UNIVERSITY OF VAASA

FACULTY OF BUSINESS STUDIES

DEPARTMENT OF ACCOUNTING AND FINANCE

Taru Pajunen

LINEAR HEDGE FUND INDEX REPLICATION

Revolutionizing Hedge Fund Industry or Introducing Poor-performing Alternatives for Hedge Funds?

Master's Thesis in
Accounting and Finance
Finance

VAASA 2016

TABLE OF CONTENTS **page**

LIST OF FIGURES page

LIST OF TABLES **page**

UNIVERSITY OF VAASA
Faculty of Business Studies
Author: Taru Pajunen
Topic of the Thesis: Linear Hedge Fund Index Replication Revolutionizing Hedge Fund Industry or Introducing Poor-performing Alternatives for Hedge Funds?
Name of the Supervisor: Jussi Nikkinen
Degree: Master of Science in Economics and Business Administration
Department: Department of Accounting and Finance
Major Subject: Accounting and Finance
Line: Finance
Year of Entering the University: 2010
Year of Completing the Thesis: 2016 **Pages:** 74

ABSTRACT

Hedge funds have historically been important investments in diversified portfolios of wealthy individuals and institutional investors. However, recent economic environment and events including the financial crisis of 2008 have increased investors' awareness of the restrictions related to hedge funds such as high fees, lock-up periods, illiquidity and lack of transparency. Roused by these problems some investors have begun to look for products yielding returns similar to hedge funds without their disadvantages. The goal of this thesis is to conduct and examine the linear hedge fund replication portfolios that aim to generate returns comparable to hedge funds with lower fees and increased transparency, functioning as potential components of alternative investment allocation.

In this thesis, linear multivariate factor models are estimated to ten Credit Suisse Hedge Fund Indices from the Credit Suisse Asset Management LLC –database in order to examine risk exposures of these indices to common factors during time period from 2004 to 2015. Eight different factors, selected based on previous research and their ability to explain the hedge funds' risk exposures are included in the model. The estimated beta coefficients from the risk exposure analysis are then used as portfolio weights for the eight factors in order to conduct monthly returns for the replication products. Both fixed-weight linear clones and 24-month rolling-window linear clones are conducted. The monthly clone returns for both fixed-weight and rolling-window clones are compared to their target Credit Suisse Hedge Fund Indices.

Results suggest that for certain indices a significant fraction of their risk can be captured by common factors in the linear factor model. Although the performance of the linear clones can be inferior to their hedge fund index benchmarks, they still offer similar levels of diversification benefits as the target indices. Finally, neither the fixed-weight nor the 24-month rolling window linear clones do perform well enough to be considered as alternatives to hedge funds.

KEYWORDS: Hedge fund replication, passive hedge fund replication, risk exposure analysis, linear factor model

1. INTRODUCTION

Hedge funds have gained enormous popularity in recent decade. The notable growth in the hedge fund industry is largely due to their promises to create above average market neutral returns. Due to variety of investment strategies and assets that hedge fund managers are able to utilize, the funds have been able to generate returns with relatively low correlation with common asset classes like stocks and bonds. Unlike managers of mutual funds, hedge fund managers have got a possibility to invest in more exotic assets such as derivatives, use leverage and sell short (Duanmu, Li and Malakhov 2015). Historical evidence, however, claims that hedge funds have failed to fulfill these attempts in many cases. According to Hedge Fund Research (2015), in 2014 hedge funds gained 4,10 percent being behind the Standard & Poor's 500 which gained 9,87 percent. Hedge funds are no longer giving superior performance and therefore, they are progressively sold on the back of a diversification argument (Kat and Palaro 2005: 62).

At the same as popularity towards hedge funds increased, they became a subject to criticism. The most common critiques are towards their lack of liquidity, transparency, opaque holdings and 2-20 fee structures. After the financial crisis in 2008 investors became even more aware of issues such as illiquidity and lockup periods that are often associated with hedge funds. Many investors increased their awareness about hedge funds and began to look more closely not only how the funds generated returns but also where these return flows came from (Jaeger and Wagner 2005). Due to the financial crisis many investors realized that they were actually paying alpha-level hedge fund fees for beta-only performance. After these challenges, alternative investment products have become a focus area for investors.

To create demand for alternative investments, avoiding the problems of hedge funds, numerous financial institutions have developed new products and portfolios that attempt to clone the returns of hedge funds offering liquidity and transparency with lower-cost (Bollen and Fisher 2013: 80). This thesis aims to capture the appropriate use of these hedge fund clones by building a replication model using risk exposures of hedge fund indices and further empirically examine the hedge fund replication procedure.

The performance of the hedge funds has largely been questioned among pension funds and other large institutional investors after the year 2014 showed to be the weakest for the hedge funds since the financial crisis and year 2008. In September 2014, The California Public Employees' Retirement System (Calpers) announced to stop investing in the hedge funds. This largest U.S. pension fund decided to pull out its 4 billion that it had invested across 24 hedge funds and six hedge fund-of-funds. With over 300 billion dollars in assets, the fund announced making the decision because their investments were no longer cost-efficient and also, because the investments had become too complicated. Calpers wrote that in July, their investments returned 18,4 percent during the fiscal year that ended on June 30 with hedge funds gaining 7,1 percent whereas private equity investments returned 20 percent (Reuters 2014, Fortune 2014a.) After the announcement, Fortune (2014b) wrote that, "this will not kill the industry, but will require a lifestyle change for it". This suggests that the financial markets are in a need of new hedge fund replication products – alternatives for actual hedge funds.

There are replication products that are already available to institutional investors, such as Goldman Sachs Absolute Returns Tracker Index, Merrill Lynch Factor Index, Long Barclays Alternatives Replicator USD TR Index and Morgan Stanley Altera index. These products are either for the specified hedge fund strategy or for the overall broad hedge fund industry. Moreover, imitation funds such as Global X Guru Index and Alpha Clone Alternative Alpha also exist. The imitation funds invest directly to long positions that are observed from the 13F filings of top fund managers. (Subshash and Enke 2014: 1959.) IndexIQ, one of leading investment solution providers globally, has continuously announced new hedge fund replication indices (IndexIQ 2015). IQ Hedge Indices aim to replicate the performance by utilizing replication and alternative beta strategies. The IndexIQ was established in 2006 and since then it has been growing significantly with popularity and established more replication indices. Despite the existence of replication products for investors who seek alternatives for hedge funds, these replication products are still often functioning like hedge funds: charging high fees with methods that are largely unknown.

1.1. Background

The history of researchers attempting to build hedge fund replication strategies and portfolios aiming to generate returns similar to hedge funds is relatively short. A study performed by Hasanhodzic and Lo (2007) has undoubtedly paved the way for more recent research attempts. They showed that for certain hedge fund categories it is possible to obtain comparable returns using a linear factor model approach. To justify the novelty of hedge fund replication research, Duanmu et al. (2014) point out there is no set of factors that would be globally accepted when conducting factor based replication procedure. Although the hedge fund replication is a relatively new field of finance, investors have aimed to find and understand the source of excess returns of the best portfolio managers' portfolios for a much longer time. Sharpe (1992) introduced a method that benchmarks mutual fund performance explaining the portfolio returns in terms of various asset classes. He conducted an asset class factor model to analyze mutual fund performance and suggested that the fund return has two components: asset class factors, which he calls "style", and uncorrelated residual, which he calls as "selection".

At the time of writing, there is a lack of existing studies; in particular lack of jointly accepted methods. This is to be concluded, because there is no globally accepted way to execute the replication process even though it has been examined for over ten years. There is an ongoing discussion of the best replication method and researchers try to find new techniques that could bring better replication performance.

1.2. Purpose and hypothesis

The hypothesis of this thesis relies on prior literature. Earlier research has shown that common factors are able to explain hedge funds' risk exposures but the results from the replication attempts vary substantially (Fung and Hsieh 2004, Hasanhodzic and Lo 2007, Hayes 2012). There is no widely accepted method to compute the replication procedure and therefore, this thesis presents novel aspects for the replication process by applying the earlier research findings. The goal is to strengthen earlier findings and pave way for larger acceptance for those findings. However, since novel data and new methodology combinations are applied, new findings can be obtained. The linear factor model applied is a new combination of factors used in prior literature (e.g. Fung and Hsieh 2004). Finally, this thesis hypothesize that the linear factor model constructed can explain major part of the hedge fund indices' risk exposures to common factors and further, the conducted replication products outperform their target indices. Methods to measure the performance of the conducted products are introduced in chapter 5. Sample period is 11 years: from September 2004 to September 2015. As we have 7 years after the financial crisis and year 2008, the results also reveal how well the replication products have performed during and after the financial crisis.

1.3. Structure of the thesis

The structure of the thesis is following: first, a closer look at the basic blocks under the hedge fund replication procedure is given. Thereafter, a preview of prior literature is given with a discussion of benefits and weaknesses of replication procedures. The fourth and fifth sections present data and methodology applied. Finally, the last sections introduce empirical results and make a discussion of them.

The next section introduces a theoretical framework for the topic and aims to clarify the idea behind the overall replication process. A brief introduction to different replication methods is given. Also, a review to concepts of alpha, alternative alpha and alternative beta is given. The third section, the literature review, introduces research papers that all together aim to give a broad picture of different aspects of the hedge fund replication.

Fourth section introduces the data employed. Summary statistics of all data is presented. Fifth section presents the methods. Models are showed with explanations why they are applied with chosen data. Finally, results are given for both the fixed-weight and the 24-month rolling window linear clones. The estimated monthly returns are further compared to the target indices. The thesis concludes with a discussion of the results and a brief comparison with earlier research.

2. THEORETICAL FRAMEWORK

To a large extent, empirical research has shown that the hedge fund returns can be explained by market exposures to common factors and therefore the returns are possible to replicate (e.g. Fung and Hsieh 2004, Roncalli and Jerome 2007, Hasanhodzic and Lo 2007). There are a number of replication products already available for investors, mainly created by banks that have utilized the factor-based approach created by academic research. In the factor-based approach one tries to decompose returns of a group of hedge funds into factors. When the returns of target hedge funds are broken into these chosen factors it is possible to create a strategy attempting to replicate the performance of these hedge funds. These factors should be investable and liquid.

2.1. Concept of hedge fund replication

The simplest concept of asset replication is a mutual fund or exchange-traded fund (ETF) on the S&P 500 index (Chatterjee 2014: 333). The purpose behind the hedge fund replication is that investors could earn the same returns than hedge funds with lower costs, increased transparency and possibly even better liquidity and diversification. In order to mimic the risk-return profile of different hedge fund strategies, one has to utilize either common factors or liquid products like futures contracts (Bollen and Fisher 2013). The factors used are often investments in different asset classes: equities, bonds, fixed income and commodities. This thesis applies the linear factor approach in order to find the risk profile of ten target indices by employing eight factors identified in previous research. Further, these risk exposures are then used as portfolio weights of the common factors in order to construct the clone portfolios.

As discussed earlier in chapter 1, the factor-based replication can be attributed already to Sharpe (1992) who utilized a linear factor model in order to measure the relation between the returns of specific investments to returns of standard asset classes. Further, he applied the model to mutual funds and found that estimates of factor exposures correspond to certain mix of assets in these funds. This combination of linear replication and buy-and-hold factors has been distinguished e.g. by Fung and Hsieh (2004) and Bollen and Fisher (2012). The approach may be unable to capture the nonlinearities between hedge fund returns and those of standard assets. Nonlinearities arise for example by positions in securities such as credit default swaps that have option-like payoffs (Bollen and Fisher 2013: 4). Further, the dynamic exposures can be captured in linear factor models whether the factor loadings can vary over time. Due to these arguments, a rolling-window approach is applied besides the fixed-weight approach in this thesis. The rolling-window approach is argued to capture the time-varying exposures.

2.2. Different replication strategies

The hedge fund replication can be based on three different methods. The most popular approach involves estimating the target fund's factor exposures using Sharpe's (1992) asset-class factor model approach (e.g. Hasanhodzic and Lo 2007) to find beta coefficients and determine the weights for the clone portfolios. Briefly, this method often referred to *as* ***linear*** *replication method* tracks hedge fund returns by estimating exposures to different risk factors with a linear regression model and then invest in different asset classes according to risk factor exposures. The rationale behind this method is that a significant part of the hedge fund returns can be explained by a linear relationship to a set of common assets.

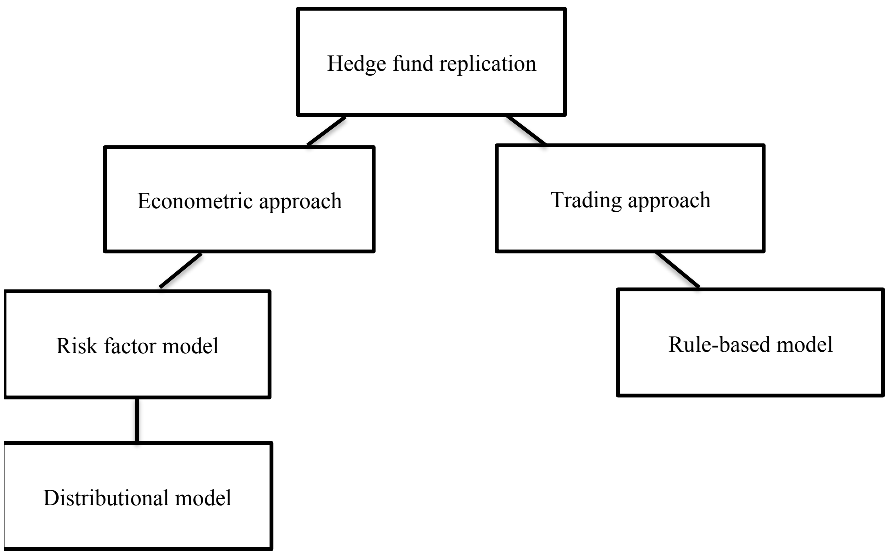


Figure 1. Hedge fund replication methods.

The second method is called a ***rule-based*** method. This method is sometimes referred to as the mechanical or trade-related method. Traders try to isolate broad fundamental concepts of hedge fund strategies and mimic these with automated trading algorithms (Wallerstein, Tuchschmid and Zaker 2010: 38).

The third approach to hedge fund replication is the so called ***distributional*** replication method first suggested by Kat and Palaro (2005). This approach uses complex trading strategies to find matches from historical returns of a target fund. Distribution-based clones try to mimic the historical return distribution of the target out-of-sample. Amin and Kat (2003) conduct an unconditional distribution in their paper whereas the paper of Kat and Palaro (2005) conducts a bivariate distribution of the target's return and return of another asset, for example a stock market index.

Each method has its proponents but the commercial applications currently available to investors mostly rely on the factor-based approach with a smaller number of investors using the mechanical approach. This thesis applies the factor-based replication due to several reasons. First, Amenc et al. (2008) argues that using the distributional approach would require a relatively long estimation period to establish the target distribution using historical returns. In addition, the distributional replication processes utilize complex mathematical techniques to create high-frequency trading systems that are not in a purpose of this thesis.

Earlier studies do not provide much results of market-timing ability of the target. However, Bollen and Fisher (2013) conclude that it is a substantial issue in replication process. According to them it can be examined in two different ways. Firstly, one can estimate exposures to factors that are constructed to reflect the returns of active market-timing strategies. Another way is to use a model that allows exposures to standard asset classes to vary conditional on the magnitude of asset returns. In other words, larger exposure is allowed during higher market returns and vice versa.

Of the earlier research, Griffin and Xu (2009) attempt to find market timing ability. They use equity holdings of hedge funds from quarterly SEC Form 13F filings. However, they do not find significant evidence concerning hedge fund managers able turn capital among different styles in advance of high returns. Also Cheng and Liang (2007) find some evidence of the market timing ability, but only from a small set of hedge funds. Finally, Hayes (2012) in his paper completely fails to find market timing in hedge fund index clones. Despite possible interesting aspects of the replication products' market timing ability, a deeper market timing analysis is not made in this thesis in order to keep the research comprehensive.

2.3. Alpha & alternative beta

Alpha – or managerial skill, as many financial analysts may call it – is a correlation of returns with undefined factors in a regression. It is the part of the returns that cannot be explained by traditional factors. The hedge fund industry used to think that fund managers can generate alpha through their skills and again, high hedge fund returns. The academic studies have, however, shown that much of the hedge fund returns are actually due to systematic risk exposures rather than alpha and therefore, the arisen popularity of term "alternative beta". It would not be even possible to replicate the alpha, since it includes superior information about market inefficiencies (Jaeger and Pease 2008: 5).

In contrast, Fung and Hsieh (1997) argue that hedge funds tend to have lower correlations with traditional asset classes and that this is a consequence of better performing hedge fund managers with more skills compared to those of mutual funds. However, later they realize that the interpretation is inconsistent with evidence that hedge funds often perform poorly when asset markets perform very poorly (Fung and Hsieh 2004: 67). They conclude that the same way as mutual funds, hedge funds are exposed to risks that are just different of those of mutual funds.

Hasanhodzic and Lo (2007) include the alpha in their model. For all hedge funds included in the sample, positive average alphas are found ranging from 0,42% per month to 1,41% per month. They argue that for their sample of 1610 individual hedge funds, 61% of the average total return is due to the manager specific alpha. The values are still ranging a lot between the strategy specific funds. Over 80% of the average total return of Equity Market Neutral funds is due to alpha. The same value for Managed Futures is -27,5%.

Mikhail Tupitsyn and Paul Lajbcygier (2015) examine passive hedge funds in their recent study and find that two-third of hedge funds exhibit only linear exposures and therefore, are passive. According to their research, most hedge fund managers do not generate returns through managerial skill. Moreover, these passive portfolios are found to outperform most of the active managers. They also show that active managers often eventually become passive. Their recent findings justify the use of passive linear replication in this thesis.

Some studies may also refer to *alternative alpha*, which is an additional return on top of existence alpha (Lin 2014: 1). The concept was first proposed to distinguish outperformed hedge funds to others. Fung and Hsieh (2003) even suggested decomposing the hedge fund return into an idiosyncratic (alternative alpha) and a systematic (alternative beta) component. Whereas the term “alternative beta” refers to the part of returns that is achievable, “alternative alpha” refers to the part of the returns that is not easily achievable by replication methods (Fung and Hsieh 2007: 47). However, in this thesis an alpha referring to the managerial skill return and a traditional beta are the terms that are used further and analyzed.

But if it really is so that the hedge fund returns are more due to beta rather than alpha, it makes more sense to replicate the hedge funds rather than to directly invest in them. Alternative beta is a modified version of the traditional beta. Sharpe introduced the parameter with capital asset pricing (CAPM) model in 1992. He stated that in equilibrium after risk adjustment assets have same return:

$$E(r_i) = r_f + \beta_i[E(r_m) - r_f] \tag{1}$$

From this model, the unexplained excess return (or alpha) can be expressed as:

$$\alpha_i = E(r_i) - \beta_i\left[E(r_m) - r_f\right] - r_f \tag{2}$$

where β_i presents the asset’s risk and can be formulated as following:

$$\beta_i = \frac{COv\ (r_i, r_m)}{Var(r_m)}\ . \tag{3}$$

To conclude, traditional betas are referred to traditional investments, for example stocks and bonds. To compare, the definition of alternative beta requires techniques different from traditional ones, such as short selling and use of derivatives. These techniques are usually associated with hedge funds, and hence the term of alternative beta in context of hedge funds.

3. LITERATURE REVIEW

Several publications have dealt with pros and cons of hedge fund replication and the theory of alternative beta. Researchers have tried to replicate individual funds, funds-of-funds indices and strategy specific indices. The results have been mixed. Other studies find the passive fixed-weight linear clones to generally perform better compared to their benchmarks whereas other find the rolling-window approach with time varying beta coefficient to yield better performance. The pros and cons may also vary between academic literature and practise. Although the rolling-window approach would bring better results in the academic research, it may require frequent rebalancing of a portfolio in practise and therefore turn out to be unpractical and costly. In this chapter a discussion about the aforementioned themes is given. Different methods, approaches and their results are introduced trough prior literature. In particular, main studies in the field of linear factor replication are presented more detail.

3.1. Prior literature

Already in 1992, William Sharpe performed a study that later inspired many researchers to study the concept of hedge fund replication. He decomposed returns of a mutual fund into two components: asset class factors such as growth stocks and government bonds, which he calls as “style”, and an uncorrelated residual part that he interprets as “selection”. He constructed a replicating portfolio by relying on constrained beta from linear regressions on a set of factors and empirically demonstrated that only a limited number of major asset classes are needed to replicate the performance of U.S. mutual funds.

Inspired by Sharpe´s (1992) findings William Fung and David A. Hsieh (1997) extended his model into hedge funds and added new factors: short selling and derivatives. They argued that the reason why Sharpe’s study got success was that most mutual fund managers invest similarly with traditional asset managers and therefore, they are likely to generate returns that are highly correlated to returns in major asset classes. Fung and Hsieh (1997) framework takes into account traditional managers as well as alternative managers with absolute, not only relative target returns and conclude that hedge funds apply dynamic strategies and generate nonlinear return profiles and therefore, follow strategies totally different from mutual funds.

Fung and Hsieh have paved the way for later replication attempts. Without denying, their most famous paper in this field is the “Hedge Fund Benchmarks: A Risk-Based Approach” from 2004. In this paper, they further examine the finding that the hedge fund returns are less correlated to traditional asset classes. They introduce a model that has later given motivation for a majority of replication researchers using linear factor models. As a result, their seven asset-based style factors (ABS) were able to explain up to 80 percent of monthly return variations in the hedge funds.

As a proxy for hedge fund portfolios Fung and Hsieh (2004) exploit monthly returns for the HFR Fund of Fund Index. The returns of the index are then regressed on the seven factors from 1995 to 1998 and 2000 to 2002. Two of the factors are stock-factors, two interest-rate factors and last three option factors. The two stock factors are the return on S&P 500 (S&P) and the difference between returns on Wilshire 1750 Small Cap and Wilshire 750 Large Cap (SC-LC). As interest rate factors, the change in the 10-year U.S treasury bonds (10Y) and the difference between Moody´s Baa bonds and U.S. Treasury bond (CredSpr) are included. The three option factors include lookback options on bonds (BdOpt), currencies (FXOpt) and commodities (ComOpt). Lookback option is an option that gives the buyer an option to buy the underlying asset at the lowest price during its duration. Similarly, a seller gets an option to sell the option at the highest price during the duration. When regressed the factors against HFRFOF, HFR fund of funds index, the two equity factors (S&P500 and SC-LC) and the two fixed-income factors (10Y and CredSpr) show statistical significance for the whole first estimation period from 1994 to 2002. For the two trend-following factors (BdOpt and ComOpt) the exposures are statistically significant whereas FXOpt shows to be insignificant for the full period. To summarize the findings of Fung and Hsieh (2004), on average, hedge funds have systematic risk exposures to equity and interest rate bets as well as to long-short equity and credit spread bets. Their findings motivate the factor selection of this thesis.

Jasmina Hasanhodzic and Andrew Lo also perform a study that has gained popularity. They published a paper in 2007 titled “Can Hedge Fund Returns Be Replicated?: The Linear Case.”. By analyzing the returns of over 1600 individual hedge funds from the TASS Hedge fund live database they find that for certain hedge fund style categories, a notable part of the funds’ expected returns is due to risk premium. All funds in the dataset can be divided into five categories: Long/Short Equity Hedge (520), Fund of Funds (355), Event Driven (169), Managed Futures (114), and Emerging Markets (102). The categories underperforming are Event Driven and Emerging Market. For all other categories, the replication works well and the clones are found to be relatively liquid and transparent.

In the approach of Hasanhodzic and Lo (2007) a time-series regression is made for each hedge fund to see how much of the returns are due to the common risk factors. The estimated regression coefficients are then used as portfolio weights for six factors. The factors for which each fund's monthly returns are regressed are: the US Dollar Index return (USD), the return on the Lehman Corporate AA Intermediate Bond Index (BOND), the S&P 500 total return (S&P), the spread between the Lehman BAA Corporate Bond Index and the Lehman Treasury Index (CREDIT), the Goldman Sachs Commodity Index total return (CMDTY) and the first difference of the end of the month value of the CBOE Volatility Index (DVIX). The authors justify the use of these factors by their ability to provide risk exposures for common hedge funds. However, when conducting a fixed-weight linear clone, the DVIX-factor is dropped out because its returns are not easy to realize with liquid instruments in practice.

Beside fixed-weight clone portfolios, the authors apply rolling-window approach. As a result, a huge gap in performance between these two approaches is found. The fixed-weight clones are found to yield better historical performance with lower turnover although they are subject to look-ahead bias. The authors conclude that for certain funds the replication is possible and profitable. An important finding is that a proportion of hedge funds' expected returns are due to the beta coefficients. Only in some occasions the manager specific alphas are found to be significant. Hasanhodzic and Lo are one of the first ones to find what they were looking for: funds' beta exposures, the part of the returns that can actually be replicated. However, the performance varies largely within clones across the hedge fund categories and the authors point out a question: What really is the source of the clones' value-added?

Noël Amenc, Lionel Martellini, Jean-Christophe Meyfredi and Volker Ziemann (2010) extend the Hazanhodzic and Lo (2007) model considering non-linearity and conditional models. They apply option-based factor model, Markow regime-switching model and Kalman filter. Their motivation is to better capture the dynamical characteristics of the dynamical trading strategies the hedge funds apply. They find that selecting factors for each hedge fund category separately yields better out-of-sample replication quality. They do not find that going beyond the linear models would however accelerate the replication performance.

Three researchers, Jun Duanmu, Yongjia Li and Alexey Malakhov have recently written two studies about hedge fund replication with ETFs. Due to their new approaches these papers are introduced. Their approach includes replication of hedge fund indices with futures contracts. In the first paper "In Search of Missing Risk Factors: Hedge Fund Return Replication with ETFs" (2014) a new factor selection methodology is applied to examine through all potential hedge fund risk factors. They make a separation for skill driven and risk driven hedge fund returns. This includes identifying hedge fund managers with high skills and replicating the component including the risk driven hedge fund return. The main idea of Duanmu et al. is to span a large set of potential risk factors with ETFs during a time period of 1997 to 2012. Interesting is that the number of U.S. listed passively managed ETFs increased from 19 to 1313 in these 15 years. The whole ETF industry is relatively new and explored large growth in recent years just as hedge funds.

Duanmu et al. (2014) introduce a methodology that is based on cluster analysis and LAR LASSO factor selection methodology. They argue that the new linear return replication methodology they apply controls multicollinearity issue among ETFs and reduces data mining. This is important since they include all ETFs available in the data. By applying the out-of-sample method they find that the replication accuracy increases with the number of ETFs available. They demonstrate "cloneable" and "non-cloneable" hedge fund portfolios defined as top and bottom in-sample R2 matches. As a result, superior risk-adjusted performance for "non-cloneable" funds is found. This suggests that there are high skilled managers among managers in "non-cloneable" funds. The "cloneable" funds are not found to deliver any significant positive risk-adjusted performance. The authors conclude that there is no statistical significance of managers' skills in sample of "cloneable" funds indicating that these funds can actually be replicated with ETFs.

The authors argue that their replication method provides understanding to identify skilled hedge fund managers in "non-cloneable" funds. These returns are result of alternative risk exposures of "cloneable" funds offering liquidity and transparency. They also argue that the ETF returns can be used as proxies to alternative risk factors driving the hedge fund returns. Finally, their methodology requires several adjustments already when selecting the ideal ETFs and become very complex. Therefore, their methodology is hard for investors to adapt in practice and will not be focused in this thesis.

Another paper is written more recently by the same authors: “Smart Beta ETF Portfolios: Cloning Beta Active Hedge Funds” (2015). According to the authors only hedge funds which returns are driven by beta management risk exposures to the factors are possibly to clone. They call this method as replicating the beta exposures of the best beta active hedge funds that deliver significant long-term risk-adjusted performance. The methodology consists creating a portfolio of ETFs replicating risk factor exposures taken by top beta active hedge funds that could be cloned. In conclusion, Duanmu et al. combine methodologies developed in their earlier research and make and algorithm for creating smart beta ETF portfolios. These portfolios replicate the risk factor exposures taken by the best beta active hedge funds. They result with smart beta ETF portfolios that either match or exceed the risk-adjusted performance of their corresponding portfolios of hedge funds. Finally, they conclude that the smart beta ETF portfolios only rely on annual rebalancing. One of the reasons why Duanmu et al. (2014, 2015) take into account the risk factor exposure approach in their replication efforts is that some fund managers’ strategies are far beyond replication methods. These strategies trade utilizing insider tips. This means that the information cannot be replicated with any algorithms. Instead, the authors argue that the returns are driven by beta exposures to risk factors that all of the investors may not observe.

Bollen and Fisher (2013) argue that in previous research some of the factors used are not investable. Instead, they use factors that are returns on liquid futures contracts. Relatively long sample period is chosen and it is divided into two sub periods: crisis and post-crisis. Ten Dow Jones Credit Suisse indices are used as target investments. The authors find that the clone returns have high correlations with their hedge fund targets meaning that the replicating is possible. The performance of the indices however varies substantially during the estimation period from 1994 to 2011. The broad Hedge Fund Index outperforms the S&P 500 with significantly lower volatility bringing annual Sharpe ratio of 0,73 compared to 0,37 of the S&P 500. Only three indices deliver poorer Sharpe ratio than the S&P 500. Given the impact of financial crisis as can be expected, significant variation is obtained across the sub periods. The Hedge Fund Index for example, delivers Sharpe ratio of -2,01 during the crisis and 1,51 after crisis.

The procedure of Bollen and Fisher (2013) begins by taking positions in five futures. The returns of the futures are generated by holding nearby contract and rolling to the next maturity 5 days prior to expiration. Five different futures contracts are chosen due to their liquidity, low trading costs and coverage of the major asset classes: The U.S. Dollar Index contract (USD), the 10-year T-Note contract (TY), the Gold and the Crude

Oil contracts (GC & CL) and the S&P 500 contract (S&P). In addition, they conduct an analysis with an extended set of factors, to see possible variations in the results. The additional set includes five more factors: monthly returns of the MSCI World Index, the Fama-French size and value factors (SMB and HML), the change in the 10-year Treasury yield (DIOYR) and the change in the credit spread (Spread).

In spite of large data available, the authors argue that there is no data mining. Larger set improves the opportunity for finding better replicators and also an out-of-sample approach is applied. In addition, a big number of factors on a relatively short time period could lead to sampling errors. In order to mitigate this issue, they use a factor selection approach at every estimation date in order to limit the number of factors used to form a clone. Clone construction requires estimating the linear factor model's coefficients each month. These coefficients are then used as position sizes for the set of factors in the linear model. The positions are entered with one-month lag and to be able to get the clone's return on month *t*, data from time *t*-2 is employed. The index performance is typically available on the 15th of a month meaning that the mechanism gives two weeks time to obtain the new index returns and entering to new positions. The authors drop out the alpha that Hasanhodzic and Lo (2007) apply. Omitting the intercept Bollen and Fisher focus on the factors playing bigger role fitting the targets' returns.

Four estimation periods (T=12, 24, 36, 48) are applied, and factor loadings are examined with four different sets of factors. In first set, Bollen and Fisher (2013) include all five futures. To look for possible unrelated factors, second set includes a subset of factors for each index based on the investment strategy. For example, the broad Hedge Fund Index utilizes again all five futures but the Convertible Arbitrage only the TY and the SP. In third set, an estimation regression is run on estimation date using all subsets of the five futures. Then, a subset that brings out the best model fit is selected. Fourth and the final set include a subset bringing the best fit but subsets are first being selected among the set of 10 factors. Estimation may bring some excess returns so the beta coefficients are interpreted as percentage allocation proportions of clone capital to corresponding futures positions. Furthermore, a negative beta is recognized as s short position in the futures contract.

In-sample relation between indices and the other factors is examined through several regressions. The results are largely consistent with other studies. The R-squared in regressions varies significantly over the indices: Managed Futures Index generates R-squared of 9,9% whereas Short Bias Index brings value of 60,3%. According to the authors the low level of fit should not be concerned too much because most of the indices are statistically significantly related to most of the factors. Moreover, the relatively low fit-levels are in line with previous research. When the authors start dropping factors, the fit begins to decline. High average adjusted R-squared tells that the subsets mentioned earlier are a good addition to the replication process. Small improvement in fit is observed when factor subsets are selected in order to maximize the R-squared for the indices. When the larger 10-factors set is employed, the average R-square improves significantly. The fit in the in-sample examination is also improved when different time periods are considered. The fit is highest during the post-crisis period that begins in their sample in 2009. In this case, five indices generates R-squared over 70%. This finding is notable since it motivates to use the rolling-window approach in the replication research.

As mentioned above, also an out-of-sample test is done in research of Bollen and Fisher (2013). A sample period from 1998 to 2011 is applied to measure the ability of clones' returns to fit the index returns. During the pre-crisis 1994-2007, the clones tend to show underperformance whereas at time of the crisis large variation is obtained across the investing styles. The larger 10-factor set is used when the clones manage to outperform their target indices. Better results and higher Sharpe ratios are obtained when no lag between the end of the estimation period and the opening of futures positions to begin the replication process is applied. The index returns are typically available after the mid-month, so the for the time without real returns the performance is conducted hypothetically. In most cases average returns are not statistically significantly different across the clones and indices but in all cases the clones have statistically significantly lower volatility. Therefore, the clones can be a good alternative to the indices.

Even though the results of the paper from Bollen and Fisher (2013) are not overwhelming, they test whether the replication products can serve as a tool to hedge against systematic risk in target fund or index. The results indicate that clones actually can be used for hedging market risk. One unsettle result is found in their study. In most cases, the correlations between the clones and the indices are lower than the correlations between the clones and the S&P 500. The correlations become even higher closer to the crisis time. This decreases the diversification opportunities for investors that are willing to use alternative investments. The study reveals that it is possible to match time series properties of hedge fund indices by estimating factor loadings with a backward-looking rolling-window approach. After this, portfolio weights are conducted going forward. The results suggest that the clones perform worse than the indices. Furthermore, since the indices do not show timing ability, it is not likely that the clones do either. Finally, the study of Bollen and Fisher (2013) has been scrutinized. It makes strong background examination of related issues, but an important question is that why do the clones perform relatively bad. Whether it is due the methodology, factors or data chosen, this thesis aims to further examine these questions.

Hayes (2012) clones six popular hedge fund indices. His main purpose is to examine market timing ability of the factor-based clones. He finds that the clones do not bring any significant market-timing alphas. The reason for the lack of market-timing alphas is probably due to lags caused by reporting delays that contribute to beta estimations. The factors he includes to his model sets are: the S&P 500 equity index (S&P), Fama-French small minus large cap factor (SMB), Fama-French high minus low book value factor (HML), change in the U.S. 10-year Treasury note (USIO), Goldman Sachs commodity index (GSCI), U.S. dollar index (DXY), monthly change in the volatility index (DVIX), the Barclays Aggregate bond index (AGG) and the Barclays High Yield bond index (HY).

Subhash and Enke (2014) make a similar study to Hasahodzic and Lo (2007) showing that the fund and factor selection may have a significant impact for the replication results. They extend earlier analysis by focusing on selecting the relevant factors for each fund strategy. In other words, the authors select three to six factors separately for each hedge fund strategy. With data of 1495 hedge funds from 1996 to 2008 they conduct both fixed-weight and rolling-window clones. The hedge funds are classified into eleven categories sorted by the strategies used: Event Driven, Long/Short Equity Hedge, Managed Futures, Fixed Income Arbitrage, Global Macro, Emerging Markets, Convertible Arbitrage, Multi-Strategy, Dedicated Short-Bias, Equity Market Neutral and Fund-of-Funds. The hedge fund data is also divided into two data sets in which the other one, funds with higher Sharpe ratios are identified and replicated. This results in clones with higher average returns compared to clones from all of the funds in each category. Also better risk-to-reward ratios are obtained. Finally, the authors find that selection of the factors depending of the underlying hedge fund strategy can have advantages over those constructed using a broad set of factors for each strategy. The approach of Subhash and Enke is not further applied in this thesis. Their method does not show to be easy to implement in practice. Moreover, they select the factors used in each strategy randomly instead choosing factors whose use would be empirically proved and tested.

Chen and Tindall (2014) replicate major Hedge Fund indices employing alternative methods. These methods include for example a stepwise regression, lasso method, ridge regression, partial least squares regression and ridge regression among several other advanced regressions. Their findings suggest that the best replication results are discovered with methods applying shrinkage of parameters. Their findings represent new approaches to hedge fund replication processes, however, without support from earlier empirical research. Therefore despite their findings this thesis rely on the linear factor replication methodology with Ordinary Least Squares –regression as it is more justified by empirical research.

Table 1. Summary of main previous studies.

Study	Purpose	Data	Method and Model	Findings
Fung and Hsieh (2004): "Hedge Fund Benchmarks: A Risk Based Approach"	To analyze hedge fund risk exposures	Monthly returns for the HFR Fund of Funds index from January 1994 to December 2002	OLS regression analysis with 7 factors; two stock factors: S&P 500 and the difference between Wilshire 1750 Small Cap (SC) and Wilshire 750 Large Cap (LC), two interest rate factors: the change in the 10-year U.S treasury bonds, and the difference between Moody s Baa bonds and U.S. Treasury bond and three option factors: lookback options on bonds, currencies and commodities.	Finally, the adjusted R-squared of the model is 0.405 between February 1995 and September 1998, and even 0.540 between April 2000 and December 2002. The significant variables for the first time period is the SC-LC and for the second period the SC-LC and the 10Y.
Hasanhodzic and Lo (2007): "Can Hedge-Fund Returns Be Replicated?: The Linear Case"	To replicate the hedge fund returns	Monthly returns for 1610 TASS Hedge Fund Live Database hedge funds, from February 1986 to September 2005	OLS regression analysis with 6 factors: the U.S. Dollar Index, the Lehman Corporate AA Intermediate Bond Index, the spread between the Lehman BAA Corporate Bond Index and the Lehman Treasury Index, the S&P 500, the Goldman Sachs Commodity Index total return, and the CBOE Volatility Index.	In several categories the average return of the comparison index is slightly better, but for five strategies, the passive fixed weight replicators outperform the comparison indexes.
Amenc, Martellini and Meyfredi (2010): "Passive Hedge Fund Replication - Beyond the Linear Case"	To improve the replication methods of Hasanhodzic and Lo (2007) by applying e.g. Non-linear models	Monthly returns for 1610 TASS Hedge Fund Live database hedge funds, from January 1999 to December 2006	OLS regression analysis: conditional linear models and unconditional Kalman filter and Regime switching models.	Going beyond the linear models does not enhance the replication power.
Hayes (2012): "On the Market Timing Ability of Factor-Based Hedge Fund Clones"	To examine whether factor-based clones generate market-timing alpha and market-timing ability.	Monthly returns of four HFRI indices from January 1990 to September 2009 and two DJCS indices from January 1994 to September 2009.	The clones are constructed using four models and five estimation periods. Market timing alphas are measured in three different ways.	Factor clones constructed from six popular hedge fund indices on asset and style factors do not generate significant market-timing alpha. The authors find several reasons for this, i.a. lags caused by reporting delays and beta estimation intervals.
Bollen and Fisher (2013): "Send in the Clones? Hedge Fund Replication Using Futures Contracts"	To analyze the performance of the clones constructed by taking positions in five liquid futures contracts.	Monthly returns of 10 DJCS Indices, three sub-periods: 1994 – 2003, 2004 – 2007, and 2008 – 2011.	OLS regression analysis and the coefficients are used as position sizes for the five futures contracts that perform as factors in the model.	The results are mixed. Correlations with their targets are high, but average returns and Sharpe ratios of the clones are generally low.

3.2. Criticism of hedge fund replication – benefits and weaknesses

Replication products may help portfolio managers in many ways: as an investable benchmark or an alternative asset in a portfolio (Freed 2013: 32). Some argue that although hedge fund clones can offer increased transparency compared to actual hedge funds, due to their wide geographical spread they still cannot offer same level of alphas than the top hedge funds. This is because they react with a lag utilizing information from the past returns of hedge funds. This can be called as *reverse engineering*. Many funds wait the full 45 days permitted for them to disclose their holdings and many of the funds may have changed their holdings from the reported ones. This may cause failures in the replication process since replication processes use the reported fund returns.

Dor, Jagannathan and Meier (2012) examine performance of hedge fund clones as a group against hedge funds, and find that the reverse engineering is not even the primary cause for poor performance. They identify two other important drivers of tracking errors in the clones. First one is change in the market liquidity and the second one is biases in measuring returns arising due to attrition among hedge funds that have effects on commonly used hedge fund indices and their performance. The authors argue that together these two drivers account half of the variation in clones' tracking errors over the time.

In recent paper from O'Doherty, Savin and Tiwari (2015), the authors criticize that in practice, the linear replication approach suffers from high turnover rate and poor performance. They argue that it is difficult to identify which really are the appropriate factors in replication models. Secondly, they argue that those clones that are estimated using rolling-window portfolios and require position updating frequently, make cloning very costly in practice. These costs rise from high turnover of the portfolio. To address this issue they introduce "a model combination approach" in which they pool a set of diverse factor models and clone ten Dow Jones Credit Suisse indices. To choose the combination of factors used, they utilize a decision-theoretic framework.

Wallerstein, Tuchschmid and Zaker (2010) examine the performance of existing hedge fund replication products that banks offer for their customers. According to their findings hedge fund replication products can deliver competitive performance to their benchmark hedge funds. Moreover, the products in most cases offer low-correlation with common market indices and therefore offer diversification opportunities. This already gives enough motivation to further develop the replication methods and gives more motivation for new research in the future. It is not clear, however, that under which market conditions different methods deliver the best results. Although Wallerstein et al. results generally brings high returns for the clones, it must be kept in mind that their sample period covers only recessionary economic time when replication products are found to deliver higher returns and better liquidity.

There is also critique of the hedge fund indices. Asset-class indices rely on assumption that the underlying assets are mainly homogenous and the dominant strategy underlying is the buy-and-hold strategy (Fung and Hsieh 2004: 3). In contrast, the hedge funds do not even need to report for the indices and the strategies are dynamic and appears as black boxes to investors.

To summarize, many critics state that there are hedge fund strategies that cannot be broken into liquid and investable factors. Therefore, the replication works only for certain strategies. Secondly, as it has come up several times, the replication products are based on historical data and therefore they are always mimicking the funds with a lag. Lastly, the performance of the replicators has been relatively poor in academic research.

To answer to the critiques, firstly, this thesis can replicate returns of the funds even with a historical data. Even if the hedge funds change their holdings, the replication is possible and it is not even any purpose for the replicators to be one-step-ahead. The purpose is to gain similar returns than hedge funds, no matter whether they are constructed from historical or future returns. The aim is to obtain whether it is still possible to gain similar returns with the holdings used in hedge funds. Furthermore, it is not obvious that the hedge funds change their holdings and strategies frequently. Secondly, in this thesis hedge fund indices are replicated, not individual hedge funds. By doing this the replication results will be for different perspective. The purpose is to get practical and simple results that could be utilized by any investor regardless of his or her skills. For this purpose, the indices are seen as more suitable targets. Also, many of the factors used in the model are investable.

4. DATA

This section provides information of the data and the estimation period applied. The estimation period is chosen in order to conduct a comprehensive replication analysis and to observe possible impacts of the financial crisis. Descriptive statistics of the data is presented.

This thesis applies ten Credit Suisse hedge fund indices as target investments. Monthly returns for all indices are gathered from the hedgeindex.com database that is maintained by the Credit Suisse Asset Management LLC ("Credit Suisse"). The dataset includes both the database's flagship index *the Credit Suisse Hedge Fund Index* and individual strategy indices – *the Credit Suisse Hedge Fund Strategy Indexes.* All indices are asset-weighted portfolios of hedge funds selected on the basis of their capacity to meet a number of requirements: assets under management of at least $50 million, current audited financial statements and a minimum one-year track record (hedgeindex.com, 2015). Instead of individual hedge funds, hedge fund indices are chosen (e.g. Fung and Hsieh 2004, Hayes 2012 and Bollen and Fisher 2013) due to their practical aspects. If hundreds of individual hedge funds were included the dataset became complex and would not offer the promised simplicity and practicality for the investors. As pension funds and other institutional institutions often invest in portfolios of funds instead of individual funds, is the use of indices more justified (Bollen and Fisher 2013: 82). Asset weighted indices are chosen instead of equal weighted indices. This is because the asset-weighted indices reflect the performance of the asset classes better as it represents the total performance of the assets invested.

Certain biases can be related with selection of the data among large set of data available. Selection and survivorship biases are related to the fact that hedge funds are not obliged to report their holdings and returns to the indices. This leads to a sample of funds in the database that is not a true sample of funds in a real hedge fund universe. Survivorship bias is typical in a case in which funds stop reporting to the index and are finally purged from the database. These funds are typically seen as worse performance funds than the surviving ones and this can cause an upward skew in the remaining data. Instant history bias occurs when a new fund is added to the database with its past performance. This is often the case since reporting is voluntary and the hedge fund managers most likely report only the returns of the best performing funds.

In order to reduce the aforementioned biases Fung and Hsieh (2004) apply fund-of-hedge fund data arguing that it is less prone to these biases. The authors claim that the selection bias decreases because the performance of a fund that does not report to the index is still reflected to the fund-of-hedge funds if these are investing to this hedge fund. Secondly, the survivorship bias reduces when a fund-of-hedge fund invested in a fund that quit its operations and its performance still remains in the historical return of the fund-of-hedge funds. In order to reduce the survivorship bias the Credit Suisse Hedge Fund Indexes -database do not remove a fund from an index before it is fully liquidated or fail to meet the financial reporting requirements (hedgeindex.com, 2015). Lastly, the instant history bias is reduced when a fund-of-hedge funds invests in a hedge fund and the history of the hedge fund is not included in the historical return of the fund-of-hedge funds. This thesis performs a study of relative performance of hedge fund indices versus relatively passive replicating clones. Therefore, any survivorship bias impacts both the index and the clone resulting unaffected relative performance. Finally, it should be academically possible and correct to compare the performances of the clones and corresponding indices.

No hedge fund is obliged to report its holdings to the indices. The returns are reported only if it fits for the hedge fund's interests. The funds may stop reporting either when they have sufficient capital and performance or when they suffer significant losses. According to Hayes (2012) the latter dominates biasing hedge fund index returns upwards towards "true" returns. To that extent that this bias is uncorrelated with the factors acting, the clones may underperform their target indices. In this thesis, also a broad index is included and indices are used instead of individual funds in order to reduce possible biases related to the data selection.

Summary statistics for the 10 indices and the total return of the S&P 500 for comparison are shown in table 2. Full years are listed. Sample period is also divided into two sub-periods in order to obtain whether the financial crisis affects to the returns. All indices tend to outperform the S&P 500. The effect of the financial crisis is obvious for the S&P 500 as observed from panel B that includes the year 2008. The broad index shows high Sharpe ratios varying from 0,22 to 0,37 thus showing relatively high volatility in times. The other indices feature substantial variation in performance. In panel B, a large variation in standard deviations is obtained. Annualized average returns range from -15,76% for the Short Bias Index to 11,94% for the Convertible Arbitrage Index. One can also observe that during the financial crisis the indices generally performed better than the S&P500.

Table 2. Summary statistics of the monthly returns of the 10 CS indices and the total return of the S&P500 are listed below. All columns presented are annualized. Data are from the full years, from January 2004 to December 2014. Panel A shows the full sample period. Panel B shows years from 2005 to 2008 and panel C from 2009 to 2014. "Average" is the average of the annualized returns. Standard deviation "Std Dev", skewness "Skew" and kurtosis "Kurt" are calculated for all indices. "Sharpe" is the Sharpe ratio defined as the average return in excess of the 3-month T-Bill rate divided by standard deviation. "%Neg" shows the percentage of months with a negative return.

2005-2014

CS Index	Average	Std Dev	Sharpe	Skew	Kurt	% Neg
Hedge Fund	6,35%	10,6%	0,30	-1,69	3,48	32%
Convertible Arb	5,70%	19,4%	0,26	0,39	3,35	33%
Short Bias	-6,33%	16,3%	0,16	0,17	-1,65	61%
Emerg.Market	8,29%	17,1%	0,19	-1,31	2,24	34%
Equity Neutral	0,29%	14,9%	0,24	-2,68	7,82	31%
Event Distr	7,25%	12,1%	0,27	-1,50	2,45	30%
Fixed Inc Arb	4,81%	14,0%	0,31	-1,30	4,34	21%
Global Macro	7,90%	6,4%	0,35	-0,47	0,18	28%
Long Short	7,09%	12,0%	0,24	-1,47	1,91	36%
Managed Fut	4,66%	9,3%	0,25	0,44	-1,38	43%
S&P 500	9,49%	18,8%	0,01	-1,73	4,38	34%

2005-2008

CS Index	Average	Std Dev	Sharpe	Skew	Kurt	% Neg
Hedge Fund	3,74%	15,4%	0,22	-1,82	3,34	33%
Convertible Arb	-3,66%	19,8%	0,20	-1,30	1,93	44%
Short Bias	7,82%	10,7%	0,23	-1,02	-0,19	48%
Emerg.Market	6,92%	24,9%	0,13	-1,98	3,93	31%
Equity Neutral	-3,44%	24,7%	0,15	-1,96	3,86	17%
Event Distr	3,80%	16,5%	0,23	-1,81	3,38	31%
Fixed Inc Arb	-3,93%	16,9%	0,25	-1,77	3,30	38%
Global Macro	8,89%	9,6%	0,24	-1,32	1,80	25%
Long Short	4,49%	16,3%	0,20	-1,91	3,66	38%
Managed Fut	8,07%	7,7%	0,29	0,78	1,51	42%
S&P 500	-2,70%	23,4%	0,01	-1,72	3,26	40%

2009-2014

CS Index	Average	Std Dev	Sharpe	Skew	Kurt	% Neg
Hedge Fund	8,09%	7,1%	0,37	-0,07	0,82	31%
Convertible Arb	11,94%	17,9%	0,32	2,10	4,71	26%
Short Bias	-15,76%	12,0%	0,12	1,14	-0,39	69%
Emerg.Market	9,21%	12,3%	0,26	0,74	1,66	36%
Equity Neutral	2,78%	4,0%	0,54	0,79	-0,04	40%
Event Distr	9,56%	9,1%	0,30	-0,47	-0,48	29%
Fixed Inc Arb	10,63%	9,0%	0,37	1,62	2,68	10%
Global Macro	7,24%	4,3%	0,45	0,80	-1,44	29%
Long Short	8,81%	9,6%	0,27	-0,78	0,81	35%
Managed Fut	2,39%	10,3%	0,23	1,04	-0,96	44%
S&P 500	17,62%	10,6%	0,01	0,03	-0,04	31%

Factor data are gathered from Thomson Reuters Datastream database through University of Vaasa. All factors are chosen inspired by prior academic research and existing commercial clone products. The model employed in this thesis is similar to the updated Fung and Hsieh (2004) seven-factor model on David A. Hsieh web site (faculty.fuqua.duke.edu/~dah7, 2015). The updated model includes three trend-following factors that are excess returns on trend following factors constructed of look-back straddles on futures contracts of bonds, commodities and currencies. Instead of their bond, commodity and currency trend-following factors, factors that are easier to implement in practice are applied in this thesis. As Fung and Hsieh, this thesis adds two equity- and two bond-oriented risk factors in the model. Furthermore, as in Fung and Hsieh updated model also this thesis introduces a relatively new factor to be implemented in replication models: the emerging market risk factor.

The trend-following factors applied by Fung and Hsieh are not relevant in practice. The use of those factors would require trading of derivative securities and therefore this thesis criticizes the use them in the replication process. They may be relevant when describing the assets that hedge funds use, but in the concept of replication they make the replication models unpractical and therefore are not further applied in the concept of this thesis.

The aim of this thesis is to keep the replication procedure achievable in practice. Therefore the factors in the model employed are relatively easy to realize through liquid instruments. For example, the USD, the S&P 500 and the BOND factors can be realized through using forward contracts. Also, there are futures contracts for components of the commodity index (Hasanhodzic and Lo 2007: 14). Hayes (2012: 12) argues that one should only use factors that are liquid and easy to implement. By adding some spreads into the model, he argues that one can also decrease multicollinearity. This is because several equity factors can be highly correlated with each other. Therefore, spreads are added into the model. Bollen and Fisher (2012: 8) bring up the issue with choosing factors such as the S&P 500 when one goal for investors is to gain diversification. First reason to include also factors of standard asset classes is the possible match between these factors and the target. Whether there is correlation between the target and standard assets then the clone will inherit these features. Second reason is that although the whole clone portfolio was built of factors representing standard asset classes, the rolling-window approach would allow the time-varying exposures and still could result a clone delivering low correlation with a buy-and-hold investment in stocks and bonds.

Monthly descriptive statistics of the factor returns are presented in table 3 on the next page. The time period covers the whole sample period from September 2004 to September 2015. These returns are not annualized as the returns in table 2. The monthly average returns between the factors vary from -0,27% for Commodity to 1,25% for Credit. Standard deviations vary from 1,15% for the Bond to 9,75% for the Size-spread. According to Jarque-bera tests for normality, all of the variables except two of them follow normal distribution. The Size-Spread and USD factors are non-normal. Breusch-Pagan test is run in case of heteroscedasticity. Heteroscedasticity exists in almost all of the variables at 1% level. Only the Size-Spread shows no heteroscedasticity.

The raw returns for the factors are presented in figure 2 on page 36. For the Commodity factor, the returns have radically come down although its returns have been the highest among the factors before the turn of the year from 2014 to 2015 when the S&P 500 passed it. The effect of the financial crisis at the end of 2008 can be obtained as a drop in returns in case of all the factors. One can also easily obtain that the overall return for the S&P 500, MSCI Index and Size-Spread has increased from 2004 to 2015. Also the Credit and USD factors show positive returns, but the variation in returns is small. The average monthly changes in the returns are shown in appendix 1, separately for each factor.

Table 3. Summary statistics of the monthly returns of the eight factors are listed below. Average return, median, min and max of the monthly returns, standard deviation, skewness and kurtosis are calculated. “%Neg” presents again the amount of months with negative returns. “***”, “**”, and “*” indicate significance at the 1%, 5%, and 10% level, respectively.

	SP500	EM	SIZE-SPREAD	CREDIT	COMMODITY	BOND	10YEAR	USD
Average return	0,68%	0,90%	1,22%	1,25%	-0,27%	-0,02%	-0,13%	0,09%
p.a.	8,21%	12,17%	8,94%	26,08%	-3,26%	-0,13%	-0,17%	2,10%
Median	1,30%	0,90%	1,09%	3,25%	0,23%	-0,02%	-0,24%	-0,03%
Max	10,93%	17,14%	29,24%	6,64%	19,67%	6,35%	29,00%	7,78%
Min	-16,80%	-27,35%	-27,74%	-22,58%	-28,20%	-5,36%	-25,53%	-6,59%
Std Dev	4,14%	6,72%	9,75%	5,80%	7,01%	1,15%	8,82%	2,49%
Skewness	-0,84	-0,58	-0,01	-2,45	-0,51	0,66	0,14	0,28
Kurtosis	2,19	1,88	0,27	6,12	1,31	9,46	1,51	0,72
% Negative	34%	43%	45%	21%	47%	50%	51%	51%
Normality	38,83***	24,45***	0,26	319,77***	13,79***	464,20***	11,38**	3,96
Autocorrelation	-2,79	1,26	-8,54	7,63	3,17	-5,96	0	5,41
Heteroscedasticity	0,46***	0,27***	0,14	0,19***	0,19***	1,22***	0,15***	0,54***
Observations	133	133	133	133	133	133	133	133

Figure 2. Monthly raw returns of the eight factors.

5. METHODOLOGY

This thesis examines the performance of the clones constructed using a linear factor model with eight different factors. These factors are selected based on their economic relevance and prior academic research. Both a passive model with constant portfolio weights and an active model with frequent rebalancing of the weights are constructed. This chapter is divided into three main sections. The first part includes an introduction to the *risk exposure analysis* and the *statistical estimation method* used. After finding the risk exposures for the factors, they are used for *building the replicators.* Lastly, the theory is given to compare the performance of the replicators with their benchmarks in terms of risk and return. All results are given in the next chapter.

5.1. Hedge fund risk exposure analysis

First step in the replication process is to find out how much of the hedge fund's expected return is due to risk exposures to identified factors, therefore the name "risk exposure analysis". The goal of the statistical estimation procedure is to estimate the monthly beta coefficients for the factors in the regression model. Further, there are two different methods to perform this analysis: the fixed-weight and rolling-window multiple regressions. The first method includes fixed-weight portfolios where the entire sample history of fund or index and factor returns are used to estimate the portfolio weights whereas the rolling-window approach uses returns of a specified period and yields true out-of-sample results. The both methods have their limitations. The fixed weight method may suffer of a look-ahead bias whereas rolling window approach regularly requires rebalancing. Rolling-window estimators can also be subject to larger estimation errors because of a smaller sample size (Hasanhodzic and Lo 2007: 22). In practice the first method is suitable for passive investors whereas the rolling-window estimation method may fit better for investors who are more active and willing to conduct the monthly rebalancing.

A rolling analysis of time series is claimed to assess the model´s stability over time. Because the economic environment changes over time it is not reasonable to assume that the parameters would stay constant either. Therefore, the rolling-window estimation procedure is applied. If the parameters are constant over time then the rolling-window estimates should not differ too much from the fixed-weight ones. However if the parameters change during the sample period, the rolling estimates should be able to capture the instability. (Zivot and Tang 2006: 313.)

Among several methods to perform the estimation analysis, an ordinary least squares (OLS) regression method is applied. OLS is best fitted for estimating linear relationships, such as factor exposures (Bruno and Whitelaw 2012: 44). Simple rolling-window regressions are performed by the add-in functions of the statistical software used.

The model applied is a unique version of factors presented in previous studies. However, no study has earlier applied exactly this combination of the factors. In addition, the Emerging Market Index factor is a relatively new component in the replication models. Since the results of factors presented in prior research are not in line and do not conclude any factor combination to perform best, this thesis has really no earlier guidelines it should follow in the factor selection process. However, as even the largest banks have already utilized findings of Fung and Hsieh, the replication model of this thesis is largely build on their original model. The multiple regression model of this thesis consists of eight different common factors. The linear eight-factor model is:

(4)

$$r_i = (\alpha_i) + \beta_{1i}SP500_t + \beta_{2i}EM_t + \beta_{3i}Size\text{–}Spread_t + \beta_{4i}CREDIT_t + \beta_{5i}BOND_t + \beta_{6i}Commodity_t + \beta_{7i}10Year_t + \beta_{8i}USD_t$$

The multiple regression's eight factors are: (1) *SP500*: the S&P 500 index total return, (2) *EM*: the MSCI Emerging Markets Index total return, (3) *Size-Spread*: the Russell 2000 index total return minus the S&P500 total return, (4) *Credit*: the difference between the Barclay's U.S. Baa Intermediate Corporate bonds and the Barclay's U.S. 3-5 year treasury index, (5) *Bond*: the return on the Barclay's intermediate corporate bond (AA) index, (6) *Commodity*: the return of the S&P GCSI Commodity index, (7) *10Year*: the change in the 10-year U.S. treasury benchmark bond and (8) *USD*: the U.S. Dollar index return. All returns are monthly total returns, except the U.S. Dollar return that is a price index for data availability reasons. However, using a price index in case of the Dollar return will most likely not disturb the results. Monthly return of the 3-month U.S. Treasury bill is used as a risk-free rate. These factors are chosen due to their ability to correspond to a large set of risk exposures to hedge funds; stocks, bonds, commodities, currencies, etc.

5.2. Building the replicator

After the factor exposures are known, they are used as portfolio weights for the eight factors in order to examine how much of the index' return is due to risk premiums of identified factors. The model describing how the estimates are used to construct returns for the replication products (r_{it}^*) can be written as:

(5)

$$r_{it}^* = \beta_{ti1}^* SP500_t + \beta_{ti2}^* EM_t + \beta_{ti3}^* Size\text{-}Spread_t + \beta_{ti4}^* CREDIT_t + \beta_{ti5}^* BOND_t + \beta_{ti6}^* Commodity_t + \beta_{ti7}^* 10Year_t + \beta_{ti8}^* USD_t + \epsilon_{ti}$$

$$\beta_{i1} + \cdots + \beta_{i8} = 1$$

This regression is performed to each hedge fund index in the sample. It simply includes multiplying the estimated beta coefficients with monthly variable returns in order to achieve monthly clone returns. Possible support for the hypothesis is obtained through the regression models (4), (5) and (6). Model (6) for the rolling approach is introduced in the next chapter. The results are dependent on the beta exposures obtained through model (4) together with the factor returns in model (5). After, the clone results are compared against the targets and therefore, the return characteristics of the hedge fund indices play a big role when conducting the final results.

As in the research of Hasanhodzic and Lo (2007), the constant term is omitted to obtain the best average of the factors that can explain the most of the index returns. By doing this the OLS regression constrains the factor means to fit the means of the index. In addition the coefficients are constrained to equal one so that they yield true portfolio weights. Negative coefficients are allowed because some of the factors in the model can be sold short and it can be even required to achieve the right risk exposures the hedge funds of the indices exhibit. According to Hasanhodzic and Lo (2007), for example a clone of the Short Bias index will require shorting of the S&P 500. This is in line with the results of this thesis as proven later. Moreover, when negative coefficients are allowed, as well as time varying factor exposures, the results may give products with very low correlation with for example, the buy-and-hold investments in stocks and bonds (Bollen and Fisher 2013: 84).

5.3. Measuring clone performance

After the estimated factor exposures are employed as portfolio weights for the replicating portfolios, the results of the conducted replication products are analyzed. In order to outline the performance of the replication products, their return characteristics are analyzed and compared against the same characteristics of the underlying hedge fund indices. The performance is analyzed with *return component* (raw- and risk adjusted) and *volatility*. Return is examined with the average annual return and the annual standard deviation is used as a metric for the volatility. Sharpe ratio is used as a measure for the risk-adjusted return.

Beside the clones' expected return characteristics, portfolios' correlation with major market indices such as the S&P 500 is another characteristic that concerns the hedge fund investors. Investors are expecting to achieve diversification benefits that alternative investments have traditionally provided. Therefore, regression results concerning the correlation with the S&P 500 are provided. The replication quality is analyzed by regressing correlations between the clones and corresponding indices. The results are presented in the next chapter.

6. RESULTS

This chapter largely follows same structure as the methodology section. First the results of the risk exposure analysis are given followed by the clone construction. The section concludes with an analysis of the replicators' performance.

6.1. Risk exposure analysis

Risk exposure analysis examines how much of a hedge fund index returns are due to risk premiums of identified factors. Table 4 on the next page presents summary statistics for the beta coefficients or factor exposures in Eq. (4) estimated for each 10 indices. Note that the coefficients are constrained sum to one and the intercept is omitted. Figure 3 (page 43) represents the factor exposures of regressions in which the coefficients are constrained to sum to one and intercept dropped. For comparison, a figure with unconstrained coefficients and included intercept is presented (figure 4 on page 43). The figures show that it is possible to find risk exposures for the hedge fund indices and try to clone them constructing a portfolio based on these exposures. Therefore separate regressions with unconstrained beta coefficients are not performed for each index and results with constrained betas are conducted immediately. This is due to the fact that it is confirmed in previous research (e.g. Hasanhodzic and Lo, 2007) that it is possible to clone at least part of the hedge fund or hedge fund index returns.

The results of the figures are parallel and similar to Hasanhodzic and Lo (2007) with exception of the manager specific alphas. They get significantly larger exposures to alphas. However, compared to those factor exposures that also Hasanhodzic and Lo (2007) includes in their model the exposures are similar. When no coefficients are constrained the Short Bias has an average S&P 500 beta of -0,507, which is consistent with an approach to sell short. In contrast, the Equity Neutral has an average S&P 500 beta of 0,017, which is consistent with their market neutrality. When the coefficients are constrained to sum one, larger variation is obtained for the Equity Neutral index. On average, the risk exposures do vary considerably across the indices. The adjusted R-squared mean is relatively high, 0,52. This means that the model can explain 52% of the returns of underlying hedge fund indices. Finally, the multivariate regressions results suggest that by the linear clones it is possible to replicate part of the risk exposures of hedge funds. The Broad Hedge Fund Index and the Convertible Arbitrage Index have even six out eight factors that are statistically significant at least at 10% level.

Table 4. Results for the multivariate linear regressions of the monthly index returns from the Credit Suisse Hedge Fund database from September 2004 to September 2015 on eight factors: (1) *SP500*: the S&P 500 index total return, (2) *EM*: the MSCI Emerging Markets index total return, (3) *Size-Spread*: the Russell 2000 index total return minus the S&P 500 total return, (4) *Credit*: the difference between the Barclay's U.S. Baa Intermediate Corporate bonds and the Barclay's U.S. 3-5 year treasury index, (5) *Bond*: the return on the Barclay's intermediate corporate bond (AA) index, (6) *Commodity*: the return of the S&P GCSI Commodity index, (7) *10Year*: the change in the 10-year U.S. treasury benchmark bond, and (8) *USD*: the U.S. Dollar index return. "***", "**", and "*" indicate significance at the 1%, 5%, and 10% level, respectively.

CS Index	S&P500	MSCI	Size-Spread	Credit	Bond	Commodity	10Year	USD
Hedge fund	0,077**	0,12***	-0,008	0,06***	0,53***	0,05***	0,05***	0,11***
Convertible Arb	0,03	0,12***	-0,02	0,05*	0,66***	0,05*	0,08***	0,04
Short Bias	-0,49***	-0,11*	-0,17***	0,11**	1,25***	0,08*	0,06*	0,27***
Emerg. Market	-0,05	0,34***	-0,02	0,09***	0,50***	0,04**	0,05***	0,05
Equity Neutral	0,04	-0,06	0,05	0,22***	0,60***	0,07	0,14***	-0,05
Event Distr.	0,09**	0,06***	-0,005	0,10***	0,52***	0,04***	0,09***	0,10**
Fixed Inc Arb	0,08	0,05	-0,02	0,10***	0,60***	0,07***	0,04**	0,08
Global Macro	-0,007	0,09***	-0,03*	0,04**	0,69***	0,06***	0,01	0,14**
Long/Short	0,16***	0,15***	0,006	0,03	0,49***	0,04**	0,07***	0,06
Managed Fut	0,14	0,05	-0,02	-0,002	0,58***	0,04	-0,06***	0,28**

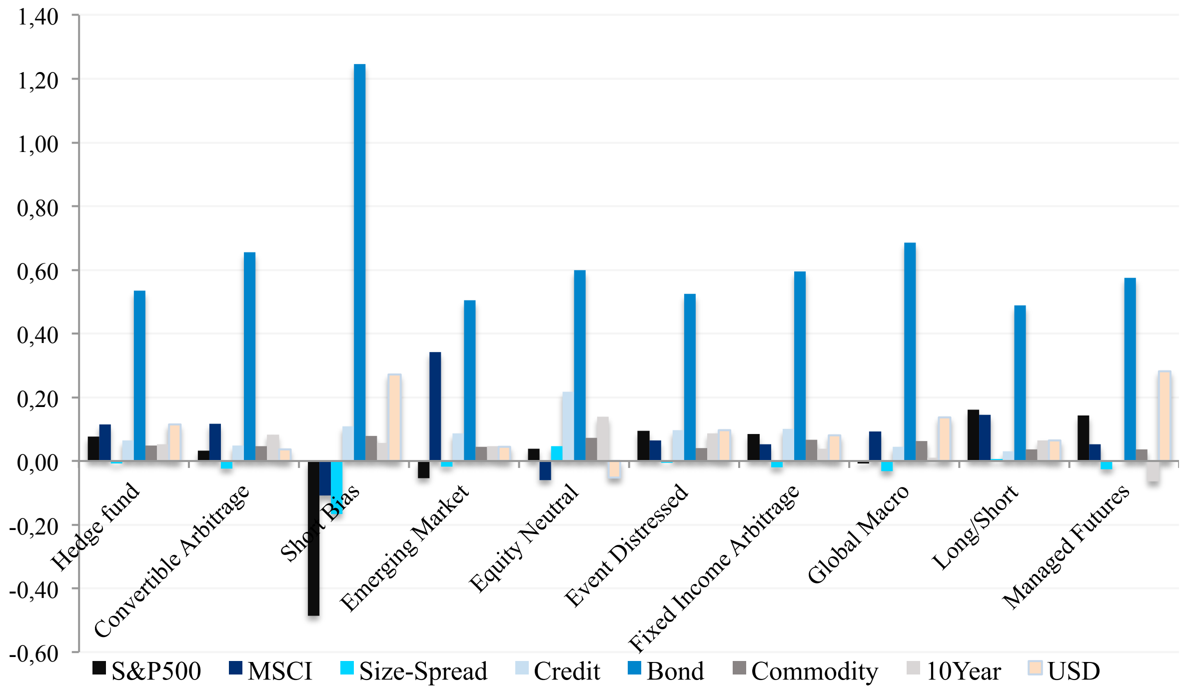


Figure 3. Average regression coefficients for the multivariate linear regressions of monthly returns of the Hedge Fund Indices from September 2004 to September 2015 on eight factors. The regression coefficients are constrained to sum to one.

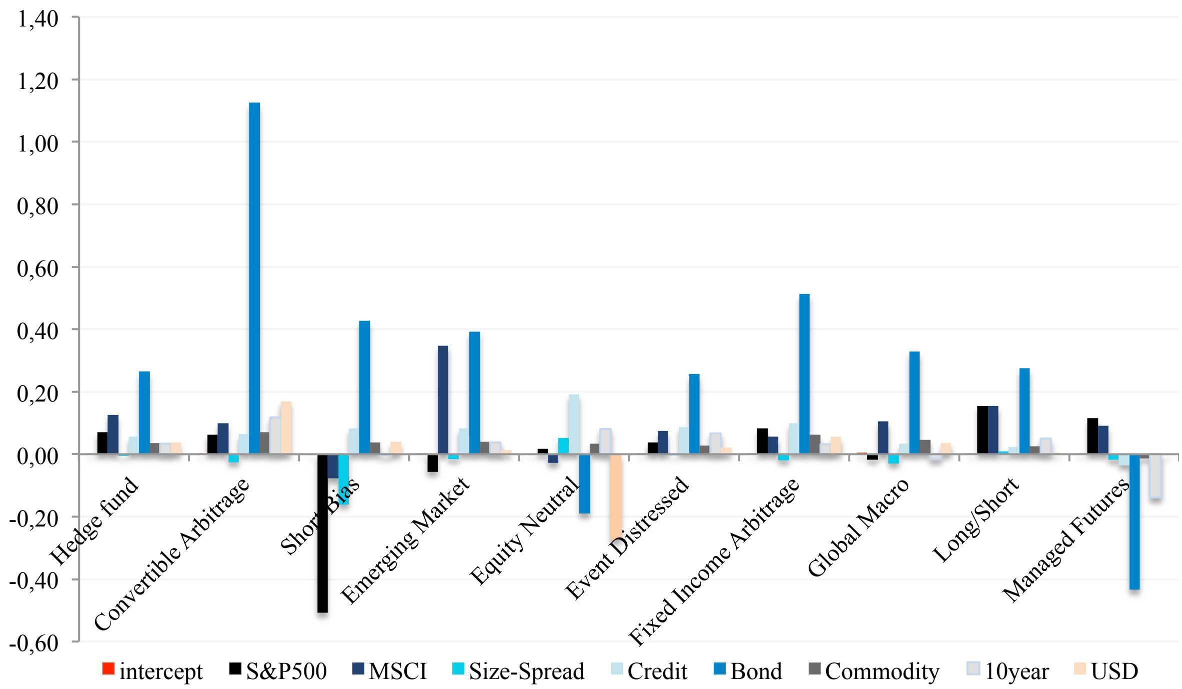


Figure 4. Average regression coefficients for the multivariate linear regressions of monthly returns of the Hedge Fund Indices from September 2004 to September 2015 on eight factors and the intercept. Regression coefficients are unconstrained.

6.2. Linear clones

The multivariate regression results in previous section suggest that it is possible to replicate at least part of the hedge fund returns. This supports the hypothesis. In this section the replication procedure is brought further, by considering two types of clones. The first type consists of fixed weight portfolios, where the whole sample of index and factor returns is used in the regressions. The portfolio weights are fixed through time, hence the term fixed-weight. As discussed earlier, these clones have their limitations and therefore also another type of clones are constructed. The second type of the linear clones allows time varying in the returns and is constructed using the rolling-window regressions.

6.2.1. Fixed-weight clones

In order to construct a fixed-weight clone for index *i*, its returns $\{R_{it}\}$ are first regressed on eight factors introduced in chapter 4. The intercept is dropped and the beta coefficients are constrained to sum to one. The regression model (4) is introduced on page 38. In order to construct the clone returns the estimated regression coefficients $\{\beta^{*}ik\}$ are then used as portfolio weights for the eight factors as described in model (5) on page 39. The expected return decomposition for the linear clones is presented in table 5 (pages 45 and 46). Each row in the panels shows the average mean return for the index clone and the averages of the percentage contributions of each of the eight factors to that to the total mean return. Note that in each row the average percentage contribution adds up to 100% when summed across the eight factors. Significances of the estimated beta coefficients are added into the tables to facilitate the interpretation.

The first row in panel A indicates that during the whole estimation period the most significant contributors to the average monthly return of 0,21% for the Broad Hedge Fund Index are the Bond (53,42%) and MSCI (11,53%). From panel C one can obtain that the monthly average returns are significantly lower than in panel A and panel B. This confirms that the financial crisis has affected the clone returns. Another question is that whether these returns are, however, higher than the returns of the original indices. Noticeably, most of the factors are statistically significant at 1%, 5% or 10% level. Moreover, the adjusted R-squares are relatively high: 51,4% for the whole sample period, 48,4% for the pre-crisis period and 59,72% for the post-crisis period.

Table 5. Expected return decomposition of the linear fixed-weight clones: decomposition of total mean returns of the broad index and nine sub-indices in CS hedge fund database: the average percentage contributions from eight factors. The p-values of the regression coefficients are marked with "***", "**", and "*" indicating significance at the 1%, 5%, and 10% level, respectively.

Panel A From September 2004 to September 2015.

CS Index	Included observations	Avg.monthly return	S&P500	MSCI	Size-Spread	Credit	Bond	Commodity	10Year	USD	Adj. R-squared
Hedge fund	133	0,21%	7,69%**	11,53%***	-0,79%	6,43%***	53,42%***	4,79%***	5,23%***	11,42%***	70,41%
Convertible Arb	133	0,13%	3,31%	11,74%***	-2,32%	4,81%*	65,52%***	4,67%*	8,35%***	3,71%	52,89%
Short Bias	133	-0,52%	-48,54%***	-10,90%*	-16,58%***	10,88%**	124,62%***	7,81%*	5,62%*	27,15%***	65,25%
Emerging Market	133	0,34%	-5,37%	34,24%***	-1,69%	8,63%***	50,39%***	4,43%***	4,57%***	4,54%	85,06%
Equity Neutral	133	0,25%	3,86%	-5,92%	4,73%	21,72%***	59,89%***	7,28%	13,87%***	-5,24%	20,02%
Event Distressed	133	0,21%	9,43%**	6,36%***	-0,59%	9,60%***	52,38%***	4,14%***	8,66%***	9,70%**	68,83%
Fixed Income Arb	133	0,18%	8,47%	5,34%	-2,06%	10,12%***	59,51%***	6,65%***	3,84%**	7,98%	47,75%
Global Macro	133	0,08%	-0,73%	9,25%***	-3,23%*	4,48%**	68,65%***	6,24%***	1,06%	13,76%**	28,29%
Long/Short	133	0,27%	16,12%***	14,56%***	0,69%	2,97%	48,78%***	3,56%**	6,54%***	6,45%	77,82%
Managed Futures	133	0,13%	14,26%	5,24%	-2,49%	-0,25%	57,60%***	3,63%	-6,49%***	28,15%**	-2,76%

Panel B From September 2004 to August 2008 (Pre-crisis).

CS Index	Included observations	Avg.monthly return	S&P500	MSCI	Size-Spread	Credit	Bond	Commodity	10Year	USD	Adj.R-squared
Hedge fund	48	0,28%	-3,42%	12,71%***	1,63%	4,94%	73,91%***	3,27%	15,35%***	-8,84%	70,28%
Convertible Arb	48	0,07%	-7,11%	4,97%	1,54%	6,46%	82,99%***	-0,14%	20,86%***	-9,70%	42,36%
Short Bias	48	-1,10%	-104,47%***	-7,87%	-13,72%**	9,98%	150,03%***	0,12%	32,73%***	31,85%	55,74%
Emerging market	48	0,73%	-23,43%**	37,93%***	0,86%	9,51%**	69,17%***	2,55%	8,24%**	-5,20%	84,92%
Equity Neutral	48	-0,14%	-9,11%	1,26%	-1,27%	0,61%	94,49%***	1,03%	19,33%***	-7,13%	1,13%
Event Distressed	48	0,20%	4,38%	2,63%	1,37%	12,21%***	66,78%***	2,30%	15,12%***	-5,37%	56,74%
Fixed Income Arb	48	-0,05%	-3,69%	0,01%	-1,38%	6,20%*	89,32%****	0,63%	22,58%***	-13,91%*	45,61%
Global Macro	48	-0,01%	-31,52%**	13,14%**	-0,32%	-0,11%	112,48%***	1,23%	20,62%***	-16,50%	33,31%
Long/Short	48	0,55%	10,77%	18,95%***	2,72%	4,42%	54,70%***	5,44%**	10,86%***	-8,14%	81,17%
Managed futures	48	0,21%	-20,02%	9,26%	12,56%*	-4,57%	113,24%***	3,34%	23,83%*	-38,19%	12,77%

Panel C From September 2008 to September 2015 (Post-crisis).

CS Index	Included observations	Avg.monthly return	S&P500	MSCI	Size-Spread	Credit	Bond	Commodity	10Year	USD	Adj.R-squared
Hedge fund	85	-0,34%	16,48%***	8,49%***	-2,31%	5,68%***	50,09%***	3,27%	4,35%***	13,81%***	76,14%
Convertible Arb	85	-0,56%	-2,44%	19,11%***	-3,87%	3,53%	54,64%***	9,74%**	6,22%***	12,62%	59,17%
Short Bias	85	-1,70%	-27,93***	-14,29%**	-20,25%***	11,42%***	125,72%***	-0,48%	4,91%*	21,75%**	78,85%
Emerging market	85	-0,32%	3,93%	32,58%***	-3,21%*	7,64%***	44,81%***	2,42%	4,29%***	7,43%	85,22%
Equity Neutral	85	-0,22%	3,67%	-3,11%	7,19%	26,71%***	51,96%*	2,62%	14,13%**	-2,51%	22,11%
Event Distressed	85	-0,28%	13,77%***	7,24%**	-1,87%	8,14%***	45,46%***	4,33%*	7,69%***	15,06%***	73,42%
Fixed Income Arb	85	-0,32%	2,82%	12,18%**	-1,99%	9,70%***	46,21%***	10,84%***	1,12%	18,83%**	56,66%
Global Macro	85	-0,49%	13,81%**	6,50%	-5,23%***	3,76%	58,66%***	3,04%	-0,63%	19,88%***	45,43%
Long/Short	85	-0,36%	28,48%***	5,99%*	-0,56%	1,73%	53,68%***	0,86%	6,51%***	3,15%	81,79%
Managed futures	85	-0,32%	49,70%***	-6,87%	-11,95%**	-1,43%	55,99%***	-5,41%	-7,87%**	27,96%*	18,41%

6.2.2. 24-month rolling-window clones

To construct the second types of clones for each month t, a 24-month rolling-window method is applied. All results are out-of-sample. The coefficient estimates are constructed from month t-24 to t-1with similar regression as before:

(6)

$$r_{it-k} = \beta_{1it}SP500_{t-k} + \beta_{2it}EM_{t-k} + \beta_{3it}Size\text{–}Spread_{t-k} + \beta_{4it}CREDIT_{t-k} + \beta_{5it}BOND_{t-k} + \beta_{6it}Commodity_{t-k} + \beta_{7it}10Year_{t-k} + \beta_{8it}USD_{t-k} + \epsilon_{it-k}$$

$$k = 1, \ldots, 24$$

The estimated regression coefficients $\{\beta^{*}ik\}$ are then used as portfolio weights for the eight factors. Here the coefficients are indexed by both i and t, because the regression is repeated every month for each index. Indexation by time t reflects the fact that the coefficients are computed by the rolling-window method. An example of the monthly return decompositions is presented in the appendices (see appendix 2). The example is given for the Broad Hedge Fund Index. Note that the data in the rolling-window clones begins already in 2002, in order to conduct the first clones in September 2004. Also, at the time this thesis is being done, there is yet no data available for the Credit Suisse Hedge Fund Indices for October 2015 and therefore the regression coefficients are estimated until August 2015 for the rolling-window clones. In summary tables the data for the corresponding indices is also given until the August 2015.

The choice between the two types of the clones depends of the investor. A passive investor with little interest or expertise may prefer the fixed-weight linear clones whereas an active investor with more capabilities relies on using the rolling-window clones (Hasanhodzic and Lo 2007: 22). For these reasons, both the fixed-weight and rolling-window linear clones are considered and both of their results are compared to their benchmarks in the next section.

6.3. Performance results

In this section, an analysis of the performance and quality is given. The performance is first analyzed by examining the *return component* of both the fixed-weight and rolling-window clones and those are compared to the underlying indices. The return component is analyzed by calculating the annual mean return, annual mean standard deviation and annual Sharpe ratio. Standard deviation gives a demonstration of the *annual volatility* and Sharpe ratio describes the *risk-adjusted return component.* The Sharpe ratio can be expressed as follows:

(7) $$Sharpe\ ratio = \frac{r_{i\ annual - r_f}}{\partial\ annual}$$

Where $r_{i\ annual}$ is annual mean portfolio return and r_f is the risk-free rate. Monthly return of the 3-month U.S. Treasury bill is used as the risk-free rate. The annual excess return is then divided by the annual standard deviation in order to find the risk adjusted return component. The higher the ratio, the more attractive the investment can be kept. The results are presented in tables 6 and 7 on pages 49 and 51.

During the estimation period from September 2004 to September 2015 only one category of the fixed-weight clones generates higher annual mean return compared to the underlying index. This clone is the Equity Neutral that yields 2,98% annual mean return compared to 0,52% for the Equity Neutral hedge fund index. As shown earlier in tables 4 and 5, three out of eight factors in the clone are statistically significant. Therefore, the conclusion is not that the clone necessarily outperforms the target index. In addition, the Sharpe ratio of the clone, 0,72 is significantly lower than that of the index: 2,35.

During the post-crisis period from September 2008 to September 2015 (panel C) again the Equity Neutral clone generates higher returns than the index (-2,60% vs -2,97%). This result is again not statistically significant because only one out of eight factors showed statistical significance earlier in the factor exposure analysis.

Table 6. Annual mean return, standard deviation and Sharpe ratio for the fixed-weight linear clones and the target indices. Panel A presents results for the whole estimation period, panel B for the Pre-crisis and panel C for the Post-crisis period.

Panel A. September 2004-September 2015

	Fixed-weight linear clone			CS Hedge fund index		
	Annual mean return	Annual mean Stdev	Annual mean Sharpe	Annual mean return	Annual mean Stdev	Annual mean Sharpe
Hedge fund	2,50 %	0,56 %	0,55	5,80 %	9,79 %	2,73
Convertible Arb	1,55 %	0,55 %	0,22	4,98 %	17,59 %	2,53
Short Bias	-6,23 %	1,73 %	-2,49	-5,98 %	15,56 %	1,46
Emerging market	4,05 %	1,40 %	1,09	7,42 %	15,80 %	1,81
Equity Neutral	2,98 %	1,23 %	0,72	0,52 %	13,49 %	2,35
Event Distressed	2,54 %	0,58 %	0,56	6,40 %	11,35 %	2,56
Fixed Income Arb	2,17 %	0,62 %	0,44	4,23 %	12,78 %	3,08
Global Macro	0,93 %	0,49 %	0,00	6,87 %	6,37 %	3,26
Long/Short	3,19 %	0,68 %	0,79	6,90 %	11,03 %	2,32
Managed Futures	1,50 %	0,49 %	0,20	5,05 %	8,98 %	2,26

Panel B. September 2004-August 2008
(Pre-crisis)

	Fixed-weight linear clone			CS Hedge fund index		
	Annual mean return	Annual mean Stdev	Annual mean Sharpe	Annual mean return	Annual mean Stdev	Annual mean Sharpe
Hedge fund	3,42 %	1,24 %	0,15	7,44 %	6,87 %	3,19
Convertible Arb	0,84 %	0,82 %	-0,29	2,03 %	8,45 %	4,15
Short Bias	-13,22 %	2,38 %	-2,66	2,22 %	13,07 %	2,44
Emerging market	8,79 %	3,42 %	1,06	11,43 %	12,85 %	2,11
Equity Neutral	-1,72 %	0,62 %	-0,72	6,27 %	3,99 %	4,92
Event Distressed	2,34 %	0,82 %	-0,03	7,92 %	7,34 %	3,85
Fixed Income Arb	-0,64 %	0,70 %	-0,54	2,01 %	5,01 %	6,05
Global Macro	-0,09 %	1,60 %	-0,45	9,79 %	5,72 %	3,33
Long/Short	6,60 %	1,64 %	0,68	8,35 %	8,25 %	3,10
Managed Futures	2,50 %	1,59 %	-0,01	7,03 %	5,01 %	3,21

Panel C. September 2008-September 2015
(Post-crisis)

	Fixed-weight linear clone			CS Hedge fund index		
	Annual mean return	Annual mean Stdev	Annual mean Sharpe	Annual mean return	Annual mean Stdev	Annual mean Sharpe
Hedge fund	-4,12 %	2,63 %	-0,79	3,98 %	10,52 %	3,05
Convertible Arb	-6,70 %	2,72 %	-1,28	5,94 %	20,12 %	2,53
Short Bias	-20,39 %	6,11 %	-3,90	-10,41 %	14,22 %	1,08
Emerging market	-3,85 %	2,35 %	-0,74	3,71 %	15,45 %	2,05
Equity Neutral	-2,60 %	3,06 %	-0,50	-2,97 %	16,18 %	1,37
Event Distressed	-3,39 %	2,41 %	-0,65	4,57 %	12,56 %	2,48
Fixed Income Arb	-3,83 %	2,42 %	-0,73	4,92 %	14,71 %	2,66
Global Macro	-5,91 %	3,00 %	-1,13	4,24 %	7,00 %	3,94
Long/Short	-4,37 %	2,90 %	-0,84	5,02 %	11,64 %	2,47
Managed Futures	-3,78 %	3,41 %	-0,72	3,09 %	9,19 %	1,97

From panel B it is obtained that no clone manages to generate higher average returns than the target. The conclusion is that the fixed-weight linear clones do not outperform their target indices in any of the three estimation periods. However in some cases the clone return is only slightly lower than the returns of the index: the Short Bias (-6,23% vs -5,98%) in panel A. Again, some of the clones stay far away from their counterparts: the Short Bias (-13,22% vs 2,22%) in panel B.

All annual standard deviations are notably lower for the fixed-weight clones than for the underlying indices. This suggests that the clones tend to be less volatile than their counterparties. For example, the annual mean standard deviation for the Convertible Arbitrage clone in panel C is 2,72% whereas the same parameter for the index is 20,12%. The results are different from the rolling-window linear clones (table 7 on page 51). Annual mean standard deviations of the clones, on average are very close to those of the targets. Some of the values are even higher, for example the Hedge Fund (13,47% vs 9,72%), Long/Short (14,56% vs 10,99%) and Managed Futures (21,63% vs 9,15%).

In seven out of ten cases the linear 24-month rolling-window clone outperforms the index during the post-crisis period from September 2008 to August 2015 measured by annual returns. This is in line with Wallerstein et al. (2010, 2012) who find that the clones do better in economic downturn than the actual hedge funds. On the other hand, the annual Sharpe ratios of the clones are notably lower compared to the underlying indices. Also Hasanhodzic and Lo (2007:23) find that the clone Sharpe values are generally lower than those of the target funds.

There are three clone-types that yield higher average annual returns than the actual indices during the whole estimation period from 2004 to 2015: the Hedge Fund (6,10% vs 5,92%), the Long/Short (7,75% vs 6,99%) and the Managed Futures (16,30% vs 4,82%). In panel B, during the pre-crisis period, no clone yields higher average returns than the actual hedge fund index. The clone returns are rather far behind from the index returns: the Convertible Arbitrage (-5,03% vs 2,03%), Emerging Market (3,74 vs 11,43%), Event Distressed (-0,36% vs 7,92%). Nevertheless, these results suggest that for certain hedge fund index categories the performance of the rolling-window clones may be comparable to that of the corresponding indices. Although the results would not be revolutionizing in terms of the clones' performance, these findings may still offer value for the future research.

Table 7. Annual mean return, standard deviation and Sharpe ratio for the 24-month rolling-window linear clones and the target indices. Panels present different estimation periods.

Panel A. September 2004-August 2015

	24-month Rolling-window linear clone			CS Hedge fund index		
	Annual mean return	Annual mean Stdev	Annual mean Sharpe	Annual mean return	Annual mean Stdev	Annual mean Sharpe
Hedge fund	6,10 %	13,47 %	1,28	5,92 %	9,72 %	2,76
Convertible Arb	0,79 %	15,91 %	0,08	5,00 %	17,59 %	2,52
Short Bias	-7,09 %	13,65 %	-0,53	-6,39 %	15,25 %	1,48
Emerging market	7,28 %	16,91 %	1,07	7,49 %	15,75 %	1,82
Equity Neutral	-2,32 %	14,61 %	0,41	0,47 %	13,49 %	2,36
Event Distressed	4,73 %	14,97 %	0,90	6,52 %	11,25 %	2,60
Fixed Income Arb	2,76 %	12,03 %	0,74	4,26 %	12,76 %	3,08
Global Macro	4,98 %	9,40 %	0,91	7,00 %	6,22 %	3,33
Long/Short	7,75 %	14,56 %	1,56	6,99 %	10,99 %	2,31
Managed Futures	16,30 %	21,63 %	1,00	4,82 %	9,15 %	2,24

Panel B. September 2004-August 2008
(Pre-crisis)

	24-month Rolling-window linear clone			CS Hedge fund index		
	Annual mean return	Annual mean Stdev	Annual mean Sharpe	Annual mean return	Annual mean Stdev	Annual mean Sharpe
Hedge fund	2,28 %	6,71 %	1,12	7,44 %	6,87 %	3,19
Convertible Arb	-5,03 %	4,51 %	-0,83	2,03 %	8,45 %	4,15
Short Bias	-4,78 %	13,04 %	-0,56	2,22 %	13,07 %	2,44
Emerging market	3,74 %	10,18 %	0,94	11,43 %	12,85 %	2,11
Equity Neutral	0,51 %	3,09 %	0,43	6,27 %	3,99 %	4,92
Event Distressed	-0,36 %	7,03 %	0,30	7,92 %	7,34 %	3,85
Fixed Income Arb	0,80 %	6,15 %	0,26	2,01 %	5,01 %	6,05
Global Macro	1,49 %	2,79 %	0,55	9,79 %	5,72 %	3,33
Long/Short	5,38 %	8,94 %	1,80	8,35 %	8,25 %	3,10
Managed Futures	5,20 %	4,33 %	0,61	7,03 %	5,01 %	3,21

Panel C. September 2008-August 2015
(Post-crisis)

	24-month Rolling-window linear clone			CS Hedge fund index		
	Annual mean return	Annual mean Stdev	Annual mean Sharpe	Annual mean return	Annual mean Stdev	Annual mean Sharpe
Hedge fund	7,51 %	14,79 %	0,90	4,16 %	10,44 %	3,11
Convertible Arb	3,96 %	17,23 %	0,26	5,98 %	20,11 %	2,52
Short Bias	-7,66 %	14,09 %	-0,43	-11,02 %	13,45 %	1,09
Emerging market	8,15 %	18,28 %	0,73	3,81 %	15,41 %	2,08
Equity Neutral	-3,98 %	17,26 %	0,21	-3,05 %	16,16 %	1,38
Event Distressed	7,04 %	16,17 %	0,83	4,74 %	12,45 %	2,53
Fixed Income Arb	3,40 %	12,94 %	0,67	4,98 %	14,69 %	2,66
Global Macro	6,49 %	10,90 %	0,91	4,44 %	6,87 %	4,08
Long/Short	8,04 %	16,06 %	0,86	5,16 %	11,61 %	2,46
Managed Futures	21,20 %	25,43 %	1,14	2,74 %	9,37 %	1,95

Next figures (5-14) display the comparison of the Credit Suisse Indices and their rolling-window clones: the monthly average return for the index and clone. Each figure displays also the monthly average p-value for the clone. The p-values indicate statistical significance for the computed rolling-window beta coefficients that are further multiplied with the monthly factor returns in order to gauge the monthly clone returns. As it can be observed from the figures, the p-values are generally high among the clones. This is in contrast with the fixed-weight coefficients that showed well higher statistical significance. The left axis in the figures shows the average monthly return-% whereas the right axis shows the average p-value for the replication products.

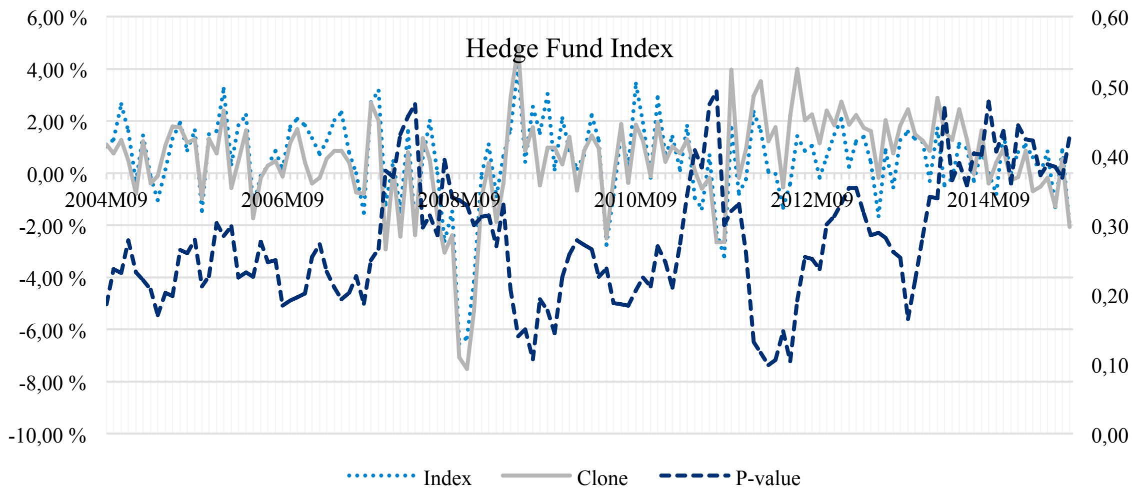
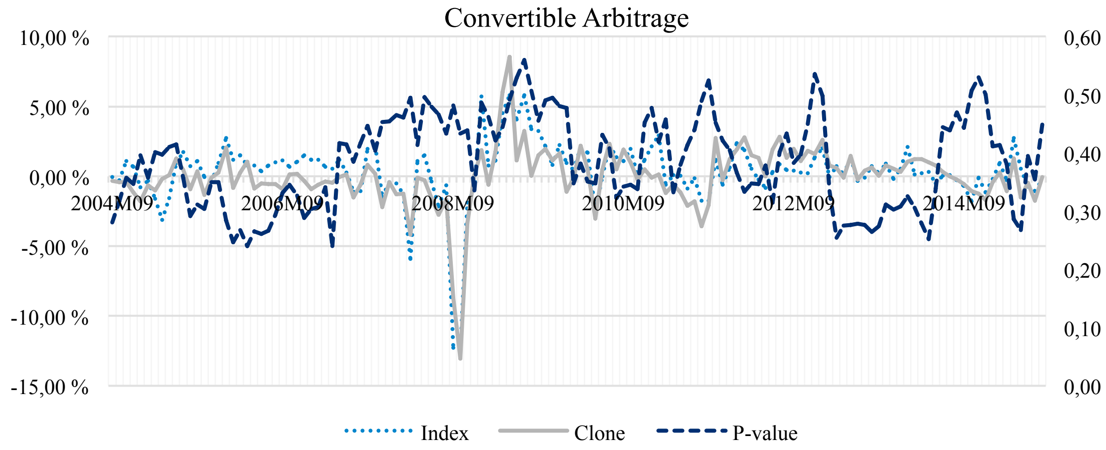
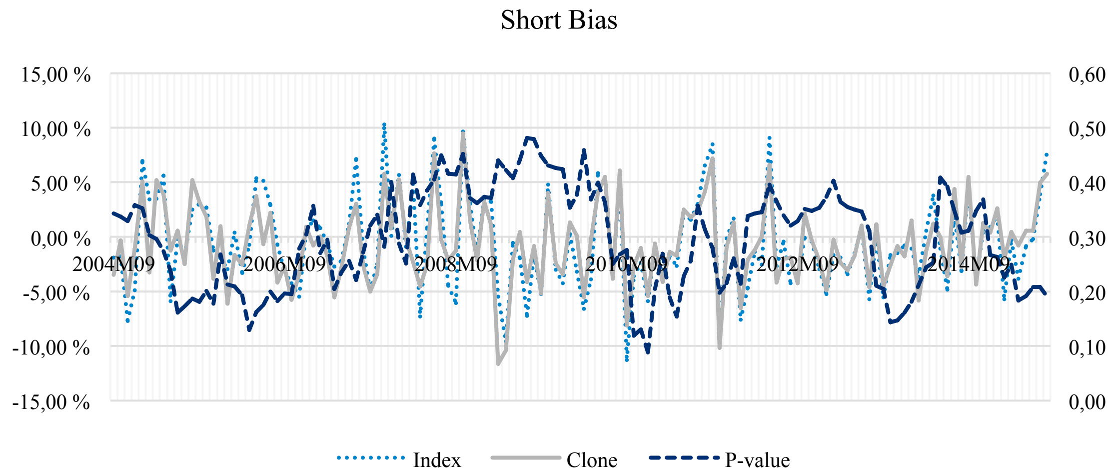
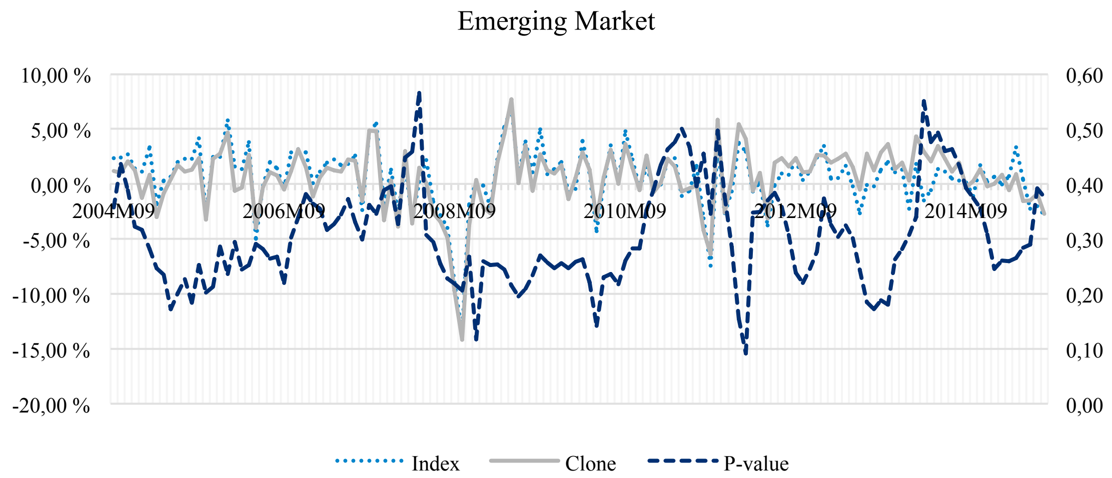


Figure 5. Monthly returns of the Broad Hedge Fund Index and the Hedge Fund clone and the Hedge Fund clone's average monthly p-value during September 2004 and August 2015.

The average monthly p-values for the Hedge Fund clone are very high (figure 5 above). This means that the clone returns are statistically insignificant. The figure shows a notable drop in both index and clone returns in September 2008 as expected due to the financial crisis. On average the index and the clone returns follow the same pattern index returns being slightly higher. From the beginning of 2011 almost till the end of 2014 the clone shows higher average monthly returns, thus insignificant. According to the low performance and insignificant coefficient values, the conclusion is that the Hedge Fund clone does not outperform the Credit Suisse Hedge Fund Index in any of the sample periods. In case of the Hedge Fund category, the hypothesis is not confirmed in terms of the clone performance.







Figures 6 (above), 7 (middle) and 8 (below). Monthly returns for the Convertible Arbitrage, Short Bias and Emerging Market Indices and their clones. Also clones' average monthly p-values are presented. Data are from September 2004 to August 2015.

As obtained from figure 6, the p-values for the Convertible Arbitrage clone are highly statistical insignificant. The p-value patterns of the Short Bias and the Emerging Market clones touches the 0,1-level indicating significance at 10% level however not clearly demonstrating statistical significance for the estimates. The returns of these three indices and their clones largely follow similar patterns the index showing higher returns in times and the opposite. For the Emerging Market clone there is a longer period from early 2011 to late 2014 when it seems to generate higher returns. Interestingly, in all other categories, the index and the clone returns start to decline in August-September 2008, but the Short Bias category shows returns falling much later. As shown in figure 7, the returns drop just a little, showing a sharp peak upwards straight after in October-November 2008. The real drop in the returns comes later in early 2009 and lasts about three months from March to June. Thus, the p-values are very high at that time showing value over 0,4.

Below is shown a figure for the Equity Neutral category and on the next page a figure for the Event Driven category. Event Driven clone (figure 10) has significant coefficients at 10%-level from May 2005 to January 2007 and from September 2008 to November 2011. However during these years the clone generates lower returns than the target index and therefore does not outperform the index. In times the Equity Neutral index (figure 9 below) generates higher returns than the index, but these values are not statistically significant. A drop after the crisis is very deep, normally almost flat curve dramatically drops and exhibits -40,45% downturn in the returns.

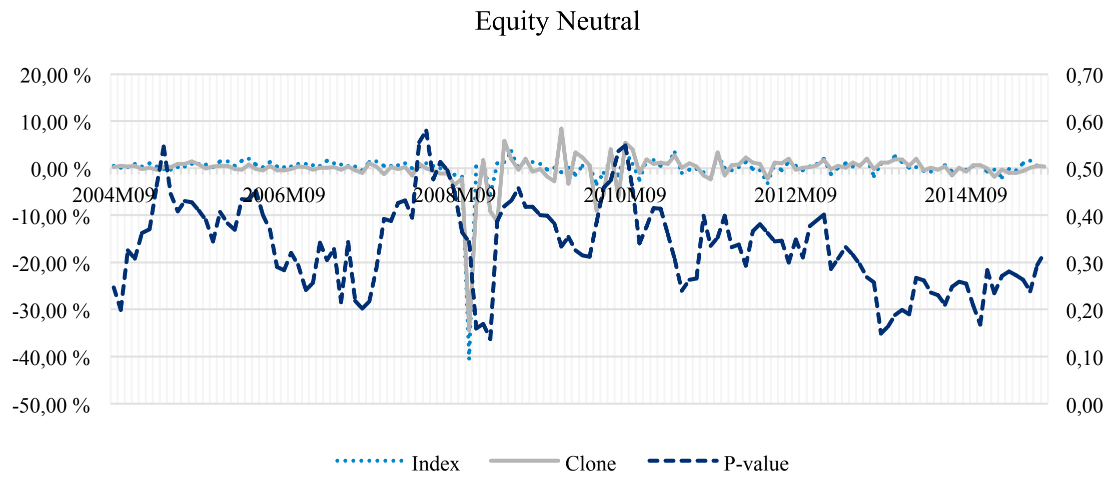


Figure 9. Monthly returns for the Equity Neutral Index and its clone. Also clone's average monthly p-values are presented. Data are from September 2004 to August 2015.

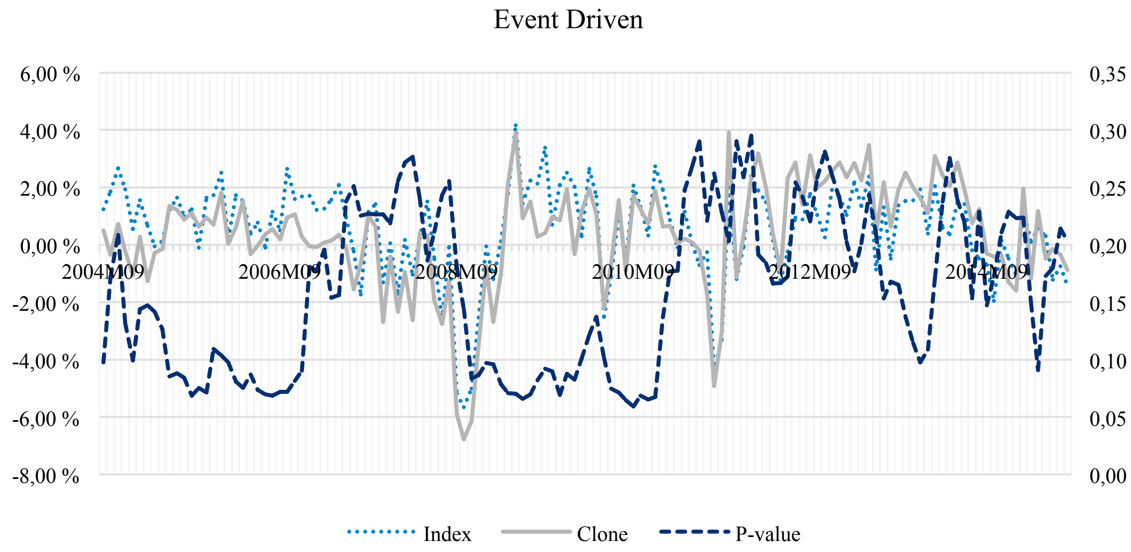
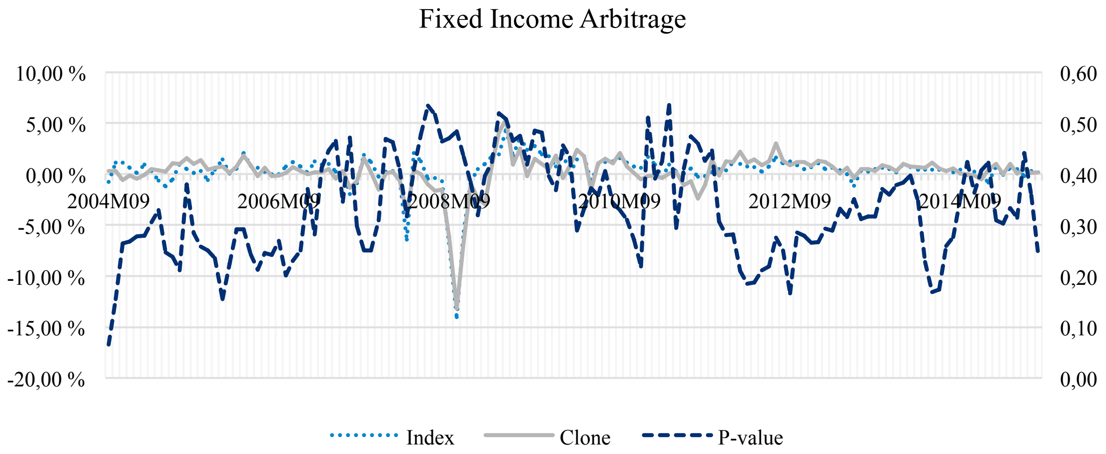
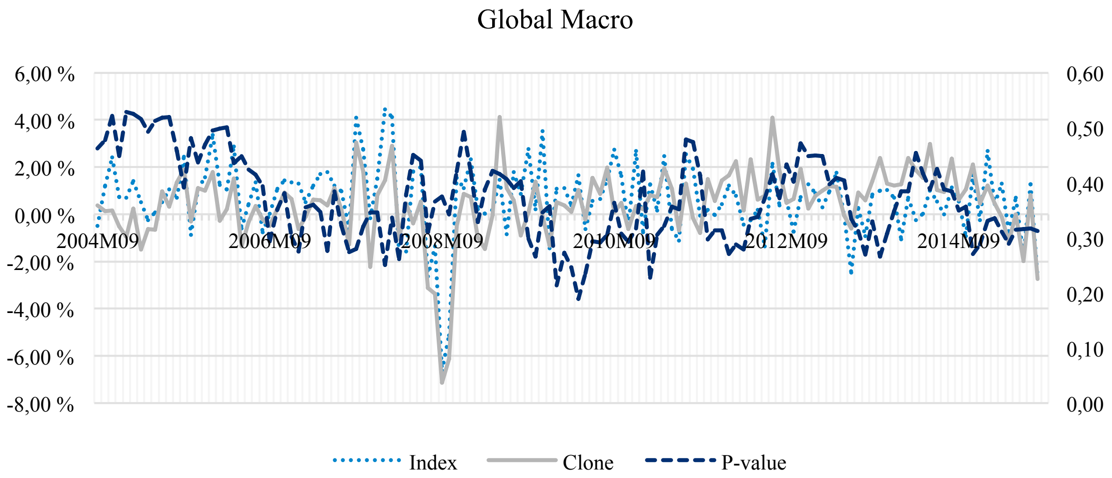


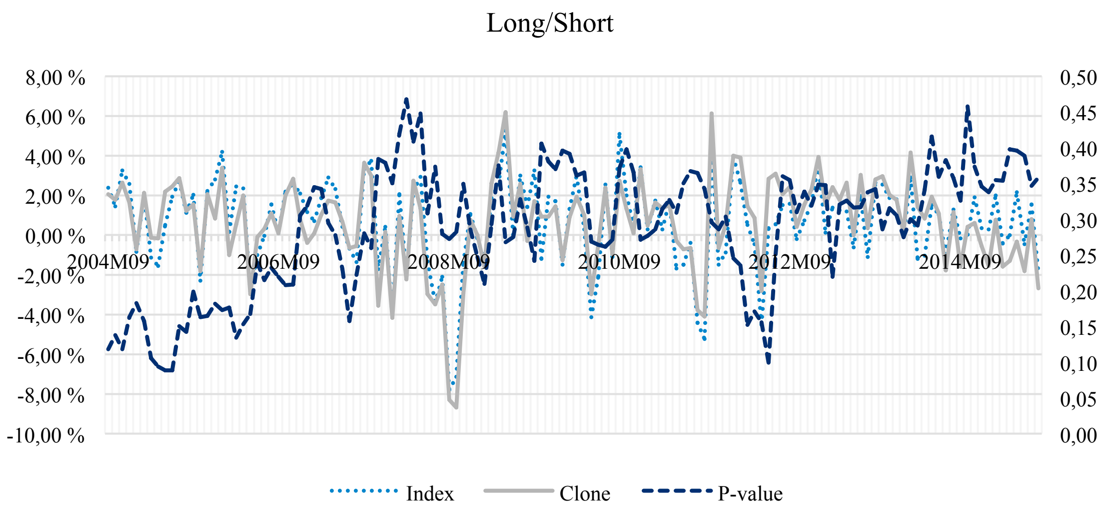
Figure 10. Monthly returns for the Event Driven Distressed Index and its clone. Also clone's average monthly p-values are presented. Data are from September 2004 to August 2015.

P-values for the Fixed Income Arbitrage, Global Macro and Long/Short strategies are not overwhelming (figures 11-13 on page 56). The Fixed Income Arbitrage clone (figure 11) shows statistical significance in the very beginning of the estimation period but the clone returns do not tend to be higher than the index returns. In 2008 the drop in the return pattern is well noticed: normally flat returns exhibit almost -14% downturn. The Long/Short index clone has two times statistically significant average monthly returns: from April to July 2005 and in June 2012 when the p-value is exactly 0,1 indicating statistical significance at 10%-level. Also in 2005 the significance is obtained at 10%-level. What is important is that in both times the clone return is higher than that of the index. This means that during some months, the Long/Short clone outperforms the Credit Suisse Long/Short Hedge Fund Index.

All three clones in figures 11-13 yield higher returns than the hedge fund indices at the end of the estimation period. These returns are usually from the end of 2011 to the end of 2014. Also similar pattern was obtained in earlier graphs. This may be due to August 2011 and heightened uncertainty in stock markets when the markets fell in many countries. Some countries were concerned about their credit ratings, e.g. United States and France and at the same time the European debt crisis was still novel. This would be in line with Wallerstein et al. (2010) who find that during economic downturns the replication products perform better than their target funds.







Figures 11 (above), 12 (middle) and 13 (below). Monthly returns for the Fixed Income Arbitrage, Global macro and Long/Short Indices, their clone returns and the clones' average monthly p-value during September 2004 and August 2015.

Below is shown a figure for the Managed Futures category. Unlike other strategies, Managed Futures does not suffer from a big downturn in returns at the end of 2008. The return pattern for both the clone and the index is more like a movement going upwards and downwards without showing any pattern easy to interpret. Scrutinizing the figure, similar result is obtained than from the previous graphs. The clone generates higher average monthly returns than its counterpart from the August 2011 till the end of 2014. P-value is significant only one time and it is in October 2011: 0,089. In November 2011 the p-value is already 0,103 indicating statistical insignificance.

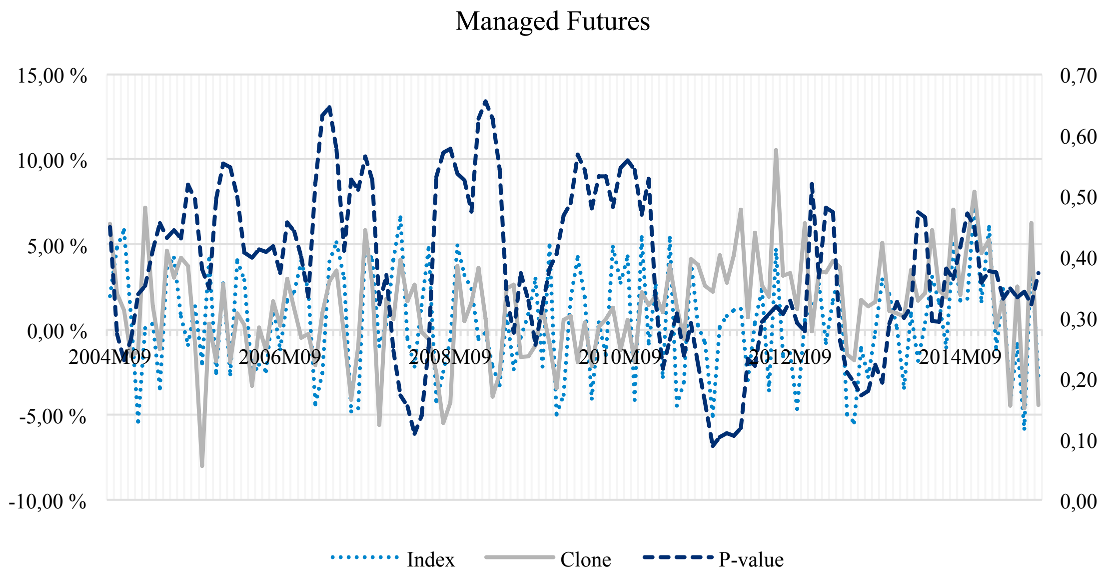


Figure 14. Monthly returns for the Managed Futures Index, its clone's monthly return and the clone's average monthly p-value during September 2004 and August 2015.

To conclude the findings from the figures (figures 5-14), the Long/Short rolling-window clone performs the best from all of the rolling-window clones. Two times during the estimation period it generates higher monthly returns than the Long/Short Hedge Fund Index. A clear conclusion, however, is not that the clone would still outperform the index. It only managed to generate higher returns during few sample months: on average, the index still outperforms the clone. Also, all figures 5-14 supports the findings in table 7 and confirm that the clones yield higher average returns during the post-crisis period.

The estimated beta coefficients used as portfolio weights for the fixed-weight clones were largely statistically significant. This suggests that the factors chosen have a good fit in the risk-factor regression model. Despite the high significance of these fixed-weight estimated coefficients, the clones showed bad performance when monthly returns were computed. In order to obtain whether the significances of the factors are different among the rolling-window linear clones, table below was computed. All of the factors are insignificant with only few exceptions: the Bond and the 10Year during the pre-crisis. This may indicate that some other factors in the linear factor model could work better and have higher ability to explain the hedge fund index risk exposures. On the other hand as mentioned above the same factors showed a good fit for the fixed-weight linear clones.

Table 8. Averages of the monthly p-values for the eight factors in the linear factor model. The whole period covers estimation period from September 2004 to August 2015, the Pre-crisis from September 2004 to August 2008 and the Post-crisis from September 2008 to August 2015.

	Whole period *avg p-value*	Pre-crisis *avg p-value*	Post-crisis *avg p-value*
SP500	0,35	0,44	0,31
MSCI	0,36	0,34	0,38
Size-Spread	0,45	0,38	0,49
Credit	0,37	0,46	0,31
Bond	0,13	0,06	0,17
Commodity	0,43	0,51	0,38
10Year	0,23	0,10	0,30
USD	0,37	0,38	0,36

Hasanhodzic and Lo (2007: 24) explain higher average performance of fixed-weight clones by combined effects of look ahead bias for fixed-weight clones and increased estimation errors implicit in the rolling-window clones. The rolling-window clones are based on smaller sample size and therefore easier object for the estimation errors. These effects may partly explain the low significance of the factors estimated for the rolling-window linear clones in this thesis, although they delivered higher average returns than the fixed-weight linear clones. Due to these higher average returns, they are next analyzed further.

In order to test not only the replication performance, but also quality, correlations between the Credit Suisse Hedge Fund Indices and the 24-month rolling-window clones are computed. Regression results are presented in table 9 below. Correlations are relatively high as expected. During the whole estimation period from 2004 to 2015 the correlation coefficients vary from 0,54 for the Managed Futures to 0,98 for the Short Bias. Bollen and Fisher (2013) used two different length for the estimation windows; 12-month and 48-month and they did not find that the length of the window would significantly affect to the correlation between the index and its clone. However, in this thesis only estimation window is applied. According to the finding of Bollen and Fisher mentioned above it should be enough to bring comprehensive results.

Table 9. Correlation coefficients of the monthly return of 10 Hedge Fund Indices and the corresponding clones. Also adjusted R-squares for the regressions are shown. The "whole period" is estimation period from September 2004 to August 2015, the "Pre-crisis" from September 2004 to August 2008 and the "Post-crisis" from September 2008 to August 2015.

	Whole period		Pre-crisis		Post-crisis	
CS Index	ρ $Clone$	R^2	ρ $Clone$	R^2	ρ $Clone$	R^2
Hedge fund	0,76	0,70	0,91	0,77	0,74	0,73
Convertible Arb	0,89	0,70	1,05	0,51	0,90	0,75
Short Bias	0,98	0,75	0,95	0,61	0,99	0,84
Emerging Market	0,88	0,81	0,95	0,87	0,87	0,82
Equity Neutral	0,82	0,71	0,39	0,17	0,82	0,71
Event Distressed	0,72	0,68	0,82	0,60	0,75	0,76
Fixed Inc Arb	0,87	0,75	0,96	0,51	0,86	0,79
Global Macro	0,67	0,42	0,92	0,61	0,63	0,43
Long/Short	0,87	0,79	0,95	0,83	0,85	0,79
Managed Futures	0,54	0,26	0,58	0,28	0,58	0,29

The table above presents correlations between the Credit Suisse Hedge Fund Indices and the clones. Earlier studies argue that in order to make hedge fund replication products attractive alternatives to investors, they should offer diversification opportunities as actual hedge funds are argued to offer. In the interest of these blames, also correlations between the rolling-window linear clones and the S&P 500 are regressed. The results are presented in table 10 on the next page.

Table 10. Listed correlations between the Hedge Fund Index clones and the S&P 500. The Whole period is September 2004 through August 2015. The Pre-crisis period is from September 2004 to August 2008 and the Post-crisis periods covers a time period from September 2008 to August 2015.

	$\rho\ S\&P500$		
CS Index clone	Whole period	Pre-crisis	Post-crisis
Hedge fund	0,33	0,32	0,33
Convertible Arb	0,33	0,17	0,36
Short Bias	-0,73	-1,05	-0,67
Emerging Market	0,51	0,43	0,52
Equity Neutral	0,39	0,07	0,45
Event Distressed	0,32	0,26	0,33
Fixed Income Arb	0,28	0,09	0,32
Global Macro	0,14	0,05	0,15
Long/Short	0,46	0,53	0,44
Managed Futures	0,09	0,47	0,01

The correlation coefficients between the Hedge Fund Index clones and S&P 500 are generally quite low. Some of the clones show higher values - values over 0,5 – the Emerging Market during the whole sample period (0,51) and post-crisis (0,52) and the Long/Short during the pre-crisis (0,53). Without few exceptions the correlations are higher, on average, during the post-crisis period. Moreover, to investigate whether the clones rather than the target indices have lower correlations with the S&P 500 table below is computed. Table 11 presents correlations between the target Hedge Fund Indices and the S&P 500.

Table 11. Listed correlations between the Hedge Fund Indices and the S&P 500. The Whole period is September 2004 through August 2015. The Pre-crisis period is from September 2004 to August 2008 and finally the Post-crisis periods covers a time period from September 2008 to August 2015.

	$\rho\ S\&P500$		
CS Index	Whole period	Pre-crisis	Post-crisis
Hedge fund	0,29	0,28	0,30
Convertible Arb	0,29	0,22	0,31
Short Bias	-0,79	-1,23	-0,71
Emerging Market	0,46	0,41	0,48
Equity Neutral	0,31	0,01	0,37
Event Distressed	0,28	0,24	0,29
Fixed Income Arb	0,24	0,13	0,27
Global Macro	0,11	-0,02	0,14
Long/Short	0,44	0,49	0,43
Managed Futures	0,07	0,25	0,04

Comparing the tables 10 and 11 on the previous page one can observe that the indices rather than the clones have lower correlation with the S&P 500. There are however few exceptions. During the pre-crisis period the Convertible Arbitrage clone has a correlation of 0,17 with the S&P 500 whereas the Convertible Arbitrage Hedge Fund Index shows correlation of 0,22. Also the Fixed Income Arbitrage clone delivers lower correlation with the S&P 500 than the index during the pre-crisis period (0,09 vs 0,13). During the post-crisis period the Managed Futures clone shows lower correlation than the index (0,01 vs 0,04).

The findings in previous tables suggest that on average, the correlations between the target indices and corresponding clones are high. On the other hand, the correlations between the clones and the S&P 500 are lower. Although the clones show relatively low correlation with the S&P 500, the actual target indices tend to be even less correlated with the S&P 500. Also Bollen and Fisher (2012) examine these correlations with the same Hedge Fund Index catgories in their sample. They find similar results: clones have higher average correlation with the S&P 500. Their results also suggest higher average correlation between the clones and the S&P 500 than the clones and target indices. This suggestion, however, differs from the results in this thesis. Finally, the correlation between the clones and the S&P 500 is only slightly higher than the correlation between the counterparty index and the S&P 500.

These findings are crucial for the thesis as they suggest achieving diversification from standard asset classes such as U.S. equities, at some extend. This finding is in line with Hasanhodzic and Lo (2013) who suggest that the hedge fund clones exhibit correlations that are similar to those of the target portfolios, thus their results showing larger variation. For example, in their results the Convertible Arbitrage hedge fund portfolio has a correlation of 0,48 with the S&P 500, correlation of -0,29 with the 3-month LIBOR, correlation of 0,06 with the US Dollar Index and correlation of 0,79 with the CSFB/Tremont Convertible Arbitrage Index. In comparison, the fixed-weight Convertible Arbitrage clone has correlations of 0,63, -0,35, 0,01 and 0,37, respectively.

Finally, according to the findings, the replication products can offer relatively good diversification benefits for the investors. For the most of the strategies these diversification benefits are only slightly lower than those of the matching indices and in few of the cases, even slightly higher.

6.4. Discussion

Findings of this thesis suggest that the rolling-window clones perform relatively poorly. However, it is hard to make a conclusion stating which clone type performs better than the other one. Both clone types show different abilities when measured with different tools: the average monthly return, the p-values and the correlation coefficients. These mixed results are in line with earlier literature. The estimated monthly regression coefficients for the fixed-weight clones were largely highly statistically significant whereas the average monthly p-values for the rolling-window coefficients were almost all insignificant.

Comparing the fixed-weight and the rolling-window linear clones to each other as well as to the corresponding indices, the results are mixed. In times the rolling-window linear clones managed to deliver higher average annual returns than the targets hence these results being insignificant. The fixed-weight linear clones instead did not really yield higher average returns than the indices in any of the three sample periods. One clone, the Equity Neutral showed higher average returns thus them being also statistically insignificant. Also when looking at the factors over the three sample periods mixed results were obtained. Same eight factors were used in order to conduct both clone types. However, the chosen factors showed higher statistical significance among the fixed-weight clones rather than the rolling-window clones. This may be explained for example by a smaller sample size in the rolling-window approach that leads to sensitiveness to estimation errors.

7. CONCLUSIONS

Hedge fund replication products are a relatively new choice for a large group of investors. The approach aims to bring risk-adjusted returns similar to hedge funds with lower costs and increased transparency. In the replication procedures the focus is on the hedge fund beta exposures rather than the manager specific alphas. In this thesis ten Credit Suisse Hedge Fund Indices: a broad based flag ship index and nine strategy-based sub-indices are replicated. Two different replication approaches are conducted: a passive fixed-weight and a time-varying rolling-window in which a 24-month window is applied. In both cases first the monthly returns of the target indices are regressed with factor returns in order to estimate monthly beta coefficients that are then used as portfolio weights in the replicating portfolios. The regression model includes eight different common factors that are chosen based on previous literature suggesting their ability to gauge the common hedge fund risk exposures. The final monthly replicator returns are conducted by multiplying the estimated portfolio weights with the monthly factor returns.

The findings suggest that although in some hedge fund categories the clones show higher average annual raw returns than the targets, their performance is not directly comparable with the corresponding indices. When measured on a risk-adjusted basis, the clones deliver lower annual Sharpe ratios suggesting that the clones perform worse. In terms of the annual volatility, the fixed-weight clones outperform the indices whereas the rolling-window clones deliver similar volatilities than the indices, on average. However, an important finding is that it is possible to identify risk factors that affect part of the hedge fund returns and to obtain similar returns to hedge funds using these identified risk exposures.

The fixed-weight linear clones were found to deliver higher statistical significance than rolling-window clones. However, the rolling-window clones generally yielded higher average monthly and annual raw returns than the fixed-weight linear clones. In addition, the clones with rolling-window approach may be more attainable and flexible in terms of capturing non-stationarities such as the time-varying means. This is largely in contrast with earlier research (e.g. Hasanhodzic and Lo 2007) that has found the fixed-weight clones to deliver higher average return performance on both raw- and risk-adjusted basis. During the whole estimation period from 2004 to 2015, one fixed-weight linear clone and three rolling-window linear clones were found to outperform their counterparties. The estimation period was also divided into two sub-sample periods: pre-crisis and post-crisis. The findings suggest that the post-crisis clone performance was better than that of the Hedge Fund Indices. This finding was found when using the rolling-window out-of-sample estimation approach. The finding is partly in line with earlier research (Wallerstein et al. 2010) suggesting that the clones can outperform the hedge funds during economic downturns. However, the clones delivered higher returns with a lag after the crisis time. Furthermore, the higher annual returns among the clones were largely statistically insignificant. The fixed-weight linear coefficients showed high statistical significance in the risk exposure analysis, but the clone that outperformed its counterparty was statistically insignificant. Also the rolling-window linear clones showed high statistical insignificancy.

In order to analyze the replicating quality, the correlations between the clones and the indices were regressed. As expected, clones were found to have relatively high correlations with their target indices. This indicates that the clones are able to mimic their targets well. Moreover, the correlations between the clones and the S&P 500 and the targets and S&P 500 were computed. The clones were found to have only slightly higher correlation with the S&P 500 than what the target indices have. This finding suggests that the replication products offer diversification benefits similar to those of the target indices.

Finally, the findings partly support the hypothesis. The passive linear hedge fund clones did not outperform the corresponding hedge fund indices. Although the results seen in this thesis were promising at early stage – high statistical significance was shown in the beta coefficient estimation part – the final replication products did not unambiguously outperform their target indices. The results however give hope for the future replication attempts and replication research, as hedge fund risk exposures were obtained with common factors as well as higher clone returns were found in few of the index categories. All these findings together with earlier research give hope for investors of cheaper investments in the future. With more research of different methods or only different factors, better results may be obtained in the future.

As replication products become available for investors like mutual funds some investors may use them as another type of equity investment. Finally, it will be interesting to follow how the hedge fund and the hedge fund replication industries will develop in the future and whether other will replace the other.

REFERENCES

Amenc, N., Gehin, W., Martellini, L. and J. C. Meyfredi (2008). Passive Hedge Fund Replication: A Critical Assessment of Existing Techniques. *Journal of Alternative Investments* 11:2, p. 69-83.

Amenc, N., Martellini, L. and J. C. Meyfredi (2010). Passive Hedge Fund Replication - Beyond the Linear Case. *European Financial Management* 16:2, p. 191–210.

Amin, G.S. and H.M. Kat (2003). Hedge Fund Performance 1990-2000: Do the “Money Machines” Really Add Value? *The Journal of Financial and Quantitative Analysis* 38: 2, p. 251-274.

Bollen, N. and G. Fisher (2013). Send in the Clones? Hedge Fund Replication Using Futures Contracts. *The Journal of Alternative Investments* 16:2, p. 80-95.

Bruno, S. and R. Whitelaw (2012). Selecting A Hedge Fund Replication Approach. *Journal of Indexes*, p. 40-47.

Chatterjee, R. (2014). *Practical Methods of Financial Engineering and Risk Management.* [online] [cited 15.12.2015]. Available on World Wide Web: <http://www.bookmetrix.com/detail/chapter/35b7c0c2-6b14-4d0e-bd37-9ddb16cf4a8f#downloads> .

Chen, J. and M. Tindall (2014). Hedge Fund Replication Using Shrinkage Methodologies. *Journal of Alternative Investments* 17:2, p. 26-49.

Cheng, Y. and B. Liang (2007). Do Market Timing Hedge Funds Time the Market? *Journal of Financial and Quantitative Analysis* 42:4, p. 827-856.

Credit Suisse Hedge Fund Database (2015). Available on World Wide Web: <https://hedgeindex.com>

Dor, A., Jagannathan, R. and I. Meier (2012). What Drives the Tracking Error of Hedge Fund Clones?. *The Journal of Alternative Investments* 15:2, p. 54-74.

Duanmu, J., Li, Y. and A. Malakhov (2015). Smart Beta ETF Portfolios: Cloning Beta Active Hedge Funds. Available at SSRN: <http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2532806>

Duanmu, J., Li, Y. and A. Malakhov (2014). In Search of Missing Risk Factors: Hedge Fund Return Replication with ETFs. Available at SSRN: http://ssrn.com/abstract=2411910 or http://dx.doi.org/10.2139/ssrn.2411910

Fortune (2014a). *Biggest U.S. pension just gave hedge funds the boot* [online]. 15.9.2014 [cited 17.5.2015]. Available on World Wide Web: < http://fortune.com/2014/09/15/calpers-pension-manager-divesting-four-billion-hedge-funds/>

Fortune (2014b). *Why America's largest pension fund dumped hedge funds* [online]. 16.9.2014 [cited 17.5.2015]. Available on World Wide Web: < http://fortune.com/2014/09/16/calpers-hedge-funds/>

Freed, M. (2013). Hedge Fund Indexation and Replication. Look at Different Approaches. *Journal of Indexes*, p. 30-37.

Fung, W. and D.A. Hsieh (1997). Empirical characteristics of dynamic trading strategies: the case of hedge funds. *Review of Financial Studies* 10:2, p. 275-302.

Fung, W. and D.A. Hsieh (2003). The Risks in Hedge Fund Strategies: Alternative Alphas and Alternative Betas. In Lars Jaeger ed. The New Generation of Risk management for Hedge Funds and Private Equity Funds. *Euromoney Institutional Investors PLC*, p. 72-87.

Fung, W. and D.A. Hsieh (2004). Hedge Fund Benchmarks: A Risk-Based Approach. *Financial Analysts Journal* 60:5, p. 65-80.

Fung, W. and D.A. Hsieh (2007). Will Hedge Funds Regress Towards Index-Like Products? *Journal of Investment Management* 5:2, p. 46-65.

Griffin, J. and J. Xu (2009). How Smart are the Smart Guys? A Unique View from Hedge Fund Stock Holdings. *Review of Financial Studies* 22: 7, p. 2531-2570.

Hasanhodzoc, J. and A.W. Lo (2007). Can Hedge-Fund Returns Be Replicated?: The Linear Case. *Journal of Investment Management* 5:2, p. 5-45.

Hayes, B. (2012). On the Market Timing Ability of Factor-Based Hedge Fund Clones. *The Journal of Alternative Investments* 15:1, p. 8-42.

Hedge Fund Research, Inc. (2015). Website. [online]. [cited 18.12.2015]. Available on World Wide Web: <hedgefundresearch.com>

Hsieh, D.A. (2015). Website. [online]. [cited 18.12.2015]. Available on World Wide Web: <Fuqua.duke.edu/~dah7>

IndexIQ (2015). Website. [online]. [cited 18.12.2015]. Available on World Wide Web: <www.indexiq.com>

Jaeger, L. and C. Wagner (2005). Factor Modelling and Benchmarking Hedge Funds: Can Passive Investments in Hedge Fund Strategies Deliver? [online]. Available on World Wide Web at SSRN: <http://ssrn.com/abstract=811185>

Jaeger, L. and J. Pease (2008). Alternative Beta Strategies and Hedge Fund Replication. West Sussex, England: John Wiley & Sons Ltd, The Atrium. 253p., ISBN 978-0-470-75446-7.

Kat, H. M. and H. P. Palaro (2005). Hedge Fund Returns: You Can Make Them Yourself!. *Journal of Wealth Management* 8:2, p. 62-68.

Lin, P. (2014). Alternative Alphas from Hedge Fund ETF Speculation. [online]. Available on World Wide Web at SSRN: <http://ssrn.com/abstract=2570656> or <http://dx.doi.org/10.2139/ssrn.2570656>.

O'Doherty, M., Savin, N. and A. Tiwari (2015). Hedge Fund Replication: A Model Combination Approach. [online]. Available on World Wide Web at SSRN: <http://ssrn.com/abstract=2554686> or <http://dx.doi.org/10.2139/ssrn.2554686>.

Reuters (2014). *Calpers dumps hedge funds citing cost, to pull $4 billion stake* [online]. 16.9.2014 [cited 17.5.2015]. Available on World Wide Web: < http://www.reuters.com/article/2014/09/16/us-pensions-calpers-hedgefunds-idUSKBN0HA2D120140916>

Roncalli, J. and T. Jerome (2007). An Alternative Approach to Alternative Beta. [online]. Available on World Wide Web at SSRN: <http://ssrn.com/abstract=1035521>

Sharpe, W. F. (1992). Asset Allocation: Management Style and Performance Measurement. *Journal of Portfolio Management* 18:2, p. 7–19.

Subhash, S. and D. Enke (2014). Hedge fund replication using liquid ETFs and regression analysis. *IIE Annual Conference and Expo 2014*, 1959-1967.

Tupitsyn, M. and P. Lajbcygier (2015). Passie Hedge Funds. [online]. Available on World Wide Web at SSRN: <http://ssrn.com/abstract=2642057>

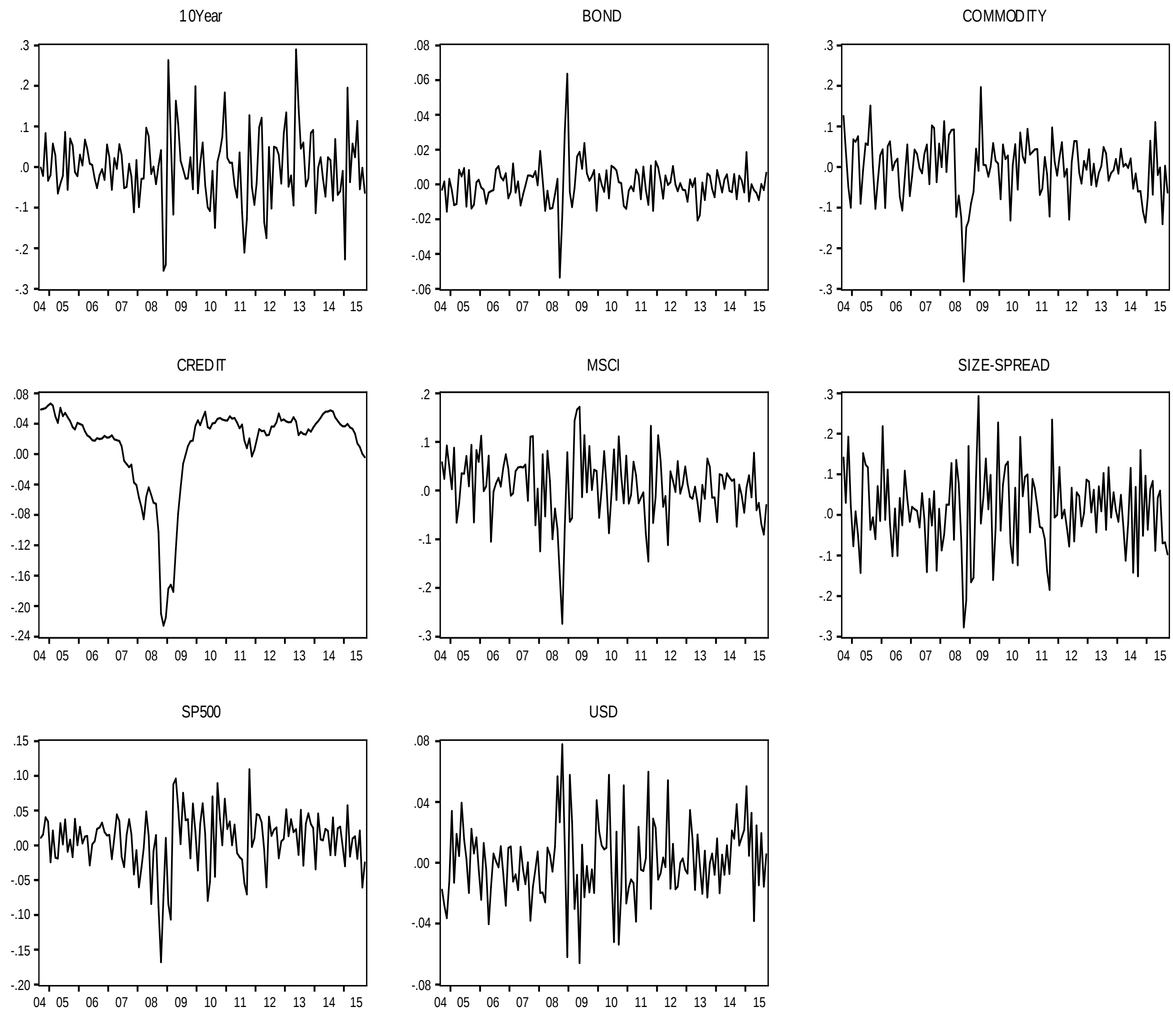
Wallerstein, E., Tuchschmid, N. S. and S. Zaker (2010). How do hedge fund clones manage the real world? *Journal of Alternative Investments* 12: 3, p. 37-50.

Wallerstein, E., Tuchschmid, N. S., and S. Zaker (2012). Hedge fund replication in turbulent markets. *Managerial Finance* 38:1, p. 67-81.

Zivot, E and J.Wang (2006). *Modeling Financial Time Series with S-PLUS®.* [online]. New York, Springer New York, 2006. Available on World Wide Web: < http://link.springer.com/chapter/10.1007%2F978-0-387-32348-0_9>

APPENDICES

Appendix 1. Monthly returns (%-change) for the factors between 2004 and 2015.



Appendix 2. Monthly return decomposition for the Credit Suisse Broad Hedge Fund Index rolling-window clone.

	SP500	MSCI	Size-Spread	Credit	Bond	Commodity	10Year	USD	Tot.return:
2004M09	0,067 %	-0,022 %	0,408 %	0,290 %	-0,261 %	0,383 %	-0,017 %	0,237 %	1,085 %
2004M10	0,143 %	0,004 %	0,057 %	0,147 %	0,145 %	0,130 %	-0,224 %	0,345 %	0,746 %
2004M11	0,298 %	0,205 %	0,443 %	0,165 %	-1,381 %	-0,110 %	1,017 %	0,633 %	1,270 %
2004M12	0,193 %	0,137 %	0,045 %	0,166 %	0,290 %	-0,144 %	-0,411 %	0,217 %	0,492 %
2005M01	-0,233 %	0,006 %	-0,173 %	0,489 %	-0,275 %	0,064 %	-0,198 %	-0,471 %	-0,790 %
2005M02	0,203 %	0,269 %	0,020 %	0,889 %	-0,894 %	-0,008 %	0,547 %	0,185 %	1,212 %
2005M03	-0,202 %	-0,134 %	-0,131 %	0,813 %	-0,800 %	0,053 %	0,256 %	-0,252 %	-0,396 %
2005M04	-0,225 %	-0,059 %	-0,402 %	0,790 %	0,567 %	-0,154 %	-0,569 %	-0,063 %	-0,116 %
2005M05	0,238 %	0,137 %	0,294 %	1,247 %	0,336 %	-0,011 %	-0,451 %	-0,728 %	1,063 %
2005M06	0,010 %	0,118 %	0,273 %	1,121 %	0,676 %	0,095 %	-0,229 %	-0,291 %	1,773 %
2005M07	0,096 %	0,423 %	0,286 %	0,750 %	-0,990 %	0,055 %	1,190 %	-0,048 %	1,763 %
2005M08	-0,026 %	0,048 %	-0,088 %	0,857 %	0,623 %	0,148 %	-0,761 %	0,375 %	1,176 %
2005M09	0,013 %	0,929 %	-0,011 %	0,612 %	-0,959 %	0,000 %	0,970 %	-0,255 %	1,301 %
2005M10	-0,123 %	-0,710 %	-0,097 %	0,295 %	-0,759 %	-0,237 %	0,700 %	-0,051 %	-0,983 %
2005M11	0,338 %	0,953 %	0,085 %	0,225 %	0,075 %	-0,088 %	-0,159 %	-0,101 %	1,328 %
2005M12	0,004 %	0,718 %	-0,006 %	0,055 %	0,178 %	0,080 %	-0,297 %	0,032 %	0,764 %
2006M01	0,216 %	1,480 %	0,103 %	-0,067 %	-0,120 %	0,122 %	0,442 %	0,223 %	2,400 %
2006M02	0,015 %	-0,013 %	-0,011 %	-0,090 %	-0,228 %	-0,201 %	0,065 %	-0,120 %	-0,582 %
2006M03	0,105 %	0,109 %	0,094 %	-0,261 %	-0,848 %	0,134 %	1,092 %	0,040 %	0,465 %
2006M04	0,096 %	0,861 %	-0,027 %	-0,151 %	-0,350 %	0,150 %	0,711 %	0,349 %	1,638 %
2006M05	-0,338 %	-1,169 %	-0,084 %	-0,094 %	-0,279 %	-0,022 %	0,124 %	0,142 %	-1,719 %
2006M06	0,014 %	-0,024 %	0,014 %	-0,008 %	-0,219 %	0,030 %	0,076 %	-0,058 %	-0,175 %
2006M07	0,044 %	0,169 %	-0,149 %	0,047 %	0,602 %	0,045 %	-0,461 %	-0,010 %	0,286 %
2006M08	0,128 %	0,315 %	0,063 %	0,076 %	0,749 %	-0,122 %	-0,780 %	0,034 %	0,463 %
2006M09	0,084 %	0,101 %	-0,057 %	0,111 %	0,312 %	-0,243 %	-0,298 %	-0,137 %	-0,127 %
2006M10	0,133 %	0,565 %	0,257 %	0,091 %	0,167 %	-0,060 %	-0,079 %	0,096 %	1,170 %
2006M11	0,076 %	0,886 %	0,099 %	0,120 %	0,466 %	0,122 %	-0,457 %	0,380 %	1,691 %
2006M12	-0,068 %	0,656 %	-0,044 %	-0,213 %	-0,632 %	-0,240 %	0,984 %	-0,041 %	0,403 %
2007M01	-0,019 %	-0,134 %	0,052 %	-0,295 %	-0,329 %	-0,088 %	0,442 %	-0,028 %	-0,400 %
2007M02	-0,020 %	-0,077 %	0,031 %	-0,225 %	0,897 %	0,160 %	-1,000 %	0,060 %	-0,174 %
2007M03	-0,017 %	0,600 %	0,027 %	-0,196 %	-0,388 %	0,066 %	0,388 %	0,065 %	0,545 %
2007M04	0,205 %	0,668 %	-0,063 %	-0,175 %	0,125 %	-0,007 %	-0,077 %	0,182 %	0,859 %
2007M05	0,340 %	0,623 %	0,121 %	-0,193 %	-0,846 %	-0,056 %	0,904 %	-0,048 %	0,843 %
2007M06	-0,228 %	0,534 %	-0,027 %	-0,055 %	-0,362 %	0,116 %	0,419 %	0,024 %	0,420 %
2007M07	-0,541 %	0,567 %	-0,333 %	0,000 %	-0,044 %	0,263 %	-0,722 %	0,057 %	-0,752 %
2007M08	0,270 %	-0,249 %	0,026 %	-0,215 %	0,219 %	-0,220 %	-0,617 %	-0,002 %	-0,787 %
2007M09	0,644 %	1,477 %	-0,003 %	-0,353 %	0,164 %	0,615 %	0,094 %	0,061 %	2,699 %
2007M10	0,183 %	1,627 %	0,052 %	-0,188 %	0,171 %	0,482 %	-0,344 %	0,012 %	1,996 %
2007M11	-0,252 %	-1,023 %	-0,217 %	-0,139 %	0,401 %	-0,137 %	-1,534 %	-0,014 %	-2,915 %

2007M12	-0,048 %	0,052 %	0,019 %	-0,262 %	-0,026 %	0,207 %	0,213 %	0,017 %	0,172 %
2008M01	-0,138 %	-1,755 %	-0,201 %	-0,126 %	1,264 %	0,000 %	-1,563 %	0,093 %	-2,427 %
2008M02	-0,045 %	1,083 %	-0,114 %	-0,064 %	0,156 %	0,175 %	-0,473 %	0,090 %	0,809 %
2008M03	0,003 %	-0,860 %	0,040 %	-0,223 %	-1,028 %	-0,009 %	-0,436 %	0,117 %	-2,396 %
2008M04	-0,458 %	1,440 %	0,081 %	-0,547 %	-0,281 %	-0,099 %	1,315 %	-0,111 %	1,340 %
2008M05	-0,116 %	0,281 %	0,601 %	-0,452 %	-0,980 %	0,151 %	1,068 %	-0,039 %	0,515 %
2008M06	0,907 %	-1,023 %	-0,283 %	-0,844 %	-0,805 %	0,590 %	-0,237 %	0,003 %	-1,691 %
2008M07	-0,006 %	-0,236 %	0,156 %	-1,332 %	-0,242 %	-1,461 %	0,008 %	0,066 %	-3,047 %
2008M08	0,023 %	-0,486 %	0,076 %	-1,339 %	0,123 %	-0,888 %	-0,374 %	0,480 %	-2,386 %
2008M09	-0,204 %	-1,063 %	-0,087 %	-2,112 %	-2,211 %	-1,597 %	0,025 %	0,170 %	-7,079 %
2008M10	0,483 %	-2,205 %	0,227 %	-3,302 %	-0,946 %	-2,620 %	0,554 %	0,297 %	-7,512 %
2008M11	0,129 %	-0,801 %	0,241 %	-2,742 %	1,632 %	-1,268 %	-2,550 %	0,077 %	-5,282 %
2008M12	-0,041 %	0,811 %	0,160 %	-2,013 %	3,913 %	-1,122 %	-2,516 %	-0,134 %	-0,942 %
2009M01	0,413 %	-0,686 %	-0,126 %	-1,337 %	-0,281 %	-0,790 %	3,137 %	0,053 %	0,384 %
2009M02	0,853 %	-0,655 %	-0,180 %	-1,398 %	-0,843 %	-0,532 %	0,839 %	0,037 %	-1,881 %
2009M03	-0,185 %	1,648 %	0,037 %	-0,825 %	-0,121 %	0,459 %	-1,280 %	-0,143 %	-0,410 %
2009M04	-0,809 %	2,073 %	0,336 %	-0,556 %	0,885 %	-0,123 %	1,168 %	-0,117 %	2,858 %
2009M05	-0,743 %	1,956 %	-0,066 %	-0,080 %	1,067 %	3,313 %	0,636 %	-1,200 %	4,883 %
2009M06	-0,026 %	-0,150 %	0,132 %	-0,038 %	0,519 %	0,097 %	0,091 %	0,214 %	0,839 %
2009M07	-1,062 %	1,625 %	0,291 %	-0,056 %	1,330 %	0,063 %	-0,032 %	-0,391 %	1,766 %
2009M08	-0,313 %	-0,046 %	0,002 %	-0,006 %	0,351 %	-0,260 %	-0,173 %	-0,032 %	-0,478 %
2009M09	-0,441 %	1,611 %	-0,008 %	0,124 %	0,110 %	0,015 %	-0,156 %	-0,292 %	0,962 %
2009M10	0,224 %	0,021 %	-0,305 %	0,149 %	0,251 %	0,581 %	0,128 %	-0,076 %	0,974 %
2009M11	-0,468 %	0,664 %	-0,010 %	0,181 %	0,428 %	0,132 %	-0,297 %	-0,294 %	0,337 %
2009M12	-0,067 %	0,516 %	-0,205 %	0,305 %	-0,830 %	0,085 %	1,054 %	0,536 %	1,394 %
2010M01	0,129 %	-0,638 %	0,029 %	0,387 %	0,343 %	-0,791 %	-0,355 %	0,217 %	-0,678 %
2010M02	-0,175 %	0,049 %	-0,057 %	0,325 %	-0,011 %	0,557 %	0,035 %	0,133 %	0,856 %
2010M03	-0,402 %	1,167 %	-0,103 %	0,423 %	-0,237 %	0,188 %	0,300 %	0,115 %	1,451 %
2010M04	-0,064 %	0,187 %	-0,232 %	0,433 %	0,416 %	0,283 %	-0,226 %	0,152 %	0,950 %
2010M05	-0,135 %	-0,991 %	0,178 %	0,256 %	-0,455 %	-1,211 %	-0,674 %	0,514 %	-2,517 %
2010M06	-0,594 %	-0,106 %	0,628 %	0,262 %	0,540 %	0,007 %	-0,870 %	-0,069 %	-0,201 %
2010M07	0,716 %	1,270 %	-0,313 %	0,304 %	0,490 %	0,097 %	-0,080 %	-0,613 %	1,871 %
2010M08	-0,454 %	-0,302 %	0,608 %	0,317 %	0,397 %	-0,085 %	-1,118 %	0,262 %	-0,374 %
2010M09	1,023 %	1,423 %	-0,782 %	0,356 %	0,066 %	0,228 %	0,103 %	-0,566 %	1,850 %
2010M10	0,508 %	0,317 %	-0,194 %	0,358 %	0,038 %	0,058 %	0,323 %	-0,175 %	1,233 %
2010M11	0,002 %	-0,220 %	-0,536 %	0,236 %	-0,673 %	0,019 %	0,527 %	0,525 %	-0,120 %
2010M12	1,218 %	0,531 %	-0,535 %	0,229 %	-0,790 %	0,150 %	1,372 %	-0,224 %	1,951 %
2011M01	0,359 %	-0,242 %	0,168 %	0,270 %	-0,197 %	0,109 %	0,121 %	-0,150 %	0,437 %
2011M02	0,687 %	-0,096 %	-0,227 %	0,595 %	-0,047 %	0,178 %	0,018 %	-0,095 %	1,013 %
2011M03	0,009 %	0,509 %	-0,200 %	0,523 %	-0,178 %	0,173 %	0,024 %	-0,110 %	0,750 %
2011M04	0,649 %	0,280 %	-0,044 %	0,330 %	0,464 %	0,007 %	-0,186 %	-0,211 %	1,290 %
2011M05	-0,256 %	-0,182 %	0,033 %	0,396 %	0,291 %	0,004 %	-0,298 %	0,091 %	0,080 %
2011M06	-0,419 %	-0,129 %	0,047 %	0,390 %	-0,375 %	-0,117 %	0,048 %	-0,040 %	-0,596 %
2011M07	-0,425 %	-0,031 %	-0,049 %	-0,081 %	0,634 %	0,046 %	-0,245 %	-0,030 %	-0,181 %

2011M08	-1,123 %	-0,770 %	-0,093 %	-0,011 %	-0,198 %	-0,034 %	-0,455 %	0,017 %	-2,667 %
2011M09	-1,700 %	-0,882 %	0,469 %	0,198 %	-0,409 %	-0,525 %	-0,198 %	0,398 %	-2,648 %
2011M10	2,975 %	0,962 %	-1,224 %	1,004 %	0,104 %	0,472 %	-0,044 %	-0,285 %	3,964 %
2011M11	-0,054 %	-0,260 %	0,023 %	-0,140 %	-0,201 %	0,123 %	0,009 %	0,323 %	-0,177 %
2011M12	0,311 %	-0,048 %	-0,001 %	0,234 %	0,150 %	-0,172 %	0,193 %	0,266 %	0,933 %
2012M01	1,517 %	1,522 %	-0,939 %	0,713 %	-0,056 %	0,244 %	0,202 %	-0,257 %	2,948 %
2012M02	1,467 %	0,715 %	0,059 %	1,327 %	-0,014 %	0,717 %	-0,594 %	-0,163 %	3,515 %
2012M03	1,254 %	-0,422 %	-0,097 %	1,287 %	0,107 %	-0,236 %	-0,748 %	0,084 %	1,230 %
2012M04	-0,237 %	-0,149 %	0,249 %	1,277 %	-0,063 %	-0,051 %	0,795 %	-0,070 %	1,751 %
2012M05	-2,275 %	-1,280 %	0,485 %	1,057 %	0,003 %	-0,983 %	1,106 %	1,331 %	-0,556 %
2012M06	1,810 %	0,496 %	-0,490 %	1,215 %	-0,028 %	0,093 %	-0,405 %	-0,502 %	2,190 %
2012M07	0,578 %	0,198 %	0,355 %	1,703 %	-0,108 %	0,298 %	0,699 %	0,263 %	3,985 %
2012M08	0,819 %	-0,017 %	-0,192 %	1,525 %	0,000 %	0,443 %	-0,263 %	-0,292 %	2,022 %
2012M09	0,880 %	0,409 %	-0,179 %	1,723 %	-0,017 %	-0,095 %	-0,208 %	-0,263 %	2,251 %
2012M10	-0,576 %	-0,041 %	0,102 %	2,065 %	0,006 %	-0,291 %	-0,114 %	-0,004 %	1,147 %
2012M11	0,154 %	0,089 %	-0,006 %	1,805 %	0,001 %	0,135 %	0,146 %	0,066 %	2,390 %
2012M12	0,157 %	0,342 %	0,065 %	1,657 %	-0,049 %	-0,054 %	-0,188 %	-0,091 %	1,838 %
2013M01	1,007 %	0,093 %	0,086 %	1,709 %	-0,057 %	0,384 %	-0,339 %	-0,156 %	2,727 %
2013M02	0,185 %	-0,074 %	0,009 %	1,429 %	0,050 %	-0,439 %	0,042 %	0,652 %	1,854 %
2013M03	0,044 %	-0,153 %	0,256 %	1,595 %	-0,016 %	0,109 %	0,011 %	0,383 %	2,230 %
2013M04	0,268 %	0,079 %	-0,040 %	2,044 %	0,013 %	-0,448 %	0,211 %	-0,407 %	1,721 %
2013M05	0,327 %	-0,261 %	0,088 %	1,884 %	-0,058 %	-0,118 %	-0,679 %	0,434 %	1,618 %
2013M06	-0,186 %	-0,707 %	0,007 %	1,098 %	-0,068 %	0,016 %	-0,313 %	-0,033 %	-0,186 %
2013M07	0,813 %	0,115 %	0,098 %	1,263 %	0,003 %	0,317 %	-0,102 %	-0,471 %	2,036 %
2013M08	-0,434 %	-0,165 %	-0,034 %	1,156 %	-0,046 %	0,238 %	-0,137 %	0,172 %	0,748 %
2013M09	0,445 %	0,647 %	0,158 %	1,054 %	0,070 %	-0,177 %	0,099 %	-0,467 %	1,830 %
2013M10	0,759 %	0,513 %	-0,017 %	1,160 %	0,057 %	-0,078 %	0,059 %	-0,005 %	2,447 %
2013M11	0,515 %	-0,140 %	0,139 %	1,059 %	-0,045 %	-0,028 %	-0,111 %	0,094 %	1,483 %
2013M12	0,461 %	-0,120 %	0,019 %	1,155 %	-0,166 %	0,067 %	-0,076 %	-0,110 %	1,231 %
2014M01	-0,688 %	-0,384 %	-0,013 %	1,572 %	0,175 %	-0,055 %	0,084 %	0,171 %	0,862 %
2014M02	0,906 %	0,187 %	0,053 %	1,753 %	0,037 %	0,147 %	0,002 %	-0,210 %	2,874 %
2014M03	0,183 %	0,040 %	-0,068 %	1,583 %	-0,158 %	0,003 %	-0,008 %	0,031 %	1,606 %
2014M04	0,146 %	0,008 %	-0,541 %	1,592 %	0,090 %	0,021 %	0,025 %	-0,080 %	1,261 %
2014M05	0,456 %	0,089 %	-0,094 %	1,714 %	0,193 %	-0,007 %	0,016 %	0,071 %	2,438 %
2014M06	0,453 %	0,107 %	0,300 %	0,580 %	-0,197 %	0,042 %	0,041 %	-0,030 %	1,296 %
2014M07	-0,306 %	0,055 %	-0,453 %	0,849 %	-0,237 %	0,006 %	0,035 %	0,023 %	-0,028 %
2014M08	0,807 %	0,072 %	0,152 %	0,550 %	0,375 %	-0,012 %	-0,274 %	-0,035 %	1,636 %
2014M09	-0,316 %	-0,095 %	-0,190 %	0,480 %	-0,538 %	0,039 %	0,246 %	-0,037 %	-0,412 %
2014M10	0,559 %	0,027 %	-0,291 %	0,360 %	0,316 %	-0,206 %	-0,307 %	-0,046 %	0,412 %
2014M11	0,720 %	-0,006 %	0,125 %	0,222 %	0,163 %	0,133 %	-0,314 %	-0,123 %	0,920 %
2014M12	-0,080 %	0,177 %	-0,268 %	0,175 %	-0,331 %	0,234 %	-0,045 %	-0,147 %	-0,287 %
2015M01	-0,787 %	-0,005 %	0,101 %	-0,230 %	1,486 %	0,122 %	-0,861 %	0,024 %	-0,149 %
2015M02	1,530 %	-0,041 %	-0,173 %	-0,253 %	-0,782 %	-0,110 %	0,668 %	0,008 %	0,848 %
2015M03	-0,343 %	-0,014 %	-0,171 %	-0,283 %	0,008 %	0,192 %	-0,154 %	0,065 %	-0,700 %

2015M04	0,220 %	0,120 %	0,132 %	-0,423 %	-0,242 %	-0,131 %	0,216 %	-0,408 %	-0,517 %
2015M05	0,312 %	-0,032 %	-0,070 %	-0,405 %	-0,376 %	0,007 %	0,078 %	0,299 %	-0,187 %
2015M06	-0,511 %	0,016 %	-0,103 %	-0,169 %	-0,625 %	-0,001 %	0,309 %	-0,212 %	-1,295 %
2015M07	0,554 %	0,083 %	0,086 %	-0,098 %	0,013 %	-0,247 %	-0,132 %	0,268 %	0,529 %
2015M08	-1,724 %	0,014 %	0,080 %	-0,001 %	-0,201 %	0,003 %	-0,005 %	-0,235 %	-2,068 %