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HEDGE FUND PERFORMANCE PERSISTANCE AFTER WEAK MARKETS

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UNIVERSITY OF OULU ABSTRACT OF THE MASTER'S THESIS

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Abstract

Our aim for this thesis is to study whether hedge fund performance persists after weak markets, and do the results differ from performance persistence after strong markets. We are interested in overall market situations' impact on performance persistence of hedge funds. Our data is from Lipper TASS hedge fund database, with 18891 hedge funds and 1261782 observations from December 1993 to June 2013. The data is modified so that we've cleared out non-USD funds, non-monthly filing funds, and funds with unknown strategy. We've also excluded the first 18 months of returns for every fund to control the backfill bias. This leaves us with 9107 funds. We divide the time series into periods of recessions and expansions based on the overall stock market situation. The main recession periods are the dot-com bubble from 31st May 2000 to 30th September 2002 and the financial crisis from 31st August 2007 to 28th February 2009. Otherwise the time periods between 30th June 1997 to 30th June 2013 are considered as expansion periods. The main steps after cleaning our data are: First we calculate the logarithmic excess returns of the funds. Then we use the Fung and Hsieh seven-factor model over the past 12 months' returns to estimate the time-varying t-value of alpha for each fund. Next we sort the funds into decile portfolios based on their t-values of alpha. After that we calculate the monthly equal-weighted returns for the decile portfolios using three-month and twelve-month holding periods. We also calculate the monthly equal-weighted returns for the spread portfolio between the top and bottom portfolios. Next, we calculate for the decile portfolios the annualized mean, standard deviation, Sharpe ratio, t-value of Sharpe ratio, p-value of Sharpe ratio, annualized Fung-Hsieh seven-factor alpha, t-value of alpha and p-value of alpha. The null-hypothesis is that there is no difference in performance persistence after recession and expansion periods. What we can conclude from our results is that badly performing portfolios likely keep on performing badly despite the overall market situation, and even though there is some indications that the very best portfolios can make at least short-term profit even in bust periods, the performance is not persistent. We cannot identify the skilled fund managers from others by looking at hedge fund's performance during market crisis. For further studies, the Lipper TASS database's information of the hedge fund strategy categories could be used to identify the underlying factors in conditional performance persistence of hedge funds.

Keywords

Conditional, recession

Additional information

Contents

FIGURES

TABLES

1 INTRODUCTION

There's been already two recessions in the 21st century, the IT-bubble in the early 2000s and the financial crisis in 2008, the economy has not yet fully recovered from these and we are yet again facing another recession due to the coronavirus pandemic. So, in these uncertain times, is there a way to still make money? Are some hedge funds thriving in recessions and are their results consistent or just a fluke? These are the questions we are trying to explore in this thesis, or more formally, we are to study whether hedge fund performance persists conditionally. The condition here is the overall market situation divided into recessions and expansions. The interest is especially in performance persistence after recessions because one could assume that crisis separates the wheat from the chaff, also among hedge funds.

The main inspiration for this thesis came from an article 'Only winners in tough times repeat: Hedge fund performance persistence over different market conditions' (Sun et al. 2016). The study shows that there exists predictability for hedge fund's performance after weak markets but not after strong markets. When this thesis was started in 2017, there were no major signs of global recession, although the after effects of the 2008 financial crisis were still lingering, and there were growing tension between USA and China and fears of trade war. The financial markets were used to living in uncertainty and these whispers were not going to rock the boat. But what if there was some major global event lurking behind the corner, something that the markets can't anticipate? What will happen to the hedge funds? They are supposed to be operated by the most qualified financial professionals and surely they should be the ones that can make even the direst conditions into opportunities. But what does the data say? We have abundant amounts of data from the hedge funds and the financial markets in general, and we already have had two recessions. So, how did hedge funds fare during those rough times? And did those hedge funds that were successful during crisis, continue to be successful during good times? The coronavirus pandemic, this was just the kind of situation, that was in mind when this thesis begun to form.

A word about this COVID-19 and the comparison between this looming recession versus the past recessions. The mechanics of this recession are quite different than those of recent recessions. In the past the financial markets themselves were the origin

of the crisis, so the disruption was more in the realm of financials, and not directly in the real economy, although the effect rippled to common people's lives via crashing market values of shares, or unpredictable increases in the housing loan interests. This resulted in a situation, where the demand decreased while the supply remained the same. Coronavirus pandemic originates from real life, it has direct impact on people's lives, and this impacts the financial markets. Logistics worldwide are disrupted and while the demand is high on certain product areas, the supply and distribution can't keep up with the demand. So the material flows are unbalanced, but so is the service sector because of restrictions of movement of people and precautionary measures in services that are still allowed to continue.

Because this recession is so different from past recessions, the tools that hedge funds have used before may not be as effective this time. But we can analyze the data of past recessions, come to a conclusion about the results, and after this recession is over we can add valuable new data in our research, and see if some hedge funds actually can overcome market disturbances and hedge the investments against them. This is the ultimate question behind this thesis, and hopefully this topic is continued after this pandemic and its global effects are settled. What will be the new normal then? How will finance theories evolve to adapt in this new normal? The financial crisis brought us the reality of negative interests, this wasn't supposed to be possible, but here we are, a decade later, comfortably adjusted to the idea. Is this pandemic going to be the start of big reforms in capitalism and free markets?

Because of hedge funds' short history, only recently there has been studies about different market conditions' effects on hedge fund performance persistence. Does hedge fund's performance persist differently after recessions than after expansions? The dot-com bubble and financial crisis have given a lot of data on which to study this question.

The aim of this thesis is to study whether hedge fund performance persists after weak markets and does the results differ from performance persistence after strong markets. Further analysis of the hedge funds' characteristics is also needed to understand the underlying reasons for the differences in the results.

The implication of the results could be that perhaps one can identify the skilled fund managers from others by looking at hedge fund's performance during market crisis. This is important issue especially now that we are yet again facing financially uncertain times.

2 THEORETICAL FRAMEWORK

There has been numerous attempts of solving the mystery of hedge funds and what are the underlying forces of hedge fund performance and how to predict whether that performance will persist. Hedge funds differ from mutual funds by having much less regulation; hedge funds don't have to report their returns, they use dynamic strategies, they can sell short, speculate with derivatives, use leverage, and use lock-up periods. Hedge fund investors are either wealthy individuals or institutional investors.

2.1 Efficient Market Hypothesis (EMH)

The efficient market hypothesis (EMH) assumes that the stock prices always reflect reality and take into account all available information, and there isn't any chance of outperforming the market as the market is perfectly priced (Fama 1970). Under the assumptions of EMH, an investor can't find any undervalued stocks, or time their investment, and the only way to make higher returns is to buy riskier assets.

The EMH claims that the market always represents the fair value and therefore the best portfolios are those that passively follow the market and don't have high management costs, such as hedge funds have.

If the EMH was correct, then it would be impossible to make consistent risk-adjusted excess returns, also known as alpha. Real life suggests otherwise, there are well-known investors such as Warren Buffett and hedge funds that have been successful in their investments (Agarwall et al. 2013), but the question is, is that just luck? Is there reoccurring irregularities in the market that skilled individuals can spot and take advantage of, or are the gains of these individuals only outliers in the vast sea of market data, or perhaps due to some insider information that the public has no access to?

The EMH is controversial, but large amount of research backs it up (Agarwall et al. 2013, Basu 1977, Keane 1986, Lo 2007, Malkiel 2003, Sewell 2011, 2012). Only rare individuals have been generating consistent alphas and the rest would have been better off with passive investment portfolios. In the eyes of a finance student, the EMH is a

bit harsh, if it were absolutely true, then all the fundamental and technical analysis skills acquired through the studies would be pointless.

The EMH is quite important in this thesis, as we are essentially testing whether it still holds when the performance persistence is viewed conditionally in bull and bear market conditions. Is there a way to recognize the consistently outperforming individuals or funds by looking how they've performed in different market conditions?

2.2 Hedge fund vs. Mutual fund

Hedge funds are actively managed alternative investments that invest their customer's money in an effort to outperform the overall market or specified benchmark by using different and also non-traditional strategies and asset classes, such as investing in high risk derivatives, aggressive shorting, and using leverage. A hedge fund is usually a partnership, where the founders and fund managers are the general partners, and the investors are the limited partners. Hedge funds can differ from one another drastically, and they are often categorized according to their investment style. There are countless strategies the funds can employ, but the most common ones are long/short equity strategy, market neutral strategy, merger arbitrage strategy, convertible arbitrage strategy, capital structure arbitrage strategy, fixed-income arbitrage strategy, event-driven strategy, global macro strategy, and short only strategy.

Hedge fund's name comes from their original purpose to hedge against the downside risks of bear market by shorting, but nowadays hedge funds focus more on maximizing profits than minimizing risks.

Hedge funds are less regulated than mutual funds or other investment vehicles, and are often private investment partnerships. Because of hedge funds' high risk and less regulation, they are available only to accredited wealthy investors who understand the risks. Hedge funds are actively managed and they charge higher fees for their services than mutual funds, the asset management fee is typically 2% and the incentive fee is 20% (Titman & Tiu 2011). They can have strict lock-up periods and withdrawal limits, which make them illiquid investments. Hedge funds aim to make higher returns for their customers and may make aggressive high risk investments. The results are not

always better than the overall market and the performance persistence of those funds that have outperformed the market, is questionable (Agarwal & Naik 2000, Brown et al. 1999, Dichev & Yu 2011, Fung et al. 2008, Joenväärä et al. 2014, Kosowski et al. 2007, Liang 2000, Nohel et al. 2010).

Hedge funds take only accredited customers, the individual investor's annual income must exceed 200 000 US dollars for the past two years or a net worth of 1 million US dollars or more, not including their own home. These qualifiers are for the investors own protection, as it is assumed that high income or net worth are buffer enough for the potential losses of high-risk investing.

Hedge funds are less regulated than mutual funds (Stulz 2007). Hedge funds can invest in almost anything, they can short, they are not limited to only stocks and bonds, but can invest also in derivatives, land, real estate, and currencies, even cryptocurrencies, if the local legislation allows them. As private investment vehicles, hedge funds may invest their customer's funds as they please, as long as they disclose their strategies with their customer. This results in both massive gains and massive losses, the trick is to identify the hedge funds that can make consistent excess returns.

Hedge funds are more illiquid investments than mutual funds, their redemption terms can be strict and include lock-up periods. Mutual funds are liquid assets, from where the investor can redeem their investment on any business day and receive the net-asset-value of their investment.

Hedge funds often use leverage to maximize their returns, but this combined with aggressive shorting can lead to massive losses that can end the fund. Hedge funds have incentive to try to manipulate the market, in legal ways of course, when they have heavy short positions in an asset. This resulted in January 2021 in an unusual situation, where social media group in Reddit noticed that the gaming company Gamestop's stock was heavily shorted by hedge funds, and in order to save the company from plummeting market value, they raised awareness of the situation in social media amongst ordinary people, who in turn flocked to buy the share. Multiple exchanges halted trading of the stock, but the hedge funds kept shorting, the masses of small investors kept pumping the price by buying the stock, and eventually authorities had

to take stand in the matter. The aftermath of it all is still going, did some party act illegally or were the hedge funds losses due to their excessive short positions? This could be a topic of a whole another thesis, as it demonstrates the difference in old and new generations investing behavior and the power of movement of masses. The market has a new player, perhaps even new rules.

Alas, in this thesis we are only trying to find a way to recognize the consistently outperforming hedge funds by studying how they have performed in different market conditions.

Hedge funds can make speculative investments and investing in hedge funds can have some unique risks because of their strategies (Agarwall & Naik 2000, Till 2010). The use of leverage can turn minor losses into huge ones, investors might have to lock-up their money in the fund for several years, so the gains aren't even liquid, and if the hedge fund uses only few strategies, it can expose the investments to greater risks because of low diversification.

Then there's the fact that the investor has to pay hefty fees for all these potential risks that may not even end up outperforming the market. Hedge funds typically use 2 and 20 pay structure, which means that the fund manager gets 2% of the assets, whether or not he is able to generate wealth for his customers, and if the fund makes profit, the fund manager gets 20% of the yearly profits. It is understandable that the investors of hedge funds need to be wealthy and seasoned in investing, in order to make their own research before locking up their money in a fund for possibly years. Fortunately there are mechanisms to protect the investors, such as high-water mark, which means that the fund manager gets the 20% cut only from profits that exceed the previous highs. In the end everything is negotiable, including the fee structure, but supply and demand also works here, the more successful the fund, the more interested investors there are, and then the fund has the upper hand in negotiations.

What should investors consider when doing their due diligence on hedge fund candidates? First, the investor has to know their own investment preferences and risk tolerance. After that they can limit down the number of fund candidates by choosing which strategies suit them. Metrics for analyzing the funds are many, but here are a

few regular ones; five-year annualized returns, standard deviation, rolling standard deviation, months to recovery/maximum drawdown, and downside deviation.

The investor can follow some guidelines when narrowing down the hedge fund candidates. First, find out what are the annualized rates of return of the funds, and select a benchmark index you want the funds to have outperformed. This way the investor can rule out funds that haven't performed well enough in the past. After looking into the returns, the investor should compare the standard deviations of the funds' returns and compare those to the standard deviation of the benchmark index. Funds, that have higher standard deviation as the benchmark, will be dropped out of consideration at this point. Note that the compared funds should employ same strategies, no use of comparing different categories as they have different goals and time spans for those goals. Only funds, that meet the criteria for the return, the standard deviation, and peer comparison, are qualified for further consideration. There are still quite a few funds left and the investor needs to apply more criteria in order to choose the right fund for them. What are the differences between the funds that are left, what is the fund's and firm's size, what is the fund's and it's manager's track record, how old is the fund, what is their minimum investment, what are their redemption terms, and what are their other terms of contract, if they are made public.

Active management means that the investor's portfolio is handled by professional money managers who actively buy, hold, and sell on behalf of the investor in order to outperform the overall market or chosen benchmark. The fund managers are financial professionals who make investment decisions based on investment analysis, research, forecast, and their own experienced views of the market.

Passive management, or indexing, is an investment style, where the investment portfolios mirror their chosen market index, and the holdings are longer term than in active management. Passive management basically assumes that the efficient market hypothesis (EMH) is true, and the market is in itself at its most efficient. Whereas active management assumes that the EMH does not apply, and there are investment opportunities due to these inefficiencies in the market.

Active management requires constant adjustments to maintain its advantages, whereas passive management is buy-and-hold strategy that let's market do the job. Active management requires more frequent rebalancing of the portfolios. Passive management assumes that the market already provides the best returns, and active management assumes that there are still ways to improve the returns. Actively managed funds, such as hedge funds, have higher fees than passive funds, such as mutual funds, so the actively managed funds not only need to outperform their benchmark, they need to outperform the benchmark and their own fee structure.

Why would investors then pick actively managed funds? Well, the fund managers bring into the table their experience, and their knowledge of different investing instruments and strategies. Actively managed funds are less regulated and can therefore employ wider range of strategies, they also have less requirements on what assets they have to hold, so they can manage their risks more easily than passive funds. Active managers can also use hedging strategies such as short selling and using derivatives.

Mutual funds are regulated investment products, and they are available for the common people. Hedge funds are available only for accredited investors. Hedge funds and mutual funds have their differences, but also similarities. They both pool funds from their customers for managed portfolios and the goal is the same. make money for their customers.

In this thesis we try to identify if there are potential high-quality hedge funds with consistent performance persistence by researching how they have fared through different market conditions, through bear and bull markets.

2.3 Review of hedge fund research

As the world of hedge funds is so diverse, there is demand for finding the driving factors that are responsible for hedge fund performance and risk. A transition from conventional approach of researching hedge funds like asset classes to factor-based approach has taken years. The conventional approach to assessing hedge fund performance has been to compare the fund to a hedge fund index with similar investing

style. This benchmarking approach assumes that hedge fund indexes behave the same way as asset class indexes, but this can lead to misleading results.

Also the databases from which those indexes are formed can be mispresenting because funds do not have to report to them. The databases have problems such as survivorship bias, data bias, sampling differences, short history and lack of transparency. In order to find the hedge funds' underlying risk factors that don't depend on the hedge fund databases, the asset-based style factors were introduced in 1997 (Fung & Hsieh 1997) and further developed into the more known 7-factor model in the following years (Fung & Hsieh 2001, Fung & Hsieh 2002, Fung & Hsieh 2004).

Hedge funds are expensive with incentive fees of about 20% and management fees of 2% and therefore they are expected to produce superior returns. Studies have provided mixed results on whether hedge funds can produce alpha and whether the performance will persist (Agarwal & Naik 2000, Brown et al. 1999, Dichev & Yu 2011, Fung et al. 2008, Joenväärä et al. 2014, Kosowski et al. 2007, Liang 2000). These research have studied the performance persistence unconditionally without taking into account the time-varying aspect of hedge funds, but there has also been studies of conditional performance persistence (Sun et al. 2016).

Because of hedge funds short history, only recently has there been studies about different market conditions' effects on hedge fund performance persistence. The time-variation of hedge fund performance and performance persistence is surprisingly new area in hedge fund research. The dot-com bubble and financial crisis have given a lot of data on which to study this question.

The main inspiration for this thesis is an article 'Only winners in tough times repeat: Hedge fund performance persistence over different market conditions' (Sun et al. 2016). The study shows that there exists predictability for hedge fund's performance after weak markets but not after strong markets. The state of the market is divided into weak market performance and strong market performance based on the hedge fund sector's return compared to its historical median, for this they've used TASS Dow Jones Credit Suisse Hedge Fund index. The study on performance persistence uses data from Lipper TASS database, and the fund performance is evaluated using Fung-

Hsieh seven-factor alpha (Fung & Hsieh 2001), appraisal ratio, and Sharpe ratio. At the beginning of each quarter, the hedge funds are sorted to quintile portfolios by means, and then equal-weighted and value-weighted average buy-and-hold performance levels are computed for each portfolio for the subsequent three months to three years. Multivariate regression analysis is used to control for hedge fund characteristics that may affect future performance.

Hedge funds differ from traditional asset classes in that they are more flexible with their investment strategies, and because of this the funds' return distributions can differ from those of traditional asset classes. In order to study hedge funds, there needs to be proper models for these alternative investments. Perhaps the best known model for hedge fund benchmarking is the Fung Hsieh seven-factor model. The development of that model is described next.

Fung and Hsieh (1997) show that hedge funds use dynamic trading strategies that differ substantially from mutual funds' strategies. They identify five main investment styles for hedge funds: Systems/Opportunistic, Global/Macro, Value, Systems/Trend Following, and Distressed. They extend Sharpe's asset class factor model with these style factors.

Fung and Hsieh (2001) develop a new model for benchmarking trend-following hedge fund returns. They focus on trend-following funds from 1989 to 1997, and show that because hedge funds typically generate option-like returns, lookback straddles are more useful than linear-factor models in benchmarking the funds. Instead of using Sharpe's asset class factor model, which is linear model, they develop a strategy for benchmarking trend-following hedge funds by forming portfolios of lookback straddles on bonds, currencies, and commodities.

Fung and Hsieh (2002) validate their previous findings with out-of-sample study from 1998 to 2001, and they widen their research from trend-following hedge strategies to other strategies. They examine what problems are yet to be solved before hedge fund returns can be linked to the underlying asset-based style factors.

Fung and Hsieh (2004) extend their previous work and develop a seven-factor model for benchmarking hedge funds. They solve the problems in their previous study, and find a way to link asset-based style factors to hedge fund returns in a way that is applicable to different hedge fund strategies. The seven asset-based style factors i.e. risk factors are bond trend-following factor, currency trend-following factor, commodity trend-following factor, equity market factor, size spread factor, bond market factor, and credit spread factor. The benefit of this model is that it makes possible to benchmark hedge funds to readily available indexes that don't have the hedge fund databases' biases, and the model reveals the underlying risk-factor exposures of hedge funds.

Because of hedge funds' short history and limited availability of hedge fund data, the studies have different databases, time periods, and methods, so it is not a surprise that the research results about hedge fund performance and the persistence of the performance are mixed. Some of the studies and their results are described next.

Brown and Ibbotson (1999) find that offshore funds have positive risk-adjusted performance when measured with Sharpe ratio and Jensen's alpha, but they do not find evidence of performance persistence. They use annual data from the U.S. Offshore Funds Directory to study offshore hedge fund performance from 1989 to 1995, and they include both defunct and operating funds in their study. They divide the funds into ten categories based on the fund's investment style, and use the capital asset pricing model (CAPM) to calculate the fund's alpha, and they also calculate the Sharpe ratios for the funds. To test the performance persistence, they use year-by-year cross-sectional regression of past returns on current returns.

Agarwal and Naik (2000) find that hedge fund performance persistence is highest at a short-term quarterly horizon, and the persistence weakens as the time frame is extended. The short-term returns are problematic because hedge funds can use lock-up periods and thus hinder investors' ability to gain from these short-term benefits. They study both offshore and onshore hedge fund performance persistence. The data is from Hedge Fund Research Inc (HFR), and covers monthly returns from 1982 to 1998. Agarwal and Naik study hedge fund performance persistence using multi-period framework in addition to a more traditional two-period framework, that is, they

examine fund wins and losses in two and more than two consecutive time periods on a pre-fee and post-fee basis. They divide the funds the same way as Brown and Ibbotson (1999) into ten categories, but instead of CAPM they calculate the fund alpha as the difference of the fund's return and the same category's average return, and instead of Sharpe ratio, they use appraisal ratio. They examine if performance is sensitive to the length of return measurement, in this they use period-by-period cross-sectional regression of past returns on current returns on quarterly, half-yearly and yearly basis.

Fung, Hsieh, Naik and Ramadorai (2008) examine funds-of-funds, and the results reveal that the risk exposures of funds change over time, and that funds-of-funds on average have produced alpha only between October 1998 and March 2000. They use merged monthly data from HFR, CISDM, and Lipper TASS, from time period from 1995 to 2004, and calculate alphas once a year using Fung Hsieh seven-factor model on the most recent two year period. They divide the funds-of-funds into alpha-producing funds-of-funds and to those that don't produce alpha. The alpha-producing funds-of-funds have steadier capital inflows, they have more performance persistence, and they are less likely to be liquidated than those funds-of-funds that don't produce alpha.

Dichev and Yu (2011) find that hedge funds provide investors lower dollar-weighted returns than the Standard & Poor's (S&P) 500 index, and only slightly higher returns than the risk-free rate of return. The monthly data they use is a combination of Lipper TASS hedge fund database and the database of Center for International Securities and Derivatives Markets (CISDM), and the time period is from 1980 to 2008. Conventionally hedge fund performance has been studied from the fund's perspective, and thus the interest of the studies has been buy-and-hold returns. In this study, Dichev and Yu take the investor's perspective and calculate the dollar-weighted returns, which takes into account the value-weighted returns over time by the amount of invested capital. This way they take into account the timing and the size of cash flows from investor into and out of the fund.

Sun, Wang and Zheng (2016) examine conditional performance persistence of hedge funds, that takes into account the time-varying aspect of hedge funds. The study shows

that there exists predictability for hedge fund's performance after weak markets but not after strong markets. This performance persistence holds both short-term (three months) and long-term (three years), and in future weak and strong markets. The state of the hedge fund market is divided into weak market performance and strong market performance based on the hedge fund sector's return compared to its historical median, for this they've used TASS Dow Jones Credit Suisse Hedge Fund index. The study on performance persistence uses monthly data from Lipper TASS database, and the fund performance is evaluated using Fung Hsieh seven-factor alpha (Fung & Hsieh 2001), appraisal ratio, and Sharpe ratio. At the beginning of each quarter, the hedge funds are sorted to quintile portfolios by means, and then equal-weighted and value-weighted average buy-and-hold performance levels are computed for each portfolio for the subsequent three months to three years. Multivariate regression analysis is used to control for hedge fund characteristics that may affect future performance.

As hedge funds report their earnings on a voluntary basis, we get only a glimpse of the whole hedge fund universe, and that glimpse only consists of those hedge funds that want to be seen. All of the studies referred here agree on that the databases used in the studies have biases that can have an impact on the results, so the different databases and time periods may explain the differences in results. Studies on performance find both positive and negative alphas, and the persistence of returns is in most studies from nonexistent to short-term. Studies do find temporary abnormal returns in some of the funds, but as the characteristics of the winning funds vary from study to study, that result doesn't tell us much about the hedge funds as a whole. The field is still looking for a consensus concerning hedge funds' ability to produce alpha, and whether the performance persists. Further studies are therefore needed.

3 DATA AND RESEARCH METHODS

3.1 Data

Data is from Lipper TASS hedge fund database, with 18891 hedge funds and 1261782 observations from December 1993 to June 2013. The hedge funds are classified into 11 self-reported style categories, which are; convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, long/short equity hedge, managed futures, multi-strategies, and fund-of-funds. Two thirds of the sample belong in the categories of long/short equities, and fund-of-funds, rest are quite evenly divided between the remaining categories.

These categories could be of interest in further studies of conditional performance persistence of hedge funds, but in this thesis we are more interested in overall market situations impact on performance persistence of hedge funds. The data is modified so that we've cleared out non-USD funds, non-monthly filing funds, and funds with unknown strategy. We've also excluded the first 18 months of returns for every fund to control the backfill bias. This leaves us with 9107 funds.

3.2 Performance persistence measures

In this thesis we use t-statistics of alpha as our measurement of returns, but before we get to that, let's have a look on the usual measurements of return and risk.

There are different types of returns, hedge funds usually seek absolute returns whereas mutual funds seek relative returns. This means that hedge funds try to maximize their returns despite the overall market situation, and mutual funds try to beat the overall market situation. Because hedge funds are so different from mutual funds, and can vary a lot amongst each other, the hedge funds' performance needs more measures than those of mutual funds. Absolute returns are easier to compare with more traditional investments, but hedge funds should also be evaluated in terms of relative returns. We don't want to invest in a hedge fund, that while making positive absolute returns, makes less returns than the overall market. We also don't want to compare

some lower risk hedge fund to a totally different high-risk traditional investment, like emerging market equities.

When we want to compare hedge fund to other funds, we need to examine the relative returns of the two over several time periods, and also take into account the risk-levels. In this thesis, we divide the hedge funds in ten portfolios, and examine the returns over three and twelve month time periods. Those funds, that stay in the top performing portfolios, can be considered to be able to consistently generate alpha, so their performance is persistent.

3.2.1 Measures of risk

We can't be looking only at the returns, we need to take into consideration the risk-level in the investment. This we can do by examining the risk-adjusted returns. So, when we need to measure the risk of the investment, there are several metrics to choose from, and here are few of the most used ones.

Standard deviation is a way to measure the volatility of the investment, bigger standard deviation means that there is more variation in the returns compared to the mean return. The problem with standard deviation as a risk measure of hedge funds is, that it assumes normal distribution, and hedge funds rarely have symmetric returns. Also, standard deviation may not reveal if there are higher chances of huge losses.

Formula for standard deviation:

$$Standard\ Deviation = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}}$$

where $x_i = value\ of\ the\ i^{th} point\ in\ the\ data\ set$

$\bar{x} = the\ mean\ value\ of\ the\ data\ set$

$n = the\ number\ of\ data\ points\ in\ the\ data\ set$

Because of standard deviation's short-comings, we need to combine it with the mean returns, and we get the value at risk (VaR) measurement. Value at risk measures how much at most we are likely to lose, within five percent probability. There are multiple variations of the value at risk measurement. This still isn't enough for hedge fund research, as value at risk also assumes normal distribution.

We can't assume normal distribution with hedge funds, so we have to examine the skewness and kurtosis of the fund's return distribution. Skewness tells us how much the likely result differs from the mean value. Zero skewness means that the distribution of returns follows normal distribution, negative skewness indicates higher probability of negative result, and positive skewness indicates higher probability of positive result.

Formula for skewness:

$$Skewness = \frac{\sum_i^N (x_i - \bar{x})^3}{(N-1)x\sigma^3}$$

where $x_i = i^{th}\ random\ variable$

$\bar{x} = mean\ of\ the\ distribution$

$N = number\ of\ variables\ in\ the\ distribution$

$\sigma = standard\ deviation$

Kurtosis measures the weight of the distribution's tales compared to the whole distribution. High kurtosis indicates higher probability of extreme results, and lower kurtosis indicates higher probability of returns that are near the mean value.

Formula for Kurtosis:

$$Kurtosis = n * \frac{\sum_i^n (x_i - \bar{x})^4}{(\sum_i^n (x_i - \bar{x})^2)^2}$$

where $x_i = i^{th}\ random\ variable$

$\bar{x} = mean\ of\ the\ distribution$

$N = number\ of\ variables\ in\ the\ distribution$

Sharpe ratio is used as hedge fund performance measurement of risk-adjusted returns, as it takes into account how much risk an addition to the returns comes with. Sharpe ratio takes into account the mean, standard deviation, and the risk-free rate. A Sharpe ratio greater than 1 is considered good, and less than 1 not so good. Because Sharpe ratio takes the risk-free rate into account, the results vary between low- and high-interest rate periods.

Formula for Sharpe Ratio:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

where $R_p = return\ of\ portfolio$

$R_f = risk - free\ rate$

$\sigma_p = standard\ deviation\ of\ the\ portfolio's\ excess\ return$

In this thesis, the Sharpe ratio is calculated by subtracting the risk-free rate from the return of the portfolio and dividing that result by the standard deviation of the portfolio's excess return. Sharpe ratio in itself is does not hold enough explanatory power for hedge fund returns, that's why we use additional metrics in evaluating the performance persistence.

Beta is the measurement with which we compare the hedge funds to a benchmark index, which we've chosen to be S&P 500, as it is a good representation of the overall market. Beta is otherwise known as systematic risk and it measures how much a fund's returns are likely to move compared to the benchmark index's movements, thus the beta of overall market is 1. Beta is an important measurement as it shows us how sensitive our investment is to movements in compared asset class.

Correlation measures relative changes in returns, it measures how related the returns of our investments are, do they react similarly to systematic variables or react opposite ways. Correlation can have a value between -1 and 1, where -1 means perfect negative

correlation, and 1 means perfect positive correlation, and zero means that the investments are independent of each other.

Beta and correlation measurements can be used in hedging as a way to recognize assets that act opposite or neutral compared to our investments, and in comparing the funds in our portfolio against each other. After all, no point in investing in multiple asset classes, if they all go down at the same time, because there's no diversification benefits in that. On the other hand, diversification also reduces returns, so the return goals should be bear in mind.

3.2.2 Measures of return

Alpha is the most widely used measurement of return in hedge funds, it measures the excess returns of the fund, how well the fund has fared in beating overall market or its chosen benchmark.

First we take a look at the capital asset pricing model (CAPM):

$$ER_i = R_i + \beta_i(ER_m - R_f)$$

where $ER_i = expected\ return\ of\ investment$

$R_f = risk - free\ rate$

$\beta_i = beta\ of\ the\ investment$

$(ER_m - R_f) = market\ risk\ premium$

When evaluating hedge funds, we can calculate the fund's expected return by substituting the beta in the formula by the beta of the hedge fund. This way we can compare the fund's performance to its expected return, and make conclusion whether or not the fund manager has been able to add alpha on the risk taken, instead of just increasing profits with more risk.

Because alpha measures the excess return of an investment over its chosen benchmark, it is used in evaluating fund's performance persistence. It tells us whether or not the

fund manager has been able to generate additional returns, not just the same returns as the overall market would have provided in passive investment. Also the excess return has to be big enough to cover the fees of active management, otherwise the customer might end up losing money compared to passive investing.

We talked about efficient market hypothesis (EMH) earlier, it assumes that the market is always perfectly priced and there isn't a chance to systematically earn excess returns by identifying undervalued assets. The research results on performance persistence have also been mixed, so the debate still continues whether or not active management can systematically beat the market.

Note, that alpha should be used as a comparing measurement only between similar asset categories. Alpha is a measure of performance, it is the excess return between our portfolio and the market index. In our calculations, we use t-statistic of Fung Hsieh seven-factor alpha in order to get more robust results.

3.3 Fung-Hsieh seven factor model

Fung Hsieh seven-factor model (Fung and Hsieh 2001) and its variations are widely used in measuring hedge fund performance, but before we get to that, let's take a look at arbitrage pricing theory (Ross 1976), and the development of Fung-Hsieh seven factor model.

The arbitrage pricing theory (APT) expresses asset expected return as a linear model of various macro-economic factors:

$$E(r_i) - r_f = b_{i1}RP_1 + b_{i2}RP_2 + \cdots + b_{in}RP_n \quad (1)$$

where $E(r_i) = expected\ return\ on\ asset\ i$

$r_f = risk\ free\ rate$

$b_{ik} = the\ sensivity\ of\ the\ i^{th}\ asset\ to\ factor\ k$

$RP_k = risk\ premium\ of\ factor\ k$

For each asset i, the sensitivity b_k are estimated from regression:

$$R_{i,t} - r_f = \alpha_i + b_{i1}RP_{1,t} + b_{i2}RP_{2,t} + \cdots + b_{in}RP_{n,t} + \varepsilon_{it} \quad (2)$$

where $R_{i,t} = return\ on\ asset\ i\ at\ time\ t$

$r_{f,t} = risk\ free\ rate\ at\ time\ t$

$\alpha_i = intercept\ of\ the\ regression$

$RP_{k,t} = risk\ premium\ of\ factor\ k\ at\ time\ t$

$\varepsilon_{i,t} = asset\ i's\ idiosyncratic\ random\ shock\ with\ mean\ zero$

(Fama and French 1996)

In the formula (2) there is an intercept α_i whereas in formula (1) there is none. Formula (2) uses realized returns R_i and formula (1) uses expected return $E(r_i)$. Model (2) is the result of running regression on our data. From model (1) we can imply that the α of model (2) should be zero, in that case, all the excess returns would be explained by the risk factors. If α is something else than zero, it means that there are returns that are not explained by the risk factors, that is, there is abnormal risk adjusted returns. In hedge fund performance evaluation α is interpreted as the result of the hedge fund managers skills to create excess returns. If α of a hedge fund is positively significantly different from zero, then we can assume that the fund manager has been able to beat the market and add value to the fund.

APT theory does not tell us which risk factors we should be using when evaluating hedge fund performance. To answer this question there's been further studies to identify the suitable risk factors for hedge funds. Fama and French (1993) studied mutual funds and found three common factors; market, size, and value. Unfortunately these are not directly suitable for hedge fund research, as hedge funds can use dynamic trading strategies (Fung and Hsieh 1997).

Fung and Hsieh developed models for hedge fund performance evaluation, and were able to identify first five (Fung and Hsieh 1997), then two more (Fung and Hsieh 2001) hedge fund risk factors. They constructed the widely used seven-factor model in 2004, and their model can explain up to 80% of the variations in hedge fund's monthly

returns (Fung and Hsieh 2004). There have been further studies after this and more risk factors are identified (Teo 2009), but in this thesis we use the Fung Hsieh seven-factor model as it has proven to have explanatory power for hedge fund returns.

Fung Hsieh seven-factor alpha contains three trend-following risk-factors; bond trend-following factor, currency trend-following factor, commodity trend-following factor. Two equity-oriented risk factors; equity market factor, and size spread factor. Two bond-oriented risk factors; bond market factor, and credit spread factor.

Fung Hsieh seven-factor model:

$$r_t = \alpha_0 + \beta_1 PTFS_{B_i} + \beta_2 PTFS_{Cur_i} + \beta_3 PTFS_{Com_i} + \beta_4 EQ_t + \beta_5 ES_t + \beta_6 BM + \beta_7 BS_t + \varepsilon_t$$

where $r_t = return\ of\ the\ portfolio$

$\alpha_0 = intercept\ of\ the\ regression$

$\beta_i = sensitivity\ of\ the\ portfolio\ to\ a\ risk\ factor$

$PTFS_{B_i} = bond\ trend - following\ factor$

$PTFS_{Cur_i} = currency\ trend - following\ factor$

$PTFS_{Com_i} = commodity\ trend - following\ factor$

$EQ_t = equity\ market\ factor$

$ES_t = size\ spread\ factor$

$BM = bond\ market\ factor$

$BS_t = credit\ spread\ factor$

$\varepsilon_t = asset's\ idiosyncratic\ random\ shock\ with\ mean\ zero$

The Fung Hsieh seven-factor model is the econometric model in this thesis. The risk factors in our model are from David A. Hsieh's hedge fund data library[1], where the risk factors are available for academic research.

[1] https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

3.4 Chosen metrics and the research steps

This thesis' approach differs from the reference article's (Sun et al. 2016) approach in that the original study divides the time series into weak and strong markets based on whether the overall hedge fund sector return is below or above its historical median, whereas we take a more common people approach and divide the time series into periods of recessions and expansions based on the overall stock market situation. The main recession periods are the dot-com bubble from 31st May 2000 to 30th September 2002 and the financial crisis from 31st August 2007 to 28th February 2009. Otherwise the time periods between 30th June 1997 to 30th June 2013 are considered as expansion periods.

The main steps in the research are: First we clear out non-USD funds, non-monthly filing funds, and funds with unknown strategy, and we exclude the first 18 months of returns for every fund to control the backfill bias. Then we calculate the logarithmic excess returns of the funds. After that, we use the Fung and Hsieh seven-factor model (Fung & Hsieh 2001) over the past 12 months returns to estimate the time-varying t-value of alpha for each fund. Next, we sort the funds into decile portfolios based on their t-values of alpha. We use t-statistics of alpha in order to increase robustness of the model. After that we calculate the monthly equal-weighted buy-and-hold portfolio alphas for the decile portfolios using three-month and twelve-month holding periods. We also calculate the monthly equal-weighted returns for the spread portfolio between the top and bottom portfolios. Next we calculate for the decile portfolios the annualized mean, standard deviation, Sharpe ratio, t-value and p-value of Sharpe ratio, annualized Fung-Hsieh seven-factor alpha, t-value and p-value of alpha. The null-hypothesis is that there is no difference in performance persistence after recession and expansion periods.

4 DATA ANALYSIS

Before dividing the data into portfolios, the average t-values of alphas by year are as such:

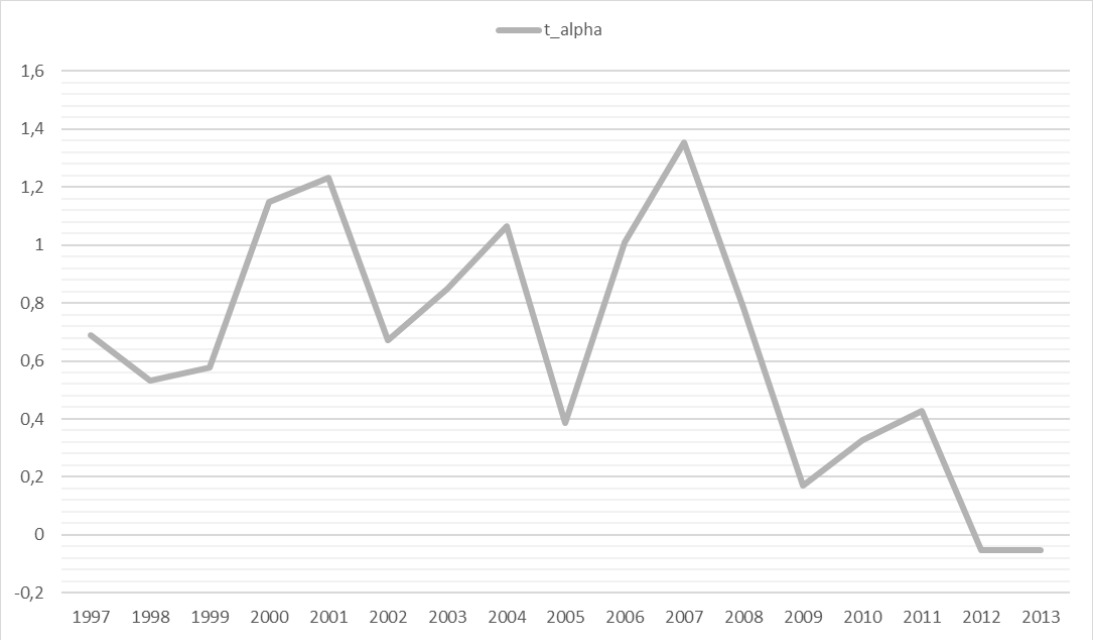

Figure 1 Average t-values of alphas by year, before ranking the funds into portfolios.

The average t-values of alpha vary in such way, that without prevailing information, it would be hard to spot the well-known recessions and expansions from the data. The dot-com bubble from 31st May 2000 to 30th September 2002 and the financial crisis from 31st August 2007 to 28th February 2009 can be seen in the graph if one knows to look for them. Further investigation is therefore needed.

4.1 Portfolios

The whole data is divided, based on their 12 month average t-value of alpha, into ten portfolios and one spread portfolio between the highest and lowest portfolios. Because of robustness, the t-value of alpha is chosen here instead of plain alpha. For all portfolios, we calculate the annualized mean, standard deviation, Sharpe ratio, t-value and p-value of Sharpe ratio, annualized Fung-Hsieh seven-factor alpha, and t-value and p-value of alpha.

Table 1 Ranking portfolios based on their 12 month average t-value of alpha

Portfolio	Mean	Std	N	Sharpe	t_Sharpe	p_Sharpe	Alpha	t_Alpha	p_Alpha
10	-0.102	0.085	187	-1.207	-4.763	0.000	-0.128	-8.863	0.000
9	-0.036	0.083	187	-0.429	-1.695	0.092	-0.063	-4.504	0.000
8	-0.001	0.075	187	-0.016	-0.063	0.949	-0.026	-2.054	0.041
7	0.026	0.076	187	0.346	1.367	0.173	0.002	0.137	0.891
6	0.059	0.074	187	0.792	3.125	0.002	0.036	2.742	0.007
5	0.073	0.070	187	1.048	4.135	0.000	0.052	4.094	0.000
4	0.100	0.073	187	1.321	5.213	0.000	0.075	5.615	0.000
3	0.118	0.066	187	1.786	7.049	0.000	0.104	7.966	0.000
2	0.115	0.057	187	2.023	7.988	0.000	0.102	9.646	0.000
1	0.125	0.042	187	2.986	11.786	0.000	0.115	13.842	0.000
0	0.228	0.072	187	3.153	12.448	0.000	0.244	14.968	0.000

After we have divided the funds into portfolios, we will check the portfolios performance after three months and rearrange the funds again into portfolios based on the new t-values of alpha. We duplicate these steps until the end of our data. We do the same procedure in twelve month intervals in order to see, if the three month and twelve month performance persistence are different.

4.2 Three month performance persistence

The funds are now divided into portfolios and the performance of the portfolios is calculated after three months and the portfolios are rearranged based on their new performance.

Table 2 Post-rank three months statistics

Portfolio	Mean	Std	N	Sharpe	t_Sharpe	p_Sharpe	Alpha	t_Alpha	p_Alpha
10	-0.006	0.080	188	-0.074	-0.293	0.470	-0.025	-1.636	0.104
9	0.016	0.073	188	0.214	0.848	0.398	-0.005	-0.415	0.678
8	0.030	0.068	188	0.435	1.721	0.087	0.011	0.962	0.338
7	0.034	0.071	188	0.471	1.864	0.064	0.011	0.949	0.344
6	0.041	0.072	188	0.567	2.246	0.026	0.020	1.629	0.105
5	0.039	0.071	188	0.543	2.148	0.033	0.018	1.488	0.139
4	0.052	0.072	188	0.726	2.874	0.005	0.031	2.489	0.014
3	0.053	0.071	188	0.756	2.994	0.003	0.032	2.593	0.010

2	0.075	0.061	188	1.226	4.854	0.000	0.058	5.254	0.000
1	0.065	0.044	188	1.497	5.927	0.000	0.051	6.388	0.000
0	0.071	0.064	188	1.118	4.427	0.000	0.076	4.979	0.000

We can see from Table 2 that the difference between the mean of the best and the worst portfolios is getting smaller, so that might suggest that the performance persistence between portfolios is weakening.

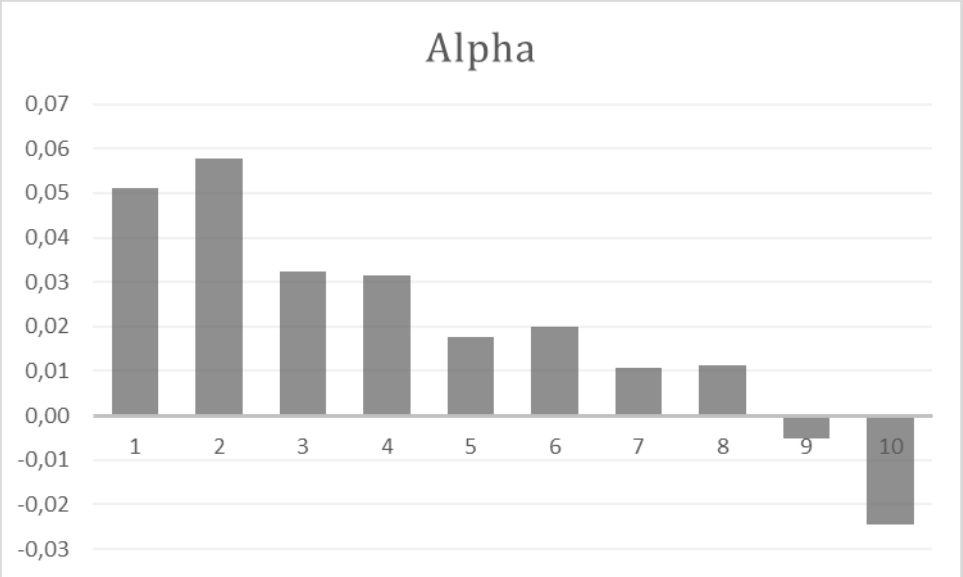

Figure 2 Post-rank three months alpha

Only two portfolios have negative alpha after three months, and those alphas are better than before, so the worst portfolios must have performed better after three months.

4.3 Twelve month performance persistence

We want to compare the performance persistence between three and twelve months. This is why we do the same calculations again with the longer time period of twelve months. The funds are now divided into portfolios and the performance of the portfolios is calculated after twelve months and the portfolios are rearranged based on their new performance.

Table 3 Post-rank twelve months statistics

Portfolio	Mean	Std	N	Sharpe	t_Sharpe	p_Sharpe	Alpha	t_Alpha	p_Alpha
10	0.021	0.075	186	0.287	1.128	0.261	0.002	0.130	0.897
9	0.025	0.065	186	0.381	1.498	0.136	0.008	0.685	0.494
8	0.037	0.069	186	0.538	2.119	0.035	0.018	1.404	0.162
7	0.043	0.068	186	0.626	2.465	0.015	0.024	2.005	0.046
6	0.043	0.072	186	0.589	2.320	0.021	0.021	1.813	0.071
5	0.034	0.071	186	0.478	1.880	0.062	0.012	1.072	0.285
4	0.054	0.074	186	0.733	2.885	0.004	0.030	2.487	0.014
3	0.045	0.073	186	0.620	2.442	0.016	0.021	1.640	0.103
2	0.050	0.060	186	0.834	3.298	0.001	0.032	3.072	0.002
1	0.052	0.048	186	1.068	4.206	0.000	0.037	4.218	0.000
0	0.030	0.055	186	0.552	2.176	0.031	0.035	2.647	0.009

The difference between means of the worst and the best portfolios is smaller after twelve months as it was after three months.

Comparing the results after three and twelve months we can see that the performance persistence weakens with time, which is expected.

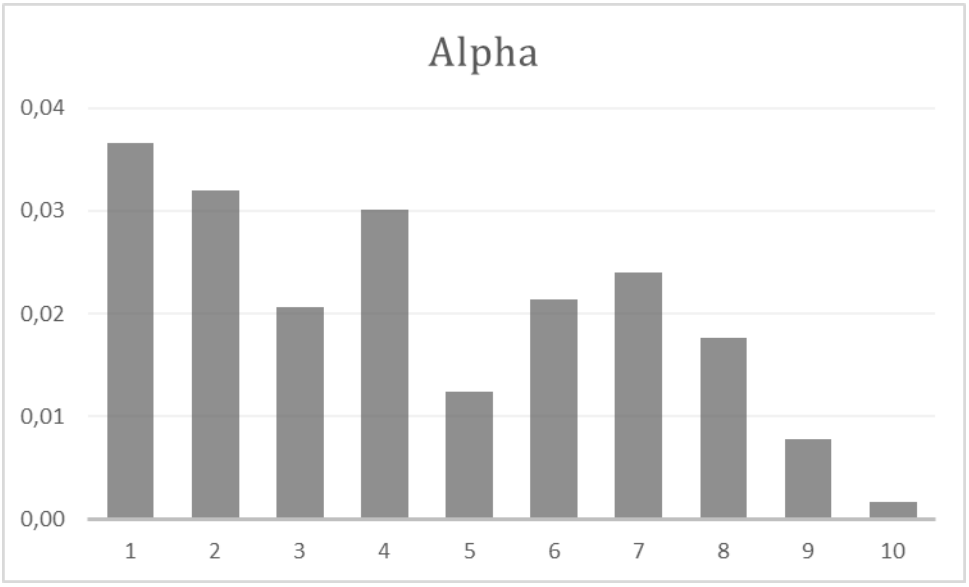

Figure 3 Post-rank twelve months alphas

All of the portfolios have positive alphas after twelve months, so the performance overall is getting better during our time period.

4.4 Performance persistence and market situation

We want to find out whether the market situation has impact on the portfolio performance. Does the portfolios picked during crisis have different performance persistence than portfolios picked during boom? This is why we divide our data into bust and boom periods. The bust periods consist the dot-com bubble from 31st May 2000 to 30th September 2002 and the financial crisis from 31st August 2007 to 28th February 2009. The boom periods consist of the rest of our data period from December 1993 to June 2013.

4.4.1 Bust vs boom market three month performance persistence

We divide the funds into portfolios same way as in previous section, but with the difference that now our portfolios are picked either during bust or boom period. The performance of the portfolios is calculated after three months and the portfolios are rearranged based on their new performance.

Let's start by looking at the alphas of the portfolios during bust and boom periods.

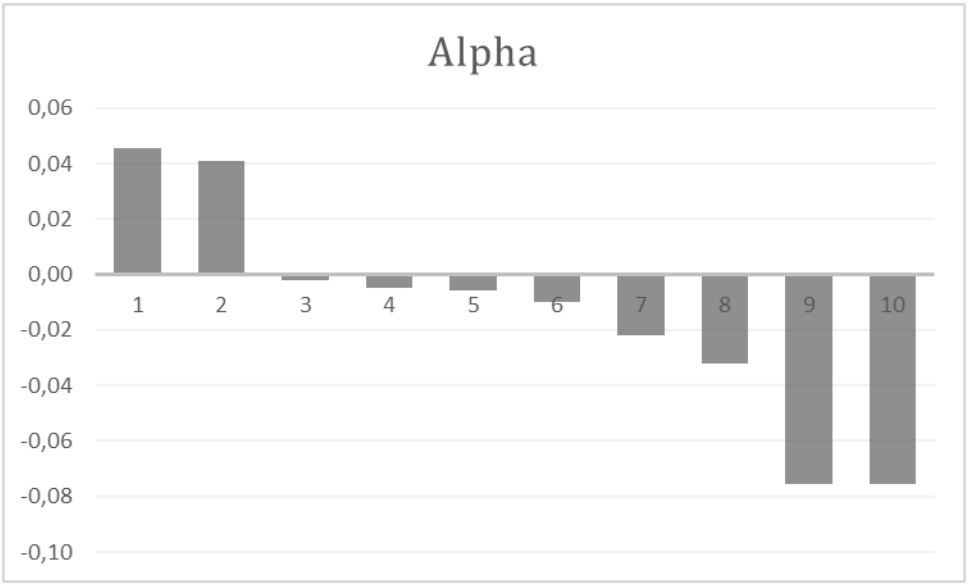

Figure 4 Bust market three month post-rank alphas

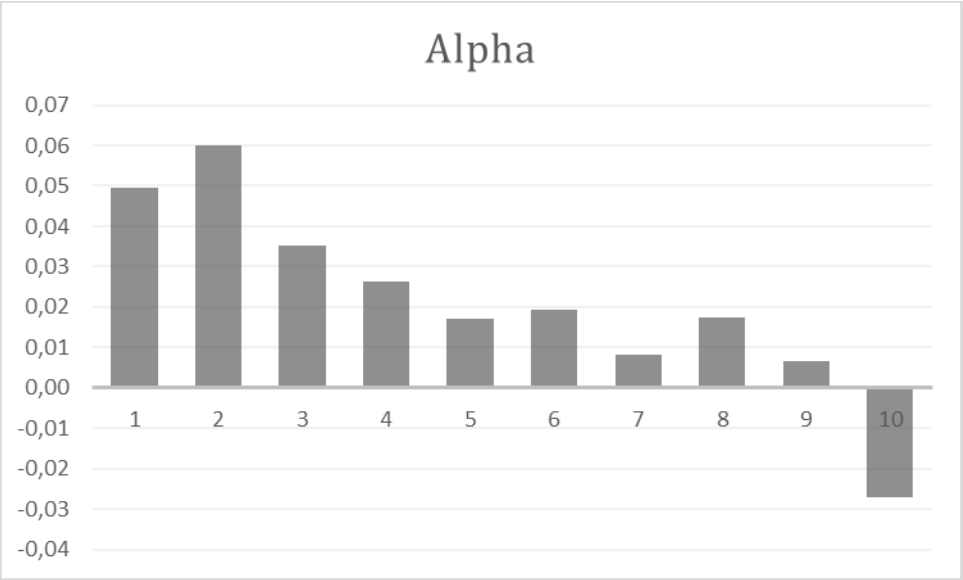

Figure 5 Boom market three month post-rank alphas

Figure 4 and Figure 5 show us the portfolio's alphas after three-month holding period during the bust and boom periods. From these we can see, that both graphs show obvious trend in alphas, but to interpret the performance persistence, we need to calculate the p-values of Sharpe and alpha and see if they are significant and do they differ greatly between bust and boom periods. So we cannot make conclusions about performance persistence based only in values of alpha.

Next we calculate the p-values of Sharpe and alpha.

Table 4 Bust market three month post-rank performance persistence

Portfolio	Mean	Std	N	Sharpe	t_Sharpe	p_Sharpe	Alpha	t_Alpha	p_Alpha
10	-0.113	0.086	41	-1.318	-2.437	0.019	-0.076	-1.815	0.079
9	-0.114	0.088	41	-1.286	-2.376	0.022	-0.075	-1.932	0.062
8	-0.082	0.076	41	-1.081	-1.999	0.052	-0.032	-0.947	0.351
7	-0.077	0.074	41	-1.046	-1.934	0.060	-0.022	-0.759	0.453
6	-0.070	0.076	41	-0.919	-1.699	0.097	-0.010	-0.286	0.777
5	-0.060	0.073	41	-0.824	-1.523	0.136	-0.006	-0.168	0.867
4	-0.053	0.074	41	-0.712	-1.316	0.196	-0.005	-0.125	0.901
3	-0.047	0.072	41	-0.644	-1.190	0.241	-0.002	-0.053	0.957
2	-0.011	0.077	41	-0.137	-0.253	0.802	0.041	1.218	0.232
1	0.004	0.054	41	0.068	0.125	0.901	0.045	1.764	0.087

0	0.117	0.067	41	1.744	3.224	0.003	0.121	2.816	0.008

We do the same calculations, but pick the portfolios from boom period.

Table 5 Boom market three month post-rank performance persistence

Portfolio	Mean	Std	N	Sharpe	t_Sharpe	p_Sharpe	Alpha	t_Alpha	p_Alpha
10	0.021	0.077	128	0.275	0.899	0.371	-0.027	-1.440	0.153
9	0.050	0.064	128	0.784	2.560	0.012	0.007	0.490	0.632
8	0.063	0.063	128	1.004	3.280	0.001	0.018	1.228	0.222
7	0.063	0.066	128	0.961	3.137	0.002	0.008	0.641	0.523
6	0.070	0.066	128	1.053	3.440	0.001	0.019	1.338	0.184
5	0.070	0.065	128	1.067	3.484	0.001	0.017	1.320	0.189
4	0.078	0.063	128	1.236	4.037	0.000	0.026	2.032	0.044
3	0.083	0.060	128	1.397	4.562	0.000	0.035	2.750	0.007
2	0.096	0.051	128	1.904	6.218	0.000	0.060	5.076	0.000
1	0.079	0.036	128	2.177	7.111	0.000	0.050	5.837	0.000
0	0.057	0.062	128	3.013	3.013	0.003	0.077	4.063	0.000

Comparing Table 4 and Table 5 we can see that portfolios with three-month holding period during the bust period has bigger difference between the mean of the best and the worst portfolios than in boom period, so there is more variety in portfolio outcomes in bust periods. This was expected, but is there a difference between the best portfolios in bust and boom periods? Are best funds keeping up their performance during recession?

When we look at the Sharpe ratios and especially the p-values of Sharpe in our two tables, we can see quite the opposite results. In bust period the worst portfolios are showing statistically significant p-values of Sharpe, whereas in boom period the best portfolios have significant p-values of Sharpe. This indicates that in bust period, the worst portfolios are more persistent with their performance than the best portfolios, and in boom period the best portfolios outperform the worst, not just in performance, but in performance persistence as well. Although, there is the portfolio 1, i.e. the very best portfolio, which is the only one with positive mean and Sharpe after three-month holding period, so it is making profit, but it is not persistent.

Alpha results are similar in bust period, the worst portfolios are more persistent with their performance in three-month holding period than the best portfolios. The best portfolio has p-value of alpha which is almost significant, and it is almost the same as in worst portfolio, so the best and portfolios are as persistent with each other. In the boom period, the p-values of alpha are significant in the best portfolios, which means that the best portfolios are better at keeping up their performance than the worst portfolios.

4.4.2 Bust vs boom market twelve month performance persistence

Let's see what happens to the same portfolios after twelve-month holding period. The performance of the portfolios is calculated after twelve months and the portfolios are rearranged based on their new performance. We are again comparing bust and boom period's results to each other.

Again we take a peek into what the portfolios' alphas look like in our different periods. With the twelve-month holding period, the portfolios' alphas have more variety during bust period than in boom period. There isn't as obvious trend in bust period with twelve-month holding period as there was with the three-month holding period. This suggests that the performance persistence lessens with longer holding period.

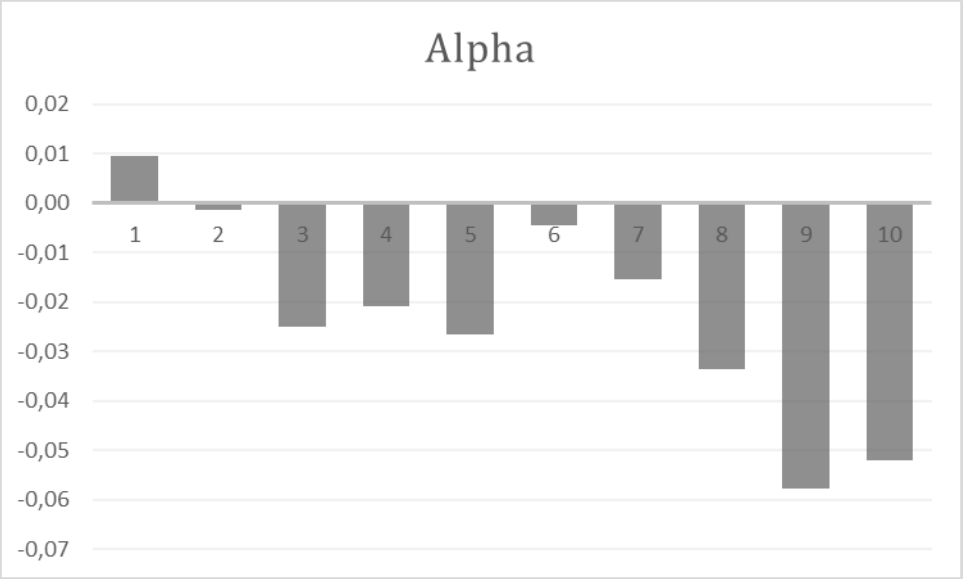

Figure 6 Bust market twelve month post-rank alphas

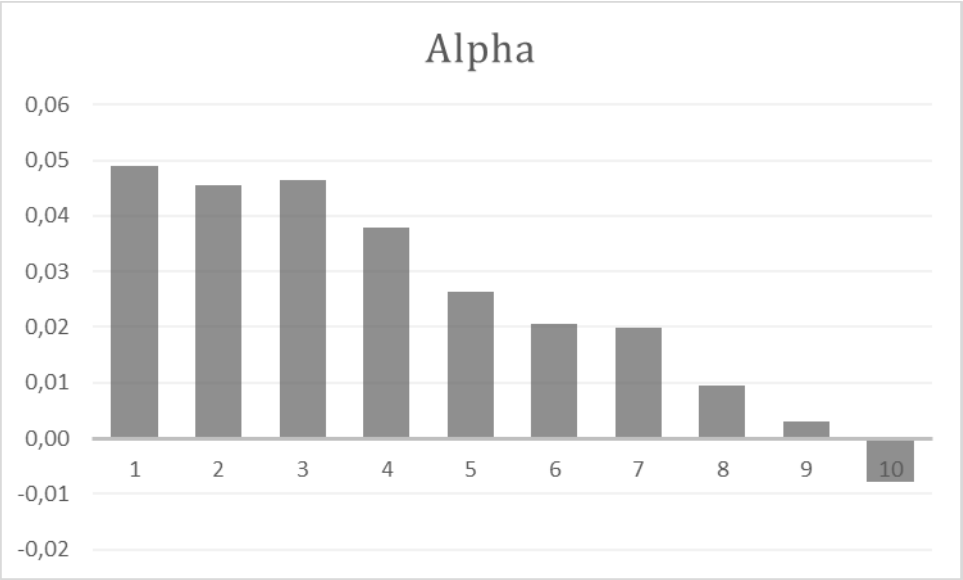

Figure 7 Boom market twelve month post-rank alphas

We need to calculate the p-values of Sharpe and alpha in order to make any conclusions about the performance persistence.

Table 6 Bust market twelve month post-rank performance persistence

Portfolio	Mean	Std	N	Sharpe	t_Sharpe	p_Sharpe	Alpha	t_Alpha	p_Alpha
10	-0.110	0.063	35	-1.747	-2.984	0.005	-0.052	-2.032	0.052
9	-0.095	0.070	35	-1.360	-2.322	0.026	-0.058	-1.509	0.143
8	-0.071	0.070	35	-1.014	-1.732	0.092	-0.034	-0.798	0.432
7	-0.082	0.071	35	-1.150	-1.965	0.058	-0.015	-0.453	0.654
6	-0.084	0.083	35	-1.009	-1.724	0.094	-0.004	-0.103	0.919
5	-0.090	0.083	35	-1.087	-1.857	0.072	-0.027	-0.712	0.483
4	-0.079	0.071	35	-1.103	-1.883	0.068	-0.021	-0.614	0.544
3	-0.088	0.077	35	-1.141	-1.949	0.060	-0.025	-0.735	0.469
2	-0.070	0.073	35	-0.957	-1.635	0.111	-0.001	-0.037	0.971
1	-0.043	0.060	35	-0.719	-1.228	0.228	0.010	0.340	0.737
0	0.066	0.034	35	1.949	3.329	0.002	0.062	3.078	0.005

Table 5 Boom market twelve month post-rank performance persistence

Portfolio	Mean	Std	N	Sharpe	t_Sharpe	p_Sharpe	Alpha	t_Alpha	p_Alpha
10	0.042	0.075	123	0.556	1.780	0.078	-0.008	-0.459	0.647
9	0.045	0.062	123	0.724	2.318	0.022	0.003	0.236	0.814
8	0.059	0.066	123	0.903	2.890	0.005	0.010	0.728	0.468
7	0.067	0.065	123	1.031	3.300	0.001	0.020	1.378	0.171
6	0.071	0.066	123	1.074	3.440	0.001	0.021	1.576	0.118
5	0.068	0.062	123	1.106	3.542	0.001	0.026	2.068	0.041
4	0.091	0.071	123	1.275	4.081	0.000	0.038	2.801	0.006
3	0.087	0.063	123	1.382	4.425	0.000	0.046	3.577	0.001
2	0.080	0.052	123	1.523	4.877	0.000	0.045	4.139	0.000
1	0.074	0.042	123	1.762	5.640	0.000	0.049	5.278	0.000
0	0.032	0.061	123	0.520	1.664	0.099	0.057	3.050	0.003

First of all, we can see that in bust period, after twelve months holding period, every portfolio is at loss, so the performance persistence worsens when the holding period lengthens. In boom period the portfolio means go up as the holding period lengthens.

In bust market, the p-value of Sharpe is significant only in the worst portfolios, where as in boom market, only the worst portfolio does not have significant p-value of Sharpe. This means that during bust periods, the worst portfolios persist being the worst with the most loss, and in boom period, their performance starts to vary more.

The p-value of alpha has similar results, in bust period, the worst portfolios have smaller p-values, and in boom periods, the best portfolios have significant t-values of alpha. This means that in bust periods, the worst portfolios make persistently bad results, and the best portfolios do not have persistent performance. In boom period, the best portfolios are persistent with their performance.

5 CONCLUSIONS

Our aim for this thesis was to study whether hedge fund performance persists after weak markets and does the results differ from performance persistence after strong markets.

Even though there is some indications that the very best portfolios can make at least short-term profit even in bust periods, the performance is not persistent. All in all, it seems that the best portfolios have more varying outcomes during recession than the worst portfolios. During expansion, the best portfolios have good performance persistence whereas the worst portfolios outcomes vary more.

What we can conclude from these results is that badly performing portfolios keep on performing badly despite the overall market situation, and the best portfolios can make consistent risk-adjusted excess returns only in good market situations. The results implicate that you cannot identify the skilled fund managers from others by looking at hedge fund's performance during market crisis.

The main inspiration for this thesis was an article 'Only winners in tough times repeat: Hedge fund performance persistence over different market conditions' (Sun et al. 2016). The study shows that there exists predictability for hedge fund's performance after weak markets but not after strong markets. Our results were similar, but not statistically significant. So, picking the best performing portfolio based on past performance during recessions does not guarantee that the outcome is favorable. This means that our null-hypothesis holds, and there is no statistically significant difference in performance persistence after recession and expansion periods.

Further analysis of the hedge funds' characteristics is needed to understand the underlying reasons for the differences in the results.

6 REFERENCES

Agarwal, V. & Naik, N. Y. (2000). Multi-period performance persistence analysis of hedge funds. *Journal of Financial & Quantitative Analysis* 35(3), 327-342.

Agarwal, V. & Kale, J. R. (2007). On the relative performance of multi-strategy and funds of hedge funds. *Journal of Investment Management* 5(3), 41-63.

Agarwal, V., & N. Y. Naik. (2000). On taking the alternative route: Risks, rewards, and performance persistence of hedge funds. *Journal of Alternative Investments* 2, 6–23.

Agarwal, V. & Naik, N. Y. (2004). Risks and portfolio decisions involving hedge funds. *Review of Financial Studies* 17(1), 63-98.

Agarwal, V., Jiang, W., Tang, Y., Yang, B. (2013). Uncovering hedge fund skill from the portfolio holdings they hide. *The Journal of Finance* 68(2), 739-783.

Ammann, M. & Moerth, P. (2008). Impact of fund size and fund flows on hedge fund performance. *Journal Of Alternative Investments*, 11(1), 78-96.

Asness, C. S., Moskowitz, T. J. & Pedersen, L. H. (2013). Value and momentum everywhere. *Journal of Finance* 68(3), 929-985.

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

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

Baltas, A.N & Kosowski, R. (2013). Momentum strategies in futures markets and trend-following funds. *Paris December 2012 Finance Meeting EUROFIDAI-AFFI Paper.*

Basu, S. (1977) Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance* 32(3), 663-692.

Brown, S. J., Goetzmann, W. N. & Ibbotson, R. G. (1999). Offshore hedge funds: Survival and performance, 1989-95. *Journal of Business* 72(1), 91-117.

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

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance* 52(1), 57-82.

Cochrane, J. H. (2005). Asset pricing (revised edition). *Princeton (N.J.): Princeton University Press.*

Connolly, C. & Hutchinson, M. C. (2011). Dedicated short bias hedge funds: Diversification and alpha during financial crises. *Journal of Alternative Investments* 14(3), 28-41.

Dichev, I. D. & Yu, G. (2011). Higher risk, lower returns: What hedge fund investors really earn. *Journal of Financial Economics* 100(2), 248-263.

Edelman, D., Fung, W. & Hsieh, D. A. (2013). Exploring uncharted territories of the hedge fund industry: Empirical characteristics of mega hedge fund firms. *Journal of Financial Economics* 109(3), 734-758.

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

Eling, M. (2009). Does hedge fund performance persist? Overview and new empirical evidence. *European Financial Management* 15(2), 362-401.

Fama, E. F. (1970), Efficient capital markets: A review of theory and empirical work, *The Journal of Finance* 25(2), 383–417.

Fama, E. F. & French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance* 47(2), 427-465.

Fama, E. F. & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33(1), 3-56.

Fama, E. F. & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51(1), 55-84.

Fung, W. & Hsieh, D. A. (1997). Empirical characteristics of dynamic trading strategies: The case of hedge funds. *Review of Financial Studies* 10(2),

Fung, W. & Hsieh, D. A. (1997b). The information content of performance track records: Investment style and survivorship bias in the historical returns of commodity trading advisors. *Journal Of Porfolio Management* 1(24), 30-41.

Fung, W. & Hsieh, D. A. (1999). A primer on hedge funds. *Journal of Empirical Finance* 6(3), 309-331.

Fung, W. & Hsieh, D. A. (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies* 14(2). Risk factor data from https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

Fung, W. & Hsieh, D. A. (2002). Asset-based style factors for hedge funds. *Financial Analysts Journal* 58(5), 16.

Fung, W. & Hsieh, D. A. (2002). The Risk in Fixed-Income Hedge Fund Styles. *Journal of Fixed Income* 12 (2),16–27.

Fung, W. & Hsieh, D. A. (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal* 60(5), 65-80.

Fung, W., Hsieh, D. A., Naik, N. Y. & Ramadorai, T. (2008). Hedge funds: Performance, risk, and capital formation. *The Journal of Finance* 63(4), 1777-1803.

Fung, W. & Hsieh, D. A. (2011). The risk in hedge fund strategies: Theory and evidence from long/short equity hedge funds. *Journal of Empirical Finance* 18(4), 547-569.

Fung, W., Hsieh, D. A., Naik, N. Y. & Ramadorai, T. (2008). Hedge funds: Performance, risk, and capital formation. *Journal of Finance* 63(4), 1777-1803.

Glosten, L. R. & Jagannathan R., (1994). A contingent claim approach to performance evaluation. *Journal of Empirical Finance* 1, 133-160.

Joenväärä, J., Kosowski, R. & Tolonen, P. (2013). New 'stylized facts' about hedge funds and database selection bias. Available at SSRN: http://ssrn.com/abstract=1989410 or http://dx.doi.org/10.2139/ssrn.1989410

Joenväärä, J., Kosowski, R. & Tolonen, P. (2014). Hedge fund performance: What do we know? *Working paper*

Keane, S. (1986). The efficient market hypothesis on trial, *Financial Analysts Journal*, 42:2, 58-63

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

Liang, B. (1999) On the performance of hedge funds. *Financial Analysts Journal* 55, 72–85.

Liang, B. (2000). Hedge funds: The living and the dead. *Journal of Financial & Quantitative Analysis* 35(3), 309-326.

Liang, B. (2004). Alternative investments: Ctas, hedge funds, and funds-of-funds. *Journal of Investment Management* 2(4), 76-93.

Lo, A.W. (2007). Efficient Markets Hypothesis. *The New Palgrave: A dictionary of economics* SSRN: https://ssrn.com/abstract=991509

Lo, A.W. (2001). Risk management for hedge funds: Introduction and overview. *Financial Analysis Journal* 57(6), 16-33.

Lustig, H., Roussanov, N. & Verdelhan, A. (2011). Common risk factors in currency markets. *Review of Financial Studies* 24(11), 3731-3777.

Malkiel, Burton, G. 2003. "The efficient market hypothesis and its critics ." *Journal of Economic Perspectives*, 17 (1): 59-82.

Moskowitz, T. J., Ooi, Y. H. & Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics* 104(2), 228-250.

Naik, N. Y., Ramadorai, T. & Stromqvist, M. (2007). Capacity constraints and hedge fund strategy returns. *European Financial Management* 13(2), 239-256.

Nohel, T., Wang, Z.J., Zheng, L. (2010). Side-by-Side Management of Hedge Funds and Mutual Funds. *The Review of Financial Studies* 23(6), 2342-2373.

Pastor, L. & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy* 111(3), 642-685.

Patton, A. J. (2009). Are 'market neutral' hedge funds really market neutral? *Review of Financial Studies* 22(7), 2495-2530.

Ramadorai, T. (2012) Capacity constraints, investor information, and hedge fund returns. *Journal of Financial Economics* 107 (2), 401-416.

Reddy, G., Brady, P. & Patel, K. (2007). Are funds of funds simply multi-strategy managers with extra fees? *Journal of Alternative Investments* 10(3), 49-61.

Ribeiro, M. M. & Machado-Santos, C. (2011). Market neutral hedge funds strategies: Are they really neutral? *European Journal of Finance & Banking Research* 4(4), 11-22.

Ross, Stephen (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory* 13 (3), 341–360

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

Scott, W. (2006). Multi-strategy funds vs. fund of funds: the future of multimanager hedge funds. *Journal of Alternative Investments* 23-28

Sewell, M. (2011). History of the efficient market hypothesis. *Research Note RN/11/04, University College London, London*.

Sewell, M. (2012). The efficient market hypothesis: Empirical evidence. *International Journal of Statistics and Probability* 1(4).

Sharpe, W. F. (1964). Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance* 19, 425–442.

Stephen, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory* 13 (3), 341-360

Stulz, R.M. (2007). Hedge Funds: Past, Present, and Future. *Journal of Economic Perspectives* 21(2), 175-194.

Sun, Z., Wang, A. W. & Zheng, L. (2016). Only winners in tough times repeat: Hedge fund performance persistence over different market conditions. *Working Papers -- U.S.Federal Reserve Board's Finance & Economic Discussion Series* 1-40.

Teo, M. (2007). Does size matter in the hedge fund industry? http://ssrn.com/abstract=1331754 or http://dx.doi.org/10.2139/ssrn.1331754

Teo, M. (2009). The geography of hedge funds. *Review of Financial Studies*, 22(9), 3531-3561.

Till, H. (2010). Risk considerations unique to hedge funds. *Quantitative Finance,* 2(6), 409-411.

Titman, S. & Tiu. C. (2011) Do the best hedge funds hedge? *Review of Financial Studies* 24, 123-168.

Yan, X. (2008). Liquidity, investment style, and the relation between fund size and fund performance. *Journal of Financial and Quantitative Analysis* 43(3), 741-767.

Yen, G., Lee, C. (2008). Efficient market hypothesis (EMH): Past, Present and Future. *Review of Pacific Basin Financial Markets and Policies* 11(2), 305-329.