weighted portfolios of these funds. They further found that optimal mutual fund portfolios constructed using modern portfolio theory optimization techniques significantly outperformed portfolios that are constructed based on the rule of past rank alone.

In Droms & Walker (2001b) the authors use a database of all international equity mutual funds in existence over the 20 year period from 1977 to 1996. They start with a very low number of funds which is eleven in 1977, and this number grows to a high of 473 in 1990. While their results show that persistence in mutual fund performance persist over one year period this is not the case over longer periods of say two, three and four years. Droms & Walker then test an investment strategy where one invest in the ten best performing

University of Cape Town

international funds at the end of each year and rebalancing this portfolio at the end of each year versus the same strategy which invest in the ten worst performing international funds. While they find that the performance differential between these two portfolios of best and worst is quite large this was not statistically significant at 0.05 levels.

Bollen & Busse (2004) use daily mutual fund returns and quarterly measurement periods to test for performance persistence in mutual funds. Their analysis is over the period 1985 to 1995 with a sample consisting of 236 US equity mutual funds. They rank the funds quarterly by abnormal returns into deciles and then measure the performance of each decile in the following quarter. They find that the post ranking abnormal return disappears when mutual funds are tested over longer time periods. They conclude from their results that superior performance is a phenomenon that is short lived and therefore observable only when mutual funds are evaluated several times in a year. The use of contrarian strategies which consist of buying stocks with low accounting ratios is utilised by Lakonishok et al. (1994). They use a sample period from 1963 to 1990 utilising different accounting ratios to rank the stocks into decile portfolios and find that long term reversal strategies of around 3 to 5 years horizon produce superior returns.

2.4.3. Momentum Strategies in Hedge Funds

In the hedge fund literature Bare et al. (2002) investigate performance persistence of portfolios ranked based on their past average returns over one month to 36 months formation periods. They then constructed 5 portfolios that contained the top performing funds and 5 other portfolios that contained the worst performers. These portfolios were held during periods extending from one month to 36 months using the data over the period January 1992 to December 2000. They find that persistence is observed over short term horizons but it rapidly vanishes as the formation or the holding period lengthens. In their analysis Guillermo et al. (2004) rank hedge funds on the basis of past average returns over the previous quarter,

University of Cape Town

previous year and previous two years. They then form decile portfolios and in the subsequent evaluation period compute the average returns for each of these deciles. They repeat the procedure over the entire sample period 1994 to 2000. They find significant positive persistence in hedge fund returns at quarterly horizons while in the annual horizon the statistical significance is weak.

Schmid & Manser (2008) follow the methodology of Hendricks et al. (1993) as described above and use CISDM database to come up with a sample of 1150 equity long short hedge funds which they analyse during the period January 1994 until December 2005. Using yearly time horizons they find that funds with the highest raw returns last year continue to outperform over the following year although this is not significant. However this persistence disappears beyond one year.

2.5. Efficient Market Hypothesis

The efficient market hypothesis (EMH) theory asserts that market prices fully reflect all available information so that it is not possible to make abnormal profits acting on this information, (Fama 1970). Eugene Fama proposed three types of market efficiency which are weak form, semi-strong form and strong form efficiency. Weak form market efficiency asserts that all past prices of a stock are reflected in today's stock price and therefore technical analysis is a useless tool in trying to predict and beat the market. Semi-strong market efficiency claims that all public information is computed into a stock's current share price and therefore neither fundamental nor technical analysis can be utilised to achieve superior gains. Strong form market efficiency states that all information in a market both public and private is accounted for in a stock price and therefore not even insider information could be used by anyone to their advantage. This as can be seen is the strongest form of market efficiency. Fama (1970) represents this concept statistically using the following fair game model:

University of Cape Town

$$r_{j,t+1} = E\left[r_{j,t+1}/\emptyset_t\right] + \varepsilon_{j,t+1} \tag{2.1}$$

where:

j= 1,2,3,…,n;

$r_{j,t+1}$ is the one period percent real rate of return for security j during the period $t+1$;

$\emptyset_t$ is the set of information available at time t;

$\varepsilon_{j,t+1}$ is the prediction error on security j in period $t+1$;

The error term $\varepsilon_{j,t+1}$ must conform to three statistical properties which means that it is unbiased, independent and efficient. In order to facilitate the testing of the efficient market hypothesis these statistical properties must be represented in a price formation process that fully reflects all available information. This process specifies that, conditional on some relevant information set, the equilibrium expected return of a security is a function of its risk. Theories do differ in how they define risk. However Fama (1970) assumes that the conditions of market equilibrium can be stated in terms of expected returns as in equation 2.2 below;

$$E_t P_{j,t+1} + E_t C_{j,t} = (1 + E_t r_{j,t+1}) \times P_{j,t} \tag{2.2}$$

where:

j= 1,2,3,…,n;

E_t is the mathematical expectation conditional on information at time t;

$P_{j,t}$ is the real price of security j at time t;

$C_{j,t}$ is the real cash flow generated by security j at time t;

Equation 2.2 can be reduced to:

$$P_{j,t} = \sum_{k=0}^{\infty}\left(\prod_{n=0}^{k} \lambda_{j,t+n+1}\right) \times E_t C_{j,t+k} = E_t P^{*}_{j,t} \tag{2.3}$$

Where $\lim_{k\to\infty} \prod_{n=0}^{k} \lambda_{j,t+n+1} \times E_t C_{j,t+k} = 0$ and $\lambda_{j,t+n+1} = {}^{1}/_{1 + E_t r_{j,t+1}}$

University of Cape Town

Observe that the investor is assumed to have an infinite investment horizon. Empirical test of equation 2.2 above is therefore a test of the three multiple hypotheses which are the efficient market hypothesis, the assumption that market equilibrium can be stated in terms of expected return and the return theory or process that is assumed to underlie $E_t r_{j,t+1}$. It is from equation 2.3 that most of the structures common to most models of market efficiency are derived. The assumption that conditions of market equilibrium can be stated in terms of expected returns and that equilibrium expected returns are formed on the basis of the information set $\emptyset_t$ rule out the possibility of trading systems based only on information in $\emptyset_t$ that have expected profits or returns in excess of the equilibrium expected profits or returns (Fama 1976). While this is the first of the two corollaries supported by efficient market hypothesis, the second one states that financial market prices represent rational assessment of fundamental values implying a fair game to participants in the market with respect to information sequence $(\emptyset_t)$. The assumptions underlying the fair game properties are that the conditions of market equilibrium can be stated in terms of expected returns and that the information set $(\emptyset_t)$ is fully utilized by the market in forming equilibrium expected returns and thus current prices. The fair game model can be better illustrated by the following tests. One test looks at the comparison of the performance of a trading rule versus a simple buy and hold strategy. The buy and hold strategy assume that $E_t[P_{j,t+1}/\emptyset_t] \geq P_{j,t}$ or equivalently $E_t[r_{j,t+1}/\emptyset_t] \geq 0$.

The second test considers whether successive one period returns or price changes are independently and identically distributed, also generally known as the Random Walk Model (RWM). Tests of the random walk model are based on the assumption that $f[r_{j,t+1}/\emptyset_t] = f(r_{j,t+1})$ that is the conditional probability distribution function equals the marginal probability distribution function of an independent random variable. This assumption implies that the sequence of past returns is of no use in assessing the distributions of future returns.

University of Cape Town

The above summarises in brief the theory that underpins the efficient market hypothesis. The clear argument is that active management cannot be used as a method of improving the risk adjusted returns of a portfolio of assets.

The work of Fama (1970) was criticised by Summers (1986) who argues that the inability of a body of data to reject a scientific hypothesis does not mean that the tests prove the validity of the hypothesis. Summers proposes the following hypothesis:

$$P_{j,t} = E_t P^*_{j,t} + \mu_t \tag{2.4}$$

$and\ \mu_t = \alpha\mu_{t-1} + v_t$ where μ_t and v_t represent the natural logarithm of random shocks and $0 \leq \alpha \leq 1$ that is assuming that deviations persist but do not grow forever. This approach is used by Summers to suggest that certain types of inefficiency in market valuations are not likely to be detected using standard methods. He argues that most tests of market efficiency have relatively little power against certain types of market inefficiency.

An alternative approach is to use measures of the variance of $P_{j,t}$ to provide evidence against simple models of market efficiency. This approach which is what I follow in this research can be used to test whether prices show too much variation to be explained in terms of the random arrival of new information about the fundamental determinants of price. The theory behind these tests is built up on the basis that in a world without uncertainty the market price of a share of common stock must equal the present value of all the future dividends, discounted at the appropriate cost of capital (Lo 2007). This hypothesis is explicitly developed and implemented by LeRoy & Porter (1981), and Shiller (1981) who compare the variance of stock market prices to the variance of *ex post* present values of future dividends. Lo argues that if the market price is the conditional expectation of present values, then the difference between the two, that is the forecast error, must be uncorrelated with the conditional expectation by construction. The premise on which this is built on is that the variances of the *ex post* present value is the sum of the variance of the market price and the

University of Cape Town

variance of the forecast error. We know that the volatilities are always non-negative, implying therefore that the variance of stock prices cannot exceed the variance of *ex post* present values. Shiller (1981) uses a constant real discount factor λ, a simplifying assumption that is consistent with that used in simple tests of market efficiency to reduce equation 2.3 to the following:

$$P_{j,t} = \sum_{k=0}^{\infty} \lambda^{k+1} \times E_t C_{j,t+k} \tag{2.5}$$

Equation 2.5 can be restated as a proportion of the long-run dividend growth factor, g:

$$p_{j,t} = \sum_{k=0}^{\infty} \bar{\lambda}^{k+1} \times E_t c_{j,t+k} \tag{2.6}$$

See Appendix, table 38 on page 108 for the definition of the elements in equation 2.6 and also some of Shiller's assumptions in coming up with the variance inequalities below. Shiller (1981) derives the following variance inequalities to test the volatility of $p_{j,t}$, and $\Delta p_{j,t}$ and $\partial p_{j,t}$.

$$\sigma(p_{j,t}) \leq \sigma(p^*_{j,t}) \tag{2.7}$$

$$\sigma(\Delta p_{j,t}) \leq \sigma(c_{j,t}) / \sqrt{2\bar{r}} \tag{2.8}$$

$$\sigma(\partial p_{j,t}) \leq \sigma(c_{j,t}) / \sqrt{2\bar{r}_2} \tag{2.9}$$

Where $\sigma(\partial p_{j,t})$ is the first differential which can be expressed as $\sigma(\Delta p_{j,t} + c_{j,t-1} - \bar{r} p_{j,t-1})$ and $\bar{r}_2$ is the two-period real discount rate for de-trended series calculated as: $\bar{r}_2 = (1 + \bar{r})^2 - 1$. Shiller (1981) uses annual US stock market data (S&P series) over the period 1871 to 1979 and find that the variance bound is violated dramatically which is what LeRoy

University of Cape Town

& Porter (1981) also found. Shiller concludes that stock market prices are too volatile and the efficient market hypothesis must be false.

The assumptions underlying Shiller's test are that equation 2.8 was derived assuming that the de-trended cash flow for dividends is stationary and that the criterion for the stability of equation is such that the efficient market hypothesis holds if and only if: $\left[\rho\sigma(c_{j,t})/_{r}\right] < 1 + \sigma^2(\Delta p_{j,t})/_{2r}$ and $\sigma^2(\Delta p_{j,t})/_{2r} < 1$. The assumption for dividends to be stationary is necessary as each cash flow is observed only once, and therefore gives no information about the variance of the observed cash flow. This means that the sample variance of the cash flow series will converge to the population variance as the sample becomes large. The work of Shiller (1981) was criticised by Flavin (1983), Marsh & Merton (1986) and Michener (1982). Flavin (1983) examines the small sample properties of volatility tests and shows that they are extremely biased toward finding excessive volatility. Marsh & Merton (1986) show that if managers smooth dividends, a well-known empirical phenomenon documented in several studies of dividend policy, and if earnings follow a geometric random walk, then the variance bound is violated in theory in which case the empirical violations may be interpreted as support for this version of the efficient market hypothesis. Michener (1982) constructs a simple dynamic equilibrium model in which prices do fully reflect all available information at all times but where individuals are risk averse and this risk aversion is enough to cause the variance bound to be violated in theory as well.

The Random Walk Model (RWM) as discussed above is generally used to test the weak-form EMH. The common empirical tests for the RWM are run tests, Unit Root Tests, Autocorrelation Function (ACF) tests and stationarity tests like the Augmented Dickey Fuller test (ADF). Fama (1970), Granger (1975), Hawawini (1984) and Lo (1997) empirically test the RWM and the weak form EMH in both emerging and developing economies and are all in

University of Cape Town

support of the conclusion that there exists empirical evidence supporting the EMH theory. These assertions are supported by earlier studies from Osborne (1959), Fama & Blume (1966) and Cootner (1962) among others. The African market is studied by Magnusson & Wydick (2000) and supports the random walk hypothesis for the African stock markets. Abraham et al. (2002) investigate the Middle East markets and observe that index in thinly traded equity markets such as the three emerging Gulf equity markets tend to exhibit a systematic bias towards rejecting the EMH.

One of the more important developments in modern capital market theory is the Sharpe-Lintner-Mossin mean-variance equilibrium model, commonly known as the Capital Asset Pricing Model (CAPM). The CAPM was independently developed by William Sharpe (1964), John Litner (1965) and Jan Mossin (1966). The model predicts that the expected excess returns from holding an asset is proportional to the covariance of its return with the market portfolio, which is the beta as in equation 2.10:

$$R_{i,t} - R_{f,t} = \alpha_0 + \alpha_i\left[R_{m,t} - R_{f,t}\right] + \varepsilon_t \tag{2.10}$$

α_i is a measure of how sensitive asset i is to the market, and $(R_{m,t} - R_{f,t})$ is the expected market premium which one can expect to get paid per unit of systematic risk. The market model is a linear equation that relates the equilibrium expected return on each asset to a single identifiable risk measure. The CAPM assumes that investors choose their portfolios according to the Markowitz mean-variance criterion, i.e. investor preferences are quadratic and that asset prices have Gaussian probability distributions (Ranaldo & Favre 2005). The assumptions and conditions necessary for the validity of the mean-variance analysis are beyond the scope of this analysis and an exhaustive analysis can be seen in Samuelson (1970). For the purposes of this analysis hedge funds have very different risk return characteristics as empirical evidence shows that the normality hypothesis has to be rejected for many hedge fund returns, see Eling (2008), Argarwal & Naik (2004), Burton & Saha

University of Cape Town

(2004) and Favre & Signer (2002) among others. These authors clearly show that hedge funds show significant negative (positive) skewness and higher (lower) kurtosis. Positive (negative) skewness indicates a distribution with an asymmetric tail extending toward more positive (negative) values. Kurtosis characterises the relative peakness or flatness of a distribution compared with a normal distribution. Kurtosis higher (lower) than three indicates a distribution more peaked (flatter) than a normal distribution.

2.5.1. Causes of Market Inefficiencies

Results of this thesis show that there are some funds that persistently outperform in different time periods suggesting that financial markets do have pockets of inefficiencies inherent in them and that some skilled hedge fund managers can successfully exploit them. Lo (2007) argues that the phrase for the efficient market hypothesis: "prices fully reflect all available information" is about two distinct aspects of prices: the information content which is the kind of information reflected in prices and the price formation mechanism which is how this information comes to be reflected in prices. From this argument I present a summary of the literature review of market inefficiencies under three broad topics which include the behavioural critiques, anomalies and overreaction/under reaction. While testing all the theories presented below is beyond the scope of this study, their discussions bring to light profound enduring elements of contention that are common to all markets when studying efficient markets theory.

University of Cape Town

The vast critiques of the efficient market hypothesis centres on the preferences and behaviour of market participants. Quantitative models of efficient market are all predicated on rational choice for investors and critics of the efficient market hypothesis argue that this is not the case. They assert that investors are often irrational, showing predictable and financially ruinous behaviour and Lo (2007) gives a comprehensive summary of these behaviours. He identifies different behavioural biases such as comfort in crowds which Huberman & Regev

(2001) call it “herding”, overconfidence based on little information, Fischoff & Slovic (1980), Barber & Odean (2001), Gervais & Odean (2001), overreaction, DeBondt & Thaler (1985), loss aversion, Kahneman & Tversky (1979), Shefrin & Statman (1985), Odean (1998), psychological accounting, Tversky & Kahneman (1981)), miscalibration of probabilities Lichtenstein Fischoff & Phillips (1982), hyperbolic discounting, Laibson (1997), and regret, (Bell 1982). One of the most famous early experiments of loss aversion was by Kahneman and Tversky (1979) in which a number of participants were quizzed about preferences for different probability costs and outcomes. They showed that when participants were presented with potential gains they chose a risk aversion strategy and when presented with potential losses they chose a risk-seeking strategy. This suggests that investors have a strong tendency to sell winning positions and keep losing positions which is very contrary to the rational assumption of the efficient market hypothesis. The argument is that irrational players in the market provide opportunity for insightful arbitrageur to trade and profit at the expense of the players with irrational beliefs.

The second part of causes of market inefficiency in this thesis looks at anomalies. This arises when a pattern in an asset’s returns is regular, widely known, reliable and inexplicable, implying a degree of predictability. The fact that the regularity is widely known implies a possibility that some investors can take advantage of it. Some of the most researched anomalies are seasonal patterns in returns and the relation between future returns with many variables such as market capitalization, market to book ratios, price-earnings ratios, accounting accruals and dividend yields. Lakonishok & Smidt (1988)’s work test for the existence of persistent seasonal patterns (calendar effects) in the rates of return. They find evidence of persistently anomalous returns around the turn of the week, around turn of the month, around turn of the year and holidays. Rozeff & Kinney (1976) document a related anomaly called “January effect” which is also reported by Keim (1983) and Roll (1983). This

University of Cape Town

anomaly sees small capitalization stocks outperforming the broader market in the month of January with the most of this disparity occurring before the middle of the month. The examples of relation between future returns with many variables can be seen in Lo (2007). These include the Value Line enigma, Copeland & Mayers (1982)), the profitability of short-term return reversal strategies in US equities, Rosenberg, Reid & Lanstein (1985), Chan (1988), Lehmann (1990), and Lo & MacKinlay (1990c), the profitability of medium-term momentum strategies in US equities Jegadeesh (1990), Chan, Jegadeesh & Lakonishok, (1996), and Jegadeesh & Titman (2001), the relation between price/earnings ratios and expected returns, Basu (1977), the volatility of orange juice futures prices (Roll 1984). The most common anomaly among these is the "size effect" which was first discovered by Banz (1981). This is the tendency of small capitalization stocks to outperform large capitalization stocks over the long term.

Finally I turn to the overreaction and under reaction phenomenon in financial markets. This tries to ascertain whether investors react in proper proportion to new information. Lo (2007) argues that in some cases investors tend to overreact to performance, selling stocks that have had recent losses or buying those that have experienced recent gains. Such overreaction will tend to push prices beyond their fair value which in turn causes rational investors to take the other side of the trades and bring prices back in line with their fair value. Price reversals are therefore experienced according to the common adage which says that what goes up must come down and vice versa. Another implication is that contrarian investment strategies in which losers are bought and winners sold will earn superior returns. This phenomenon is shown by Lehman (1990) in his study where he employs a strategy in which long positions in losers are financed by short positions in winners. Using monthly NYSE/AMEC stock returns data from 1962 to 1985 he shows that this strategy almost always yielded positive returns. DeBondt & Thaler (1985) show that the winners and losers in one 36 month period tend to

University of Cape Town

reverse their performance over the next 36 month period over the period 1926 to 1982 and that many of these reversals occur in January. The same results are obtained by Chopra et al. (1992) after correcting for market risk and the size effect. The reaction of market participants to information contained in earnings announcement was first reported by Ball & Brown (1968). They showed that up to 80% of the information contained in the earnings surprises is anticipated by market prices. They observed that the market response to the earnings announcements persisted for several months a phenomenon that later became known as the 'post-earnings announcement drift' puzzle. All these arguments present hedge fund managers with expanded opportunity set to try to successfully exploit mispricing or pockets of inefficiencies in the financial markets. Table 39, in appendix on page 109 links different hedge fund strategies to the inefficiencies discussed here.

University of Cape Town

2.6. Sources of Risks in Hedge Funds

What are the factors that might explain hedge fund returns or what are the sources of risk in hedge fund returns? Equity risk factors can be modelled using the Capital Asset Pricing Model (CAPM) or the Arbitrage Pricing Theory (APT). These separate the return of an equity investment into systematic and idiosyncratic where systematic is the common source of return which is simply the market portfolio in CAPM. The CAPM already discussed above in 2.5 helps investors to be aware of the common sources of equity risk at the portfolio level, Sharpe (1992). The difficulty in using the CAPM is that hedge fund returns are not normally distributed and so an alternative model has to be used. The APT model was first introduced by Ross (1976) and it estimates the expected return of an asset as a linear function of several factors. An asset's sensitivity to the factor is measured by beta coefficient for each factor. The ATP is less restricted by assumptions than CAPM and can be defined for an unknown number of factors as in equation 2.11.

$$E(R_i) = R_f + \sum_j \beta_j F_j \tag{2.11}$$

The most commonly used APT model is the so called Four Factor Model of Fama and French (1993) and Carhat (1997) described by equation 2.12.

$$E(R_i) = R_f + \beta_1[E(R_m) - R_f] + \beta_2 SMB + \beta_3 HML + \beta_4 MOM \tag{2.12}$$

Fama & French model includes a size factor (SMB) taking into account the difference in performance between small and large companies, a style factor (HML) that takes into account the difference in performance between growth and value players while the Carhart (1997) model adds a momentum factor (MOM) taking into account that some managers favour previously well performing stocks in their portfolios. Likewise a hedge fund risk-factor model that tries to mimic the APT helps investors identify the common sources of risk in hedge fund investing. Some models have been put forward by various academic researchers and most of them based on an extension of the multi-factor performance decomposition models that are used in the mutual fund literature for years, Fama & French (1993) and Carhat (1997) models. My model follows the APT model as explained above.

In their analysis of Asian hedge fund styles Koh et al. (2003) follow the APT model and hypothesize that Asian hedge fund returns can be explained by an Asian equity factor, an Asian bond factor, a US equity factor, Fama French (1993) factors and Carhart (1997)'s momentum factor. They further break the Asian equity factor into an Asia ex Japan factor and a Japan factor. While their aim is to try and identify the reasons why hedge fund performance persist in short term the methodology employed also gives insight to the sources of risk in Asian hedge funds. Their results yield adjusted R squared of 0.45.

In Fung & Hsieh (2004) the authors using their previous studies (see Fung & Hsieh (1997a & 1997b), Fung & Hsieh (2000a & 2000b), Fung & Hsieh (2001), Fung & Hsieh (2002b)) on asset-based style (ABS) factors propose a model of hedge fund returns that is similar to the

University of Cape Town

models based on arbitrage pricing theory (APT). The authors propose a seven ABS factor model to explain hedge fund monthly return variation of different hedge fund strategies. Equity long-short hedge fund strategies are exposed to the stock market and the spread between small-cap stock returns and the large-cap stock returns. The fixed income arbitrage hedge fund strategies are exposed to the change in the US 10-year Treasury yields and the change in the yield spread between the US 10-year Treasury bonds and the Moody's Baa bonds. The trend following (CTA) hedge fund strategies are exposed to the portfolios of look-back straddles on bonds, on currencies and on commodities. They find that for hedge fund portfolios proxied by indices of hedge funds and funds of hedge funds their seven ABS factors can explain up to 80% of monthly return variations.

The study by Argarwal & Naik (2004) introduces non-linear factors in their model by using option based strategies. Their analysis of risks and portfolio decisions involving hedge funds characterize the systematic risk exposures of hedge funds using buy and hold and option based strategies. Their research focuses on six equity-oriented hedge fund strategies namely event arbitrage, restructuring, event driven, relative value arbitrage, convertible arbitrage and equity long-short. The buy and hold risk factors consist of indices representing equities (Russell 3000 index, lagged Russell 3000 index, Morgan Stanley Capital International (MSCI) world excluding the USA index, and MSCI emerging markets index), bonds (Salomon Brothers government and corporate bond index, Salomon Brothers world government bond index and Lehman high yield index), Federal Reserve Bank competitiveness-weighted dollar index, and the Goldman Sachs commodity index. They also included Fama French (1993) factors, Carhart's (1997) momentum factor and the difference between yield on the BAA-rated corporate bonds and the 10-year Treasury bonds to capture credit risk.

University of Cape Town

The model used by Capocci (2007) utilises a multi-factor performance decomposition model of hedge funds which consists of 10 factors, US stock market, Fama French (1993) factors, Carhart's (1997) momentum factor, JPMorgan world government bond index, JPMorgan Emerging Market Bond Index, Lehman High Yield bond index, Goldman Sach commodity index, Federal Reserve Bank trade weighted Dollar index. His aim is to determine whether some hedge fund strategies significantly outperform classical markets over time. He finds that most hedge funds strategies do offer significant alpha over a long period of time and that the results were not due to lack of the power of the model since the adjusted R-squared was very high.

University of Cape Town

CHAPTER 3 Data Description

3.1. Sample Data for Hedge Funds

Obtaining hedge fund data has always been a challenge for any hedge fund research, Fung & Hsieh (2002b). This is because hedge funds are not required by law to report performance. This raises issues about the access and quality of the hedge fund data that one is able to source. There is however several databases available internationally which most of the researchers rely on for their hedge fund academic studies. The most popular ones among the academic studies include the Centre for International Securities and Derivatives Markets (CISDM) at the University of Massachusetts, Lipper TASS (TASS), The Barclay Group (Barclays), Morgan Stanley Capital International (MSCI), Eureka Hedge, Hedge Fund Research (HFR) and LaPorte, Eling (2008).

In South Africa the country's leading hedge fund database is the Hedge News Africa publication. The pattern is the same as that of the international counterparts where hedge funds report their performance on voluntary basis. Most of the data we have at Momentum Alternative Investments is sourced from Hedge News Africa. However some of the hedge funds do not report to this publication. There are other hedge fund industry surveys done by companies such as Symmetry and Peregrine Securities that provide hedge fund performance for the local industry. One of my responsibilities at work is to collate all this hedge fund data and make sure it is up to date. In this research I utilise all these institutions and the contacts we have established as a company to obtain the data for the research analysis. Since the hedge fund industry is still small in South Africa and there is huge competition for capital, most of the funds are willing to provide performance information especially to institutions like Momentum Alternative Investments as the fund of hedge funds in South Africa are the main allocators of capital to the single manager hedge fund industry (Novare Investment SA Hedge Fund Survey 2011).

University of Cape Town

My data for this thesis is sourced from the Momentum Alternative Investment database which combines data from the independent leading hedge news publication, Hedge News Africa, and other independent sources mentioned above. The database at my disposal contains monthly return net of both management and performance fees on 151 individual funds and 59 funds of hedge funds. Table 1, below, reports the number of funds in different hedge fund investment strategies/styles contained in my data base before doing any data cleaning. Fund managers report their monthly performance on a fund-by-fund basis in a net return form. The net return of a fund over a month is determined as the change in the fund's net asset value over the month, expressed as a percentage of the starting value of the fund in the month in question. The net return is always adjusted for redemptions and subscriptions (new investments that month) after fees due have been taken into account. Hedge funds normally charge two kinds of fees, a management fee and a performance fee (or incentive fee). The management fee is charged as a percentage of the size of assets under management and is generally 1% for at least 73% of the South African hedge funds (see Novare Investment SA Hedge Fund Survey 2011).

The performance fee, charged by the hedge fund manager, gives him a share of the profits earned by his fund and this is normally 20% for at least 93% of the South African hedge funds (Novare 2011). A hurdle rate is used for performance fee calculation and the fund manager needs to perform above the highest previous level (high water mark) of the net asset value of the fund before earning any additional performance fees above the hurdle rate. Most South African hedge funds use the cash rate as their hurdle rate (Novare 2011).

University of Cape Town

Table 1: Funds by Strategy Contained in my Database before Data Cleaning

Hedge Fund Strategy	Number of Funds in a Strategy		
	Alive	**Dead**	**Total**
Equity Long Short	35	20	55
Equity Market Neutral	25	12	37
Fixed Income	18	1	19
Multi-Strategies	7	5	12
Statistical Arbitrage	2	1	3
Volatility Arbitrage	2	0	2
Trend Following/CTA	3	3	6
Commodities	3	0	3
Credit	5	4	9
*Unknown	1	4	5
Total	**101**	**50**	**151**

**These funds lacked enough information to be classified in any of the strategies in the table*

University of Cape Town

I include both living and dead funds for the reasons outlined below. Amin & Kat (2001) show that concentrating on living funds only will, on average, overestimate the mean return on individual funds by approximately 2% per annum while introducing a significant downward bias in the calculations of standard deviation, an upward bias in the Skewness, and a downward bias in the kurtosis estimates of individual fund returns. They also show that for small, young and leveraged funds, the mean return bias can be as high as 4-6% per annum. This bias termed *survivorship bias*[2], is discussed in detail the next few pages. I chose a time period in the sample, January 2007 to December 2011, which gives me maximum quality

[2] *This bias arises as a result of certain funds disappearing from the database usually due to liquidation*

data for the analysis. I follow the global academic research methodologies in culling the data to prevent any spurious effects in my analysis. I do however keep in mind that the data set is very small so I might have to re consider some of these procedures where the amount of data to manipulate during the analysis, maybe compromised. First, I remove all funds of hedge funds to avoid double counting of individual funds (Herzberg & Mozes 2003). Clearly funds of hedge funds are a composite of the individual funds being investigated. My interest in my thesis clearly lies with individual funds instead of funds of hedged funds.

I then go on to remove all the funds with less than 24 months of monthly returns. Huang et al. (2009) in ensuring some degree of statistical accuracy in their analysis included only funds that had at least 30 consecutive monthly return observations. Ballew et al. (2002) argue that it is meaningless to compare very few data points to other funds as idiosyncratic movements are more than likely to overshadow any underlying patterns in an analysis. They choose funds with at least three years of history because of the main reason that very young funds usually have not had considerable time to prove their worth. This helps eliminate chancers in the market and maintains integrity of the data used.

In line with the above Fung & Hsieh (1997) and Liang (2000) eliminated funds with less than 36 monthly returns in their analysis. As a robustness test, Eling (2008) conduct performance measurement for those funds in their data set with at least 36 monthly returns and found robust results. The majority of researchers agree that the minimum requirement of return fund data for calculating meaningful performance measures is at least 24 monthly returns. This is the case with Ackermann et al. (1999), Gregoriou (2002), Capocci & Hubner (2004), Liang & Park (2007), Eling (2008). I therefore follow this standard assertion in my thesis.

Capocci (2007) argues that any use of data in any hedge fund research, is to try to represent the hedge fund industry as closely to reality as possible, though the hedge fund industry is not

University of Cape Town

limited to funds reporting to databases. I am confident in this research that these limitations cannot be compared to the global hedge fund industry as the South African hedge fund industry is small and still maturing. Another difficulty in international academic research as stated by Liang (2000) and Fung & Hsieh (2006) is that many hedge funds report to only a single database while a few of these report to more than one database. This means that the overlap between the databases used is minimal and therefore results obtained from performing an analysis based on a specific database maybe very different if another database is used to perform the same analysis (see Capocci 2007). Again this means that generalisations which are based on a certain single database may not actually be true for the entire global hedge fund industry as one database only represent a part of the hedge fund industry (Capocci (2007). Liang (2000) goes further to say that there are significant differences in returns, net assets value, inception date, management fee, performance fee and investment styles across the databases. This is another difficulty which is not of material impact in this thesis as I have already stated that the hedge fund industry I am dealing with is very small and does not have too many materially different databases compared to the global hedge fund industry.

University of Cape Town

The issues raised above about the quality of hedge fund data used in most of the global hedge fund analysis bring me to the three important biases in hedge fund academic literature. In statistical sampling theory, voluntary participation can lead to sampling biases, and the fact that hedge funds report their performance to hedge fund database providers on a voluntary basis, raises questions about such biases (Capocci 2007). The first one is *survivorship bias.* This bias arises as a result of certain funds disappearing from the database, usually due to liquidation. These funds tend to have poorer performance compared to the existing funds (Capocci 2007). If these funds are not taken into account then the performance is biased upwards leading to survivorship bias. In Table 2 below I use information from Eling (2008) to show how the attrition rates of the popular international hedge fund databases commonly used in global academic studies compare with each other, and that of our own South African data. Attrition rate is the percentage of funds exiting or defunct in a database. These figures have to be read with caution as time periods vary considerable though they still give a good indication on attrition rates for different hedge fund database providers.

Table 2: Estimation of Attrition Rates for Different Hedge Fund Databases

Database Provider	**Living Funds**	**Dead Funds**	**Attrition Rate**
CISDM	4200	2000	32%
HFR	6000	3500	37%
TASS	3900	2400	38%
***Combined Databases**	6392	2946	32%
****MAI**	101	50	34%

This table reports the attrition rate of different hedge fund databases, Eling (2008).
**Combined Databases-work of Kosowski et al. (2006) where he combines CISDM, HFR, TASS & MSCI.*
***MAI-Momentum Alternative Investment Database that I use for this research.*

There are two definitions of survivorship bias that are commonly used in the academic studies. The first one is as defined by Ackermann et al. (1999), which is the performance difference between surviving funds and dissolved funds. The other one is by Liang (2000) ,and is the performance difference between living funds and all funds. I follow these two formulas to calculate survivorship bias for the data as shown in table 3.

University of Cape Town

Table 3: Survivorship Bias in South African Hedge Funds (2007-2011)

Year	All Funds		Living Funds		Dead Funds	
	Monthly(mean)	Annually	Monthly(mean)	Annually	Monthly(mean)	Annually
2007	1.39%	17.98%	1.49%	19.45%	1.24%	15.79%
2008	0.70%	8.71%	0.94%	11.83%	0.32%	3.73%
2009	1.33%	17.20%	1.43%	18.54%	1.11%	14.19%
2010	0.91%	11.44%	1.06%	13.52%	0.23%	2.73%
2011	0.76%	9.52%	0.80%	10.00%	*-0.70%	*-7.45%
Mean	1.02%	12.97%	1.15%	14.67%	**0.72%	**9.11%

	Living Funds – Dead Funds	Living Funds – All Funds
Monthly	0.13%	0.43%
Annually	5.56%	1.7%

**I exclude these in our final mean calculations as there are only six defunct funds in 2011 and so this negatively skews my data.*
***Mean numbers exclude the 2011 figures as explained above.*

I estimate from table 3 monthly survivorship bias of 0.13%, an annual survivorship bias of 5.56% using the first formula while the second formula estimate 0.43% and 1.7% respectively. Brown et al. (1999) estimate a bias of 3% for offshore hedge funds per annum. Fung & Hsieh (2000) report an annual survivorship bias of 3% using the TASS database. Liang (2000) analyses the survivorship bias in hedge fund performance by comparing the TASS and the HFR database. He finds that the survivorship bias in the TASS database exceeds 2% annually while that of the HFR database being equal to 0.6% which is consistent with the higher attrition rate in the TASS database. Capocci (2007) reports an annual survivorship bias that lies between 1.22% and 1.68%. His annual estimate using the first formula like the one in table 7 is 4.45%. Amin & Kat (2001) stress an industry consensus of survivorship bias of 3%.

University of Cape Town

The expectation is not to get the same results as those of the international counterparts but to look at the differences if any and try and explore the causes of these differences. There are several factors that can explain the difference in the results with those of the other authors. Firstly the database only covers the local South African hedge fund while other studies utilise global databases. There is therefore a wide disparity on the nature and composition of these databases. Secondly all of the studies mentioned above cover a different investigation period than mine. This is of great importance to me, especially that my investigation period includes the massive credit crisis which brought about one of the worst global financial crises ever seen in 2008. I would have expected my results to be far worse than the studies before my investigation period. The above results fare very well in comparison with the international peers. A better picture would have been that which compares the international peers with the same investigation period of study as mine. Not only did we experience a global financial meltdown in 2008, the period since then has been marked with high volatility and uncertainty in the markets making it very different to the other market cycles before 2008.

Schmid & Manser (2008) mitigated survivorship bias in their analysis by including defunct funds. The same strategy is followed by Koh et al. (2003) in including defunct funds in their research, and this is the standard procedure I follow in the thesis. Carpenter & Lynch (1999) examine the specification and power of various persistence tests and find that the chi-square test based on the number of winners and losers is well specified, powerful, and more robust to the presence of survivorship bias compared to other methodologies. I also choose to use the chi-square test in my analysis to mitigate survivorship bias.

The second one is called *instant return history bias* or the *backfill bias.* This bias arises as a result of fund managers demanding that hedge fund database provider backfill their historical returns, whenever they are added into a database. This is common when fund managers have had a good track record and want to market themselves. Good track records in comparison to

University of Cape Town

the hedge fund universe result in overestimating hedge fund performance as bad track records are usually not backfilled, or funds with poor performance track records terminate or never report at all. This means that funds will tend to outperform during their first months of existence. The academic literature usually calculates the backfill bias using an indirect approach. This indirect approach is eliminating the first two years of reported data as stated by Posthuma & Van der Sluis (2003). Fama & French (1993) eliminate the first two years of reported data in their analysis. Brown, Goetzmann & Park (1998) follow Park's method to estimate a backfill bias of fifteen months for the TASS database. Ackermann et al. (1999) deletes the first two years of the MAR and HFR database funds using sample periods up to 1995 and get an average annual backfill bias of 0.5%. Fung & Hsieh (2000) calculate the backfill bias for the TASS database over the period 1994 to 1998 by eliminating the first 12 months of the returns and find a backfill bias of 1.4%. Edwards & Caglayan (2001) adopt the similar indirect approach of deleting the first 12 months to correct for the backfill bias of returns from the MAR database, and come up with an average annual returns of hedge funds in the first year that are 1.17% higher than the annual returns in the subsequent years.

Schmid & Manser (2008) mitigate the backfill bias in their analysis by using the standard procedure of deleting the first 12 month return observations for each fund in the CISDM database. Capocci & Hubner (2004) argue that backfilling bias is larger the longer the estimation period is and, so does Capocci (2007) report the same conclusion. Since my estimation period is not that long it helps mitigate backfill bias in the data set. I am also cognisant of the fact that my sample is small in an industry that is still maturing and deleting the first 12 or 24 months of return observations in my sample data will severely compromise the quality of my data. I will lose most of my data by eliminating funds with less than 24 months return observations as a standard rule in calculating meaningful performance measures. If I go further and remove the first 12 months return observations from my sample

University of Cape Town

data set I stand to lose more of the funds in the dataset. My investigation period is not that very long and I believe that Capocci & Hubner (2004) argument of backfill bias being larger the longer the estimation period holds. Eling (2008) puts forward a strong argument in that there is no clear direction in the academic literature to the question of which investigation period to choose in analysing performance persistence. Eling points out that there are studies with as short periods as three years as in AgarwaI & Naik (2000b), and others with time periods as long as 21 years as Harri & Brorsen (2004). He also finds that the mean investigation period in the 25 studies in his analysis is 8.5years. I am in the lower end of this mean which further strengthens my assertion above that my investigation period of 5 years is not that very long.

I therefore avoid using the common standard procedure of deleting any monthly observations in my sample data in trying to mitigate backfill bias. My hope is that the reader of the results of this thesis interprets them knowing the limitations of the quality of the data that I have already stated above. I however go ahead and estimate backfill bias in my sample by comparing the difference in performance of the mean return of a portfolio that invest in all funds and a portfolio that invest after eliminating the first 12, 24 and 36 months returns of each fund in our database following Capocci (2007) methodology. This methodology is derived from the work of Park (1995), Brown et al. (1997) and Fung & Hsieh (2000). Note that Capocci (2007) goes further to eliminate the first 60 months return observations of each fund in his database which I am not able to do due to my data constraints. This will almost wipe out more than two thirds of the data I have for this analysis. I chose to use a direct approach in that, instead of just deleting the first 12 month return observations from the start of my investigation period, I delete from the inception date of the fund. My database provides me with inception dates for each fund so I am able to carry out this exercise accurately. This method closely follows that of Posthuma & Van der Sluis (2003) in which they conclude that

University of Cape Town

the indirect approach of just eliminating the first 12 or 24 month return observations seriously underestimates the backfill bias. They find that the magnitude of the overall backfill bias averages 4% annually, a number exceeding all of the previous estimates of the backfill bias that they were aware of. Using my methodology I feel that I am able to mitigate the problems of estimating backfill bias using the pure indirect approach. I estimate an average annual backfill bias of about 1.63%. Table 4 below shows the results of the estimated backfill bias.

Table 4: Estimation of Backfill Bias in South African Hedge Funds (2007-2011)

	Mean Annual return	**Difference**	**Number of funds**
All Funds	12.97%		151
Without 12 Months	11.30%	1.67%	141
Without 24 Months	10.95%	2.02%	127
Without 36 Months	11.77%	1.20%	102

University of Cape Town

The third bias is called the *selection bias.* This bias arises as a result of hedge funds self-selecting on whether or not to report their performance to a database provider. There are different reasons why hedge fund managers may choose to do this. Some managers choose to be excluded from the databases for some time so that they can build a track record before actively marketing the fund in order that they raise more capital. Track record seems to be important in the hedge fund industry as already stated in the introduction of our thesis. Other managers will choose to be excluded from the databases because after raising enough assets they do not need to attract any new additional investors. The last ones are those that avoid voluntary reporting because of their poor performance, meaning that hedge funds in a database are likely to have a better performance than those that are excluded. Ackermann et al. (1999) and Fung & Hsieh (2002b) argue that, selection bias resulting from self-exclusion of funds with poor performance, can be counterbalanced by the fact that good managers can also stop reporting to database when they close the fund to additional new investors. This simple means that the survivorship bias and the self-selection bias offset each other. The net impact of selection bias on the returns of hedge funds in a database still seems to be ambiguous, and so far there seems to be no practical way of mitigating it (Capocci (2007). Again, I argue here that the hedge fund industry in South Africa is small and maturing, so it is difficult for a hedge fund to exist secretively. I have in my database funds that are very new, funds that have been performing poorly for some time and funds that are closed to new investment. By this I believe that selection bias is satisfactory mitigated in my sample.

I conclude by summarizing the different procedures I have taken into account in making sure that my sample data is robust enough for the thesis analysis. I have deleted all the funds with monthly return observations that are less than 24 months as argued above by most of academic researchers. By so doing I lost 37 funds in our database the most being in equity long short (21 funds), which is expected as this is the investment strategy that contains the highest number of funds and also the highest asset allocation, about 38% of hedge fund industry assets in South Africa (Novare 2011). Of these 37 funds, 18 are defunct and 19 surviving ones. I am left with a total of 114 funds, 32 defunct funds and 82 surviving funds. This number compares well with some of the global academic studies in this field that did not have too many funds in their databases. Agarwal & Naik (2000) use a sample of 167 hedge funds selected from the HFR database from January 1994 to September 1998. Brown et al. (1999) use a sample of offshore hedge funds that grew from 78 in 1989 to 399 in 1995. Hendricks, Patel & Zeckhauser (1993) analyse mutual fund performance based on net quarterly returns of 165 funds over the period 1974 to 1988. Elton et al. (1996) use a sample of 188 mutual funds over the period 1977 to 1993. Kasimov & Rosickas (2007) after

University of Cape Town

manipulating with contingency table come to the conclusion that one needs at least 12 funds in order to get statistically significant results. I follow Kasimov & Rosickas argument by combining all the strategies with less than 12 funds and come up with one strategy which I call other. This combines Credit, Trend Following/CTA, Statistical Arbitrage, Commodities, and Volatility Arbitrage, Multi-Strategies and Unknown strategies together. Table 5, below, shows the number of funds in different hedge fund investment strategies/styles contained in my final cleaned sample data base.

Table 5: Funds by Strategy after Data Cleaning

Hedge Fund Strategy	Number of Funds in a Strategy		
	Alive	**Dead**	**Total**
Equity Long Short	24	10	34
Equity Market Neutral	23	11	34
Fixed Income	17	1	18
*Other	18	10	28
Total	**82**	**32**	**114**

**Other category combines Credit, Trend Following/CTA, Statistical Arbitrage, Commodities, and Volatility Arbitrage, Multi-Strategies and Unknown strategies together*

University of Cape Town

3.2. Sample Data for the Risk Factors in Hedge Fund Returns

The sample data used to construct the different hedge fund indices used in the multi-factor regressions is the one used above for the performance persistence test in hedge funds. The sample data for the risk factors is from I-Net Bridge and Bloomberg. I-Net Bridge is a leader in South Africa's electronic providers of accurate, timely and high quality market data both real time and historically while Bloomberg is an internationally acclaimed leader as a data provider in financial markets. The specific data was collected as follows for my investigation period of January 2007 to December 2011:

- Stock market- Johannesburg Stock Exchange (JSE) All Share Index (ALSI), I-Net.
- Small cap stocks- Johannesburg Stock Exchange (JSE) Small cap Index), I-Net.
- Large cap stocks- Johannesburg Stock Exchange (JSE) Top40 index), I-Net.
- Book to Market Ratio, I-Net.
- Momentum, I-Net.
- GOVI and OTHI bond indices), I-Net.
- 10-year South African Government yields, Bloomberg.
- Portfolio of look-back straddles on bonds-from – faculty.fuqua.duke.edu/~dah7/HFData.htm

3.3. Sample Data for Efficient Market Hypothesis Test

The data that was used for testing the efficient market hypothesis consisted of the Johannesburg Stock Exchange (JSE) All Share Index (ALSI), the dividends for the calendar year accruing to the portfolio represented by the stocks in the Johannesburg Stock Exchange (JSE) All Share Index (ALSI), the ECPI (Consumer Price Index) index over a 51 year period from 31st December 1960 to 31st December 2011. This time period was primarily chosen because of the availability of a more reliable data to test the analysis. The specific sample data information was collected from I-Net Bridge which is a leader in South Africa's electronic providers of accurate, timely and high quality market data both real time and historically.

University of Cape Town

CHAPTER 4 Methodologies

In this section I present the methodology that I use to investigate the data and to answer the research questions. Firstly, I investigate the hedge fund return persistence tests followed by the performance persistence of portfolios ranked based on their past average returns, then the efficient market hypothesis, and lastly the risk factors in the decomposition of hedge fund returns. All persistence analysis is performed within individual hedge fund strategies since different hedge fund strategies usually exhibit very different risk-return levels. This means that hedge funds may have different persistence patterns because they are exposed to different levels of systematic risk (Brown et al. 1999). An analysis by hedge fund strategies allows more consistency in comparison.

4.1. Return Persistence

I test hedge fund returns for performance persistence. My analysis examines the relative performance persistence of individual hedge fund managers during the period January 2007 to December 2011. I conduct my research by distinguishing among the four different hedge fund strategies mentioned in Data Description, and extend this to other two categories of all funds and living/surviving/alive only funds in our hedge fund universe. I split the entire period of analysis into equal length of overlapping time horizons of either one, three, six or twelve months. Using overlapping time horizons gives me a higher frequency of my returns data making the analysis more robust. This allows me to test all consecutive rolling three, six and twelve months' time horizon for persistence instead of just three, six and twelve months' non-overlapping consecutive calendar periods. I investigate whether an individual fund is consistently over or underperforming by defining my performance measure during the time horizon as the fund's simple net return computed over the period in question. One of the aims of Eling (2008)'s research was to find out why studies on hedge fund performance persistence come to widely divergent conclusions. He uses all the different measures that are

University of Cape Town

found in hedge fund academic research, and concludes that the use of different performance measures is not the reason for the conflicting results found in hedge fund performance persistence literature. Eling's conclusion underpins my decision to use only the simple net return of the individual fund to test performance persistence.

Studies have also used different statistical methodologies. These studies show that we can distinguish between two-period and multi-period statistical approaches in our examination of hedge fund performance persistence. In the two-period approach, two consecutive time units, e.g. months or quarters are compared to each other and in the multi-period case more than two consecutive time units are analysed. The two-period approach can be further divided into nonparametric and parametric approaches. The nonparametric frameworks include the binomial test, contingency table based cross product ratio test and chi-square test, Hurst exponent test, Spearman's rank correlation test and the Correlation-based rank information coefficient test. The parametric framework is a linear regression. The Kolmogorov/Smirnov test belongs to the multi-period approach. All in all are eight different statistical methodologies. I use seven of these eight except for the correlation-based rank information coefficient test as it is closely related to the Spearman's rank correlation test. My aim is to determine whether these methods give differing results.

4.1.1. Contingency Table Based Cross Product Ratio Test

I employ the methodology of Brown et al. (1999) and Agarwal & Naik (2000a) by constructing a contingency table of winners and losers. My performance measure is defined as the fund's simple net return, and the benchmark as the median performance of the set of fund managers present during the investigation period in each hedge fund investment strategy. A fund with performance higher than the median return of all funds in a similar strategy over the defined period in the study is labelled a winner, W, and a fund with performance lower than the median performance of all funds in a similar strategy is labelled a

University of Cape Town

loser, L. I take W1 to represent winners and L1 to denote losers in the first time horizon, and W2 and L2 in the second time horizon so that persistent performing funds are winners in both periods represented by W1W2 (positive persistence), and losers by L1L2 (negative persistence) in a two period framework. Winners (W1) during the first time horizon that are losers (L2) during the second time horizon are denoted by W1L2 and losers (L1) during the first time horizon that are winners (W2) during the second time horizon are denoted by L1W2. After assigning the winners (W) and losers (L) into their respective categories as defined above I calculate the cross-product ratio (CPR) for each time horizon in each hedge fund investment strategy. This is the ratio of the funds with persistent performance to the funds that did not persist:

$$CPR = \frac{W1W2 * L1L2}{W1L2 * L1W2}$$

Under the null hypothesis of no persistence the cross-product ratio (CPR) is equal to one. In other words when there is no persistence each of the four categories W1W2, L1L2, L1W2 and W1L2 represent 25% of the total number of the funds. The statistical significance of the cross-product ratio (CPR) is tested using the standard error $\sigma_{\ln(CPR)}$ of the natural logarithm of the cross-product ratio (CPR) (Christensen 1990). The ratio of the natural logarithm of the cross-product ratio to the standard error of the natural logarithm is the Z-statistic. When the Z-score is greater than 1.96(2.58) the null hypothesis of no persistence is rejected at a 5% (1%) confidence level. Z statistic is calculated as:

$$Z = \frac{\ln(CPR)}{\sigma_{\ln(CPR)}} = \frac{\ln(\mathrm{CPR})}{\sqrt{\frac{1}{W1W2} + \frac{1}{W1L2} + \frac{1}{L1W2} + \frac{1}{L1L2}}}$$

4.1.2. Chi-Square Test

In this section I use the methodology followed by Park & Staum (1998), Argarwal et al. (2005) and Kouwenberg (2003) among others to construct a contingency table of winners

University of Cape Town

(W) and losers (L) as described above in the contingency table based cross product ratio. I then move on to compare the observed frequency distribution of W1W2, W1L2, L1W2, and L1L2 to the expected frequency distribution represented by:

$$X^2 = \frac{(W1W2 - D1)^2}{D1} + \frac{(W1L2 - D2)^2}{D2} + \frac{(L1W2 - D3)^2}{D3} + \frac{(L1L2 - D4)^2}{D4}$$

With $D1 = \frac{(W1W2+W1L2)*(W1W2+L1W2)}{N}$

$D2 = \frac{(W1W2+W1L2)*(W1L2+L1L2)}{N}$

$D3 = \frac{(L1W2+L1L2)*(W1W2+L1W2)}{N}$

$D4 = \frac{(L1W2+L1L2)*(W1L1+L1L2)}{N}$

Where N is the number of all funds.

Following the chi-square distribution with one degree of freedom, when the value of X^2 is greater than 3.84 (6.64) the null hypothesis of no persistence is rejected at the 5% (1%) confidence level.

4.1.3. Spearman's Rank Correlation Coefficient Test

In this test I follow the work of Park & Staum (2008) and compare performance rankings for different time horizons where my performance measure is the fund's simple net return. I let R1 to represent the rank of a fund in the first time period and R2 the rank of the fund in the second time period and then define d_i = R1-R2 as the distance between these rankings. Spearman's rank correlation coefficient is then obtained using the following formula:

$$r_s = 1 - 6\left[\frac{\sum_{i=1}^{n} d_i^2}{n^3 - n}\right]$$

The result will always range from a coefficient of 1 to -1. A coefficient of one indicates a perfect positive correlation which means a perfect positive persistence of performance, and minus one indicates a perfect negative correlation which means negative persistence of

University of Cape Town

performance. A coefficient that is close to zero indicates an absence of performance persistence over two periods. I test Spearman rank correlation coefficient's statistical significance using the Fisher T-statistic as follows:

$$T_{RIC_i} = \sqrt{N_i - 2}\left(\frac{RIC_i}{\sqrt{1 - RIC_i^2}}\right)$$

Where N is the number of returns of Fund i. When the value under the T-distribution is greater than 1.96 (2.58) then the null hypothesis of no persistent is rejected at the 5% (1%) confidence level.

4.1.4. Cross-Sectional Regression Test

In this method I take the fund's simple net return of one time horizon and regress it on the same measurement value of the previous time horizon as given in the equation below (Agarwal & Naik 2000a), (Boyson & Cooper 2004), (De Souza & Gokcan 2004).

$$r_t = \alpha + \beta * r_{t-1}$$

I then test statistical significance of the slope β using the T-statistic. Corresponding to the standard normal distribution, if t-value is greater than 1.96 (2.58) then the null hypothesis of no persistence is rejected at the 5% (1%) confidence level.

4.1.5. Hurst Exponent

I utilise the work of De Souza & Gokcan (2004) and Eling (2008) to come up with Hurst exponents of each individual fund. The Hurst exponent measures whether a trend which maybe positive or negative persists or mean reverts to some historical average. It has the advantage that it makes no assumptions on either the nature of the return distribution or relative value of returns. I calculate the Hurst exponent of each individual fund for each time horizon using the formula:

University of Cape Town

$$H_i = \ln\left(\frac{R_i}{\sigma_i}\right)/ln(N_i/2)$$

Where R is the range of the cumulative deviations from the mean return and σ_i is the standard deviation of the returns. The Hurst exponent gives a direct indication of the managers who persistently display positive or negative returns. A Hurst exponent of 0.5 indicates a manager performance that is truly random, which means the returns in a given period are completely independent of the returns in the previous period. The Hurst exponent that lies between 0.5 and 1, ($0.5 <$ Hurst Exponent ≤ 1) describes performance that is persistent either positive or negative. Finally the Hurst exponent that lies between zero and 0.5, ($0 <$ Hurst Exponent ≤ 0.5) describes anti-persistent or mean reverting performance. This simple means that a period of poor performance will generally be followed by a period of good performance and vice versa. I then use Eling (2008)'s methodology and calculate the T-statistic using the annualised standard deviation (σ_{ann}) to determine statistical significance of the Hurst exponent. When the value is greater than 1.96 (2.58) then the null hypothesis of no persistence is rejected at the 5% (1%) confidence level. T-statistic is calculated as follows:

University of Cape Town

$$T_{H_i} = (H_i - 0.5)/(\frac{\sigma_{ann_i}}{\sqrt{N_i}})$$

4.1.6. Binomial Test

I use the methodology of constructing contingency tables of winners and losers as described in the contingency table based cross product ratio test. Again, my performance measure is defined as the fund's simple net return and the benchmark as the median performance of the set of fund managers present during the investigation period in each hedge fund investment strategy. A fund with performance higher than the median return of all funds in a similar strategy over the defined time horizon in the study is labelled a winner, W, and a fund with performance lower than the median performance of all funds in a similar strategy is labelled a loser, L. I follow Bares et al. (2002) methodology where for each fund I count the number of overlapping time horizons k_i during which the fund dominates the investment strategy median (that is during which the fund is a winner), and then test the null hypothesis with the binomial representation$b(k_i, n_i, p = {}^1\!/_2)$: the fund performance is equally distributed on each side of the median, where n_i is the total number of time horizons during which fund i is reporting performance. My approach tests for the existence of persistence throughout the fund's performance history using the time horizons mentioned above. This combined with the overlapping time horizons I use allows me to carry out a more exhaustive analysis that is robust and it also means that I can use the normal approximation for the binomial test where Z is calculated as follows:

$$Z = \frac{\frac{X}{n} - p}{\sqrt{\frac{pq}{n}}}$$

Where *X, is* the number of wins or losses in a fund's performance history. When the Z-score is greater than 1.96(2.58) the null hypothesis of no persistence is rejected at a 5% (1%) confidence level.

University of Cape Town

4.1.7. Kolmogorov/Smirnov Test

The above methodologies utilise two-period framework except for the Hurst exponent. I now turn my attention to the multi-period framework as used by Agarwal & Naik (2000a), Koh et al.(2003) and Eling (2008). The Kolmogorov/Smirnov goodness-of-fit test is used in the multi-period approach as an extension to the traditional two-period framework. I use this method to improve the robustness of results (Agarwal & Naik 2000a). I come up with an observed frequency distribution which I construct using a series of wins and losses for each fund using the same methodology of contingency tables as described in contingency table based cross product ratio test above. This is then compared with the theoretical frequency distribution of two or more consecutive wins and losses. If a null hypothesis of no persistence is considered as an example, the theoretical probability of WWW and LLL is ${}^{1}/_{8}$ and that of WWWW and LLLL is ${}^{1}/_{16}$. Using the two-sample Kolmogorov/Smirnov goodness of fit test, we can check whether the observed distribution is statistically different from the theoretical distribution. I use Eling M (2008)'s methodology as follows:

$$KS = \max(\frac{WWW}{I} - \frac{1}{8}, \frac{WWL}{I} - \frac{1}{8}, \frac{WLW}{I} - \frac{1}{8}, \frac{WLL}{I} - \frac{1}{8}, \frac{LWW}{I} - \frac{1}{8}, \frac{LWL}{I} - \frac{1}{8}, \frac{LLW}{I} - \frac{1}{8}, \frac{LLL}{I} - \frac{1}{8})$$

A value greater than ${}^{1.22}/_{\sqrt{I}}$, (${}^{1.92}/_{\sqrt{I}}$) indicates significant persistent at the 5% (1%) confidence level where *I* is the number of funds.

University of Cape Town

4.2. Duration of Performance Persistence of Hedge Fund Portfolios

The objective of this part of the study is to investigate the duration of the performance persistence of hedge fund portfolios. I want to examine whether the quarterly, semi-annual and annual performance persistence found in my analysis continue positively or reverses over longer investment horizons. Using the Kolmogorov/Smirnov test which improves the robustness of my performance persistence test results I have already seen that hedge fund returns do not persist on month by month basis so I have chosen to avoid doing the monthly duration test. I follow Bares et al. (2002) methodology by ranking hedge fund managers according to their average returns which is their past realised return over the period January 2007 to December 2011, and perform the analysis irrespective of the different investment hedge fund strategies. I use non-overlapping formation time periods of 3, 6 and 12 months to compute the average return of each fund over formation time periods. I then rank the funds from the best to the poorest performing ones, and use holding time periods of 3, 6, 12, 18 and

24 months depending on the formation time period in question. Non- overlapping periods are chosen to ensure that each month enters the formation time period once, preventing the tests from being affected by a single return exercising influence over multiple time periods (Bares et al. 2002). Again, the holding time periods are chosen to be greater or equal to those of the formation time periods to avoid overlapping the two.

I then form two equally weighted portfolios, attributing to portfolio 1 the 10 funds that have performed the best, during the formation time period and to portfolio 2 the 10 funds that have performed the worst. For all quarterly formation periods, I construct best and worst portfolios with holding time periods of 3, 6 and 12 months. For all semi-annual formation periods, I construct best and worst portfolios with holding periods 6, 12 and 18 months. For all annual formation periods, I construct best and worst portfolios with holding periods 12, 18 and 24 months. The funds have to report during the entire formation time period, in order to enter the ranking process. My methodology does not prohibit a fund disappearing from the portfolios during the holding time periods and so survivorship bias might occur here. However this seems to be the standard practice found in literature (Bares et al. 2002). I concentrate on the top and bottom ten funds because the motivation of the investigation is aimed at discovering on whether winner portfolios remain winners or not, same as loser portfolios. Thus can an investor gain by holding winner or loser portfolios and on the other hand by selling winner or loser portfolios?

4.3. Efficient Market Hypothesis

In testing the efficient market hypothesis, I chose to follow Shiller (1981)'s work where he tests the assertion that share price indices look to be too volatile, meaning that the movements in share price indices cannot realistically be fully attributed to any objective new information, as these price indices movements seem to be far much bigger relative to actual subsequent events. From Shiller (1981), the efficient markets model can be stated as asserting that the

University of Cape Town

price P_t of a stock or index equals the mathematical expectation, conditional on all information available at the time of the present value P_t^* of actual subsequent dividends accruing to the share or index. P_t is not known at the time t and has to be forecasted and according to the efficient market hypothesis that price has to be equal to the optimal forecast of it, Shiller (1981). In general efficient market model can therefore be written as $P_t = E_t(\, P_t^*)$ where E_t refers to the mathematical expectation conditional on public information available at time t. It then follows from the efficient market model that $P_t^* = P_t + \mathcal{E}_t$ where $\mathcal{E}_t$ is a forecast error. Since the price P_t itself is information at time t, P_t and $\mathcal{E}_t$ should be uncorrelated with each other. We know that the variance of the sum of two uncorrelated variables is the sum of their variances. From above it follows that the variance of P_t^* must be equal to the variance of P_t plus the variance of $\mathcal{E}_t$. Again, mathematically variances are non-negative so $\mathcal{E}_t$ cannot be negative which means that the variance of P_t^* must be greater than or equal to that of P_t .

Using this theoretical framework as discussed in Chapter 2, Shiller (1981) comes up with the three inequalities that we test below. I take p for 1960 to 2011 to represent the Johannesburg Stock Exchange (JSE) All Share Index (ALSI) for December deflated by the ECPI (Consumer Price Index) scaled to base year $T = 2011$ multiplied by a scale factor λ^{T-t} . The parameter λ equals one plus the long term growth rate of the real value of the portfolio of the ALSI plus dividends and this scale factor has the effect of removing heteroscedasticity due to the gradually increasing size of the market (Shiller R 1981). I take d for 1960 to 2011 to represent the total dividends paid over the year deflated by the ECPI (Consumer Price Index) scaled to base year $T = 2011$ multiplied by a scale factor λ^{T-t-1}. The discount rate r is estimated as the average d divided by the average p. My analysis using JSE ALSI tests Shiller's three main inequalities as follows: Inequality 4.1 also similar to equation 2.7 is:

University of Cape Town

$$\sigma(p) \leq \sigma(p^*) \tag{4.1}$$

Where $\sigma(p)$ is the standard deviation for the real JSE ALSI and $\sigma(p^*)$ is the standard deviation of the present value of the actual subsequent real de-trended dividends subject to an assumption about the value in 2011 of dividends thereafter. This assumption is that the terminal value of p^* is taken as the average p. Inequality 4.2 also similar to equation 2.8 is:

$$\sigma(\Delta p) \leq \sigma(d)/\sqrt{2\overline{r}} \tag{4.2}$$

Where $\sigma(\Delta p)$ is the standard deviation of the first difference of the real JSE Stock Price Index, $\sigma(d)$ is the standard deviation of the dividends on JSE Stock Price Index and $\overline{r}$ is the real discount rate for de-trended series calculated as: $\overline{r} = {}^{1-\Upsilon^i}/_{\Upsilon^i}$ where Υ^i is the real discount factor for de-trended series derived as $\Upsilon^i = \lambda\,\Upsilon$. λ is as defined above and Υ is the real discount factor for series before de-trending calculated as: $\Upsilon = {}^{1}/_{1+r}$ and r is the discount rate noted above. Inequality 4.3 also similar to equation 2.9 is:

$$\sigma(\partial p) \leq \sigma(d)/\sqrt{2\overline{r}_2} \tag{4.3}$$

Where $\sigma(\partial p)$ is the first differential which can be expressed as $\sigma(\Delta p + d_{-1} - \overline{r}p_{-1})$ and $\overline{r}_2$ is the two-period real discount rate for de-trended series calculated as: $\overline{r}_2 = (1+\overline{r})^2 - 1$. I use the Dicky-Fuller Test to test the stationarity assumption of the dividends in order for equation 2.8 (4.2) to hold. The data set contained a 52 annual data points for testing the following hypothesis test:

H0: Dividends follow a non-stationary process, i.e. $\rho = 1$ vs.

H1: Dividends follow a stationary process, i.e. $\rho < 1$

University of Cape Town

A Dicky-Fuller Test was used to test H0 v.s. H1 using EViews version 7. Again I use the method to test stationarity of the first order differences of the dividends following the hypothesis:

H0: The first order difference of dividends follow a non-stationary process, i.e. $\rho = 1$ vs.

H1: The first order difference of dividends follow a stationary process, i.e. $\rho < 1$

Finally I test the stability of equation 2.8(4.2) where stability requires that: $\left[\rho\sigma(c_{j,t})/_r\right] < 1 + \sigma^2(\Delta p_{j,t})/_{2r}$ and $\sigma^2(\Delta p_{j,t})/_{2r} < 1$.

4.4. Sources of Risk in Hedge Funds

My methodology follows that of Fung & Hsieh (2004) where they use the seven asset-based style (ABS) factors. We know that the equity risk factors can be modelled using the Capital Asset Pricing Model (CAPM) or the Arbitrage Pricing Theory (APT). These separate the returns of an equity investment into systematic and idiosyncratic where systematic is the common source of return which is simply the market portfolio in CAPM and market portfolio combined with a few other risk factors in APT.

In the same way my hedge fund model which follows that proposed by Fung & Hsieh (2004) tries to mimic the APT to help investors identify the common sources of risk in hedge fund investing. I use Fung and Hsieh (2004) seven asset-based style factors proxied as follows:

- Stock market- Johannesburg Stock Exchange (JSE) All Share Index (ALSI).

Fung & Hsieh (2004) use S&P500.

- Small cap stocks- Johannesburg Stock Exchange (JSE) Small cap Index.
- Large cap stocks- Johannesburg Stock Exchange (JSE) Top40 index.

This is to capture the spread between small cap stock returns and large cap stock returns. Fung & Hsieh (2004) use Wilshire Small Cap 1750 and Wilshire Large Cap 750.

- 10-year South African Government yields.

University of Cape Town

- GOVI and OTHI bond indices.

The 10 year South African Government bond is used where Fung & Hsieh (2004) use the US 10 year Treasury yield. The GOVI and OTHI are used to proxy the South African yield spread where the authors use the spread between 10-year Treasury bonds and Moody's Baa bonds. The South African fixed income landscape is not as developed as the international one and so data availability is always a challenge. The GOVI and OTHI spread is the nearest one can get in pursuing approximate reliable information.

- Portfolio of look-back straddles on bonds-from – faculty.fuqua.duke.edu/~dah7/HFData.htm

I use Fund & Hsieh library to collect the returns for the portfolios of look back straddles on bonds, currencies and commodities. I chose to use their data as the South African market lacks the ability to provide adequate data for me to construct my own local portfolios across these three factors of look back straddles. Additionally I include Fama & French's (1993) spread between the high book to market ratio stocks and the low book to market ratio stocks and Carharts' (1997) one year momentum factor. This gives me a total of nine factors.

Using my hedge fund data I then construct six equally weighted hedge fund indices with monthly returns. The indices consist of the Composite hedge fund index that incorporates all hedge funds in our sample data, fund of hedge funds index incorporating all funds of hedge funds in our data, the equity long-short index, equity market neutral index, fixed income index and the index for other hedge fund strategies as described in the data. I then regress the monthly net returns of the hedge fund indices on the monthly returns of my nine risk factors in a multi-factor framework. I estimate the following regression:

$$R_i = \alpha_i + \sum_{k=1}^{K} \lambda_k^i F_k^i + \varepsilon_i$$

University of Cape Town

Where R_i is the monthly returns on hedge fund index i and α_i is the intercept or alpha for hedge fund index i over the regression period, λ_k^i is the average factor loading of hedge fund index i on the k^{th} factor during the regression period, F_k^i is the beta on the k^{th} factor during the regression period. The regression is conducted over the period January 2007 to December 2011.

University of Cape Town

CHAPTER 5 Results

5.1. Results on Hedge Fund Return Persistence

5.1.1. CPR and Chi-Square Test Results

The table below reports the results of the equity long short investment strategy:

Table 6-Equity Long Short CPR and Chi-Square Test Results

Panel A: Equity Long Short Results							
Period	WW	WL	LW	LL	CPR	Z-statistic of CPR	X^2-statistic
1 months	454	363	359	428	1.4911	3.9792^^	15.8867**
3 months	623	177	170	566	11.7188	20.1601^^	460.5707**
6 months	612	121	115	579	25.7565	22.7998^^	644.9217**
12 months	565	73	70	521	57.6057	22.7769^^	723.0117**

*^^ Significant at the 1% level (Z-statistic critical value=2.58) **Significant at the 1% level (chi-square critical value=6.63)*

Table 6 reports significant evidence of performance persistence in equity long short hedge funds for all time horizons tested. I clearly observe that for all the time horizons, winners followed by winners (WW) dominate all the possible outcomes and increases as the time horizon is increased from 1 month to 6months, where it reaches the maximum, and then decreases for the 12 month time period. This dominance of winners indicates positive performance persistence. These results are all significant at the 1% level for both the Z-statistic of the CPR and the chi-square statistic. Fixed income arbitrage strategy shows similar results as the equity long short, except that the number of losers followed by losers (LL) dominates all the time horizons tested indicating negative performance persistence for the fixed income arbitrage strategy (see results in appendix Table 26, page 101).

I report a similar set of results for the other hedge fund strategies (as described in Chapter 3) that can be seen in Table 27 and 28 in the appendix on page 101. Other hedge fund strategies' results (see results in appendix Table 27, page 101) are similar to those obtained for equity long short strategy. Results of the equity market neutral strategy are shown in Table 28(see

University of Cape

appendix). A few differences can be noted in this strategy. Firstly the 1 month performance persistence is only significant at the 5% level for both methodologies while the other time horizons are significant even at the 1% level. Secondly, the number of losers following losers (LL) dominates the 1 month and 3 months' time horizon signifying negative performance persistence for these periods while for the 6 months and 12 months' time horizon this is reversed to positive performance persistence.

Table 7-All Hedge Funds CPR and Chi-Square Test Results

Panel A:All Hedge Funds Results							
Period	WW	WL	LW	LL	CPR	*Z*-statistic of CPR	X^2-*statistic*
1 months	1411	1262	1255	1493	1.3301	5.2362^^	27.4647**
3 months	1955	612	598	2027	10.8280	36.2805^^	1479.531**
6 months	1946	396	379	2135	27.6826	42.3590^^	2247.6844**
12 months	1804	258	240	1864	54.3065	41.7985^^	2412.0160**

*^^ Significant at the 1% level (Z-statistic critical value=2.58)   **Significant at the 1% level (chi-square critical value=6.63)*

Table 7 reports significant evidence of performance persistence in all the hedge funds strategies grouped together for all the time horizons tested in both the Z-statistic of the CPR and the chi-square statistic. All the time horizons tested are significant at the 1% level. The rationale is to try and see whether there is any difference in performance persistence if the funds are analysed by their investment strategy, compared with the analysis combining all the strategies. The notable difference is that the results for all the hedge funds combined together show negative performance persistence, as the number of (LL) dominates all the time horizons tested as we saw in parts of market neutral and fixed income arbitrage strategies. This could be due to the fact that hedge funds are exposed to different levels of systematic risk and so may have different persistence patterns, (Brown et al. 1999). We should note that there is no consensus in the literature on whether the investment strategy of a hedge fund is a driver of persistence. While Agarwal & Naik (2000a) conclude that persistence is not related

University of

to the investment strategy, Brown & Goetzmann (2003), Harri & Brorsen (2004) and Eling (2008) find that persistence is related to style of fund management. Again, the number of (WW) increases from 1 month to 3 months and then decreases for 6 and 12 months, while in each investment strategy it increased from 1 month to 6 months and decreased for the 12 months' time horizon. One of the reasons for this difference might be attributed to the small number of funds in each data sample of hedge fund investment strategy that I use in the analysis.

Table 8-Surviving/Living Hedges Funds Only CPR and Chi-Square Test Results

Panel A:Surviving/Living Hedge Funds Only Results							
Period	WW	WL	LW	LL	CPR	Z-statistic of CPR	X^2-*statistic*
1 months	1054	977	980	1171	1.2891	4.0941^^	16.7841**
3 months	1486	469	462	1600	10.9730	32.0257^^	1154.5032**
6 months	1461	320	313	1678	24.4764	36.6795^^	1659.3565**
12 months	1395	200	196	1488	52.9531	37.0295^^	1885.3433**

*^^ Significant at the 1% level (Z-statistic critical value=2.58) **Significant at the 1% level (chi-square critical value=6.63)*

Table 8 reports significant evidence of performance persistence in surviving/living only hedge fund strategies grouped together, for all the time horizons tested in both the Z-statistic of the CPR and the chi-square statistic. All the time horizons tested are significant at 1% level. We have already discussed the problems of survivorship bias in Chapter 3. The funds disappearing from the database, usually due to liquidation, tend to have poorer performance compared to the existing funds (Capocci 2007). If these funds are not taken into account, then the performance of hedge funds is biased upwards leading to survivorship bias. My motivation for the above test was to see whether survivorship bias does affect my results. It is clear that the results in table 7 and table 8 are similar. Both tables show significant evidence of performance persistence for all the time horizons tested, in both the Z-statistic of the CPR and the chi-square statistic and all the time horizons tested are significant at the 1% level. Again, the results show negative performance persistence for both tests, as the number of (LL) dominates all the time horizons tested in the two tables. I can therefore infer from the results that survivorship bias has minimal impact on my analysis.

5.1.2. Cross-Sectional Regression Test Results

The table below show the percentage of cases exhibiting statistically significant performance using cross-sectional regression test at 5% level, during the period that extends from January 2007 to December 2011, across *Equity long short (EQLS), Equity Market Neutral (EQMN), Fixed Income Arbitrage (FIA), Other Strategies* and include two additional tests of *All funds* and *Living/Surviving (Alive) funds*. I consider four different time horizons namely; 1, 3, 6, and 12 months.

Cape Town

Table 9-Cross Sectional Regression at 5% Level

INVESTMENT STRATEGIES	PERIOD			
	1 month	3 months	6 months	12 months
EQLS	25%	93%	100%	98%
EQMN	19%	96%	98%	100%
FIA	29%	85%	94%	100%
OTHER	21%	85%	96%	98%
ALL FUNDS	29%	96%	100%	100%
ALIVE FUNDS	40%	94%	100%	100%

I observe a pattern from the above results where the cases of funds exhibiting statistically significant performance, at the 5% level, increases drastically from 1 month to 3 months then levels off at 6 months. At 6 months, most of the investment strategies show approximately 100% of cases being significant at the 5% level. Equity long short strategy is the only one that reports a drop in number of cases showing statistically significant performance, from 100% in 6 months to 98% in 12 months. I believe this marginal reversal to be the noise due to the small number of funds in our sample. Table 29 in appendix on page 103 shows results for, when the level of significance is tightened to 1%. The reversal in the equity long short strategy is no longer observed. I do observe that the percentage of cases exhibiting statistically significant performance both at 1% and 5% level is quite high for 1 month test for Alive funds, compared with the category of All funds. I can argue with caution that the cross-sectional regression methodology is more sensitive to survivorship bias because of this increase since survivorship bias causes performance of hedge funds to be biased upwards. However it must be noted that this pattern is not seen in other tested time horizons of 3, 6 and 12 months which is why I choose to exercise caution in the observations. In general the result from the cross-sectional regression test corroborates the results obtained in the first two performance persistence tests, the CPR and Chi-square tests.

5.1.3. Spearman's Rank Correlation Test Results

The table below show the percentage of cases exhibiting statistically significant performance using spearman's rank correlation test at the 5%, level during the period that extends from January 2007 to December 2011, across *Equity long short (EQLS), Equity Market Neutral (EQMN), Fixed Income Arbitrage (FIA), Other Strategies* and include two additional tests of *All funds* and *Living/Surviving (Alive) funds*. I consider four different time horizons namely 1, 3, 6, and 12 months.

University of Cape Town

Table 10-Spearman's Rank Correlation Test at 5% Level

INVESTMENT STRATEGIES	PERIOD			
	1 month	3 months	6 months	12 months
EQLS	25%	91%	100%	96%
EQMN	14%	91%	100%	100%
FIA	15%	79%	93%	98%
OTHER	19%	86%	87%	98%
ALL FUNDS	27%	96%	98%	100%
ALIVE FUNDS	24%	95%	100%	100%

Both tables for Spearman's rank correlation test at 5% and 1% (see appendix table 30 on page 103) significant level give a similar pattern observed with the other results above. Performance persistence is almost non-existent at 1 month time horizon, but then drastically increases to 3 months, after which there is then a marginal increase at 6 and 12 months. Again, at 6 months, most of the investment strategies show approximately 100% of cases being significant at both 5% and 1% level. Equity long short strategy is the only strategy again that reports a drop in number of cases showing statistically significant performance from 100% in 6 months to 96% in 12 months. I still believe that this marginal reversal is caused by the noise due to the small number of funds in the sample. The result from the Spearman's rank correlation test corroborates the other results obtained from the CPR test, Chi-square test and the cross-sectional regression test. There is not much difference in the 1 month results for Alive funds compared with the category of All funds, as seen with the cross-sectional regression test.

University of Cape Town

5.1.4. Binomial Test Results

The table below show the individual performance persistence of the hedge fund managers during the period that extends from January 2007 to December 2011. I distinguish between four investment strategies: *Equity long short (EQLS), Equity Market Neutral (EQMN), Fixed Income Arbitrage (FIA), Other Strategies* and include two additional tests of *All funds* and *Living/Surviving (Alive) funds*. I consider 4 different time horizons namely 1, 3, 6, and 12 months. I report the total number of managers under consideration, the number of managers with a significant tendency to perform above or below the median manager of the strategy, denoted ↑ and ↓, respectively (determined with a one sided binomial test at the 1% and 5% level). Table 13 reports the binomial test at the 5% level and Table 31 (in appendix) at the 1% level.

Table 11-Binomial Test at 5% Level

PERIOD	FUNDS	INVESTMENT STRATEGIES					
	SELECTION	EQLS	EQMN	FIA	OTHER	ALL FUNDS	ALIVE FUNDS
	Total	34	34	18	28	114	82
1 month	Signif. ↑ or ↓	6 (18%)	12 (35%)	9 (50%)	9 (32%)	37 (32%)	25 (30%)
	Signif. ↑	4 (12%)	4 (12%)	4 (22%)	5 (18%)	17 (15%)	10 (12%)
	Signif. ↓	2 (6%)	8 (24%)	5 (28%)	4 (14%)	20 (18%)	15 (18%)
3 months	Signif. ↑ or ↓	14 (41%)	17 (50%)	11 (61%)	17 (61%)	60 (53%)	34 (41%)
	Signif. ↑	9 (26%)	7 (21%)	4 (22%)	10 (36%)	30 (26%)	17 (21%)
	Signif. ↓	5 (15%)	10 (29%)	7 (39%)	7 (25%)	30 (26%)	17 (21%)
6 months	Signif. ↑ or ↓	12 (35%)	20 (59%)	11 (61%)	20 (71%)	63 (55%)	49 (60%)
	Signif. ↑	7 (21%)	10 (29%)	4 (22%)	13 (46%)	29 (25%)	22 (27%)
	Signif. ↓	5 (15%)	10 (29%)	7 (39%)	7 (25%)	34 (30%)	27 (33%)
12 months	Signif. ↑ or ↓	17 (50%)	19 (56%)	12 (67%)	19 (68%)	71 (62%)	57 (70%)
	Signif. ↑	9 (26%)	12 (35%)	5 (28%)	12 (43%)	33 (29%)	28 (34%)
	Signif. ↓	8 (24%)	7 (21%)	7 (39%)	7 (25%)	38 (33%)	29 (35%)

I observe from the two tables that performance persistence as measured by the binomial test is almost non-existence at monthly time periods, across all hedge fund investment strategies (except for fixed income arbitrage) and it then increases drastically in 3 months' time period, after which there is a gradual increase at 6 to 12 months' time horizons. Across all the hedge fund investment strategies, the equity long short and other strategies categories show positive performance persistence, as the number of winners tends to dominate in most of the time periods tested. Fixed income arbitrage and market neutral strategies show negative performance persistence, as the number of losers tends to dominate in most of the periods tested as was the case with results obtained using the CPR test and Chi-Square test. The reversal in negative performance that is seen in market neutral strategy, at 12 months' time horizon can be attributed to noise caused by the small number of funds used in the sample data. The results for all funds category show negative performance persistence, as losers dominate all the time horizons tested corroborating the results obtained from the CPR test and Chi-Square test. I also test the category of Alive funds to evaluate the impact of survivorship bias on the results. I note that negative performance persistence was present as was in the Alive funds. The percentages for both All funds and Alive funds categories across the time periods tested are not far different form each other confirming again as I saw with the CPR test and Chi-Square test results that survivorship bias has a minimal effect on my analysis. These results were again in congruency with the results already obtained from the Spearman's rank correlation test, CPR test, Chi-square test and the Cross-sectional regression test.

University of Cape Town

5.1.5. Hurst Exponent Test Results

The tables show the percentage of cases exhibiting statistically significant performance using Hurst exponent test, at the 5% level for Table 12, and at the 1% level for Table 32 in appendix, during the period that extends from January 2007 to December 2011,across *Equity long short (EQLS), Equity Market Neutral (EQMN), Fixed Income Arbitrage (FIA), Other Strategies* and include two additional tests of *All funds* and *Living/Surviving (Alive) funds*. I consider four different time horizons namely 1, 3, 6, and 12 months.

Table 12-Hurst Exponent Test at 5% Level

INVESTMENT STRATEGIES	PERIOD			
	1 month	3 months	6 months	12 months
EQLS	94%	100%	100%	97%
EQMN	100%	100%	100%	100%
FIA	94%	100%	100%	100%
OTHER	86%	100%	100%	100%
ALL FUNDS	94%	100%	100%	99%
ALIVE FUNDS	94%	100%	100%	100%

The results in the above tables show that the Hurst exponent methodology was probably not the best to use in my analysis. Eling (2008) argues that the application of Hurst exponent methodology is problematic with hedge funds as only a few monthly returns are available. The literature emphasises that the Hurst exponent requires much more data than what we can usually get from the hedge fund databases. This assertion is portrayed clearly by Lo (1991) and Couillard & Davison (2005). This makes it even more difficult for my analysis as I have already stated that the South African hedge fund industry is still in its infancy and so data is still minimal.

5.1.6. Kolmogorov-Smirnov Test Results

Eling (2008) argues that the multi-period framework is better able to differentiate performance persistence due to chance and that due to manager skill than the traditional two-period framework, see also Agarwal & Naik (2000a). They attest that the multi-period Kolmogorov-Smirnov test produces robust results and conclude that it is the most useful method of evaluating persistence of hedge funds.

University of Cape Town

Table 13-Equity Long Short Kolmogorov-Smirnov Test Results

Panel B-Equity Long Short Results		
Period	**Kolmogorov-Smirnov Statistic**	
	Wins	**Losses**
1 month	0.0519	0.0314
3 months	0.1945**	0.1689**
6 months	0.2534**	0.2196**
12 months	0.2834**	0.2611**

*** Distribution of wins/losses significant at the 1% level*

** Distribution of wins/losses significant at the 5% level*

Table 13 reports significant evidence at the 1% level of performance persistence, in equity long short hedge funds for time horizons 3, 6 and 12 months both winners and losers. The KS (Kolmogorov-Smirnov) statistic is greater for winners in all the time periods tested indicating positive performance persistence as we have seen with the CPR test, Chi-Square test and the Binomial test for equity long short strategy. Persistence at 1 month time horizon is not significant. Again, the pattern of performance persistence where it increases drastically from 1 month to 3 months, and then increases gradually from 3 to 6 and 12 months is corroborated by the size of increase of KS statistic from each time horizon to the next. This is the pattern that I observed with the other persistence test methodologies used above.

Table 33, in appendix on page 105 reports similar results for the equity market neutral strategy. The KS (Kolmogorov-Smirnov) statistic is greater for winners in all the time periods tested (except for 3 months where the KS statistic is equal for both), indicating positive performance persistence and this result differs with that obtained using the CPR test, Chi-Square test and the Binomial test, where I observed negative performance persistence. Since the Kolmogorov-Smirnov test has been proven to produce much more robust results compared to the other methodologies I will infer that the KS test results are more useful. Persistence at 1 month time horizon is not significant.

University of Cape Town

Table 34, in appendix on page 105 shows results of the fixed income arbitrage strategy. The results are similar to the equity long short strategy except for that the (Kolmogorov-Smirnov) statistic is greater for losers in all the time periods tested indicating negative performance persistence as we have seen with the CPR test, Chi-Square test and the Binomial test for fixed income arbitrage strategy.

Table 35, in appendix on page 105 reports results for other hedge fund strategies, and these are similar to the equity long short strategy results. Again they are in tandem with the CPR test, Chi-Square test and the Binomial test results. The above results for all the strategies except for equity market neutral strategy were comparable to those obtained using other test but Hurst exponent.

Table 14-All Hedge Funds Kolmogorov-Smirnov Test Results

Panel B-All Hedge Funds Results		
Period	**Kolmogorov-Smirnov Statistic**	
	Wins	**Losses**
1 month	0.0277	0.0321*
3 months	0.1547**	0.1744**
6 months	0.2137**	0.2436**
12 months	0.2693**	0.2744**

*** Distribution of wins/losses significant at the 1% level*
** Distribution of wins/losses significant at the 5% level*

Table 14 reports significant evidence at the 1% level of performance persistence in all hedge funds category for time horizons 3, 6 and 12 months both winners and losers. I also report significant evidence, at the 5% level, of performance persistence in the 1 month time horizon for losers which is different from when the analysis is done by hedge fund strategy. The KS (Kolmogorov-Smirnov) statistic is greater for losers in all the time periods tested indicating negative performance persistence as we have seen with the CPR test, Chi-Square test and the Binomial test for all hedge funds category. Again, the pattern of performance persistence where it increases drastically from 1 month to 3 months, and then increases gradually from 3 to 6 and 12 months, is corroborated by the size of increase of KS statistic from each time horizon to the next. This is the pattern that I observe with the other persistence test methodologies used above.

Table 15-Surviving/Living Hedge Funds Only Kolmogorov-Smirnov Test Results

Panel B-Surviving/Living Hedge Funds Only Results		
Period	**Kolmogorov-Smirnov Statistic**	
	Wins	**Losses**
1 month	0.0111	0.0345*
3 months	0.1481**	0.1790**
6 months	0.2014**	0.2503**
12 months	0.2604**	0.2780**

*** Distribution of wins/losses significant at the 1% level*
** Distribution of wins/losses significant at the 5% level*

I again turn my attention to testing the category of Alive funds using Kolmogorov-Smirnov test, to assess the impact of survivorship bias on the results. Table 15 reports significant evidence, at the 1% level, of performance persistence in surviving/living hedge funds only category for time horizons 3, 6 and 12 months both winners and losers. I also report significant evidence, at the 5% level of performance persistence, in the 1 month time horizon for losers. The KS (Kolmogorov-Smirnov) statistic is greater for losers in all the time periods tested indicating negative performance persistence as I have seen with the CPR test, Chi-Square test and the Binomial test for surviving/living hedge funds only category. Again, the pattern of performance persistence where it increases drastically from 1 month to 3 months, and then increases gradually from 3 to 6 and 12 months, is corroborated by the size of increase of KS statistic from each time horizon to the next. This is the pattern that I observe with the other persistence test methodologies used above. The KS statistic for both All funds

University of

and Alive funds categories across the time periods tested were not far different form each other indicating again, as I have already observed with other persistence test methodologies that survivorship bias has a minimal effect on the analysis.

5.2. Summary of Results and Comparative Analysis

In this section I compare my findings with those from the previous global literature. Most literature use two or three of the methodologies used in my analysis except Eling (2008) who uses all of the methodologies but binomial test. Eling (2008)'s overview of the main results of hedge fund performance persistence studies finds that short-term persistence for horizons of up to six months is reported by nearly all authors, e.g. Agarwal & Naik (2000a), Agarwal & Naik (2000b), Bares et al. (2002), Amenc et al. (2003). The evidence for longer time horizons is mixed as the studies arrive to conflicting conclusions. He reports that at 12 months' time horizon there are eight studies which find performance persistence, e.g. Agarwal et al. (2007), and Kosowski et al. (2007), while ten of them find no evidence of performance persistence, e.g. Amenc et al. (2003) and Jagannathan et al. (2006).

My results for short term hedge fund performance persistence were similar to those of the global literature, and for longer term at annual time horizons, they were similar to those studies which found performance persistence at annual time horizon.

University of Cape Town

5.3. Duration of Performance Persistence of Hedge fund Portfolios' Results

Table 16-Quarterly Momentum Portfolio Results

Best funds' Portfolio	**Total Cumulative Return**	**Annualised Return**	**Mean Monthly Return**	**Standard Deviation**
Quarterly rank-hold 3 months	127.46%	18.89%	1.47%	6.04%
Quarterly rank-hold 6 months	79.37%	13.09%	1.05%	6.18%
Quarterly rank-hold 12 months	87.09%	14.10%	1.12%	6.58%
Worst funds' Portfolio				
Quarterly rank-hold 3 months	31.47%	5.93%	0.49%	5.14%
Quarterly rank-hold 6 months	43.33%	7.87%	0.65%	5.72%
Quarterly rank-hold 12 months	70.28%	11.86%	0.95%	5.14%
Benchmarks				
All funds' Portfolio	68.69%	11.64%	0.92%	2.60%
JSE ALSI Total Return	33.64%	6.29%	0.66%	18.95%
All Bond Index Return	48.58%	8.69%	0.72%	7.39%

**ALSI-All Share Index*

Table 16 reports clear indication of short term portfolio performance persistence at 3 months' time horizon with different holding periods. Using a two-sample t-statistic, at a 5% level, assuming unequal standard deviation to compare the monthly mean return of the best portfolios with the average monthly return of the worst portfolios, I find that the mean monthly return of Best funds' portfolio (quarterly rank- hold 3 months) is statistically significant compared with the peer Worst funds' portfolio, and also with the All funds' portfolio mean monthly return. As I increase the holding period for the Best fund's portfolio to 6 months, the returns decrease quite a lot, and then increase with a small margin for the annual holding period, though still far less than the 3 month holding period portfolio. There is reversal of performance as the holding period is lengthened. One of the explanations of this reversal could be that different hedge fund strategies tend to outperform at different market environments. Some funds favour highly volatile environment, others trending markets, others high dispersion environment while others sideways markets. This can be illustrated by looking at the annual performance of the different strategies during the investigation period as in Table 37 in appendix on page 107. Viewing the annual performance at different varying times of the investigation period shows this reversal in performance as reported above. This

University of Cape Town

means that the longer one holds these funds in an unfavourable period, then the higher the likelihood that the portfolio performance is negatively affected while the reverse is also true. It must be noted that my study covers these different types of market environment. It begins in January 2007 which was the peak of the bull market, 2008 was one of the worst market stresses with high volatility and high dispersion through to 2009. From 2010 to 2011 it was a period of low volatility and sideways market. All the holding periods of the Best funds' portfolio outperform all the benchmarks in the table, that is All funds' portfolio, JSE ALSI Total Return and the ALL Bond Index Return.

I again observe a different reversal performance when I look at the Worst funds' portfolio. As I increase the holding period for these funds the performance gets better, and at 12 months holding period the portfolio for the worst funds outperformed all the benchmarks. Again, the intuition could be that I was holding funds which suddenly experience a change in performance due to the change in the market environment becoming more favourable. These results are similar to those of Bares et al (2002) who found that best portfolios with short formation periods exhibit downward performance tendency as the length of the holding period increases, while the mean returns of the worst portfolios showed an upward tendency. This fund performance persistence observed here is closely related and comparable to the "hot hands" effect reported in Hendricks et al. (1993) for mutual funds.

University of Cape Town

Table 17-Semi-Annual Momentum Portfolio Results

Best funds' Portfolio	Total Cumulative Return	Annualised Return	Mean Monthly Return	Standard Deviation
Semi-annual rank hold six months	94.67%	15.95%	1.25%	5.22%
Semi-annual rank hold 12 months	84.71%	14.61%	1.16%	5.91%
Semi-annual rank hold 18 months	66.70%	12.03%	0.97%	6.64%
Worst funds' Portfolio				
Semi-annual rank hold six months	28.06%	5.65%	0.48%	7.09%
Semi-annual rank hold 12 months	38.13%	7.44%	0.62%	7.23%
Semi-annual rank hold 18 months	75.21%	13.27%	1.06%	5.80%
Benchmarks				
All funds' Portfolio	61.31%	11.21%	0.89%	2.58%
JSE Total Return	28.14%	5.66%	0.61%	19.41%
All Bond Index Return	51.08%	9.60%	0.79%	7.42%

**ALSI-All Share Index*

The results in table 17 are similar in style to those already discussed in the quarterly momentum portfolios, except that the Best funds' portfolios show a consistent downward performance tendency as the holding period is increased without any reversal as seen in the Best funds' portfolios above. Using a two-sample t-statistic, at a 5% level, assuming unequal standard deviation to compare the monthly mean return of the best portfolios with the average monthly return of the worst portfolios, I find that the mean monthly return of Best funds' portfolio (semi-annually rank- hold 6 months) is statistically significant, compared with the peer Worst funds' portfolio, but is not significant when compared with the All funds' portfolio mean monthly return. All the holding periods of the best funds' portfolio outperformed all the benchmarks in the table, which is All funds' portfolio, JSE ALSI Total Return and the ALL Bond Index Return.

The Worst funds' portfolios reveal a similar pattern to that of the quarterly ones where I observe reversal of performance, in that as I increase the holding period for these funds the performance of the portfolios gets better, and at 18 months holding period the portfolio for the worst funds outperformed all the benchmarks.

University of Cape Town

Table 18-Annual Momentum Portfolio Results

Best funds' Portfolio	Total Cumulative Return	Annualised Return	Mean Monthly Return	Standard Deviation
Annual rank hold 12 months	43.19%	9.39%	0.77%	7.44%
Annual rank hold 18 months	21.32%	4.95%	0.42%	6.98%
Annual rank hold 24 months	57.97%	12.11%	0.98%	7.29%
Worst funds' Portfolio				
Annual rank hold 12 months	29.33%	6.64%	0.55%	5.72%
Annual rank hold 18 months	55.29%	11.63%	0.93%	5.51%
Annual rank hold 24 months	20.36%	4.74%	0.39%	4.39%
Benchmarks				
All funds' Portfolio	51.82%	11.00%	0.88%	2.67%
JSE Total Return	23.77%	5.48%	0.61%	20.13%
All Bond Index Return	44.89%	9.71%	0.80%	7.73%

**ALSI-All Share Index*

A two-sample t-statistic of the results in table 18, at a 5% level, assuming unequal standard deviation to compare the monthly mean return of the best portfolios with the average monthly return of the worst portfolios finds no statistical significance in the monthly mean return of the portfolios in the table. The Best funds' portfolio results mimic the ones for the best fund portfolios for quarterly momentum except that the return differences are much bigger. The reason for the reversal in performance where its high at holding periods of 12 months, then dips at holding periods of 18 months, and finally shoots up again at holding periods of 24 months, is similar to the one given above in that the performance of hedge funds tend to vary with different market environments. The differences are more pronounced here because of the longer holding periods.

The Worst funds' portfolio pattern strengthens the argument about hedge funds' performance in different market conditions. When the performance of the Worst funds' portfolio is low (see Annual Rank-hold 12 months and Annual Rank-hold 24 months) the performance of the Best funds' portfolios is higher in comparison. I observe a reversal of this trend in the Annual Rank-hold 18 months portfolios. This clearly shows that there is a tendency for worst performing funds to reverse this downward trend whenever market environment changes to favour them and in general this change in market environment negatively impact the best

University of Cape Town

performing funds resulting in bad performance. There will always be a crossover depending on the formation and holding periods of the portfolios. This knowledge of hedge funds performing differently in different market environments is therefore invaluable for both the investor and the portfolio manager.

5.4 Efficient Market Hypothesis

Table 19-Results of Principal Symbols for the Inequalities

λ	103.55%
r	4.16%
$\overline{r}$	0.59%
$\overline{r}_2$	1.17%
Υ	96.01%
Υ^i	99.42%
$\sigma(p)$	2.99%
(p^*)	1.22%
$\sigma(\Delta p)$	117.98%
$\sigma(d)$	1.96%
$\sqrt{2\overline{r}}$	10.82%
$\sigma(\partial p)$= $\sigma(\Delta p + d_{-1} - \overline{r}p_{-1})$	56.92%
$\sqrt{2\overline{r}_2}$	15.33%

Table 20-Results for the Elements of R. Shiller's Three Variance Inequalities

Inequality 1: $\boldsymbol{\sigma(p) \leq \sigma(p^*)}$	
$\sigma(p)$	2.99%
$\sigma(p^*)$	1.22%
Inequality 2: $\boldsymbol{\sigma(\Delta p) \leq \sigma(d)/\sqrt{2\overline{r}}}$	
$\sigma(\Delta p)$	117.98%
$\sigma(d)/\sqrt{2\overline{r}}$	18.15%

University of Cape Town

Inequality 3: $\boldsymbol{\sigma(\partial p) \leq \sigma(d)/\sqrt{2\bar{r}_2}}$	
$\sigma(\partial p)$	56.92%
$\sigma(d)/\sqrt{2\bar{r}_2}$	12.82%

All inequalities in table 20 assert that the standard deviation in above row for each inequality should be less than or equal to that in the row below. I note from the results that all the inequalities are clearly violated by the sample statistics for the data set suggesting that the South African market being analysed here shows signs of inefficiency.

The first Dicky-Fuller Test for the de-trended dividends yielded results with the test statistic -1.87 versus a 10% critical value of -3.180. This simple hypothesis test therefore does not reject H0: (Dividends follow a non-stationary process, i.e. $= 1$) in favour of H1: (Dividends follow a stationary process, i.e. $\rho < 1$) at the 10% level, which casts some doubt on the validity of the stationarity assumption that was made about the dividends. The next step was to test the first order differences of the dividend series for stationarity using the same method. The test statistic was -6.22 versus a 1% critical value of -4.157. There is significant evidence that the first order difference of dividends is stationary as this test rejects H0: (The first order difference of dividends follow a non-stationary process, i.e. $\rho = 1$) in favour of H1: (The first order difference of dividends follow a stationary process, i.e. $\rho < 1$). The interested reader is referred to Shiller (1981)'s work for the exploration of the Lagrangean as a function of the variance of the first order difference in de-trended price series and the first difference of the de-trended dividend series as this idea will not be explored in this analysis.

Stability requires that: $\left[{}^{\rho\sigma(c_{j,t})}/_{r}\right] < 1 + {}^{\sigma^2(\Delta p_{j,t})}/_{2r}$ and ${}^{\sigma^2(\Delta p_{j,t})}/_{2r} < 1$. Using the data set described above I calculate that ρ =3.51%, $\sigma(c_{j,t})$ = 1.22%, $\sigma(\Delta p_{j,t})$= 117.98% and

University of Cape Town

r = 4.16%. Substituting these values I get $\left[{}^{\rho\sigma(c_{j,t})}/_{r}\right]$= 0.010, ${}^{\sigma^2(\Delta p_{j,t})}/_{2r}$= 15.022. These values show that the solution above to equation 2.8 (4.2) is asymptotically unstable. Thus we have that the efficient market hypothesis cannot be rejected using this methodology.

5.5. Sources of Risks in Hedge Fund Returns

Table 21 below shows the results of the multi-factor regression by using the composite hedge fund index (HFI) that incorporates all hedge funds in our sample data to proxy a typical equally weighted diversified hedge fund of funds.

Table 21-Regression of the HFI on Nine Hedge Fund Risk Factors

(standard errors in parentheses)

Factor	01/2007-12/2011
Intercept	0.02033
	(0.01047)*^
ALSI	0.14956
	(0.01668)*^
SMB	0.05799
	(0.02128)*^
HML	-0.01716
	(-0.01101)
MOM	-0.01258
	(-0.01416)
10Y Gov B	-0.13514
	(0.12175)^
CredSpr	-0.19547
	(-0.12953)
PTFSBD	-0.00299
	(0.00445)^
PTFSFX	0.00555
	(-0.00384)
PTFSCOM	-0.00256
	(-0.000521)
Adjusted r^2	0.70

* *significant at the 5% level for multi-factor regression*

^ *significant at the 5% level for single factor regression*

Notes: ALSI=All Share Index; SMB=Small Cap Index-Large Cap index; HML= Fama and French's (1993) spread between the high book to market ratio stocks and the low book to market ratio stocks; MOM=Carharts' (1997) one year momentum factor; 10Y Gov B=10 year Government bond yield in South Africa; CredSpr=spread between GOVI and OTHI; PTFSBD=Return of a portfolio of lookback straddles on bond futures; PTFSFX= Return of a portfolio of lookback straddles on currency futures; PTFSCOM= Return of a portfolio of lookback straddles on commodity futures.

I extend my regression results by doing a single factor regression on the nine hedge fund risk factors to isolate the combined impact of the factors. The results show that by so doing two more factors, the 10 year government bond yield and the portfolio of straddles on bond futures are significant in addition to the All Share Index and the SMB factors which are significant in both the single factor and multi-factor regression model. The adjusted R^2 of the regression is 0.70 and there is a statistically significant intercept term of approximately 2.03% a month. These results suggest that, on average, hedge fund portfolios have systematic exposures to directional equity (ALSI), spread between small-cap stock returns and large cap stock returns (SMB), interest rate bets (10 year Government bond yield) and the trend following in bonds (PTFSBD). This means that after adjusting for these risk factors, an investor can earn an average alpha of approximately 2.03%. Although my composite hedge fund index (HFI) has no CTAs that are solely dedicated to bonds, the results displayed a significant beta with respect to the trend following factor on bonds during the investigation period. I infer that some of the hedge fund managers might have adopted trend following strategies on bonds during this period but more work is needed to be able to fully explain this observation. The high R^2 from these results is comparable to the result of Fung W. & Hsieh D. A. (2004) and affirms their assertion that only a limited number of risk factors are needed to capture the risk attributes of large diversified hedge fund portfolios.

Single factor regression on each of the nine factors revealed more about the results. The $R^2$of the regression on the ALSI factor is 0.67 confirming its dominance as a source of risk in hedge funds. The ALSI beta is highly significant and so is the intercept term which is

University of Cape Town

approximately 0.92%. The sample data is dominated by the equity hedge funds where equity long short and equity market neutral funds form 60% of the total funds in the sample data. This might be one of the reasons why exposures to directional equity were this high. Following ALSI's high R^2 is the SMB factor with R^2 of 0.08. This enormous difference in the explanatory power of the two factors again reveals the extent of dominance of the directional equity (ALSI) factor as a source of risk. Most of the other risk factors have R^2 that are below 0.05. These results are available as attachment to the thesis.

I further do regressions for each hedge fund investment style indices, equity long short, and equity market neutral, fixed income arbitrage and other hedge fund strategies. A multifactor regression by using an equally weighted equity long short index gives an adjusted R^2 of 0.84 which is much higher than that of the composite hedge fund index (HFI). The same risk factors that are significant on the above regression of the HFI are also significant in this regression analysis. Although the intercept term of approximately 1.54% is not significant on the multifactor regression, the intercept terms of single factor regressions are significant.

Regressing by using an equally weighted equity market neutral index gives an adjusted R^2 of 0.28. Only the ALSI factor is significant on a multifactor regression and on single factor regressions both the ALSI and the trend following in bonds (PTFSBD) factor are significant. Again the intercept term of approximately 1.05% is not significant on the multifactor regression while the intercept terms of single factor regressions are significant.

An equally weighted fixed income arbitrage index has an adjusted R^2 of -0.01 with no significant risk factor on the multi-factor regression including the intercept term. Intercept terms of single factor regressions are significant and also the spread between small-cap stock returns and large cap stock returns (SMB) factor. It is difficult to interpret why this term is significant with fixed income strategies. More work is needed for the explanation. A multi

University of Cape Town

factor regression by using an equally weighted other hedge fund strategies yields an adjusted R^2 of 0.24 with a significant ALSI factor which is the only factor significant in single factor regressions. The intercept term of approximately 2.53% is not significant on the multifactor regression while the intercept terms of single factor regressions are significant. The nine hedge fund risk factors seem to explain more of the equity long short risk exposures than other strategies. These results are again available as attachment to the thesis.

The last part looks at regression by using an equally weighted fund of hedge fund index (FoHF) and the results are shown in table 36 in appendix. There are a few differences to note in comparison with the regression by using hedge fund composite index (HFI). Firstly is that the adjusted R^2 for FoHF regression is a little lower than that for HFI. The intercept term for the FoHF on multifactor regression is not significant but significant only on single factor regressions. Only The ALSI factor is significant in both single factor and multi-factor regression. The trend following in bonds (PTFSBD) factor is not significant in FoHF single factor regression as it is in HFI regression. The main reason for these differences is that FoHF index is overweight the equity long short hedge fund managers as most of the funds of hedge funds are dedicated to this strategy only. This also explains the higher betas on the ALSI and SMB factors for the FoHF compared to the HFI. A diversified portfolio of funds of hedge funds is therefore more appropriate for my analysis.

5.6. Limitation of the Research

The main limitation in my thesis is the amount of data available in the hedge fund industry in South Africa. The industry is still small and maturing compared to the global one. The sample data used in this thesis is small and also the time period tested is not very long. I use Fund and Hsieh library to collect the returns for the portfolios of look back straddles on bonds, currencies and commodities as the South African market lacks the ability to provide

University of Cape Town

adequate data for me to construct local portfolios across these three factors of look back straddles. Local data will be more appropriate for my analysis.

The sample data used for the efficient market hypothesis test is very small. The data spans 52 years compared to the one used by Shiller (1981) which spanned 109 years. Flavin (1983) examines the small sample properties of volatility tests and shows that they are extremely biased toward finding excessive volatility. While my nine factor risk model for hedge funds has high explanatory power statistically, another set of variables that have high correlations with these nine factors would produce similar results. Moving away from diversified hedge fund of funds' portfolios to more specific hedge fund styles including individual funds one will require additional risk factors that are specific to the styles.

University of Cape Town

CHAPTER 6 Conclusion

6.1. Concluding Remarks

In this thesis I have analysed hedge funds in South Africa regarding different characteristics about their performance. In the first stage I investigated whether hedge funds' relative performance was persistent at four different time horizons– monthly, quarterly, semi-annually and annually. I divided hedge funds into different classifications to control for differences in investment strategy that they employed. Seven types of tests were used, Cross product ratio test, Chi-square test, Spearman rank correlation test, Hurst exponent, Cross-sectional regression test, Binomial test and the Kolmogorov-Smirnov test. I found statistically significant performance persistence of net returns at quarterly, semi-annually and annual time periods in all persistence test methodologies but Hurst Exponent. Performance persistence seemed to be at its peak in quarterly horizons across all different hedge fund investment styles.

The second stage then aimed to ascertain whether statistically significant persistence of relative performance in hedge funds has any implications for investors. I examined the duration of hedge fund portfolios performance persistence by ranking managers according to their past realised returns averaged over three to twelve months formation periods. I then formed two portfolios that contained the top ten performing funds and the other that contained the worst performing bottom ten funds. Portfolios were held during periods extending from three to twenty four months. Understanding the duration and also the patterns in hedge fund portfolios persistence can offer valuable insights regarding the type of strategies that are better suited for hedge funds investors whether these are momentum or contrarian. I observed clear indication of statistically significant short term portfolio performance persistence at three months' and six months' time horizon with three months and six months holding periods respectively for the portfolios with top performing funds. The duration of hedge fund portfolios performance

University of Cape Town

persistence seemed stronger at three months' time horizon. These results infer that an investor could have utilised a quarterly momentum strategy to gain superior returns during my investigation period. Such a method is possible in South Africa as the majority of hedge funds offer monthly liquidity with no lock up period (see, Novare Investment SA Hedge Fund Survey 2011) compared to their global counterparts. I also found a reversal in performance for the worst fund portfolios at longer holding time horizons. And importantly investors and portfolio managers can gain invaluable insights through the knowledge of how hedge fund styles perform differently in different market environments.

In the third stage I used the method followed by Shiller (1981) to test whether the market in South Africa as represented by the JSE All Share Index is efficient or not. Using extensive data that stretches over five decades from 31st December 1960 to 31st December 2011 I observed that measures of stock price volatility appeared to be far too high to be attributed to new information about future real dividends if uncertainty about future dividends is measured by the sample standard deviation of real dividends around their long run exponential growth path. The conclusion is similar to that of Shiller (1981). Although the results of the test showed that markets are more volatile than one would expect under the efficient market hypothesis I also found that we cannot accept the assumption that dividends are stationary and that the test results are not stable. Furthermore the sample data I used is small increasing the likelihood of inherent bias as argued by Flavin (1983) who examined the small sample properties of volatility tests and showed that they are extremely biased toward finding excessive volatility. The results therefore do not present a robust framework from within which the validity of the efficient market hypothesis can be challenged.

Finally, the last stage of my thesis investigated the different sources of risks in hedge funds using asset-based style (ABS) factors adapted from Fung & Hsieh (2004) work. The nine hedge fund risk factors can explain a significant part of the systematic risk (75%) of a typical

University of Cape Town

diversified hedge fund portfolio by using conventional securities prices. The implication is that the model can help investors and portfolio managers alike to understand how funds of hedge funds are placing their bets over time and more importantly identify alternative alphas inherent in the total return of these funds. I observed that directional equity exposure forms a larger and dominant risk factor in funds of hedge funds investing in South Africa. The nine hedge fund risk factors seemed to explain more of the equity long short risk exposures than other strategies.

I concluded in the same manner as Fung & Hsieh (2004) that knowing a fund's exposures to common securities risk factors helps hedge fund managers to report the systematic risks inherent in their strategies and investors can use this information in constructing hedge fund portfolios, managing risks, designing suitable performance benchmarks and detecting style drift through inconsistent bets by managers. This in turn improves the processes of risk disclosure and transparency in the hedge fund industry without the need for the investor to analyse large volumes of individual hedge fund transactions. The risk factor exposures can also help regulators identify converging bets in the hedge fund industry where certain trades become crowded as more and more hedge fund managers enter the same bet for different reasons. The danger is that if something wrong happens in these trades a financial meltdown can occur that can result in forced liquidations and further price declines as we saw with the Long Term Capital Management (LTCM) in 1998 following the Russian financial crisis. Regulators can therefore act in advance as they observe converging bets through use of these risk exposures to avert market stress.

University of Cape Town

6.2. Suggestions for Further Research

Kosowski et al. (2007) investigated performance of hedge funds by applying a new methodology of bootstrapping and found that there is evidence of performance persistence at annual horizon. Further research on the application of bootstrapping methodology to detect hedge fund performance persistence in South Africa may shed more light on the value of track record of hedge fund managers. One of the limitations in my analysis was that the sample data used was small and the period tested short due to the fact that hedge fund industry in South Africa is still growing. A study with a much bigger sample data and much longer testing period would improve the credibility of these results. Further research on how performance persistence relate to hedge fund attributes such as age, size of assets and compensation may reveal more on this topic.

The efficient market hypothesis test can be done once a much bigger data set can be assembled to improve the results. While the nine hedge fund risk factors can explain a significant part of the systematic risk of a typical diversified hedge fund portfolio, more work is needed to identify any additional risk factors that could improve the model and also for explaining individual hedge funds risks. More work could be done on analysing the time-varying characteristics of these risk factors and alpha to reveal the value added by the fund of hedge funds. Similarly more work is needed to explain the results on why the risk exposures display a significant beta with respect to the trend following factor on bonds when there are no CTAs solely dedicated to bonds during the investigation period.

University of Cape Town

Bibliography

Abraham, A. Seyyed, F. & Alsakran, S., (2002): Testing the Random Behavior and Efficiency of the Gulf Stock Markets, *The Financial Review*, 37, 3, pp. 469-480.

Agarwal, V. & Naik, N. Y., (2000): On Taking the Alternative Route: Risks, Reward, Style and Performance Persistence of Hedge Funds, *Journal of Alternative Investments*, 2, pp. 6-23.

Agarwal, V. & Naik, N. Y., (2000b): On Taking the Alternative Route: Risks, Rewards, and Performance Persistence of Hedge Funds, *Journal of Alternative Investments*, Vol. 2, No.4, pp. 6–23.

Agarwal, V. N., D. Daniel, & Naik, N. Y., (2007): Role of Managerial Incentives and Discretion in Hedge Fund Performance, *Working Paper*, October 2007.

Ackermann, C., McEnally, R. & Ravenscraft, D., (1999): The Performance of Hedge Funds: Risk, Return, and Incentives, *Journal of Finance 54*, No. 3, pp. 833-874.

Amenc, N. S., El. Bied, & Martellini, L., (2003): Predictability in Hedge Fund Returns, *Financial Analysts Journal*, Vol. 59, No. 5, pp. 32–46.

Amin, G. S. & Kat, H. M., (2001): Welcome to the Dark Side: Hedge Fund Attrition and Survivorship Bias 1994-2001, Working Paper ISMA Centre, University of Reading.

Baquero, G. J., ter Horst, & Verbeek, M., (2005): Survival, Look-Ahead Bias and the Persistence in Hedge Fund Performance, *Journal of Financial and Quantitative Analysis,* Vol. 40, No. 3, pp. 493–517.

Ball, R. & Brown, P., (1968): An empirical evaluation of accounting income numbers. *Journal of Accounting Research,* 6, pp. 159–78.

Ballew, A. Gupta, M., Lasry, & G. Weinberger A., (2002): *Hedge Funds: Approaches to Diversification,* Kellogg School of Management.

Banz, R., (1981): The relationship between return and market value of common stock: *Journal of Financial Economics,* 9, pp. 3–18.

Bares P. A., Gibson, R. & Gyger, S., (2002): Performance in the Hedge Fund Industry : An analysis of Short and Long-Term Persistence. NCCR-Working Paper No. 29.

Boyson, N. M. & Cooper, M. J., (2004): Do Hedge Funds Exhibit Performance Persistence?A New Approach, Working Paper, November 2004.

Brown, S. J. &Goetzmann, W. N., (1995): Performance Persistence, *Journal of Finance,* 50, pp. 679–698.

Brown, S. G., Goetzman, W. N. & Park J., (1997): Conditions for Survival: Changing Risks and Performance of Hedge Fund Managers and CTAs, Working Paper, NYU Stern School of Business,Yale School of Management, Paradigm Capital Managent Inc.

University of Cape Town

Brown, S.J., Goetzmann, W.N. & Ibbotson, R.G., (1999): Offshore Hedge Funds: Survival and Performance 1989-1995, *Journal of Business,* 72, No1, pp. 91-118.

Brown, S. J. & Goetzmann, W. N., (2001): Hedge Funds with Style, NBER Working Paper No. W8173.

Brown, S. J. & Goetzmann, W. N., (2003): Hedge Funds with Style, *Journal of Portfolio Management,* Vol. 29, No. 2 (Winter), pp. 101–112.

Bollen, Nicholas P. & Busse, J. A., (2004): Short-Term Persistence in Mutual Fund Performance. *The Review of Financial Studies,* 18, pp. 569–597.

Capocci, D., Corhay, A. & Hübne, G., (2005): Hedge Fund Performance and Persistence in Bull and Bear Markets, *European Journal of Finance,* Vol. 11, No. 5, pp. 361–392.

Capocci, D. & Hubner, G., (2004): Analysis of Hedge Fund Performance, *Journal of Empirical Finance,* Vol. 11, No. 1, pp. 55–89.

Capocci, D. P. J., (2007): An Analysis of Hedge Fund Strategies, HEC-School of Management, University of Liege, Belgium.

Capon, N., Fitzsimons, G. J. & Prince, R. A., (1996): An Individual Level Analysis of the Mutual Fund Investment Decision, *Journal of Financial Services Research,* Vol.10, No. 1, pp. 59–82.

Carhart, Mark M., (1997): On Persistence in Mutual Fund Performance. *Journal of Finance,* 52: pp. 57–82.

Carpenter, J. & Lynch A., (1999): Survivorship bias and attrition effects in measures of performance persistence, *Journal of Financial Economics,* 54, pp. 337-374.

Chen, K. & Passow A., (2003): Quantitative Selection of Long-Short Hedge Funds, FAME Research Paper No. 94.

Chopra, N., Lakonishok, J. & Ritter, J., (1992): Measuring Abnormal Performance: Do Stocks Overreact? *Journal of Financial Economics,* 31, pp. 235–86.

Connor, G. & Lasarte, T., (2004): An Introduction to Hedge Fund Strategies, Introductory Guide.

Cootner, P., (1962): Stock prices: random vs. systematic changes. *Industrial Management Review,* 3, pp. 24–45.

DeBondt, W. and Thaler, R., (1985): Does the stock market overreact? *Journal of Finance,* 40, pp. 793–807.

De Souza, C. & Gokcan S., (2004): Hedge Fund Investing: A Quantitative Approach to Hedge Fund Manager Selection and De-Selection, *Journal of Wealth Management*, Vol. 6, No. 4, pp. 52–73.

University of Cape Town

Droms, William G. & David A. Walker., (2001a): Persistence of Mutual Fund Operating Characteristics. Applied Financial Economics, 11, pp. 457–466

Droms, William G. & David A. Walker., (2001b): Performance Persistence of International Mutual Funds. *Global Finance Journal,* 12, pp. 1–13.

Droms, W. G., (2006): Does Past Performance Predict Future Returns? *Journal of Financial Plannin,* Vol. 19, No. 5, pp. 60–69.

Edwards, F. R. & Caglayan, M. O., (2001): Hedge Fund and Commodity Fund Investments in Bull and Bear Markets, *Journal of Portfolio Management,* 27, No.4, pp. 97-108.

Eling, M., (2008): Does Hedge Fund Performance Persist? Overview and New Empirical Evidence: Working Paper Series in Finance. Paper No. 41.

Elton, E., Gruber, M., Das, S. & Blake, C., (1996): The Persistence of Risk-adjusted Mutual Fund Performance, *Journal of Business 69,* No. 2, pp. 133-157.

Fama, E. & Blume, M., (1966): Filter rules and stock market trading profits. *Journal of Business,* 39, pp. 226–41

Fama, E., (1970): Efficient Capital Markets: A Review of Theory and Empirical Work *Journal of Finance, 25*, pp. 383 – 417.

Fama, E.F. & French, K.R., (1993): Common risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics,* 33, No.1, pp. 3-56.

Fung, W. & Hsieh, D.A., (1997): Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds, *Review of Financial Studies,* 10, No. 2, pp. 275-302.

Fung, W. & Hsieh, D.A., (2000): Performance Characteristics of Hedge Funds and Commodity Funds: Natural vs. Spurious Biases, *Journal of Quantitative and Financial Analysis,* 35, No. 3, pp. 291-307.

Fung, W. & Hsieh, D.A., (2002b): Benchmarks of Hedge Fund Performance: Information Content and Measurement Biases, *Financial Analyst Journal,* 58, pp. 22-34.

Fung, W. & Hsieh, D.A., (2006): Hedge Funds: An Industry in its Adolescence, Economic Review 91.

Garbaravicius, T. & Dierick F., (2005): Hedge Funds and Their Implications for Financial Stability, ECB. Occasional Paper Series, 34.

Goetzmann, W. N. & Ibbotson. R. G., (1994): Do Winners Repeat? Patterns in Mutual Fund Performance, *Journal of Portfolio Management,* 20, pp. 9–18.

Goetzman, W. N., Goetzmann W. N. & Ibbotson R. G., (1999): Offshore Hedge funds: Survival and Performance 1989-1995, *Journal of Business*, 72, pp. 91-117.

University of Cape Town

Gregoriou, G. N. & Rouah F., (2001): Last Year's Winning Hedge Fund as this Year's Selection: A Simple Trading Strategy, *Derivatives Use, Trading & Regulation*, Vol. 7, No. 3, pp. 269–274.

Gregoriou, G. N., (2002): Hedge Fund Survival Lifetimes, *Journal of Asset Management,* Vol. 3, No. 3, pp. 237-252.

Harri, A. & Brorsen B. W., (2004): Performance Persistence and the Source of Returns for Hedge Funds, Applied Financial Economics, Vol. 14, No. 2, pp. 131–141.

Hawawini, G., (1984): European Equity Markets: Price Behavior and Efficiency, Monograph Series in Finance and Economics*,* Saloman Center, New York University.

Hendricks, D., Patel, J. & Zeckhauser, R., (1993): Hot Hands in Mutual Funds: Short-run Persistence of Performance: 1974-88, *Journal of Finance 48,* No.1, pp. 93-130.

Henn, J. & Meier I., (2004): Performance Analysis of Hedge Funds, in: Dichtl, H., J.M. Kleeberg, and C. Schlenger (eds.): Handbuch Hedge Funds, Uhlenbruch, Bad Soden/Ts., pp. 435–466.

Herzberg, M. M. & Mozes H. A., (2003): The Persistence of Hedge Fund Risk: Evidence and Implications for Investors, *Journal of Alternative Investments,* Vol. 6, No. 2, pp. 22–42.

Huang, J., Liechty, J. & Rossi M., (2009): Smoothing, Persistence and Hedge Fund Performance Evaluation, http://ssrn.com/abstract=1363957, Pennsylvania State University.

Huberman, G. & Regev, T., (2001): Contagious speculation and a cure for cancer: a non-event that made stock prices soar.:*Journal of Finance,* 56, pp. 387–96.

Jagannathan, R., Malakhov, A. & Novikov D., (2006): Do Hot Hands Persist Among Hedge Fund Managers? An Empirical Evaluation, NBER-Working Paper 12015, January 2006.

Jan, Yin-Ching & Mao-Wei Hung, (2004): Short-Run and Long-Run Persistence in Mutual Funds. *Journal of Investing,* 13, pp. 67–71.

Jegadeesh, N. & Titman, S., (1993): Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance,* 48, pp. 65-91.

Jegadeesh, N. & Titman, S., (2001): Profitability of momentum strategies: an evaluation of alternative explanations. *Journal of Finance,* 56, pp. 699–720.

Kahneman, D. & Tversky, A., (1979): Prospect theory: an analysis of decision under risk. *Econometrica,* 47, pp. 263–91.

Kasimov, B. & Rosickas J., (2007): Performance Persistence and Hedge Funds' Attributes, Stockholm School of Economics.

Kat, H. M. & Menexe F., (2003): Persistence in Hedge Fund Performance: The True Value of a Track Record, *Journal of Alternative Investments,* Vol. 5, No. 4, pp. 66–72.

University of Cape Town

Keim, D., (1983): Size-related anomalies and stock return seasonality: further empirical Evidence: *Journal of Financial Economics,* 12, pp. 13–32.

Koh, F., & Koh, W. T. H. & Teo M., (2003): Asian Hedge Funds: Return Persistence, Style, and Fund Characteristics, Working Paper, Singapore Management University - School of Business.

Kosowski, R., Naik, N. Y. & M. Teo M., (2007): Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis, *Journal of Financial Economics,* Vol. 84, No. 1, pp. 229–264.

Kouwenberg, R., (2003): Do Hedge Funds Add Value to a Passive Portfolio? *Journal of Asset Management,* Vol. 3, No. 4, pp. 361–382.

Lakonishok, J. & Smidt, S., (1988): Are seasonal anomalies real? A ninety-year perspective: *Review of Financial Studies,* 1, pp. 403–25.

Lakonishok, J., Shleifer, A. & Vishny' R. W., (1994): Contrarian Investment, Extrapolation, and Risk, *The Journal of Finance*, 49, pp. 1541-1578.

Lehmann, B. (1990): Fads, martingales, and market efficiency. *Quarterly Journal of Economics,* 105, pp. 1–28.

LeRoy, S. & Porter, R., (1981): The present value relation: tests based on variance bounds. *Econometrica,* 49, pp. 555–74.

Liang, B., (2000): Hedge Funds: The Living and the Dead, *Journal of Financial and Quantitative Analysis,* 35, No. 3, pp. 309-325.

Liang, B. & Park, H., (2007): Risk Measures for Hedge Funds: A Cross-sectional Approach, European Financial Management, Vol. 13, No. 2, pp. 333-370.

Litner, J., (1965): The valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, Review of Economics and Statistics, 47, pp. 13-37.

Lo, A. W., (1997): Market Efficiency: Stock Market Behaviour in Theory and Practice Volume I and II, Chethenham, UK. An Elgar Reference Collection.

Lo, A. W., (2007): L. Blume and S. Durlauf, *The New Palgrave: A Dictionary of Economics*, Second Edition, 2007. New York: Palgrave McMillan.

Magnusson, M. & Wydick, B., (2000): How Efficient are Africa's Emerging Stock Markets, *Journal of Development Studies,* 38, 4, pp. 141-156.

Malkiel, B. G. & Saha, A., (2005): Hedge Funds: Risk and Return, *Financial Analysts Journal,* Vol. 61, No. 6, pp. 80–88.

Marsh, T. & Merton, R., (1986): Dividend variability and variance bounds tests for the rationality of stock market prices. *American Economic Review,* 76, pp. 483–98.

University of Cape Town

Michener, R., (1982): Variance bounds in a simple model of asset pricing. *Journal of Political Economy,* 90, pp. 166–75.

Osborne, M., (1959): Brownian motion in the stock market. Operations Research 7, pp. 145–73

Park, J., (1995): Managed Futures as an Investment Set, Ph.D. Dissertation, Columbia University.

Posthuma, N. & Van der Sluis, P. J., (2003): A Reality Check on Hedge Fund returns, working paper ABP Investments.

Ranaldo, A. & Favre L., (2005): Hedge Fund Performance & Higher-Moment Market Models. *Journal of Alternative Investments,* Winter Issue 8(3), pp. 37-51.

Roll, R., (1983): The turn-of-the-year effect and the return premia of small firms: *Journal of Portfolio Management,* 9, pp. 18–28.

Ross, S., (1976): The arbitrage Theory of Capital Asset Pricing, *Journal of Economic Theory*, 13, pp. 341-360.

Rouwenhorst, K. G., (1998): International Momentum Strategies, *The Journal of Economic Theory,* 13, pp. 341-360.

Rozeff, M. & Kinney, W. Jr., (1976): Capital market seasonality: the case of stock returns. *Journal of Financial Economics,* 3, pp. 379–402.

Samuelson, P. A., (1970): A Fundamental Approximation Theory of Portfolio Analysis in Terms of Means, Variance, and Higher Moments, Review of Economic Studies 37, pp.537-542.

Schmid, M. M. & Manser S., (2008): The Performance Persistence of Equity Long/Short Hedge Funds, Swiss Institute of Banking and Finance, University of St. Gallen, CH-9000 St. Gallen, Switzerland

Sharpe, W. F., (1966): Mutual Fund Performance, *Journal of Business,* Vol. 39, No. 1, pp. 119–138.

Shiller, R., (1981): Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review,* 71, pp. 421–36.

Summers, L.H., (1986): Does the stock market rationally reflect fundamental values? *Journal of Finance,* 41, pp. 591-601.

University of Cape Town

Appendix

Table 22: Summary of Hedge Fund Strategies

STRATEGY	HEDGE FUNDS
Equity Long Short	-the funds go long (buy) equities expected to rise in value and sells short those expected to fall. These managers generally run their portfolios with variable net long market exposure.
Equity Market Neutral	-similar to equity long short except portfolios are run with little to no net market exposure, through balancing their long and short positions.
Short Sellers (Bias)	-maintains a net short equity position over various market cycles.
Convertible Arbitrage	-focuses on pricing discrepancies between convertible bonds and the equity portion of the issuing firm. The value of the option portion of the bond is hedged by using a short position in the stock or options.
Distressed Securities	-invest (long or short) in securities of companies that have been or will be affected by a distressed situation such as reorganisation bankruptcies, distressed sales and corporate restructuring.
Event Driven	-opportunities utilised include events such as industry consolidations, mergers, acquisitions, spin-offs, recapitalisation, share buybacks, liquidations, leveraged buyouts and hostile takeovers. Funds are generally long firms being acquired and short the stock of the acquiring firm.
Fixed Income Arbitrage	-managers exploit inefficiencies in the pricing of interest rate risk across the yield curve and derivative markets. The main aim is to capitalise on changes in curve shape.
Emerging Markets	-hedge funds investing in asset classes in countries that are classified as emerging.
Global Macro	-Incorporates a global macro analysis approach in order to identify extreme price valuations and any anticipated price movements in all types of securities.
Volatility Arbitrage	-trade volatility as an asset class, employing arbitrage, directional, market neutral or a mix of types of strategies and can include exposures which can be long, short, neutral or variable to the direction of implied volatility.
Trend Following	-investment processes is built as a function of mathematical, algorithmic and technical models, with minimal or no influence of individuals over the portfolio positioning.
Statistical Arbitrage	-similar to market neutral but employ sophisticated quantitative techniques of analysing price data to ascertain information about future price movement and relationships between securities, select securities to go long (buy) and those to short sell.
Commodities	-strategies are reliant on the evaluation of market data, relationships and influences as they pertain primarily to commodity markets which include energy, agriculture and metals.
Credit Arbitrage	-isolate attractive opportunities in corporate fixed income securities such as senior and subordinated claims and bank debt.
Funds of Hedge Funds	-fund managers invest in a series of other hedge funds in pursuit of diversification.

University of Cape Town

Table 23: Summary of Measures for Testing Performance Persistence

Measure			Used in:
Return		only post fee	Agarwal et al. (2005), Amenc et al. (2003) Baquero et al. (2005), Bares et al. (2003) Brown & Goetzmann (2003) De Souza & Gokcan (2004) Harri & Brorsen (2004), Henn & Meier (2004), Herzberg & Mozes (2003) Kat & Menexe (2003) ,Kouwenberg (2003) Malkiel & Saha (2005) Haung et al. (2009), Eling M (2008)
		post fee and pre-fee	Brown et al. (1999) Koh et al. (2003), Eling M (2008)
Risk	Standard deviation		De Souza & Gokcan (2004) Herzberg & Mozes (2003) Kat & Menexe (2003), Eling M (2008)
Higher Moments	Maximum drawdown		Herzberg & Mozes (2003), Eling M (2008)
	Skewness		Kat & Menexe (2003), Eling M (2008)
	Kurtosis		Kat & Menexe (2003), Eling M (2008)
Correlation			Herzberg & Mozes (2003) Kat & Menexe (2003), Eling M (2008)
Risk Adjusted Performance	Information ratio		Harri & Brorsen (2004), Eling M (2008)
	Sharpe ratio		De Souza & Gokcan (2004) Harri & Brorsen (2004) Herzberg & Mozes (2003) Schmid M & Manser S (2008)
	Alpha	Hedge fund style adjusted	Agarwal & Naik (2000a) Agarwal & Naik (2000b), Baquero et al. (2005), Bares et al. (2003) Boyson & Cooper (2004) Brown et al. (1999), Eling M (2008)
		Market adjusted(Fama/French,Carhart)	Capocci et al. (2005) Capocci & Hubner (2004) Chen & Passow (2003) Edwards & Caglayan (2001) Gregoriou & Rouah (2001) Harri & Brorsen (2004), Koh et al. (2003) Kosowski et al. (2006), Kouwenberg (2003)
		Market and hedge fund style adjusted	Jagannathan et al. (2006) Schmid M & Manser S (2008), Eling M (2008)
	Appraisal ratio		Agarwal & Naik (2000a), Eling M (2008) Agarwal & Naik (2000b) Brown et al. (1999), Park & Staum (1998)

University of Cape Town

Table 24: Summary of Methodologies for Testing Performance Persistence

Period Framework	Methodological Basis	Test(Statistic)	Used in (authors)
Two-Period	Contingency table-based (*nonparametric*)	Cross-product ratio test (*Z-statistic*)	Agarwal & Naik (2000a) Agarwal & Naik (2000b), Brown et al. (1999) DeSouza & Gokcan (2004 Edwards & Caglayan (2001) Henn & Meier (2004) Kat & Menexe (2003), Koh et al. (2003) Eling (2008)
		Chi-square test (X^2-*Statistic*)	Agarwal et al. (2005) Agarwal & Naik (2000a), Koh et al. (2003) Kouwenberg (2003) Malkiel & Saha (2005) Park & Staum (1998) Eling (2008)
		Binomial test	Bares, et al. (2002)
	Correlation-based (*nonparametric*)	Rank information coefficient (*Fisher T-Statistic*)	Herzberg & Mozes (2003) Eling (2008)
		Spearman rank correlation test (*Fisher T-Statistic*)	Harri & Brorsen (2004) Park & Staum (1998) Eling (2008)
	(*nonparametric*)	Hurst exponent (*D-Statistic*)	Amenc et al. (2003) De Souza & Gokcan (2004) Eling (2008)
	Regression-based (*parametric*)	cross-sectional regression (*T-statistic*)	Agarwal et al. (2005), Agarwal & Naik (2000a), Agarwal & Naik (2000b) Amenc et al. (2003), Bares et al. (2003) Boyson & Cooper (2004), Brown et al. (1999), Brown & Goetzmann (2003), Capocci et al. (2005), Capocci & Hubner (2004), Chen & Passow (2003), De Souza & Gokcan (2004), Edwards & Caglayan (2001), Harri & Brorsen (2004), Jagannathan et al. (2006), Kat & Menexe (2003) ,Kosowski et al. (2006), Schmid & Manser (2008)
Multi Period		Kolmogorov/Smirnov test	Agarwal & Naik (2000a) Koh et al. (2003), Eling (2008)

University of Cape Town

Table 25: Summary of Advantages and Disadvantages of the Methodologies

Methodology Test (Statistic)	Used In	Assessment
cross-product ratio test (Z-statistic)	1. Agarwal & Naik (2000a) 2. Agarwal & Naik (2000b) 3. Brown et al. (1999) 4. DeSouza & Gokcan (2004 5. Edwards & Caglayan (2001) 6. Henn & Meier (2004) 7. Kat & Menexe (2003) 8. Koh et al. (2003)	+ Data requirement low + Simple to calculate (implemented in standard software such as Excel or SPSS) + Easy to communicate - Large differences in the evaluation of nearly identical funds at the thresholds (see Blake & Timmermann, 2003)
chi-square test (X^2-statistic)	1. Agarwal et al. (2007) 2. Agarwal & Naik (2000a) 3. Koh et al. (2003) 4. Kouwenberg (2003) 5. Malkiel & Saha (2005) 6. Park & Staum (1998)	+ Data requirement low + More robust in the presence of survivorship bias (see Carpenter and Lynch, 1999) - Large differences in the evaluation of nearly identical funds at the threshold (see Blake and Timmermann, 2003) - More complicated to calculate and to communicate than the CPR test
rank information coefficient (Fisher T-statistic)	1. Herzberg & Mozes (2003)	+ Data requirement low + Simple to calculate (implemented in standard software such as Excel or SPSS) + Easy to communicate - Displays serial correlation
Spearman rank correlation test (Fisher T-statistic)	1. Harri & Brorsen (2004) 2. Park & Staum (1998)	+ Data requirement low + No requirement that the variables must be measured on interval scales + No assumption that the relationship between the variables is linear + Simple to calculate (implemented in standard software such as Excel or SPSS) - Displays serial correlation
cross-sectional regression (T-statistic)	1. Agarwal et al. (2007) 2. Agarwal & Naik (2000a) 3. Agarwal & Naik (2000b) 4. Amenc et al. (2003) 5. Barès et al. (2003) 6. Boyson & Cooper (2004) 7. Brown et al. (1999)	+ Simple to calculate (implemented in standard software such as Excel or SPSS) - Assumption of normally distributed residuals is critical - Assumption of uncorrelated residuals is critical, but modified test statistics for

University of Cape Town

	8. Brown & Goetzmann (2003) 9. Capocci et al. (2005) 10. Capocci & Hübner (2004) 11. Chen & Passow (2003) 12. De Souza & Gokcan (2004) 13. Edwards & Caglayan (2001) 14. Harri & Brorsen (2004) 15. Jagannathan et al. (2006) 16. Kat & Menexe (2003) 17. Kosowski et al. (2007)	auto-correlated data are available (see Newey & West, 1987) - Too few data, especially at the annual and the biannual horizon, to run a sound regression analysis
Binomial test	1. Bares, et al. (2002)	+ Data requirement low + More exhaustive analysis compared to CPR and chi-square test (see Bares, P. et al. (2002) - Large differences in the evaluation of nearly identical funds at the threshold (see Blake & Timmermann, 2003).
Kolmogorov-Smirnov test (KS-statistic)	1. Agarwal & Naik (2000a) 2. Koh et al. (2003)	+ Data requirement low + Very robust compared to other methodologies (see Agarwal & Naik, 2000a) + More efficient than chi-square test for small samples (see Géhin, 2004) + Differences in the evaluation of nearly identical funds at the threshold (see Blake & Timmermann, 2003) is less severe problem compared to the CPR and chi-square test (evaluation based on more than one threshold) - Test is designed to use with independent data, but modified test statistics for auto-correlated data are available (see Weiss, 1978)

University of Cape Town

Table 26-Equity Market Neutral CPR and Chi-Square Test Results

Panel A: Equity Market Neutral Results							
Period	WW	WL	LW	LL	CPR	Z-statistic of CPR	X^2-statistic
1 months	439	396	394	450	1.2662	2.4131^	5.8531*
3 months	605	199	193	617	9.7192	19.5868^^	426.8179**
6 months	637	132	129	607	22.7073	22.9306^^	644.8119**
12 months	627	80	76	525	54.1406	23.376^^	755.5507**

^Significant at the 5% level (Z-statistic critical value=1.96) **Significant at the 5% level (chi-square critical value=3.84)*

^^ Significant at the 1% level (Z-statistic critical value=2.58) ***Significant at the 1% level (chi-square critical value=6.63)*

Table 27-Fixed Income Arbitrage CPR and Chi-Square Test Results

Panel A:Fixed Income Arbitrage Results							
Period	WW	WL	LW	LL	CPR	Z-statistic of CPR	X^2-statistic
1 months	216	196	195	271	1.5316	3.1299^^	9.8340**
3 months	282	94	92	374	12.1957	15.0200^^	257.3659**
6 months	292	51	47	398	48.4839	17.9369^^	448.0398**
12 months	265	42	38	334	55.4574	16.8354^^	422.4425**

^^ Significant at the 1% level (Z-statistic critical value=2.58) ***Significant at the 1% level (chi-square critical value=6.63)*

Table 28-Other Hedge Fund Strategies CPR and Chi-Square Test Results

Panel A:Other Hedge Funds Strategies Results							
Period	WW	WL	LW	LL	CPR	Z-statistic of CPR	X^2-statistic
1 months	344	289	285	338	1.4117	3.0433^^	9.2845**
3 months	498	141	142	419	10.4216	17.2190^^	332.3664**
6 months	504	89	88	437	28.1216	20.3538^^	520.3491**
12 months	485	49	44	378	85.0325	20.3129^^	620.3771**

^^ Significant at the 1% level (Z-statistic critical value=2.58) ***Significant at the 1% level (chi-square critical value=6.63)*

University of Cape Town

Table 29-Cross Sectional Regression at 1% Level

The table below show the percentage of cases exhibiting statistically significant performance using cross-sectional regression test at 1% level during the period that extends from January 2007 to December 2011 across Equity long short (EQLS), Equity Market Neutral (EQMN), Fixed Income Arbitrage (FIA), and Other Strategies and include two additional tests of All funds and Living/Surviving (Alive) funds. We consider 4 different time horizons namely 1, 3, 6, and 12 months.

INVESTMENT STRATEGIES	PERIOD			
	1 month	3 months	6 months	12 months
EQLS	19%	89%	98%	98%
EQMN	15%	92%	98%	100%
FIA	19%	75%	90%	100%
OTHER	15%	83%	92%	98%
ALL FUNDS	25%	94%	100%	100%
ALIVE FUNDS	33%	94%	100%	100%

Table 30-Spearman's Rank Correlation Test at 1% Level

The table below show the percentage of cases exhibiting statistically significant performance using spearman's rank correlation test at the 1% level during the period that extends from January 2007 to December 2011 across Equity long short (EQLS), Equity Market Neutral (EQMN), Fixed Income Arbitrage (FIA), Other Strategies and include two additional tests of All funds and Living/Surviving (Alive) funds. We consider 4 different time horizons namely 1, 3, 6, and 12 months.

INVESTMENT STRATEGIES	PERIOD			
	1 month	3 months	6 months	12 months
EQLS	14%	88%	100%	96%
EQMN	10%	88%	100%	100%
FIA	8%	76%	89%	90%
OTHER	10%	73%	85%	98%
ALL FUNDS	19%	96%	98%	100%
ALIVE FUNDS	14%	95%	100%	100%

Table 31-Binomial Test at 1% Level

The table below show the individual performance persistence of the hedge fund managers during the period that extends from January 2007 to December 2011. We distinguish between four investment strategies: Equity long short (EQLS), Equity Market Neutral (EQMN), Fixed Income Arbitrage (FIA), and Other Strategies and include two additional tests of All funds and Living/Surviving (Alive) funds. We consider 4 different time horizons namely 1, 3, 6, and 12 months. We report the total number of managers under consideration, the number of managers with a significant tendency to perform above or below the median manager of the strategy, denoted ↑ and ↓, respectively (determined with a one sided binomial test at the 1%).

PERIOD	FUNDS SELECTION	INVESTMENT STRATEGIES					
		EQLS	EQMN	FIA	OTHER	ALL FUNDS	ALIVE FUNDS
	Total	34	34	18	28	114	82
1 month	Signif. ↑ or ↓	3 (9%)	2 (6%)	7 (39%)	5 (18%)	17 (15%)	10 (12%)
	Signif ↑	2 (6%)	0 (0%)	3 (17%)	3 (11%)	7 (6%)	4 (5%)
	Signif ↓	1 (3%)	2 (6%)	4 (22%)	2 (7%)	10 (9%)	6 (7%)
3 months	Signif. ↑ or ↓	9 (26%)	14 (41%)	10 (56%)	10 (36%)	42 (37%)	30 (37%)
	Signif ↑	7 (21%)	7 (21%)	3 (17%)	5 (18%)	19 (17%)	14 (17%)
	Signif ↓	2 (6%)	7 (21%)	7 (39%)	5 (18%)	23 (20%)	16 (20%)
6 months	Signif. ↑ or ↓	11 (32%)	14 (41%)	11 (61%)	16 (57%)	46 (40%)	33 (40%)
	Signif ↑	6 (18%)	6 (18%)	4 (22%)	9 (32%)	19 (17%)	11 (13%)
	Signif ↓	5 (15%)	8 (24%)	7 (39%)	7 (25%)	27 (24%)	21 (26%)
12 months	Signif. ↑ or ↓	13 (38%)	16 (47%)	10 (56%)	17 (61%)	53 (46%)	41 (50%)
	Signif ↑	8 (24%)	11 (32%)	5 (28%)	11 (39%)	25 (22%)	16 (20%)
	Signif ↓	5 (15%)	5 (15%)	5 (28%)	6 (21%)	28 (25%)	25 (30%)

Table 32-Hurst Exponent Test at 1% Level

The table below show the percentage of cases exhibiting statistically significant performance using Hurst exponent test at the 1% during the period that extends from January 2007 to December 2011across Equity long short (EQLS), Equity Market Neutral (EQMN), Fixed Income Arbitrage (FIA), Other Strategies and include two additional tests of All funds and Living/Surviving (Alive) funds. We consider 4 different time horizons namely 1, 3, 6, and 12 months.

INVESTMENT STRATEGIES	PERIOD			
	1 month	3 months	6 months	12 months
EQLS	94%	100%	100%	97%
EQMN	100%	100%	100%	97%
FIA	100%	100%	100%	94%
OTHER	100%	100%	100%	96%
ALL FUNDS	100%	100%	100%	97%
ALIVE FUNDS	100%	100%	100%	98%

Table 33-Equity Market Neutral Kolmogorov-Smirnov Test Results

Panel B-Equity Market Neutral Results		
Period	**Kolmogorov-Smirnov Statistic**	
	Wins	**Losses**
1 month	0.0214	0.0020
3 months	0.1538**	0.1538**
6 months	0.2242**	0.2083**
12 months	0.3177**	0.2328**

*** Distribution of wins/losses significant at the 1% level*
** Distribution of wins/losses significant at the 5% level*

Table 34-Fixed Income Arbitrage Kolmogorov-Smirnov Test Results

Panel B-Fixed Income Arbitrage Results		
Period	**Kolmogorov-Smirnov Statistic**	
	Wins	**Losses**
1 month	-0.0072	0.0568
3 months	0.1080*	0.1868**
6 months	0.1739**	0.3041**
12 months	0.2217**	0.3150**

*** Distribution of wins/losses significant at the 1% level*
** Distribution of wins/losses significant at the 5% level*

Table 35-Other Hedge Fund Strategies Kolmogorov-Smirnov Test Results

Panel B-Other Hedge Fund Strategies Results		
Period	**Kolmogorov-Smirnov Statistic**	
	Wins	**Losses**
1 month	0.0365	0.0199
3 months	0.1780**	0.1250**
6 months	0.2582**	0.2038**
12 months	0.3269**	0.2404**

*** Distribution of wins/losses significant at the 1% level*
** Distribution of wins/losses significant at the 5% level*

Table 36-Regression of the FoHF on Nine Hedge Fund Risk Factors

(standard errors in parentheses)

Factor	01/2007-12/2011
Intercept	0.02135
	0.01582^
ALSI	0.20241
	(0.02521)*^
SMB	0.12903
	(0.03216)*
HML	-0.03084
	(-0.01663)
MOM	-0.02188
	-0.02140
10Y Gov B	-0.18721
	(0.18397)^
CredSpr	-0.32889
	-0.19574
PTFSBD	-0.00067
	-0.00672
PTFSFX	0.00616
	-0.00581
PTFSCOM	-0.00018
	0.00788
Adjusted r^2	0.61

* *significant at the 5% level for multi-factor regression*

^ *significant at the 5% level for single factor regression*

Notes: ALSI=All Share Index; SMB=Small Cap Index-Large Cap index; HML= Fama and French's (1993) spread between the high book to market ratio stocks and the low book to market ratio stocks; MOM=Carharts' (1997) one year momentum factor; 10Y Gov B=10 year Government bond yield in South Africa; CredSpr=spread between GOVI and OTHI; PTFSBD=Return of a portfolio of lookback straddles on bond futures; PTFSFX= Return of a portfolio of lookback straddles on currency futures; PTFSCOM= Return of a portfolio of lookback straddles on commodity futures.

Table 37-Annual Performance of Hedge Funds Strategies

The table below show the annual performance of hedge funds strategies during the period that extends from January 2007 to December 2011 across Equity long short (EQLS), Equity Market Neutral (EQMN), Fixed Income Arbitrage (FIA), Trend Following (CTA), Credit, Multi-Strategies (Mstrat), Statistical Arbitrage (Stat arb), Volatility Arbitrage (Vol arb) and Unknown.

Strategy	2007	2008	2009	2010	2011
EQLS	23.00%	-0.95%	18.28%	12.29%	8.32%
EQMN	16.01%	9.89%	15.72%	6.64%	7.07%
FI	14.63%	16.76%	20.70%	21.16%	9.90%
CTA	20.51%	23.68%	18.42%	12.70%	4.07%
Credit	22.62%	17.74%	12.88%	13.93%	12.56%
Mstrat	14.48%	10.23%	13.83%	7.46%	11.34%
Stat arb	16.73%	11.67%	11.98%	1.37%	0.55%
Vol	8.10%	15.91%	1.50%	-4.94%	-8.22%
Unknown	38.61%	0.08%	15.18%	15.38%	-7.98%

University of Ca

Table 38-Eqautions

Equation 2.6

$$p_{j,t} = \sum_{k=0}^{\infty} \bar{\lambda}^{k+1} \times E_t c_{j,t+k}$$

Where; $\gamma^{t-T} = (1+g)^{t-T}$, where T is the base year;

$p_{j,t} = {}^{P_{j,t}}\!/_{\gamma^{t-T}}$;

$c_{j,t} = {}^{C_{j,t}}\!/_{\gamma^{t+1-T}}$;

$\bar{\lambda} = {}^{(1+g)}\!/_{(1+r)} = {}^{1}\!/_{(1+\bar{r})}$ and $g < r$ such that $\bar{r} > 0$

By taking unconditional expectations on both sides of 2.5, Shiller R. (1981) finds that:

$E(p_j) = {}^{\bar{\lambda}}\!/_{(1-\bar{\lambda})} \times E(c_t) \rightarrow \bar{r} = {}^{E(p_j)}\!/_{E(c_j)}$

If $p^*_{j,t}$ is the present value of actual subsequent dividends, then $p_{j,t} = E_t p^*_{j,t}$, where $p^*_{j,t} = \sum_{k=0}^{\infty} \bar{\lambda}^{k+1} \times c_{j,t+k}$.

Since this summation extends to infinity, $p^*_{j,t}$ cannot be observed without some error. A long enough price and dividend series may allow us to approximate $p^*_{j,t}$, whilst we can examine sensitivity of the test results by using alternative terminal value for $p^*_{j,t}$. Shiller uses the average of the series $\{p^*_{j,t}\}$ as the terminal value for $p^*_{j,t}$ at time T.

University of Cape Town

Table 39-Linking Market Inefficiencies to Hedge Fund Strategies

The table below show how market inefficiencies as described in Chapter 2 can be utilised by the managers in the different Hedge Fund Strategies (see Chapter 3) used in the research.

Hedge Fund Strategy	**Market inefficiencies that can be utilised by hedge fund managers***
Equity Long Short	Momentum strategies, overreaction/underreaction, Price reversals, herding, overconfidence, psychological accounting, hyperbolic discounting, regret, loss aversion, miscalibration of probabilities, seasonal patterns, size effect, post-earnings announcement drift, market to book ratios, price earnings ratios, dividend yield and contrarian strategies
Equity Market Neutral	These utilise the same inefficiencies as the equity long short except that portfolios are run with little to no net market exposure, through balancing their long and short positions.
Fixed Income	Miscalibration of probabilities, herding, overconfidence, loss aversion, price reversals and contrarian strategies
Statistical Arbitrage	Miscalibration of probabilities, momentum, overreaction/underreaction and price reversals
Volatility Arbitrage	Overreaction/underreaction, price reversals, loss aversion and volatility of futures prices
Trend Following/CTA	Herding, momentum, overconfidence, loss aversion, volatility of futures prices, overreaction/underreaction and regret.
Commodities	Seasonal patterns, volatility of future prices and contrarian strategies
Credit	Miscalibration of probabilities, overreaction/underreaction and price reversals
Multi-Strategies	This will involve combination of all the strategies.

**See 2.5.1.causes of market inefficiencies in Chapter2 Literature Review*

University of Cape Town