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Master Thesis:

«Performance analysis of niche alternatives and hedge fund strategies»

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Management Summary

The interest of institutional investors in hedge funds as alternative investments has grown substantially over the last decade. The key reason for adding alternative investments to a well-diversified institutional portfolio is the risk-return profile, which is achieved by reducing the risk through diversification and enhancing the returns through alpha.
In addition to the well-known hedge fund investment strategies, the Swiss investment company Progressive Capital Partners Ltd. offers its own specialized niche alternative assets consisting of music royalties, appraisal and litigation rights. Due to their performance characteristics, the alternative investments are intended to provide an opportunity for pension fund portfolios.

The purpose of this master thesis is to analyze the monthly returns of twelve hedge fund strategies, and niche alternatives of Progressive Capital. In addition, the performance of a self-created representative Swiss pension fund portfolio is examined quantitatively with niche alternatives as an alternative asset class.
The methodology for the analysis is based on a combination of principal component analysis with three different multi-factor models to explain the returns of hedge fund strategies. An extensive aggregated hedge fund database and a universe of 25 risk factors are employed for the full sample period from August 2007 to December 2018.
Furthermore, a portfolio optimization analysis is used on the Swiss pension fund portfolio to evaluate the niche alternatives and other traditional alternative assets based on pension fund investment restrictions.

The results showed small differences in the alphas resulting from the three different multi-factor models. The average monthly alpha is highest 0.22 % for the Fung and Hsieh eight-factor model, 0.19 % for the stepwise regression model and lowest with 0.16 % for Fung and Hsieh seven-factor model over all thirteen hedge fund strategies including the niche alternatives. According to these results, Progressive Capital performs better in all three models than the average alphas do. The highest alpha of 0.47 % was gained by the stepwise regression, followed by 0.44 % in the Fung and Hsieh eight-factor model, and 0.37 % in the Fung and Hsieh seven-factor model.

The results of the portfolio-optimization demonstrate that niche alternatives provide a better performance through a higher Sharpe ratio and better risk/reward trade-off compared to the other alternative investments.

These empirical results lead to a strong argumentation that the representative Swiss pension fund may consider including niche alternatives from Progressive Capital in their asset allocation due to the higher alphas and better portfolio performance in order to achieve a better risk-return profile.

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First, I want to thank my supervisor Dr. Orpiszewski Tomasz for his constant support and for being passionate, as well as patient, with me throughout this master thesis. His professional and entrepreneurial attitude gave me inspiration and allowed me to learn a lot.

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Formula sheet

Monthly simple returns: **(1)**

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}}$$

Where: p_t: stock price at the end of month t

Principal component analysis (PCA):

(2)

$$S_{\underline{x}} = A\ L\ A^T$$

Where: $S_{\underline{x}}$: Covariance matrix $S_{\underline{x}}$

A: Matrix with eigenvectors a_k of the matrix $S_{\underline{x}}$

L: Diagonal matrix with eigenvalues $l_k, k = 1, \dots, p$

Multi factor model: **(3)**

$$R_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} * F_{k,t} + E_{i,t} \qquad \forall i = 1, \dots, N \qquad \forall t = t_0, \dots, T$$

Where: $R_{i,t}$: Net-of-fees excess return on hedge fund index i for month t

α_i: Intercept (alpha) for hedge fund index i

$\beta_{i,k}$: Factor loading of hedge fund index i on the k-th factor

$F_{k,t}$: Excess return on the k-th risk factor for month t

$E_{i,t}$: Error term for month t.

Akaike Information criterion (AIC): **(4)**

$$AIC = -2(maximized\ Log - Likelihood) + 2$$
$$= n \log \langle \frac{1}{n} \sum_{i=1}^{n} R^2{}_i \rangle + 2p^* + constant$$

Where: R^2: Coefficient of determination

p^*: Number of estimated parameters

Expected portfolio return: **(5)**

$$E(r_p) = w^T * r_i = (w_1, \ldots, w_n)^T * \begin{pmatrix} r_1 \\ \vdots \\ r_n \end{pmatrix}$$

Where: $E(r_p)$: Expected portfolio return

w^T: Vector of portfolio weights

r_i: Vector of the assets' expected returns

Portfolio variance: **(6)**

$$Var(r_p) = w^T \Sigma\, \mathrm{w} = (w_1, \ldots, w_n)^T \begin{pmatrix} \sigma_{11} & \cdots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{1n} & \cdots & \sigma_{nn} \end{pmatrix} \begin{pmatrix} w_1 \\ \vdots \\ w_n \end{pmatrix}$$

Where: $Var(r_p)$: Portfolio variance

w^T: Vector of portfolio weights

Σ: Cov(x,x): covariance matrix

Beta factor: **(7)**

$$\beta_i = \frac{\sigma_{iM}}{\sigma^2{}_M} = \frac{cov(r_i, r_M)}{\sigma^2{}_M}$$

Where: σ_{iM}: Covariance between return of asset r_i and return of the market r_M

$\sigma^2{}_M$: Variance of the market

Sharpe Ratio: **(8)**

$$SR_A = \frac{E(r_A) - r_f}{\sigma_A}$$

Where: $E(r_A)$: Expected return of asset A

r_f: Risk-free rate

σ_A: Risk of asset A

Jensen's alpha: **(9)**

$$J_A = r_A - E(r_A) = r_A - \left[r_f + \beta_A * (E(r_m) - r_f\right]$$

Where: r_A: Realized return of asset A

$E(r_A)$: Expected return of asset A

$E(r_m)$: Expected return of the market (benchmark)

r_f: Risk-free rate

β_A: Beta factor of asset A

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1. Introduction

The following introduces the business partner for the master thesis. Thereafter, the initial situation, its problem definition, the objectives derived from it as well as the delimitations and the structure of this thesis are presented.

1.1 Progressive Capital Partners Ltd

The business partner for the master thesis is Progressive Capital Partners Ltd, hereinafter referred as Progressive Capital. Progressive Capital is an independent Swiss investment company founded in 2001 in the canton of Zug. With twelve employees and an average professional experience of 24 years per employee, Progressive Capital has around USD 550 million of assets under management (as of April 2019). They specialize in niche alternative assets and managed futures strategies. The main objective of Progressive Capital is to promote alternative investments and make them available to a wider public.

1.2 Initial position and problem definition

In recent years, the hedge fund industry has made its presence known in the financial sector through its rapid growth. According to the latest HFR Global Hedge Fund Industry Report of April 2019, the total capital invested in hedge funds increased to $3.18 trillion globally (Heinz, 2019, p. 1). The field of activity of hedge funds has also expanded. In addition to family offices and high-net-worth investors, pension funds and endowments are now also showing great interest in the financial services of hedge funds. The main reason for this interest is the performance characteristics of hedge funds, which demonstrates distinct correlation properties compared to traditional asset classes. On the other hand, many pension funds have increased their allocation to alternative investments because the returns from fixed income investments are low and global monetary policy is extremely loose. In 2015, the world's largest pension fund, the Government Pension Investment Fund (GPIF) of Japan announced a new strategic asset mix by forcing a 5 % allocation to alternative investments. Moreover, some university endowments have been benefiting from enhanced returns for years by investing in alternative investments (UBS, 2017, p. 7).

Due to the popularity of alternative investments with large institutional investors, this thesis focuses on the performance of the hedge fund strategies and niche alternative assets of Progressive Capital. While the performance of hedge fund strategies has been studied in previous scientific research papers, no studies address niche alternative assets, which makes this master thesis so unique.

However, discussion is still needed to search for adequate specifications of risk factors that are able to assess the performance of hedge funds. Therefore, the most accepted multi-factor models are used for the empirical analysis of hedge fund performance for each hedge fund strategy. A total of 25 risk factors are implemented for the empirical analysis. This thesis used an aggregated hedge fund database, which is provided by EDHEC risk institute. The consolidated database of hedge funds is applied from the following five databases: HF Net, CSFB, HFR, Barclay, and CISDM. Overall, twelve hedge fund strategies are quantitatively investigated for the full sample period ranging from August 2007 to December 2018. In addition, Progressive Capital provided the data for niche alternatives.

1.3 Objective

The master thesis consists of two quantitative areas of investigation. The first part relates to the performance analysis of hedge fund strategies including niche alternatives of Progressive Capital. Thus, three different multi-factor models are used for the performance analysis. The first model is based on the seven-factor model of Fung and Hsieh (2004). The second model is the extended Fund and Hsieh eight-factor model and, finally, the third model is based on the stepwise regression approach by Agarwal and Naik (2000).

The objective of the first part is to examine the alphas and the adjusted R^2 for each hedge fund strategy in each multi-factor model and to compare them.

In addition, a principal component analysis is applied to classify the dominating components in terms of investment strategies, and to identify the minimum number of components that explain the variance of the hedge fund returns.

The second part concerns the portfolio analysis of a representative Swiss pension fund portfolio. This portfolio is based on the Swisscanto Vorsorge AG study from 2018. Based on this Swiss pension fund portfolio, two slightly different portfolios are created.
The first portfolio includes Progressive Capital as an alternative asset in the Swiss pension fund asset allocation. The second portfolio contains the original alternative assets as hedge funds, private equity, insurance-linked securities, and commodity index instead of Progressive Capital. These four original alternative assets are based on benchmark data selected from Bloomberg terminal. All other asset classes remain unchanged for both portfolios.
The objective of the second part is to examine whether the niche alternatives of Progressive Capital perform better compared to the original alternative investment assets from the representative Swiss pension fund portfolio.

1.4 Delimitations

In this thesis, a total of 25 risk factors including the Fung and Hsieh factors were defined. The selection of the risk factors was based on their high profiles in the scientific papers. The focus was on the buy-and-hold strategies and option-based strategies were not considered. Due to the limited availability of data, the sample period was set from August 2007 to December 2018. Accordingly, the data series consist of a single full sample period. Therefore, no sub-periods were defined for the analysis.

1.5 Structure of master thesis

The thesis is organized as follows. The following chapter 2 includes the literature review, which describes the alternative investments and asset classes generally. Thereafter, the niche alternatives of Progressive Capital are discussed, followed by principal component analysis and multi-factor models. The aim is to determine the scientific approaches and findings and then apply them in the analysis. Chapter 3 addresses the definition and functioning of Swiss pension funds and their asset allocation. In addition, a representative Swiss pension fund portfolio is demonstrated. The data and the methodological approach used for the study are explained in chapter 4. The empirical results on the performance of hedge funds and the portfolio analysis based on the representative Swiss pension fund are presented in chapter 5. Finally, chapter 6 includes the conclusion and the findings are examined.

2. Literature Review

This chapter examines and describes the existing literature in relation to the topics mentioned in the previous section 1.3 in objective. The chapter starts with an overview of alternative investments and provides some essential information regarding the characteristics and purpose of alternative assets in the context of a well-diversified portfolio. Thereafter, the niche alternatives of Progressive Capital are explained, which are central to the present master thesis. Finally, the most important research papers relating to the analysis of hedge fund performance are presented,

2.1 Alternative investments and asset classes

This section explains alternative investments. First, an overview is given of the categories of alternative investments. Second, the characteristics and methods of alternative investments are briefly explained. Third, the purpose of alternative investments is briefly presented. Finally, a graph illustrates what it means from the perspective of institutional investors to invest in alternative investments.

2.1.1 An overview of alternative assets

Stocks, bonds, and cash are interpreted as traditional asset classes. Alternative or non-traditional asset classes are those that are "alternative" to the stocks, bonds, and cash of traditional portfolios. These alternative asset classes offer investors new or different risk exposures. They provide benefits in the diversification of asset classes with low correlation to the usual equity and fixed income risk factors as well as the opportunity for higher returns in less efficient market areas (Van Horne, 2016, p. 2).
The four largest categories of alternative investments include hedge funds, private equity, real assets, and structured products. These individual categories are briefly explained below.

Hedge Funds:

Measured by Assets under Management (AuM), hedge funds are one of the largest categories of alternative investments (Chambers et al., 2018, p. 20). They are typically privately organized and invest in primarily publicly traded assets such as equities, bonds, currencies, commodities, and derivatives. Unlike traditional investment pools such as mutual funds, hedge funds are able to use leverage and short selling. Generally, only qualified institutional and wealthy individual investors have access to hedge fund services. The implementation of skill-based or complex trading strategies is a key feature of hedge funds. Consequently, their strategies generate returns with different risk and return exposures than traditional investment pools do (Chambers et al., 2018, p. 1). Their returns tend to be between equities and bonds and have a lower risk than a long-only investment in stocks. Under ideal circumstances, the correlation between hedged funds and stocks/bonds is supposed to be low, but the risk mitigation capacity of hedge funds varies by strategy (Chambers et al., 2018, p. 20).

Private equity:

Innovative and potentially very high-performing assets are known as private equity investments. Private equity is characterized by its illiquidity. Similar to private real estate, illiquidity offers greater potential returns but requires effective selection and management of advanced toolsets (Chambers et al., 2018, p. 80).

Private equity comprises the common shares, preferred stock, and debt securities of companies that are not publicly traded and that have similar equity exposures. The category includes venture capital (start-up companies) and leveraged buyouts (established listed companies that are being privatized) as well as risky debt (including mezzanine and distressed debt) (Chambers et al., 2018, p. 2).

Real assets:

Any economic resources (other than human capital) that are used directly to create value are defined as real assets (Chambers et al., 2018, p. 48). As opposed to financial assets, which are cash-flow dependent, real assets include real estate, infrastructure, commodities, and natural resources. Furthermore, a distinction is made between the two main categories of real assets. There are tangible assets such as land, farmland, and timber and intangible assets or intellectual property such as patents and copyrights (Chambers et al., 2018, p. 2). For investors, real assets primarily serve as a portfolio diversifier. Previous research demonstrates that real asset classes such as land, farmland, timberland, and infrastructure have almost no correlation with traditional equities and only minimal correlations with each other (Chambers et al., 2018, p. 57).

Structured products:

Structured products are created with the help of financial engineering. They generate returns, risks, taxes, or other opportunities that are not directly available from long-only positions in traditional investments (Chambers et al., 2018, p. 2). The category of structured products varies from simple financial derivatives, which are often classified as traditional investments, to various types of more complex derivatives such as collateralized debt obligations (CDOs) and other derivatives (Chambers et al., 2018, p. 3).

2.1.2 Characteristics and methods of alternative investments

Alternative investments have three primary attributes, each of which may result in an asset being classified as an alternative investment.

1. The return on alternative investments is determined by the exposure to underlying assets with non-traditional cash flows. Those cash flows are not highly correlated with traditional stocks and bonds. While traditional investments are financed by cash flows from traditional operating companies, many alternative investments are financed by cash flows from non-traditional sources such as venture capital, life insurance contracts, art, and farmland. As a result, the returns of alternative investments are less correlated with the returns of the stock market as a whole (Chambers et al., 2018, p. 6).

2. The return on alternative investments is determined by complex trading strategies including leverage, short sales, and financial derivatives. Even though the underlying asset might be traditional securities, these strategies can cause unusual risk exposures (Chambers et al., 2018, p. 6).

3. The return on alternative investments is structured to generate non-traditional payouts, such as those found in collateralized debt securities (Chambers et al., 2018, p. 6).

For all three cases, specialized analysis methods are required, because the returns on alternative investments do not mimic the returns of traditional asset classes such as stocks

and bonds. In particular, traditional investments are analyzed and managed using established methods that are commonly found in investment books but are insufficient to manage and analyze alternative investments (Chambers et al., 2018, p. 6).
Some alternative assets offer absolute returns. The correlation of absolute returns with the returns of the major asset classes are low or zero. For example, market-neutral and arbitrage strategies belong to absolute return strategies (Chambers et al., 2018, p. 6).
Absolute returns correlate little or not at all with the returns of the major asset classes. Examples of absolute return strategies are market neutral strategies and arbitrage strategies. Virtually all traditional assets and strategies are relative return products with returns that are essentially correlated with those of traditional equities and bonds. Traditional assets and strategies are virtually all relative returns products, which means that the returns are correlated with traditional equities and bonds (Chambers et al., 2018, p. 6). Finally, in terms of risk-return profile, alternative investments involve strategies that show unusual risk and return characteristics. The reason for this could be, on the one hand, the trading and, on the other hand, the position issues. Trading leads to large risk changes over time. For positions such as short sales, non-traditional risk exposures are generated (Chambers et al., 2018, p. 6).

2.1.3 Purpose of investing in alternative investments

The three key reasons for adding alternative investments to a well-diversified portfolio are the following:

1. **Alternative investments reduce risk through diversification:**
   The primary objective of alternative investments is to reduce risk through diversification. One of the main features of alternative investments is their low correlation with the major traditional asset classes of public equities and public fixed income assets. A portfolio with a proportion of alternative assets may offer lower risk without reducing the expected return.

2. **Alternative investments enhance return through alpha:**
   A second main objective of alternative investments based on their track record is to improve the expected return of a portfolio through alpha. This is achieved with alternative assets that offer superior risk-adjusted returns.

3. **Alternative investments avoid obsolescence:**
   Suitable asset classes for institutional investments have changed considerably over time and will continue to do so in the future. From the perspective of institutional investors, it is important to identify attractive investment opportunities at an early stage in order to benefit from the first-mover advantage. On the other hand, those who have been waiting a long time to invest in alternative investments will probably achieve a disappointing performance, as alternative investments are so widespread that they are considered traditional. This effect is also known as the "last-mover disadvantage" (Chambers et al., 2018, p. 10)

2.1.4 Investing in alternatives

Alternative investments describes the process of using an extended range of investment opportunities. In recent years, conservative institutional investors have made the most use of these opportunities. Alternative institutional investing is associated with hedge funds, real assets, private equity, and structured products. Figure 1 below illustrates an investment program that includes both traditional and alternative investments. The objectives of the investment program are to look for opportunities, which increase the expected return while reducing the long-term risk. With the inclusion of alternative assets in an institutional portfolio, extensive knowledge of expanded asset sets, investing tools, investment methods, and requirements for due diligence is required.
Due to improved beta coverage, diversification and enhanced expected returns offered by alternative assets, the inclusion of alternative assets can be a prudent alternative for many institutional portfolios (Chambers et al., 2018, p. 171).

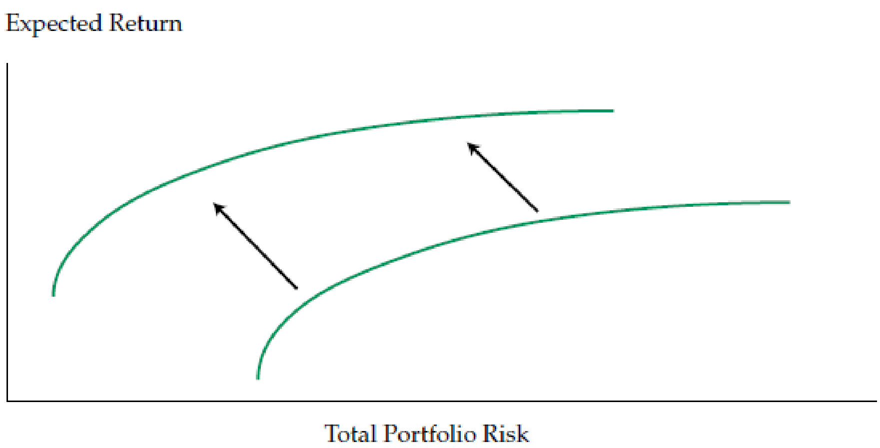

Figure 1: Enhancement of risk-return profile due to alternative investments
Source: (Chambers et al., 2018, p. 171)

2.1.5 The value of illiquidity

Investors invest more in liquid assets than in illiquid ones. As a result, they demand higher returns on assets that cannot be easily converted into cash. This is associated with the illiquidity premium. By investing in illiquid assets, investors are limited in their ability to adapt their portfolios to changes in market conditions or liquidity requirements. A major problem for investors is the scenario of falling market prices. Illiquidity becomes a problem in that investors may not be able to sell their assets quickly, which can lead to prolonged losses. Finally, the lack of transparency and incomplete data makes it difficult to assess the potential risk-return profile of assets (UBS, 2017, p. 4)

2.1.6 Hedge Fund share restrictions

Share restrictions such as lockups and redemption periods are typically used by hedge funds to manage liquidity risk.

The lockup period defines the initial period during which investors must hold their money in the fund before they can redeem shares. During the lockup period, investors cannot access their money. Once the lockup period has expired, the investor can withdraw money during the next redemption period (Ding et al., 2009, p. 16).

The redemption period defines the period during which the investor must to wait in a hedge fund before withdrawing money. The advance notice period, on the other hand, defines the period of advance notice that investors are required to grant to hedge fund managers in advance of the redemption period. The sum of redemption and advanced notice periods is defined as the total redemption period (Ding et al., 2009, p. 16).

2.2 Progressive Capital niche alternatives asset Portfolio

This section presents the niche alternatives of Progressive Capital individually. These innovative Progressive Capital financial products form the core of alternative assets in this thesis and are explored in depth in the empirical analysis part in chapter 5.

2.2.1 Music royalties

Royalties are non-correlated assets and therefore a unique form of alternative investment. Investors can participate in the buying and selling investments of music royalties, intellectual property, and other cash-generating assets (Plumb, 2016). These alternative assets offer a stable and low-risk alternative compared to stocks. They can generate steady cash flows for many years. Royalties are regarded as financial compensation paid to the owner of an asset such as music royalties or intellectual property. The owner has the option to license the asset for use by another party. Based on the use, the owner receives a percentage of the net revenue of the asset. This income is paid to the investors at certain intervals, such as annually, quarterly or monthly. Compared to shares, which fluctuate daily, royalties are distinguished by their lower volatility (Butler, 2014).

The valuation of these alternative assets is based on the income generation of different royalty categories. After a net revenue has been calculated for the royalties, the seller adds a multiple to reach the purchase or valuation price. The determination of a multiple is subjective. The following indicators could be decisive for the determination of multiples:

The celebrity of the artist or song, how often it has been licensed and whether there is a strong consistency of earnings (Plumb, 2016).

The financial analysis is based on the earnings generated in the last three to five years. Three primary sources of income are considered (Plumb, 2016):

1. **Public performance royalties:** If a song is performed at concerts, played on the radio or internet, or streamed on platforms such as Spotify, then public performance royalties are paid.
2. **Mechanical royalties:** Mechanical royalties are paid to songwriters when someone makes a copy of their song.
3. **Television and film income:** This income is generated when a song is used in a commercial or other media, such as television.

Thus, the most relevant factor in terms of how much money a song earns is how often it is used. The more popular the song, the more often it will be played and the more money it will earn (Lassiter-Lyons, 2017). On the other hand, the music industry has its own problems that can add risk to the assets. According to Hipgnosis Songs Fund, a music investment company, it is difficult to price songs because the valuation method is inherently retrospective. The music industry is in a state of rapid change, which in turn affects future revenues (Plumb, 2016).

With regard to portfolio diversification, royalties also offer a good opportunity to achieve high returns with relatively lower risk. Many pension funds are turning to royalties to increase their returns (Lassiter-Lyons, 2017). Warren Buffett compares owning royalties to owning a toll road. Once you have built the road, you can collect the cash forever, just so people can use the road (Lassiter-Lyons, 2017). According to the consulting firm PWC, the music industry is predicted to grow by 2020 because of a sharp increase in music subscription services. Thus, royalty payments to artists and benefit owners of intellectual property will increase due to the music trend (Plumb, 2016).

2.2.2 Appraisal and litigation rights

When a stock company is acquired in a merger, it is often sued by shareholders. One reason for suing is called "appraisal right" (Levine, 2018). Thus, minority shareholders who do not approve of a merger deal have some recourse. "Those stockholders that did not vote in favor of the deal were given the right to go to court to have the value of their stock judicially determined and to have that judicially determined value paid to them in cash. Those rights are referred to as appraisal rights" (Foulke, 2015).

In other words, behind the theory of appraisal right is merely that the price in the deal was too low. Possible reasons for a low price may include conflicted boards, self-interested managers, disloyal advisers, etc. (Levine, 2018).

Section 262 of the Delaware General Corporation Law (DGCL) provides shareholders that abstain from a merger appraisal rights, granting shareholders the ability to challenge the forthcoming merger price through an appraisal procedure (Boyd, 2017, p. 497). That means that a court can appraise a company's pre-merger fair value. If the court decides that the price was too low, it will order the company to pay the difference.

An increasingly popular legal arbitrage strategy is growing in Delaware appraisal litigation that allows hedge funds to take advantage of takeover deals. This investment strategy is also referred as appraisal arbitrage. Appraisal arbitrage occurs when hedge funds assert their statutory appraisal rights by acquiring a substantial number of shares shortly after the announcement of a merger in order to exercise appraisal rights in the future (Boyd, 2017, p. 498). Thus, hedge funds usually purchase stocks in the Delaware incorporated company that is being acquired and then file a claim so that the judge will determine the fair price for the shares. From the perspective of the hedge funds, they will argue in court that the fair value was unjustly low and thus they should be paid a higher price (Hals, 2015).

The strategy generates solid returns since the shareholders will be awarded an interest rate that accrues at 5 % over the Federal Reserve discount rate for the duration of their appraisal claim regardless of the outcome. Due to the long time horizon of a final judgment for a claim, this strategy has been regarded as a significantly advantageous aspect for hedge funds due to the interest rate (Boyd, 2017, p. 499).

2.2.3 Shipping

Shipping relates to the logistics and transport of goods from one place in the world to another. The market is global, both for ship owners and for customers. The factors influencing freight rates, on the one hand, and the costs of building, operating, and the residual value of a ship, on the other, depend heavily on global economic and political factors. The greatest risks for ship owners include financial risks such as exchange rates, interest rate risks, refinancing risks, economic growth, commodity prices, as well as political risks such as customs duties, regulations, wars on major trade routes, political instability and, more recently, even trade wars between the economic powers of the USA, China, and Europe (Bahl, 2018).

The shipping industry is subject to constant change. The trend is towards gigantic container ships and giant tankers. Small ships are driven out of the market, as the focus is on efficiency, lower transport costs, and automation. In addition, the increasing transparency through worldwide transponders publicizes the location of every ship on earth. A growing global population and the constant expansion of infrastructure, even in developing countries that were previously difficult to access, are leading to steadily increasing prosperity in emerging markets, which supports the demand for products and thus the transport industry (Bahl, 2018).

A ship fund is a closed-end fund. In this form of investment, the fund company collects the money of investors in order to realize a specific project. This may involve, for example, the construction of ships. When the fund is launched, a placement period is determined during which the investors can acquire shares. As soon as the required capital has been collected, the fund is closed. Closing does not only mean that no other investors can invest money in the fund, but it also means that the fund units are not freely tradable and are therefore difficult to resell before the fixed term expires. If the investor finds a buyer, the price depends on supply and demand and not on how much the fund units originally cost.

Ship funds are known for their long-term investments. The duration of the fund is generally between ten and twenty-five years. During this period, the ship must be regularly employed with orders in order to not incur a loss. The return depends on the utilization of the ship. The investors mainly finance the construction of container ships, cruise ships, tankers, and cargo ships (Auxmoney, 2015).

2.3 Principal component analysis

Pearson first described the methodology of principal component analysis (PCA) in 1901. The main objective of PCA is to explain the behavior of a number of correlated variables using a smaller number of uncorrelated and unobserved implied variables or implicit factors called principal components (Stafylas et al., 2016, p. 8).

Fung and Hsieh (1997) used PCA to extract the five most common components in order to provide a quantitative classification of hedge funds based on returns alone. Both the location (market) and the strategy (investment style) of the managers were taken into consideration in their work. Even though the returns of the investment styles might not be linearly correlated to the returns of asset markets, they are supposed to be correlated to each other. They used a database for the period between 1991 to 1995 from Paradigm LDC and TASS Management. They determined that five principal components jointly explained approximately 43% of the return variance of hedge funds (Fung and Hsieh, 1997, p. 284). They could associate their five style factors with some of commonly used qualitative style categories used by the hedge fund industry. These styles include the trading strategies system/opportunity, global/macro, value, system/trend following, and distressed style factors (Fung and Hsieh, 1997, p. 285).

Amenc, Martellini, and Faff (2003) used PCA to generate an index of indexes by using an optimal combination of competing indexes to achieve a superior representation of the underlying common style information. They extract the "best possible one-dimensional summary" of a set of competing indexes to create pure style indexes. Their method was a natural generalization of the equally weighted portfolio of competing indexes (Amenc et al., 2003, p. 17). Using PCA, they created a portfolio of indices with appropriate weights so that the combination of indices captured the largest proportion of information contained in the competing index data (Amenc et al., 2003, p. 18). The first component of a PCA was performed on the space of the competing indexes and represent as a candidate for a pure style index. This component captured a large proportion of the variance of the stock returns because those competing indices tend to be highly correlated.

From a mathematical perspective, they proved that an index of indices is always more representative than any competing index upon which it is based (Amenc et al., 2003, p. 18). Accordingly, the minimum percentage of declared variance is 85.69 % and refers to the investment style of large cap growth. The average percentage of declared variance is 90.84%. This percentage of declared variance tends to be higher when the correlation between the different competing indices is high (Amenc et al., 2003, p. 19). With regard to the minimum-bias portfolio, an index of indices is consistently less biased than the average of the set of indices it is derived from (Amenc et al., 2003, p. 20).

Christiansen, Madsen, and Christiansen (2003) used PCA to determine the classification of hedge funds endogenously from the CISDM database for the period 1999 – 2002 (Christiansen et al., 2004, p. 4). They analyze the influence on hedge fund performance including 10 different market indices and 36 different passive option strategies. The findings of their study showed, that they identify five principal components as do Fung and Hsieh (1997) but are able to explain more than 60% of hedge fund return variation compared to the 43% explanation in Fung and Hsieh (Christiansen et al., 2004, p. 21).

2.4 Multifactor model and stepwise regression

Agarwal and Naik (2000) suggest a general asset factor model consisting of excess returns on passive option-based strategies and buy-and-hold strategies. Despite the fact that many hedge funds implement dynamic strategies, they found that a few simple option writing/buying strategies were sufficient to explain a significant proportion of the variation in hedge fund returns over time (Agarwal and Naik, 2000, p. 2). By using monthly net-of-fee returns reported in Hedge Fund Research (HFR) Database from January 1990 to October 1998, they evaluated the performance of hedge funds that followed different strategies using a general asset class factor model composed of excess return on location (buy-and-hold) and on trading strategy (option writing/buying) factors (Agarwal and Naik, 2000, pp. 9, 32).

In their work, they used the stepwise regression approach in order to maintain degrees of freedom and to mitigate potential multi-collinearity problems. This method was used to identify factors that best explain the variation in hedge fund returns over time (Agarwal and Naik, 2000, p. 14).

Agarwal and Naik (2000) presented five main findings: First, their model composed of trading strategy factors and location factors was able to explain a significant

proportion (up to 93%) of the variation in the hedge fund returns over time.
Second, non-directional strategies displayed more significant loadings on trading strategy factors whereas directional strategies showed more significant loadings on location factors. Third, the results showed similarity to other earlier research by Mitchell and Pulvino (2000) and Gatev et al (1999) using detailed replication methodology, which indicates independent confirmation that the approach from Agarwal and Naik (2000) captured risk exposure of hedge funds. Fourth, they found that in the early 1990s, only 37% of hedge funds added significant value (excess return or alpha) compared to 28% of hedge funds that added value in the late 1990s. Finally, leveraged funds did not consistently perform better or worse than funds that did not use leverage (Agarwal and Naik, 2000, p. 32).

Agarwal and Naik (2004) examined the systematic risk exposures of hedge funds by using buy-and-hold and option-based strategies. For their analysis, they used hedge fund monthly returns indices from the Hedge Fund Research (HFR) and CSFB/Tremont databases for the time period between January 1990 to June 2000 (Agarwal and Naik, 2004, p. 69). The results showed that most of equity oriented hedge funds strategies had payoffs similar to a short position in a put option on the market index. They found that a short position in a put option on the market index exhibit a significant left-tail risk that was ignored by the traditional used mean-variance framework. Thus, Agarwal and Naik used a mean-conditional value-at-risk framework to show the extent to which the mean-variance framework underestimated the tail risks (Agarwal and Naik, 2004, p. 63). In order to capture the linear and non-linear risks of hedge funds strategies they used buy-and-hold and option-based risk factors. They proposed a two-step approach to characterize hedge fund risks. In the first step they estimate the risk exposures of hedge funds (betas) using a multifactor model (Agarwal and Naik, 2004, p. 65). They considered the excess returns on standard assets and options on those assets as risks factors. In the second step they examine the ability of these risk factors to replicate the out-of-sample performance of hedge funds (Agarwal and Naik, 2004, p. 66). They conducted an analysis at the index level and at the individual hedge fund level. Along with characterization of a non-linear exposure to the equity market index, Agarwal and Naik (2004) found that hedge funds exhibited significant exposures to Fama and French's (1993) three-factor model and Carhart's (1997) momentum factor (Agarwal and Naik, 2004, p. 92).

3. Pension funds in Switzerland

3.1 Introduction

This chapter briefly discusses the definition and functioning of Swiss pension funds followed by the asset allocation of pension funds in Switzerland. Afterwards, the database for a representative Swiss pension fund portfolio is presented. The aim is to create a representative pension fund portfolio that comes as close as possible to the average asset allocation of Swiss pension funds. For the representative portfolio, benchmark time series from Bloomberg are considered. Subsequently, the investment restrictions of Swiss pension funds are discussed,

This chapter forms the basis for the portfolio analysis in Chapter 5.4, which examines the performance based on the representative Swiss pension fund portfolio. The objective of this part is to examine whether the niche alternatives of Progressive Capital perform better compared to traditional alternative investments from the representative Swiss pension fund portfolio.

3.2 Alternative investments in the portfolio context of Swiss pension funds

Pension funds must increase income in order to meet the benefit commitment for their policyholders. Because traditional investments generate few returns or even charge negative interest rates, pension funds are looking for alternative investments that can optimize the overall return while accepting certain additional risks. These include hedge funds, private equity, commodities, and infrastructure investments etc.

It is clear that such investments are illiquid, which means that the invested money of pensions funds are blocked for years. However, for pension funds with a long-term investment horizon in particular, a stronger commitment could be desirable to achieve a better portfolio performance (Müller, 2018).

Therefore, alternative investments are increasingly becoming the focus of many large pension funds. A fundamental change towards alternative investments will take place in many state and public pension funds by 2020. This is the continuation of a trend that has gained momentum worldwide. For example, in April 2015, the world's largest pension fund, the Government Pension Investment Fund (GPIF) of Japan (with $1.1 billion in assets under management), announced a new strategic asset mix to generate higher returns and meet the needs of an ageing population. GPIF's new mandate foresees a 5% allocation to alternative investments, which represents a significant opportunity for alternative products and firms. By 2020, global pension fund assets are expected to reach $56.6 billion. Alternative assets will play a far greater role in the asset allocation of pension funds (PwC, 2015, p. 10)

3.3 The Swiss pension scheme

Since 1985, a pension fund, also known as “Berufliche Vorsorge”, has been the second pillar of the Swiss social system BVG (Swiss Life, 2017). It is responsible for managing the money paid in by employees and returning it after retirement. Thus, the pension fund scheme helps employees to save money for retirement and to hedge against disability and death. The payments into the pension scheme will terminate at the start of retirement, which is currently 64 years for women and 65 years for men. There are two different types of payment. Either you have your retirement pension paid out for life or you receive the sum once as capital (Vita, 2019).

All employees of a company with an annual salary of more than 21,150 (as of 2017) are compulsorily insured from 1 January after their 17th birthday until they reach the statutory retirement age (Swiss Life, 2017). Self-employed persons can also take out insurance on a voluntary basis. Pillar 2 benefits, together with the AHV, are intended to cover up to 75 percent of the final salary, but only up to an annual salary of currently CHF 85,000. According to the BVG, the company pension scheme is funded by the BVG and everyone saves and pays directly for their own benefits, while the employer pays at least half of the contributions (Swiss Life, 2017).

3.4 Key figures on Swiss pension funds

In Switzerland, a continuous decline has been noted in the number of pension funds since 2013. In 2013, the number was 1957. According to the latest figures from the "Bundesamt für Statistik", there were only 1643 pension funds in Switzerland in 2017. This corresponds to a decline of around 16% for the period from 2013 to 2017.
By contrast, the number of active people insured by a pension fund in Switzerland increased by an average of 1.6% over the same period. The number of beneficiaries has also risen since 2013. Assets under management rose from CHF 720 billion in 2013 to CHF 894 billion in 2017, representing an annual increase of 6.1%. Table 1 below provides an overview of the structural data (Bundesamt für Statistik, 2019, p. 9).

Important key figures on Swiss pension funds			
	2013	**2015**	**2017**
Number of pension funds	1957	1782	1643
Number of active policyholders	3‘932‘187	4‘068‘196	4‘177‘769
Number of benefit recipients (retirement and capital)	1 093 512	1 131 522	1 185 172
Retirement benefits (in millions of Swiss francs)	25‘992	27‘285	28‘585
Capital benefits (in millions of Swiss francs)	6‘488	7‘048	8‘129
Balance sheet total (in millions of Swiss francs)[1]	720‘237	788‘082	894‘254

Table 1: Swiss pension funds key figures,
Source: Bundesamt für Statistik, 2019, p. 9

3.5 Asset allocation of Swiss pension funds

In Switzerland, the pension funds primarily consisted of bonds and equities in their portfolios. According to the latest figures from the "Bundesamt für Statistik", which include the key figures of the 2017 pension fund statistics, bonds and equities each

[1] Excluding assets/liabilities from insurance contracts

account for approximately 31%, or more than half of the asset allocation (Bundesamt für Statistik, 2019, p. 3). Real estate is the third largest asset class and currently stands at around 19%, which is 5% more than before the financial crisis. This can be attributed to positive developments in the real-estate market. A positive change between 2013 and 2017 was achieved by alternative investments, which rose by three percentage points to around 9 % (Bundesamt für Statistik, 2019, p. 3). Another interesting insight into the asset allocation of pension funds is provided by the survey of Swisscanto Vorsorge AG in 2018. In the survey, a total of 535 pension funds with recorded assets of CHF 680 billion took part. Among the participants were the pension funds of almost all cantons, as well as most SMI companies, which have their own pension fund. The number of beneficiaries amounts to 4.1 million. Thus, the study covers approximately 80% of pension funds and reflects a high degree of representativeness for the entire second pillar (Swisscanto Vorsorge AG, 2018, p. 71).

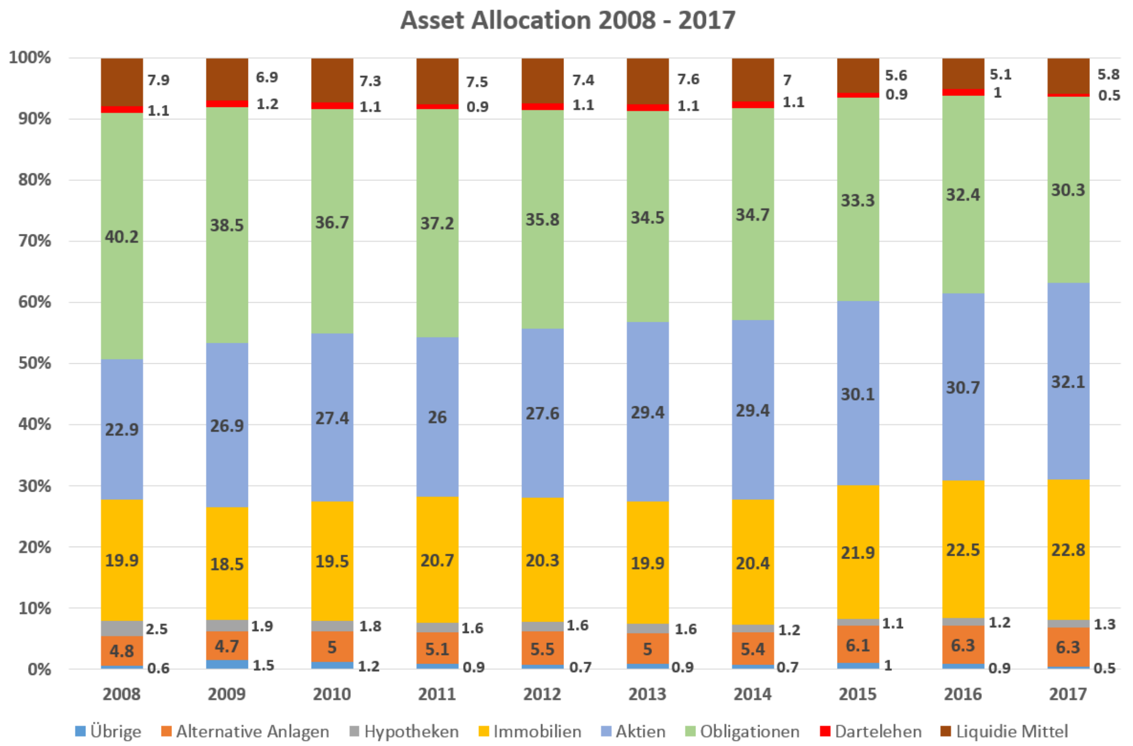

Figure 2: Asset allocation of Swiss pension funds 2008-2017

Source: In accordance with (Swisscanto Vorsorge AG, 2018, p. 26)

The figure 2 above shows the asset allocation of the Swisscanto Vorsorge AG survey over the last ten years since 2008. It can be observed that bonds have declined and real values such as real estate have increased. Compared with the previous year (22.5 %), real estate rose slightly to 22.8 % in 2017. A positive development is noted for equities, which now stand at 32.1 %. It is noteworthy that equities have surpassed bonds for the first time and are therefore the most important asset class. Liquidity rose to 5.8 %, which does not seem plausible in the overall market environment. Alternative investments remained unchanged at 6.3 % compared with the previous year. Despite indications that excellent returns can be achieved in this category, pension funds remain cautious (Swisscanto Vorsorge AG, 2018, p. 26).

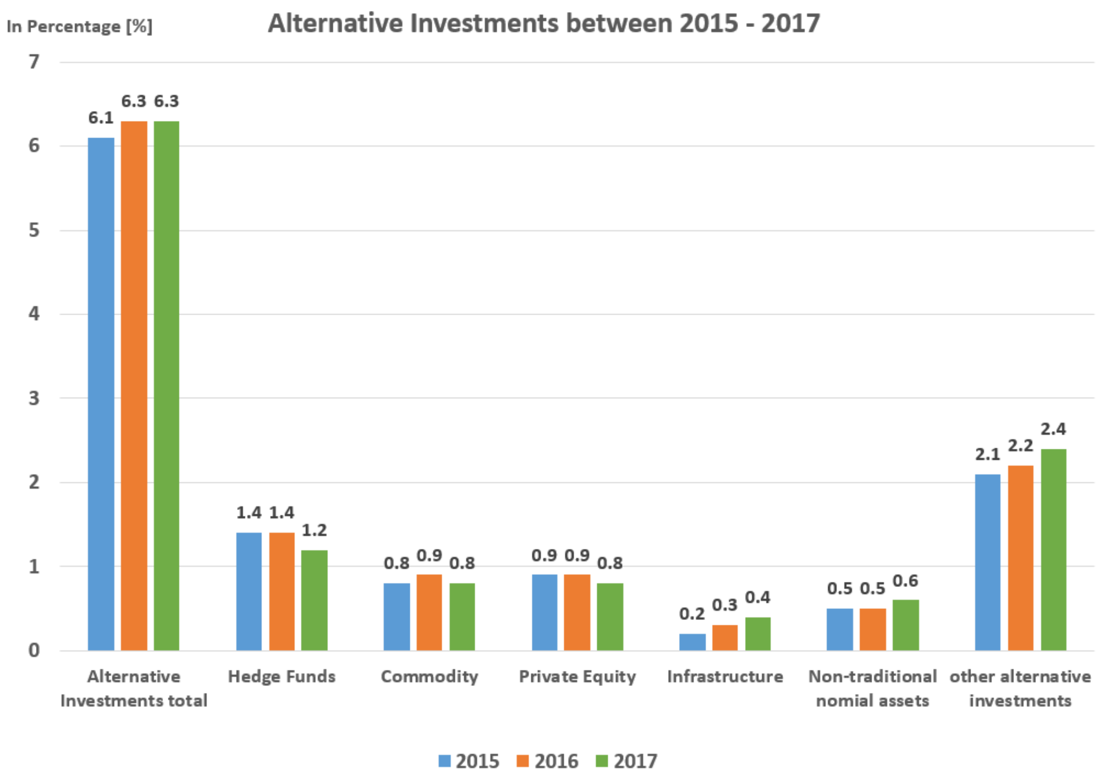

Figure 3: Alternative investments 2015-2017

Source: In accordance with (Swisscanto Vorsorge AG, 2018, p. 34)

The above figure 3 shows the development of alternative investments for the period 2015 to 2017. In 2017, non-traditional investments largely remained at the previous year's level, while hedge funds recorded a decline. The reason for this could be their poor reputation among Swiss institutions, which is widespread in the media. However, the decisive factor is likely to be the predominantly disappointing results in the fund-of-funds area. Commodities have lost investor interest following the price slumps of recent years. Pension funds are still struggling with private equity and infrastructure classes have increased marginally. For most pension funds, this investment category remains new territory, especially as the supply of suitable investments is still low (Swisscanto Vorsorge AG, 2018, p. 34).

3.5.1 Swiss pension fund database

The asset allocation of the Swiss pension funds is published on the Internet on the respective homepage or annual report. It lists investment categories such as alternative investments or equities. A representative benchmark market is selected for each investment category. Some of these benchmarks were stated in the annual report of the pension funds on which they are based. The indices of the selected benchmarks were downloaded from Bloomberg. No benchmark could be found for the asset category "Infrastructure". However, since only the pension funds of Credit Suisse and Swiss Post invested in this category (each with 2.4 %), it was decided to omit this category and distribute it evenly among the remaining alternative investments of Credit Suisse and Swiss Post. In addition, the three-month CHF Libor interest rate was used for the cash category. Since the interest rate on a loan depends on the creditworthiness of the recipient and no information is available on this, it was decided to omit the asset category “loan” for the empirical pension fund portfolio analysis.

The column Swisscanto Pension fund study 2018 represents the average asset allocation of 535 pension funds. Because of the high degree of representativeness for the entire pension funds, it was decided to use the values of the Swisscanto study 2018 as a representative portfolio.

As the alternative asset classes such as infrastructure (0.4 %), nominal value investments (0.6 %) and other alternative investments (2.4 %) could not be recorded as benchmarks, these asset classes were also distributed evenly among the other alternative investments. Table 2 on the following page lists the tickers for each asset category. Table 3 on page 23 shows the asset allocations of the eight pension funds and the Swisscanto study as a representative pension fund portfolio in a matrix. For this thesis, only the assets of Swisscanto AG (blue column in table 3) were considered for the portfolio analysis in chapter 5.4.

Index Overview		
Asset category	**Index**	**Bloombergticker**
Cash	LIBOR CHF 3M	SNB database[2]
Bonds	SBI AAA-BBB	SBR14T
Bonds foreign currency	Barclays Global Aggregate Corporate Index	LGCPTRUU
Government Bonds foreign currency hedged	Citi World Government Bond Index hedged in CHF	BCIW1K
Foreign Bonds	SBI Foreign AAA-BBB TR	SBF14T
Government Bonds developed countries	LYXOR UCITS ETF EuroMTS 15+Y Investment Grade	LYXMTFGY
Government Bonds Emerging countries	db x-trackers II EMERGING MARKETS LIQUID EUROBOND INDEX ETF	DBNELQKL
Stocks	Swiss Performance Index	SPI
Foreign stocks	MSCI World Index	MXWO
Stocks emerging countries	MSCI Emerging Markets	MXEF
Real estate	SXI Real Estate Funds TR Index	SWIIT
Foreign real estate	FTSE EPRA/NAREIT Global Index	ENGL
Mortgage	Citi Swiss GBI	SDA13T
Private Equity	S&P Listed Private Equity Index	SPLPEQTY
Hedge Funds	Hedged HFRX Global HF Index	HFRXGLC
Insurance Linked Securities	Hedged Swiss Re Cat Bond Index	SRCATPRC
Commodity	Hedged DJ UBS Commodity Index	BCOMCH

Table 2: Overview of Swiss pension fund portfolio indices

Source: Bloomberg Terminal and SNB database

[2] The three-month CHF Libor can be obtained from https://data.snb.ch/de/topics/ziredev#!/cube/zimoma

Asset allocation of Swiss pension funds in percentage [%] Date: 31.12.2017										
Description	**Bloomberg Index**	**BVK**	**Coop**	**Credit Suisse**	**Migros**	**Post**	**Publica**	**SBB**	**Stadt Zürich**	**Swisscanto Pension Fund Study 2018**
Liquidity / Cash	LIBOR	3.1	6.2	2.6	2.2	6.2	3	2.8	2.9	5.8
Loan	LIBOR				5.8			7.5	4.5	0.5
Bonds	SBR14T	16.6	12.6	1.3	3	31.6	6	35.7	6	20
Foreign bonds	SBF14T				1.4		10		6.9	
Bonds foreign currency	LGCPTRUU	18.3	19.6	17.3	22	11	18	19.6	17.7	10.4
Government bonds Emerging countries	DBNELQKL						7			
Government bonds foreign currency hedged	BCIW1K				3		6			
Government bonds developed countries	LYXMTFGY						8			
Stocks Switzerland	SPI	9.2	7.2	9.3	8.1	7.7	3	4.9	5.6	14.2
Foreign stocks	MXWO	19.7	17.7	30.5	19.3	21.6	17	9.7	21.9	18
Stocks emerging countries	MXEF	6.3			5.2		9	2.3	5	
Mortgage	SDA13T	3.8								1.3
Real estate	SWIIT	15.4	20.9	11.7	22.1	10.9	7	9.4	8.4	20.7
Foreign real estate	ENGL	1.6	3.7		8		4	1.6	4.8	2.1
Hedge funds	HFRXGLC		5.2	10.7		4.7		2.5	9.1	2
Private equity	SPLPEQTY	2.4	5.3	7.5				1.9	6.6	1.6
Insurance linked securities	SRCATPRC			4.8				2.1	0.7	0.9
Commodity	BCOMCH	3.6	1.6	4.3		6.2	2			1.7

Table 3: Asset allocation of Swiss pension funds (as of 31.12.2017)

3.6 Pension fund investment restrictions

For the determination of the asset allocation, certain requirements from the authority must be fulfilled. The “Berufliche Vorsorge Gesetz” (BVG) stipulates some maximum weightings for investment categories that may not be exceeded. The most important are summarized in table 4. In addition, short selling, in other words, the sale of financial instruments that are not in the seller's possession at the time the transaction is concluded, is prohibited. The following provisions shall apply to each investment category (Der Bundesrat, 2019):

Art. 71 Abs. 1 BVG				
	Asset classes	**Assets**	**Assets types**	**Guidelines**
a.2	Fixed-rate assets	Liquidity / cash	CHF/non-CHF	Max. 50 %
		Bonds	CH/non-CH, government/non-government	
		Other	Mortgages, etc.	
b.	Equities	Stocks	CH/non-CH	Max. 50 %
c.	Real estate	Real estate	CH/non-CH	Max. 30 % (max. 1/3 non-CH)
d.	Alternative investments	Hedge funds,	CH/non-CH	Max. 15 %
		Private equity	CH/non-CH	
		Other	Derivatives, etc.	
e.	Foreign exchange	Foreign currency	Foreign currencies without currency hedging	Max. 30 %

Table 4: Investment restrictions for Swiss pension funds

Source: In accordance with (Der Bundesrat, 2019)

The listed maximum weights in table 4 were used for the calculations in this thesis. As alternative investments, the tickers for commodities (BCOMCH), hedge funds (HFRXGLC), private equity (SPLPEQTY), and insurance linked securities

(SRCATPRC) were combined and, according to Article 71 paragraph 1d, may not together account for more than 15% of the portfolio.
In Switzerland, real estate is classified as a separate asset class, while abroad it is usually classified as an alternative investment. According to the BVV2 investment guidelines, the maximum real estate quota is 30 %. As a result of this upper limit, Swiss pension funds have by far the highest proportion of local real estate in an international comparison. By contrast, international real estate investments account for only 1% of total assets (Swisscanto Vorsorge AG, 2018, p. 11).
According to the Swiss pension fund study 2018 by Swisscanto Vorsorge AG, compliance with the BVV2 maximum limits is not a substitution for risk management, as it does not send signals on developments such as the low interest rate environment or the turnaround in interest rates, nor does it support the flexible use of different risk premiums. In the pension fund study of 2017, Swisscanto Vorsorge AG was able to identify that two thirds of pension fund managers would welcome the annulment of investment limits to achieve higher returns for the beneficiaries and better distribution of risks. This would give the managers more freedom but also more responsibility when investing the money (Swisscanto Vorsorge AG, 2018, p. 10).

4. Data and Methodology

In this chapter, the procedure for data collection and selection is explained and the methodical procedure is presented. The following subchapters present the data basis for the niche alternatives from Progressive Capital, individual hedge fund investment styles, and the risk factors. The resulting data sets are used as the basis for the empirical study in chapter 5.

4.1 Data accuracy and reliability

The reliability and accuracy of hedge fund data plays a vital role for researchers and investors, as all studies revolve around the performance and risk of hedge funds and therefore depend on the quality of the return reports. The accuracy of these reports directly affects the measurement of risk and returns. However, a number of factors complicate the calculation of hedge fund returns. Firstly, there is a confusing variety of investment opportunities. Some assets may be too illiquid to be priced clearly. The use of leverage, either directly through borrowing or indirectly in the case of derivative instruments and short positions, can further complicate the return calculations. Finally, management fees and the deduction of incentive fees above a certain hurdle rate, together with the high watermark provision, can further complicate the calculation of net asset value (Liang, 2003, p. 1). Given this complex issue, it is not surprising that researchers have repeatedly addressed the fundamental question of the trustworthiness of hedge fund data. This is especially the case as hedge funds are not regulated by the nature of the business, for example, in the USA they are not obliged to disclose information about themselves to the Security and Exchange Commission (SEC). Due to the "private partnership" structure, regular audits are not required (Liang, 2003, p. 1). Many hedge funds can be voluntarily audited for reasons of professionalism or to signal quality to investors. Nevertheless, researchers have questioned the quality and accuracy of available data on hedge fund performance. Ackerman, McEnrally, and Ravenscraft (1999), Brown, Goetzman, and Ibbotson (1999) and Fung and Hsieh (1997) all document a different survival bias for hedge funds, for example. Liang (2000) compares two of the most important hedge fund databases (TASS and HFR) and finds some inconsistencies between the two (Liang, 2003, p. 2).

4.1.1 Progressive Capital database

Data on illiquid assets is provided by Progressive Capital. These are niche alternatives of Progressive Capital such as music royalties, appraisal and litigation rights, ships etc. A distinction is made between three different funds of Progressive Capital, namely Qualitium FOHF, POF1 and POF 2. The following table 5 provides an overview of the three funds of Progressive Capital.

Niche alternative assets from Progressive Capital					
Fund	**Sample period**	**Fund assets**	**Liquidity**	**Management fee**	**Performance fee**
Qualitium FOHF	31.08.07 – 31.12.18	197.5 $ Mio.	Monthly liquid	0.5 %	10 % (high watermark)
POF 1	30.11.12 – 31.12.18	45 $ Mio.	Rolling lockup, quarterly liquid	0.75 %	10 %
POF 2	31.01.18 – 31.12.18	31 $ Mio.	Rolling lockup of 5 years	0.75 %	10 %

Table 5: Progressive Capital database

The table 5 shows that all three funds have different data histories. While the Qualitium FOHF Fund has the longest time series of performance, the other two POF 1 and POF 2 have shorter data histories. Therefore, an aggregated portfolio of all three funds was created. The following portfolio weights in table 6 are applied to the returns of each funds:

Construction of Progressive Capital Track Record / Aggregated Portfolio	
Sample period	**Portfolio weights**
08.2007 – 10.2012	100 % Qualitium
11.2012 – 31.12.2017	50 % Qualitium 50 % POF 1
01.2018 – 12.2018	33.3% Qualitium 33.3% POF 1 33.3% POF2

Table 6: Portfolio construction of Progressive Capital

This aggregated portfolio was used for the empirical study in this thesis. Table 8 on page 30 shows the summary statistics for the aggregated portfolio of niche alternatives (Progressive Capital in blue line)

4.1.2 Hedge fund aggregate database

Previous hedge fund studies often use a small number of one or two databases for their research. Joenväärä et al. (2012) presented new stylized facts regarding hedge fund performance and database selection biases based on a database aggregation and a comprehensive analysis of differences between the main commercial hedge fund databases. They found a significant difference between the main commercial hedge fund databases BarclayHedge, EurekaHedge, HFR, Morningstar, and TASS, according to the research results. Since the results based on a single database are often unrepresentative and even misleading, Joenväärä et al. (2012) demonstrated the importance of using an aggregated database in hedge fund research (Joenväärä et al., 2012, p. 1). Hence they proposed an aggregated hedge fund dataset, which is constructed from merging these five largest databases (Joenväärä et al., 2012, p. 33).

Following Joenväärä et al. (2012), this thesis used an aggregated hedge fund database provided by EDHEC risk institute. The consolidated database of hedge funds is applied from the following five databases: HF Net, CSFB, HFR, Barclay, and CISDM. The investigation period starts in August 2007 and ends in December 2018.

The EDHEC hedge fund indices have a transparent construction methodology and management principles. Therefore, the selected indices must be publicly accessible and have transparent construction methods so that the performance of the EDHEC hedge fund indices can be easily monitored. To ensure a high degree of representativeness, the indices are based on a broad database. EDEHC identified five index providers, which are listed in the table 7. These providers fulfilled all the requirements in the composition of the EDHEC index. Finally, the selection results in twelve hedge fund investment strategies with one to five index providers for each style. The table 7 below demonstrates the composition of each hedge fund style (EDHEC, 2018, p. 2).

Investment style	**Composition**
Convertible Arbitrage	Barclay, CISDM, CSFB, HF Net, HFR
CTA Global	Barclay, CSFB, HF Net
Distressed Securities	Barclay, CISDM, CSFB, HF Net, HFR
Emerging Markets	Barclay, CSFB, HF Net, HFR
Equity Market Neutral	Barclay, CISDM, CSFB, HF Net, HFR
Event Driven	Barclay, CISDM, CSFB, HF Net, HFR
Fixed Income Arbitrage	Barclay, CISDM, CSFB, HF Net
Global Macro	Barclay, CISDM, CSFB, HF Net, HFR
Long / Short Equity	Barclay, CISDM, CSFB, HF Net, HFR
Merger Arbitrage	Barclay, CISDM, CSFB, HF Net, HFR
Relative Value	HF Net, HFR
Short Selling	HF Net

Table 7: List of EDHEC Hedge fund indices and their compositions (as of June 2018)

Source: (EDHEC, 2018, p. 2)

The figure 4 below presents the correlation matrix of hedge fund returns for the sample period from August 2007 to December 2018. The highest correlation with Progressive Capital indicates the hedge fund strategy "Relative value" with 0.79. In addition, while “Short selling” shows almost negative correlations to other indices, “CTA global” behaves more neutral than the others do. For example, no correlation is noted between “CTA global” and “Distressed securities”. The highest correlation of 0.95 was achieved between the two hedge fund strategies “Distressed securities” and “Event driven”.

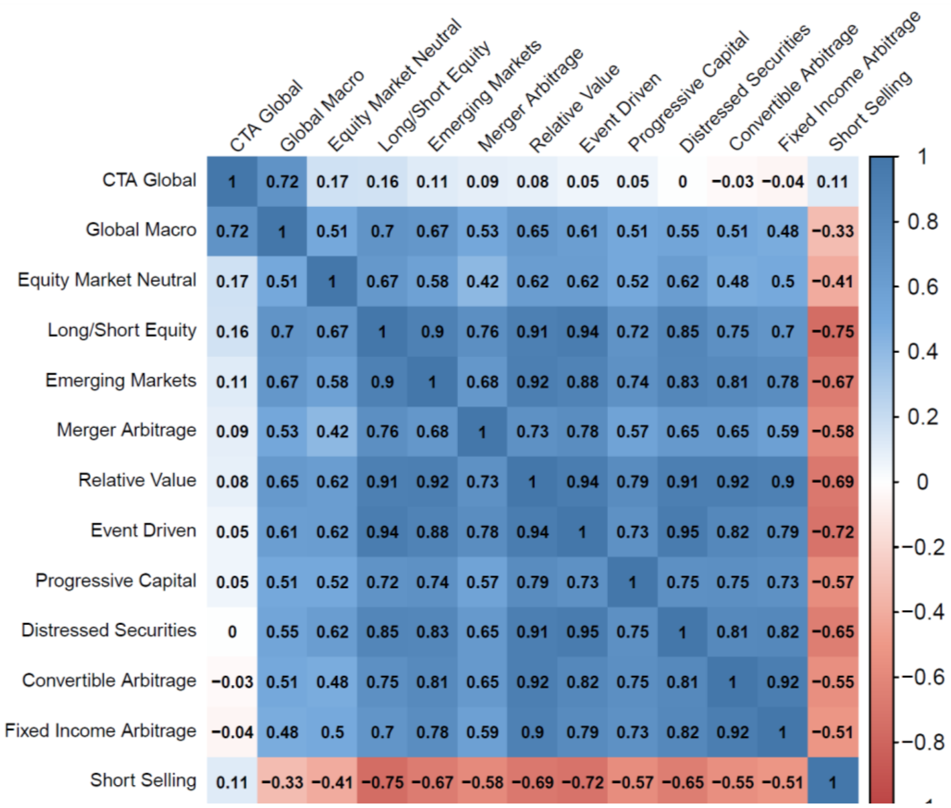

Figure 4: Correlation matrix of hedge fund returns

Factor	**Minimum**	**Quartile 1**	**Median**	**Arithmetic mean**	**Geometric mean**	**Quartile 3**	**Maximum**	**St. Dev.**	**Skewness**	**Kurtosis**
Progressive Capital	-0.1052	-0.0025	0.0061	0.0049	0.0047	0.0150	0.0559	0.0196	-1.3370	6.6620
Convertible Arbitrage	-0.1237	-0.0017	0.0038	0.0035	0.0033	0.0121	0.0611	0.0202	-2.4664	16.0067
CTA Global	-0.0568	-0.0137	0.0008	0.0020	0.0018	0.0160	0.0620	0.0208	0.1497	-0.2434
Distressed Securities	-0.0775	-0.0059	0.0058	0.0038	0.0036	0.0166	0.0504	0.0184	-0.9033	2.4120
Emerging Markets	-0.1331	-0.0122	0.0039	0.0020	0.0015	0.0166	0.0884	0.0286	-0.9496	3.8861
Equity Market Neutral	-0.0587	-0.0010	0.0030	0.0018	0.0018	0.0059	0.0168	0.0089	-2.7844	15.2605
Event Driven	-0.0627	-0.0054	0.0048	0.0032	0.0031	0.0145	0.0442	0.0173	-0.9885	2.0125
Fixed Income Arbitrage	-0.0867	-0.0003	0.0046	0.0035	0.0034	0.0086	0.0365	0.0127	-3.1527	20.2046
Global Macro	-0.0313	-0.0055	0.0020	0.0025	0.0024	0.0095	0.0348	0.0117	0.2583	0.4070
Long / Short Equity	-0.0675	-0.0076	0.0060	0.0030	0.0028	0.0144	0.0516	0.0196	-0.8130	1.4655
Merger Arbitrage	-0.0276	-0.0014	0.0045	0.0032	0.0031	0.0084	0.0191	0.0079	-0.9564	1.5814
Relative Value	-0.0692	-0.0016	0.0047	0.0037	0.0036	0.0106	0.0392	0.0129	-1.8485	9.0681
Short Selling	-0.0990	-0.0271	-0.0118	-0.0064	-0.0071	0.0109	0.1170	0.0366	0.5830	1.1408

Table 8: Summary Statistics for monthly hedge fund returns

Table 8 reports the summary statistics of hedge fund monthly returns, standard deviation, skewness, and kurtosis. The sample data includes hedge funds in the EDHEC database and the aggregated portfolio of Progressive Capital. The sample period covers August 2007 to December 2018.

4.1.2.1 Data biases

Managers who operate under the simple high water mark rule may direct their strategy on how far away they are from the high watermark. This means that the further a manager is "out of the money", the more likely he is to increase volatility. Furthermore, the manager's motivation to accept new funds decreases, as does the willingness of investors to invest in such a fund. This suggests that after just one or two years of poor performance, funds may be seriously at risk and have a high probability of being liquidated or at least shrinking to the point that they will no longer be included in hedge fund databases (Goetzmann et al., 1998, p. 9).

Survivorship bias

The quality of the past information varies depending on the date on which the database started. This is particularly the case for funds that ceased operations before the database started. Consequently, the performance of the index is strongly influenced and depends on the number of funds that no longer communicate their results annually (the so-called attrition rate) and the average performance difference between these funds and the remaining funds. This is defined as "survivorship bias". If one compares the two database providers HFR (begins in 1994) and CSFB (begins in 2000), HFR probably has more accurate information for the period 1994 to 2000 than CSFB does. Also with regard to survivorship bias, the two databases are not affected in the same way. Fung and Hsieh (2002) rated the average impact of the survivorship bias at 3%. Due to the higher attrition rate, for example, the TASS database has a higher bias than the HFR (EDHEC, 2004, p. 8).

In fact, funds are often liquidated for which there is little or no prospect that they will once again achieve the return target of the high water mark. High water mark provisions therefore suggest a strong correlation between the weak intra-year performance of hedge funds and their closure. As a result, this turn is likely to increase the survival bias of ex-post observed data (Goetzmann et al., 1998, p. 15).

Backfill bias

Databases make it possible for newly added funds to backfill their performance data.

As a result, this may give rise to a backfilling bias. As the funds have an incentive to raise capital on the basis of above-average returns, estimates of performance using backfilled data may be biased upwards (Aragon, 2004, p. 19).

The historical data period for the EDHEC indices officially started in January 2003. In order to extend the data scope, the "backfilling" was carried out as follows:
Not all competing indices had a sufficient length of historical data. EDHEC has only selected those who have published monthly performance data since January 1994. Thus, taking into account the three years required for the calibration of the principal component analysis, monthly performances were used from January 1997. Thus, they dropped the first three years of observations for each fund index. EDHEC strictly adheres to the method described in Amenc and Martellini (2003) (EDHEC, 2004, p. 13). In their work, they investigated various methods to help extract a "pure style index" from competing index returns. As a solution, they suggested the principal component analysis. The method was used to extract the "best possible one-dimensional summary" of a series of competing indices (Amenc et al., 2003, p. 4).

Self-selection bias

A selection bias results from the fact that reporting to a database is optional. Essentially, funds are only required to provide audited financial statements for fund investors on an annual basis. Due to the listing requirements of a hedge fund database, which contains a timely update of the performance indicators, a selection bias can also occur. This could mean that a database is likely to be filled by higher-quality funds as they have a greater incentive to make their performance public. Generally, it is impossible for researchers to obtain data from funds that do not report to a database. Therefore, estimating selection bias is very difficult. However, on the part of the academics and database providers, they argue that the selection bias is a small percentage number, as the only incentive for the funds is to report the raising of capital (Aragon, 2004, p. 19).

4.1.3 Risk factors considered for the factor model

Although extensive literature addresses hedge fund performance measurement, the discussion regarding a generally accepted factor model for assessing hedge fund performance is still ongoing. The most widely used and accepted factor model is the seven-factor model proposed by Fung and Hsieh (2004). The equity-oriented risk factors used in the model are the S&P 500 index monthly total return and the size spread factor (Russell 2000 index monthly total return - S&P 500 index monthly total return). The bond-oriented risk factors include the monthly change in the 10-year treasury constant maturity yield and the monthly change in the credit spread (Moody's Baa yield minus 10-year treasury constant maturity yield). The model also includes three trend-following risk factors on bonds (PTFSBD), currency (PTFSFX) and commodity (PTFSCOM). Based on Fung and Hsieh (2001), these trend-following factors labeled as “primitive trend following strategies” and constructed as portfolios of lookback straddles, which are calculated from exchange-traded options. Recently, Fung and Hsieh suggested adding an eighth risk factor to the model, namely the MSCI emerging market index monthly total return. The Fung and Hsieh factors are listed in the table 9 below.

Fung and Hsieh eight-factor model			
Factor	**Description**	**Indices**	**Bloomberg Ticker**
1. Equity	Monthly total return S&P 500	S&P 500	SPXT
2. Small-Cap	Small-cap returns minus Large-cap returns	Russell 2000 - S&P 500	RU20INTR, SPXT
3. Interest rate	Rate change 10-year Treasury Notes (TY)	10-year treasury constant maturity yield	USGG10YR
4. Credit-Spread	Spread differential Baa-Bonds (Moody’s) and 10-year TY	(Moody's Baa yield minus 10-year treasury constant maturity yield	MOODCBAA, USGG10YR
5. Bond straddle	Straddle = long call, long put	Primitive trend following strategy bond	From David[3] Hsieh’s data library
6. Currency straddle		Primitive trend following strategy currency	From David Hsieh’s data library
7. Commodity straddle		Primitive trend following strategy commodity	From David Hsieh’s data library
8. Equity	Large and mid-cap across 24 EM countries	MSCI Emerging market	MXEF

Table 9: Overview of Fung and Hsieh's eight-factor model

[3] David Hsieh supplied these risk factors. The trend-following factors can be obtained from https://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-Fac.xls.

In figure 5, the Pearson correlations of Fung and Hsieh eight-factor model are reported. The sample period covers August 2007 to December 2018. The correlation matrix indicates that the highest correlation is between the factors S&P 500 and MSCI emerging markets with 0.79. The lowest correlation with -0.61 are observed between US government 10Y bond and credit spread. MSCI emerging markets demonstrates the highest correlation of 0.68 to Progressive Capital. In contrast, besides the credit spread factor, all primitive trend following strategies are negatively correlated to Progressive Capital.

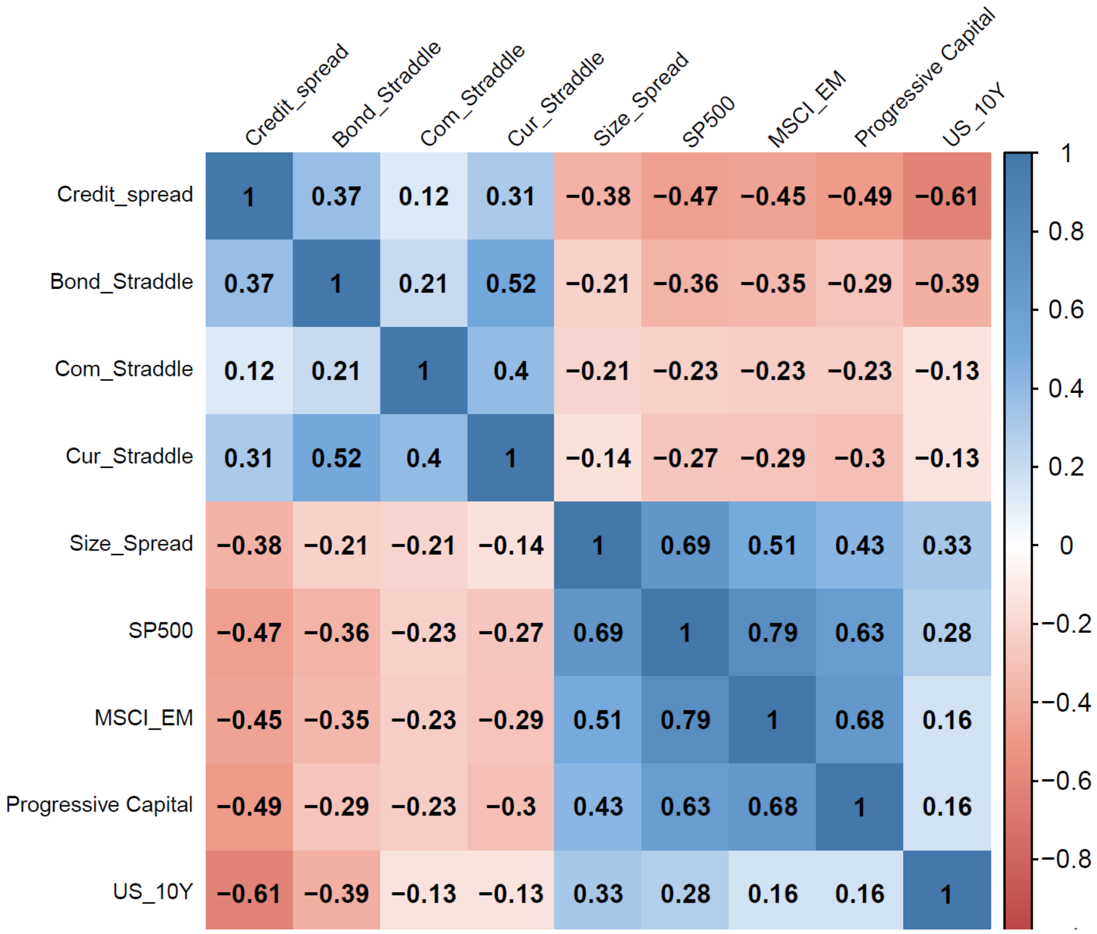

Figure 5: Correlation matrix for Fung and Hsieh 8-factor model and Progressive Capital

Typically, hedge funds are not only exposed to the seven asset classes that capture the seven-factor model of Fung and Hsieh (2004). In addition to the seven-factor model, this thesis considers a universe of risk factors to specify factor models based on the stepwise regression approach. Table 10 on the next page represents the other risk factors, which are used in this thesis. In total, 17 risk factors are considered for the empirical analysis. The table 11 on page 36 presents the summary statistics of all risk factors, including the Fung and Hsieh factors for the full sample period of August 2007 to December 2018. The most important statistical indicators are determined for all 25 risk factors.

Risk factor	Description	Bloomberg Ticker
SMB	Small minus big factor	Kenneth R. French Data library[4]
HML	High minus low factor	Kenneth R. French Data library
MSCI World ex USA	Large and mid cap representation across 22 of 23 developed markets (DM) countries – excluding USA	MXWOU
MSCI World minimum Volatility	Minimum variance strategy applied to the MSCI large and mid cap equity universe across 23 DM countries	M1WOMVOL
MSCI World Momentum	Equity momentum strategy which includes large and mid cap stocks across 23 DM countries	M1WOMOM
MSCI World Value	Value index captures large and mid cap securities exhibiting overall value style characteristics across 23 DM countries. Value investment style characteristics are book value to price, 12-month forward earnings to price and dividend yield	IWFV
HFRI	Hedge fund index	HFRIEHI
FTSE 100	Financial times stock exchange 100 index includes the 100 largest companies in UK	UKX
Nikkei 225	Stock market index for the Tokyo stock exchange. Measures the performance of 225 large companies in Japan	NKY
SPI	Swiss performance Index	SPI
VIX	Represents the market's expectation of 30-day forward-looking volatility. Derived from price inputs of S&P 500 index option	VIX
Commodity	S&P GSCI serves as a benchmark for investment in the commodity markets	SPGSCI
Gold	Most popular investment of all precious metal	XAU
Germany Bond 10Y	Germany Government Bond 10 Year	GTDEM10Y
UK Bond 10Y	UK Government Bond 10 Year	GUKG10
CH Bond 10Y	CH Government Bond 10 Year	GSWISS10
Trade Weighted U.S. Dollar Index	Value of the US Dollar relative to other world currencies	USTWBROA

Table 10: Overview of risk factors

[4] The SMB and HML data is from the website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#BookEquity

Factor	Minimum	Quartile 1	Median	Arithmetic mean	Geometric mean	Quartile 3	Maximum	St. Dev.	Skewness	Kurtosis
Eight-factor model by Fung and Hsieh										
S&P 500	-0.1680	-0.0140	0.0129	0.0067	0.0058	0.0326	0.1093	0.0430	-0.7767	1.6033
Size Spread	-0.2774	-0.0433	0.0091	0.0087	0.0038	0.0702	0.2924	0.0996	-0.0079	0.3723
US 10Y Bond	-0.2613	-0.0530	0.0033	0.0006	-0.0041	0.0548	0.3042	0.0971	0.1856	1.1306
Credit Spread	-0.1886	-0.0475	-0.0012	0.0055	0.0018	0.0607	0.4131	0.0884	0.9654	2.6401
Bond Straddle	-0.2663	-0.1419	-0.0565	-0.0257	-0.0366	0.0425	0.5050	0.1535	1.2220	1.2700
Currency Straddle	-0.3181	-0.1643	-0.0578	-0.0148	-0.0325	0.0813	0.6922	0.1994	1.3601	2.0937
Commodity Straddle	-0.2465	-0.1080	-0.0429	-0.0039	-0.0144	0.0676	0.4287	0.1495	0.8335	0.1339
MSCI Emerging markets	-0.2750	-0.0318	0.0006	0.0011	-0.0010	0.0336	0.1666	0.0647	-0.4019	2.1030
Other risk factors										
SMB	-0.0469	-0.0185	0.0017	0.0008	0.0006	0.0127	0.0611	0.0235	0.2115	-0.3954
HML	-0.1110	-0.0178	-0.0031	-0.0019	-0.0022	0.0108	0.0832	0.0271	0.1229	2.1824
MSCI World ex USA	-0.2087	-0.0216	-0.0010	-0.0005	-0.0019	0.0293	0.1239	0.0513	-0.6190	1.6651
MSCI Min Vola	-0.1586	-0.0094	0.0083	0.0052	0.0047	0.0281	0.0715	0.0332	-1.2307	3.7866
MSCI Momentum	-0.1670	-0.0136	0.0135	0.0059	0.0049	0.0317	0.1166	0.0448	-0.9494	1.7202
MSCI Value	-0.1864	-0.0235	0.0054	0.0008	-0.0004	0.0291	0.1335	0.0471	-0.5861	1.6571
HFRI	-0.0946	-0.0093	0.0051	0.0022	0.0019	0.0157	0.0637	0.0244	-0.8638	2.0000
FTSE 100	-0.1302	-0.0233	0.0053	0.0012	0.0004	0.0273	0.0845	0.0398	-0.3766	0.2865
Nikkei 225	-0.2383	-0.0259	0.0046	0.0028	0.0011	0.0400	0.1285	0.0581	-0.6689	1.3134
SPI	-0.1019	-0.0151	0.0072	0.0029	0.0022	0.0284	0.0958	0.0372	-0.4499	0.3399
VIX	-0.3849	-0.1398	-0.0154	0.0257	0.0006	0.1093	1.3457	0.2465	1.7853	6.0166
Commodity	-0.2777	-0.0368	0.0083	-0.0001	-0.0023	0.0397	0.2110	0.0653	-0.5568	2.0209
Gold	-0.1689	-0.0244	0.0037	0.0062	0.0048	0.0439	0.1301	0.0530	-0.0602	0.2662
UK Gilt 10Y	-0.3933	-0.0665	-0.0152	-0.0028	-0.0102	0.0504	0.6689	0.1255	1.1907	5.7511
Germany Bond 10Y	-2.3197	-0.1177	-0.0286	-0.0199		0.0722	1.1275	0.3762	-2.0508	14.4833
Switzerland Bond 10Y	-3.9362	-0.1744	-0.0329	-0.0036		0.0861	8.7000	1.3568	2.9249	18.9236
Trade weighted USD	-0.0287	-0.0080	0.0019	0.0017	0.0016	0.0090	0.0668	0.0137	0.7876	2.6348

Table 11: Summary statistics for risk factors

4.2 Methodology

In the present study, suitable methods are applied based on the current literature. This chapter first introduces two different statistical approaches to measure hedge fund performance statistically: principal component analysis and common factor analysis.
Following Fung and Hsieh (2002), this thesis applied a principal component analysis to identify the minimum number of components necessary to describe the return on hedge funds. In the common factor analysis, three different multi factor models are applied: the Fung and Hsieh seven-factor model, the extended Fung and Hsieh eight-factor model, and a model based on a stepwise regression approach by Agarwal and Naik (2000).
Second, a portfolio analysis is used to calculate the representative Swiss pension fund portfolio of the Swisscanto study represented in 3.5.1. The portfolio analysis is performed with two slightly different portfolios. The first portfolio includes Progressive Capital as an alternative asset in the Swiss pension fund asset allocation. The second portfolio contains the alternative assets of hedge funds, private equity, insurance linked securities, and commodity index instead of Progressive Capital. All other asset classes remain unchanged for both portfolios. Subsequently, the two portfolios are then compared based on key performance indicators. The methods were implemented with the statistics tool R-Studio.

4.2.1 Calculation of monthly simple returns

Stock prices usually have a unit root, while returns are supposed to be stationary. Stationary time series have many appropriate properties for financial analysis. Non-stationary time series means that the moments (mean and variance) will change over time. Thus, for this thesis, the monthly prices of all risk factors and pension fund assets were calculated based on simple returns. The figures for the returns are presented in appendix 8. The simple returns can be calculated as follows:

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}}$$

Where:

p_t = stock price at the end of month t

4.2.2 Principal component analysis

The handling of two variables is supported by the clarity of two-dimensional graphical representations, and the spatial imagination helps in three dimensions. For higher dimensions such representations will fail, and one is dependent on high-dimensional data being presented low-dimensionally, i.e. if possible two-dimensionally, as informative as possible (Ruckstuhl, 2015, p. 8). The principal component analysis (PCA) meets this demand. The method considers as informative those directions in which the data are highly scattered. The PCA is presented primarily as a method for visualizing high-dimensional data in low-dimensional Euclidean spaces (Ruckstuhl, 2015, p. 10).
More technically, it explains the behavior of observed variables by using a smaller set of unobserved implied variables. This is achieved by transforming a set of K correlated variables into a set of orthogonal variables or implicit factors that reflect the original information present in the correlation structure. Each implicit factor is defined as a linear combination of original variables (EDHEC, 2004, p. 23).

4.2.2.1 Geometric and statistical background

Before the data are calculated with principal components, the characteristics of the data must be made comparable. It is crucial for the outcome of the principal component analysis whether to use the raw data or standardized data. As a rule of thumb, it is reasonable to standardize the data when fundamentally different measures or units of measure are involved. The preferred variant is the statistical standardization of each individual characteristic. This procedure is equivalent to using the sample correlation matrix R_x instead of the sample covariance matrix S_x and consequently obtaining the principal components as eigenvectors of R_x (Ruckstuhl, 2015, p. 16).
Fung and Hsieh (1999) used the principal component analysis to group funds based on their correlation with each other. With other words, their quantitative classification method are based on the correlation matrix (Fung and Hsieh, 1999, p. 322). The mathematical theory for PCA is explained in detail below.

The linear algebra provides mathematical implementation of the PCA. The observation vectors $x_1, \dots, x_n$ describe the n objects with their respective p components (i.e. characteristics). These vectors can now be combined in a $(n * p)$-dimensional data matrix X. The i-th observation is therefore to be found in the i-th row of the matrix X. Under the assumption that the characteristics were centered, the respective sample averages are zero. That means that the p-dimensional sample mean vector of the zero vector is $\underline{\bar{x}} = 0$. Following formula is for the sample covariance matrix $S_{\underline{x}}$ applied (Ruckstuhl, 2015, p. 14):

$$S_{\underline{x}} = \frac{1}{n-1} \sum_{i=1}^{n} x_i \, x_i^T$$

For the one-dimensional variables $y_i = a^T x_i$ $(i = 1, \dots, n)$, which are linear combinations of the original variables, their sample mean value y is equal to $a^T \underline{\bar{x}} = 0$ and their sample variance ${s_y}^2$ is equal to $a^T S_{\underline{x}} a$ (Ruckstuhl, 2015, p. 14).

4.2.2.2 Calculation of the principal components

Algebraically, the first principal component is now the linear combination $y^{(1)} = X \, a_1$ (i.e. ${y_i}^{(1)} = {x_i}^T a, \quad i = 1, \dots, n)$ of the original variables, which maximizes the sample variance $s_y = {a_1}^T S_x a_1$ under the constraint ${a_1}^T a_1 = 1$ (Ruckstuhl, 2015, p. 14).
The determination of all principal components is based on the spectral representation of the matrix $S_{\underline{x}}$:

$$S_{\underline{x}} = A \, L \, A^T$$

Where the columns in the matrix A consist of the eigenvectors a_k to the eigenvalues $l_k, k = 1, \dots, p$, of the matrix $S_{\underline{x}}$ and L is a diagonal matrix with the eigenvalues $l_k, k = 1, \dots, p$. The eigenvalues are sorted in descending order. This means $l_1 > \ l_2 > \cdots > l_p \geq 0$. Now it can be shown that the j-th eigenvector a_j just determines the j-th principal component: ${y_i}^{(j)} = {a_j}^T x_i, \ i = 1, \dots, n$
With the help of the matrix notation, this result can be achieved with

$$Y = X \, A$$

The following result is obtained for the covariance matrix of the data in the principal component representation:

$$S_y = \frac{1}{n-1} Y^T Y = \frac{1}{n-1} (XA)^T (XA) = A^T \left(\frac{1}{n-1} X^T X \right) A = A^T S_{\underline{x}} A = A^T A L A^T A = L$$

Where the principal components are centered and the eigenvectors $a_j,\ \ j = 1, \dots, p$ are orthonormalized. Since L is a diagonal matrix, the principal components are uncorrelated, and the variance of the data projected on a principal component corresponds to the eigenvalue $var\langle y^{(j)}\rangle = l_j$ (Ruckstuhl, 2015, p. 14).

The sample correlation matrix R_x can now be displayed as a simple function of the sample covariance matrix S_x (Ruckstuhl, 2015, p. 28). Let

$$D = \begin{pmatrix} {s_1}^2 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & {s_p}^2 \end{pmatrix} \qquad D^{\frac{1}{2}} = \begin{pmatrix} s_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & s_p \end{pmatrix} \qquad D^{-\frac{1}{2}} = \begin{pmatrix} \frac{1}{s_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{1}{s_p} \end{pmatrix}$$

be the $p * p$ diagonal matrix of sample variances ${s_i}^2,\ \ i = 1, \dots, n$, the diagonal matrix of the sample standard deviations and the diagonal matrix of the reciprocal values of the sample standard deviations. It is valid that $D^{\frac{1}{2}}\, D^{\frac{1}{2}} = D$. Now the relationship between the sample covariance matrix S_x and the sample correlation matrix R_x can be expressed efficiently as

$$R_x = D^{-\frac{1}{2}}\, S_x\, D^{-\frac{1}{2}}$$

and vice versa

$$S_x = D^{\frac{1}{2}}\, R_x\, D^{\frac{1}{2}}$$

4.2.3 Multi factor model to explain hedge fund returns

Regression quantitatively examines the fundamental question of how a variable depends on other influencing factors. The main objective of the investigation will be to describe the relationship with a formula. The relationship between an explanatory variable x_i and the target variable Y is generally described as follows:

$$Y = \beta_0 + \beta_i x_i + E_i \qquad \forall i = 1, \dots, n$$

The individual variables have the following meanings:

- Y is defined as the target variable and is a random variable.
- x_i is the explanatory variable and is regarded as a fixed, non-random variable.
- β_0, β_i are unknown parameters, the so-called regression coefficients of the explanatory variables. With the help of the available observations, these parameters are to be estimated. β_0 represents the intercept and β_i the slope. The slope indicates by how much the value of the target variable increases if the x-value increases by one unit.
- E_i is the residual or error term. This is a random variable, i.e. the deviation between the observed value Y_i and the adjusted value on the straight line is interpreted randomly.

For the errors, it is assumed that the expected value $E(E_i) = 0$ and the variance $Var(E_i) = \sigma^2$ are constant. The greater the variance, the worse the estimate will be. Furthermore, the deviations must not demonstrate any correlation. These assumptions belong to the normal distribution and lead to the mathematically simplest results in statistics.

Agarwal and Naik (2004) used the multifactor model to identify statistically significant factors. Thus, the monthly returns on a hedge fund index are regressed on the returns on risk factors in a multifactor framework. Based on the model estimates, it will be decided whether risk factors have a significant influence on hedge fund strategy or Progressive Capital returns. Based on the method of Agarwal and Naik (2004), the following regression model is estimated (Agarwal and Naik, 2004, p. 71):

$$R_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} * F_{k,t} + E_{i,t} \qquad \forall i = 1, \dots, N \qquad \forall t = t_0, \dots, T$$

where $R_{i,t}$ net-of-fees excess return (risk free rate = 0 %) on hedge fund index i for month t, α_i is the intercept for hedge fund index i over the regression period, $\beta_{i,k}$ is the average factor loading of hedge fund index i on the k-th factor during the regression period, $F_{k,t}$ is the excess return on the k-th risk factor for month t, and $E_{i,t}$ is an error term for month t.

4.2.3.1 Stepwise regression on multi factor model

Since hedge funds follow different investment strategies, they are not only exposed to the seven asset classes that capture the seven-factor model of Fung and Hsieh (2004). With start of 25 risk factors (8 Fung and Hsieh factors + 17 risk factors), the interest of the research is to identify other dominant risk factors to build the best statistical model, which explain the return of hedge fund strategies including Progressive Capital niche alternatives.

This thesis therefore follows Agarwal and Naik (2000) to estimate monthly alphas based on factor models in which factors are selected using a stepwise regression approach. This approach attempts to capture the different factor exposures of hedge funds while minimizing the number of factors included in the model (Schaub and Schmid, 2013, p. 675). For the selection process, the stepwise regression approach will start with 25 risk factors (see section 4.1.3). This iterative procedure is continued until the optimal model has been simulated. Subsequently, these risk factors are applied in the multi factor model introduced in the previous section 4.2.3.

In the following, the theoretical framework of the stepwise regression approach is explained in detail.

There are different ways to use regression analysis:

1. The dependence of the target variable Y on the given explanatory variables x_1,…, x_n is already known. The interest here applies only to a classical question concerning the coefficients of the explanatory variables, interval estimation, prognosis intervals, etc.
2. The influence of the explanatory variables on the target variable is not known and must first be investigated by regression analysis. This raises the question of whether and in what form the explanatory variables influence the target variable Y.
3. The interest is only in the influence of a single explanatory variable, but considering the effects of other explanatory variables.

For points two and three, the question arises as to which explanatory variables should appear in the regression model and which should be classified as important or unimportant for the model equation (Ruckstuhl, 2015, p. 93).

Using variable selection methods, necessary and useful terms $b_i x_i$, i.e. the coefficients of the explanatory variables are measured. This method is based on model selection criteria, which evaluate on the one hand the model accuracy and on the other hand the model complexity. The model accuracy refers to a good description of the available data by the model. The simplicity of the model and the small number of explanatory variables describe the sense of model complexity.
The evaluation of model accuracy and model complexity is performed by using the information criterion of Akaike (AIC):

$$AIC = -2(maximized\ Log - Likelihood) + 2$$
$$= n \log \langle \frac{1}{n} \sum_{i=1}^{n} R^2{}_i \rangle + 2p^* + constant$$

where R^2 is the coefficient of determination and p^* the number of estimated parameters. The AIC method is regarded as the best generalized criterion and is used in time series analysis (Ruckstuhl, 2015, p. 98).
The process of the variable selection procedure can be formulated as follows:

1. **Forward selection**
   - In the initial step, the model $Y_i = \beta_o + E_i$ is selected
   - In the following steps, the explanatory variable that contributes to the greatest improvement with respect to the selected model selection criterion is included in the model.
   - The procedure is terminated when no improvement is possible by adding another explanatory variable.

2. **Backward selection**
   - In the initial step, the full model $Y_i = \sum_{k=0}^{m} \beta_k x_i^{(k)} + E_i$ is selected.
   - In the following steps, a variable is taken from the model that leads to the greatest improvement with regard to the selected model selection criterion.
   - The procedure is terminated when no improvement is possible by omitting another explanatory variable.

3. **Stepwise selection**
   The stepwise selection is a combination of forward and backward selection. In each step, it is tried out whether omitting or adding an explanatory variable improves the model selection criterion. The process is terminated when no further improvement is possible (Ruckstuhl, 2015, p. 99).

4.2.4 Modern Portfolio theory

In this chapter, the Modern portfolio theory is briefly discussed. This theory was published by Harry Markowitz in 1952 in a paper on portfolio selection and the effects of diversification. The objective of this theory is to maximize the expected return of a portfolio for a certain level of risk. In the following, the most important basic formulas for portfolio theory are presented which are used for this thesis.

Expected portfolio return

The expected return of the portfolio $E(r_p)$ is formed by multiplying the expected return of the assets r_i by the weights w_i and adding them up. The formula for the expected return $E(r_p)$ of a portfolio p is structured as follows:

$$E(r_p) = w^T * r_i = (w_1, \ldots, w_n)^T * \begin{pmatrix} r_1 \\ \vdots \\ r_n \end{pmatrix}$$

where:

$E(r_p)$: Expected portfolio return

w^T: Vector of portfolio weights

r_i: Vector of the assets' expected returns

Portfolio variance

The transposed weights w^T are multiplied by the covariance matrix Σ and multiplied again by the weights *w* of the portfolio. The portfolio variance is given by the following formula:

$$Var(r_p) = w^T \Sigma \, \mathrm{w} = (w_1, \dots, w_n)^T \begin{pmatrix} \sigma_{11} & \cdots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{1n} & \cdots & \sigma_{nn} \end{pmatrix} \begin{pmatrix} w_1 \\ \vdots \\ w_n \end{pmatrix}$$

where:

$Var(r_p)$: Portfolio variance

w^T: Vector of portfolio weights

Σ = cov(x,x): covariance matrix

4.2.4.1 Performance measures

Beta factor

Beta coefficient consists of estimating asset market systematic risk through the linear relationship between asset and market risk premiums. The beta factor is calculated as follows:

$$\beta_i = \frac{\sigma_{iM}}{\sigma^2{}_M} = \frac{cov(r_i, r_M)}{\sigma^2{}_M}$$

where:

σ_{iM}: Covariance between the return of asset r_i and the return of the market r_M

$\sigma^2{}_M$: Variance of the market

Beta measures the volatility of the asset's return to market risk factors. The volatility can be expressed as follows:

$\beta > 1$ → more volatile than the market

$\beta = 1$ → as volatile as the market

$\beta < 1$ → less volatile than the market

Sharpe Ratio

The Sharpe Ratio quotes the risk premium per unit of total risk. It describes the reward (return) which you get for taking one (additional) unit of risk. The Sharpe ratio is calculated by subtracting the risk-free rate from the expected return of an asset and dividing it by the risk. The larger the shape ratio, the better. The risk free rate for the empirical analysis is equal -0.71 % which is derived from the 3M Libor CHF. The following formula describes the Sharpe ratio mathematically:

$$SR_A = \frac{E(r_A) - r_f}{\sigma_A}$$

where:

$E(r_A)$: Expected return of asset A

r_f: Risk-free rate

σ_A: Risk of asset A

Jensen's alpha

Jensen's alpha consists of estimating asset expected excess return through the difference of realized versus expected return.

$$J_A = r_A - E(r_A) = r_A - \left[r_f + \beta_A * (E(r_m) - r_f\right]$$

Alpha is positive for undervalued assets and negative for overvalued assets.

where:

r_A: Realized return of asset A

$E(r_A)$: Expected return of asset A

$E(r_m)$: Expected return of the market (benchmark)

r_f: Risk-free rate

β_A: Beta factor of asset A

Idiosyncratic risk

Harry Markowitz quantified risk as the variance of the portfolio rate of return. This risk of a portfolio or single asset can be split into systematic or unsystematic (idiosyncratic risk). The systematic risk is a non-diversifiable or market risk, which results from macro-economic factors and influences that cannot be diversified away (Grant and Fabozzi, 2001, p. 29). The idiosyncratic risk, also called diversifiable or title/company-specific risk, describes the risk, which is of concern only to a company such as a strike. With good diversification, title-specific risk can be largely eliminated. What remains in the portfolio is systematic or market risk (Grant and Fabozzi, 2001, p. 30).

4.2.5 Portfolio Optimization

The point of the optimization problem is to construct an efficient frontier that gives the best possible tradeoff of risk against return. This objective is a quadratic problem and leads to the following optimization problem:

$$\text{Minimize } w^T \Sigma\, w$$
$$\text{Under the condition } w^T r = r_p$$
$$\text{and } \sum_{i=1}^{n} w_i = 1$$

From the upper formula, the minimum must be found. The first expression $w^T \Sigma\, w$ is the variance of portfolio returns. The transposed weights w^T are multiplied by the covariance matrix Σ and multiplied again by the weights w of the portfolio. The covariance matrix Σ is composed of the various covariances of the asset returns. The covariance is a measure of the monotonic relationship between two random variables. In the diagonal of the covariance matrix are the variances. Outside the diagonal are the covariances.

Because this is a quadratic problem, the optimization problem was solved by using a quadratic solver. Hence, the R package called "R optimization infrastructure (ROI)" are used.

The portfolio optimization are applied on two pension funds portfolio, which are constructed based on the Swisscanto study from 2018 represented in chapter 3.5.1. These two portfolios only have differences in the area of alternative assets in the Swiss pension fund asset allocation. While the first portfolio includes Progressive Capital as an alternative asset, the second Portfolio contains the alternative assets Hedge funds, Private equity, Insurance linked securities, and Commodity index instead of Progressive Capital. All other asset classes remain unchanged for both portfolios.

According to investment restrictions of pension funds (see chapter 3.6), there are some limitations for setting the weights for each asset in the pension fund portfolio. The maximum limit for alternative assets in a pension fund portfolio is 15 % (compare table 4). Consequently, the parameters for the weights of the alternative assets were chosen between 0.5 % and 15 %. The weights for all other assets remain unchanged.

5. Empirical Analysis

This chapter presents the results of the master thesis. The use of data analysis with in-depth methods as the principal component analysis and stepwise regression form the basis for examining the performance of hedge fund returns. Subsequently, the analysis of portfolio management for a representative Swiss pension fund is presented.

5.1 Data Analysis

The data analysis addresses price developments, descriptive statistics, and other graphical visualizations. Descriptive statistics serves as a quantitative method of data analysis to describe and graphically display the data in order to gain initial insights into large amounts of data.

5.1.1 Price developments

Figure 6 presents the development of the five selected MSCI indices from 1997 to 2018. The graph indicates that all MSCI indices have a similar price development from 1997 to 2013. Nevertheless, MSCI minimum volatility and MSCI momentum demonstrate a clear upward trend since the last financial crisis in 2008. MSCI Emerging markets and MSCI ex USA have been in a sideways trend since the 2008 financial crisis. It is clear that MSCI emerging markets is oscillating around the price line of 1000, whereas MSCI ex USA is positioned between 1500 and 2000.

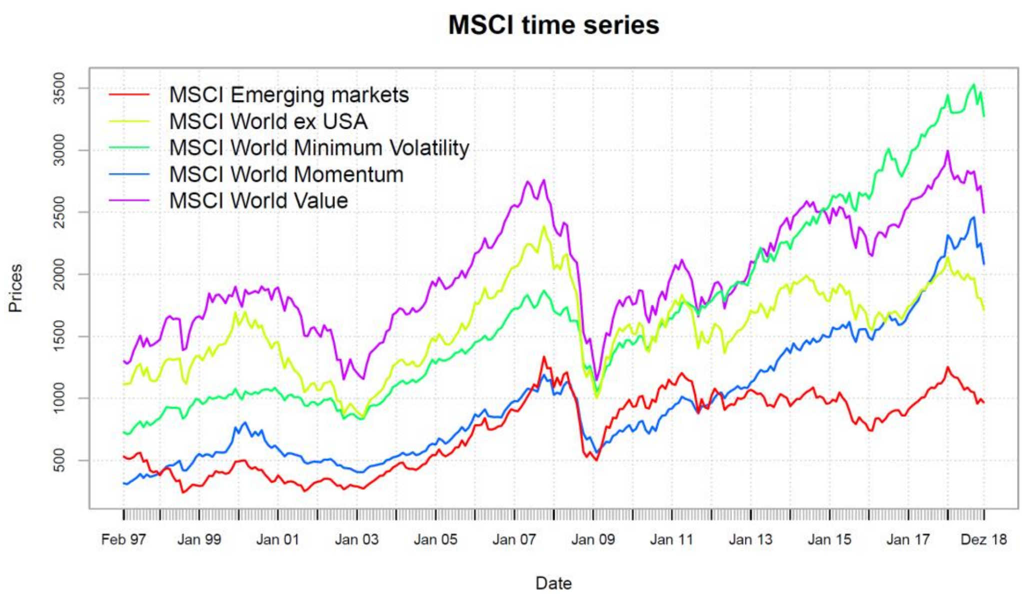

Figure 6: Price development of MSCI indices

Figure 7 exhibits the developments of major bonds. The graph depicts largely similar structures regarding all four bond-time series. It becomes apparent that all demonstrate a negative trend over the full sample period. The development of the Swiss government bond demonstrates very clearly the monetary policy measures of the Swiss national bank. It lowered the interest rates after the bursting of the dotcom bubble in 2000 and the last financial crisis in 2008. Since the introduction of negative interest rates, the Swiss bond is below the 0 % line. Furthermore, in the last two years, a clear positive trend can be observed for the USA government bond. Strong economic data, such as the rise in employment, have led to rising interest rates in the USA.

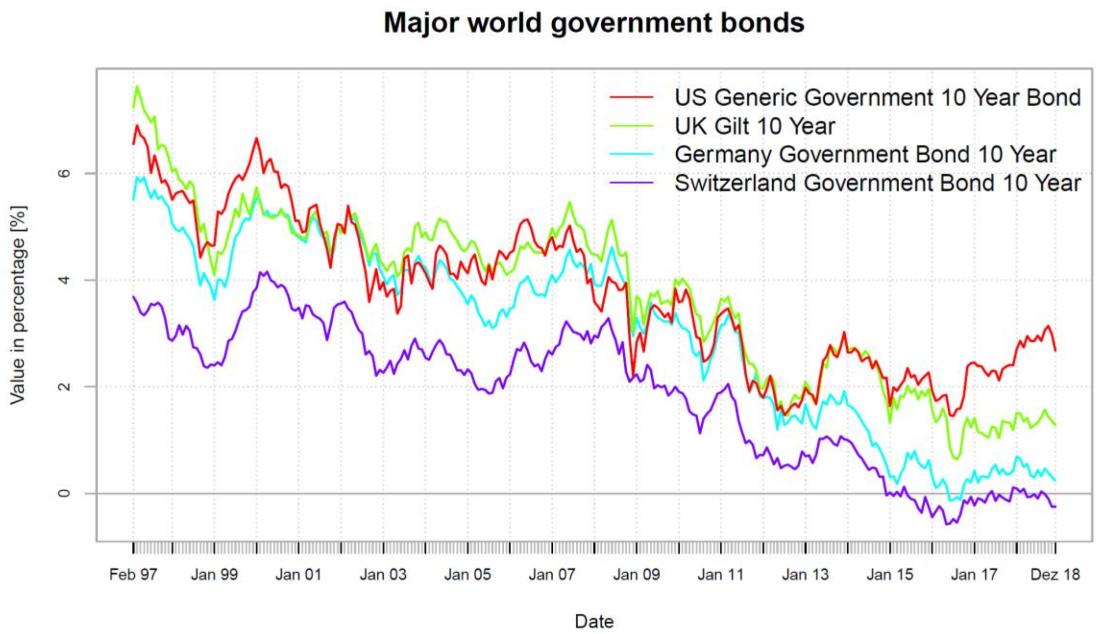

Figure 7: Development of major government bonds

Figure 8 on the following page illustrates the US 10Y Bond, Moody's Baa yield, and the credit spread, which is the difference between Moody's Baa yield minus US 10Y Bond. It becomes apparent that Credit spread and US 10Y Bond are moving in opposite directions. When the US 10Y Bond increases, a decreased credit spread is observed.

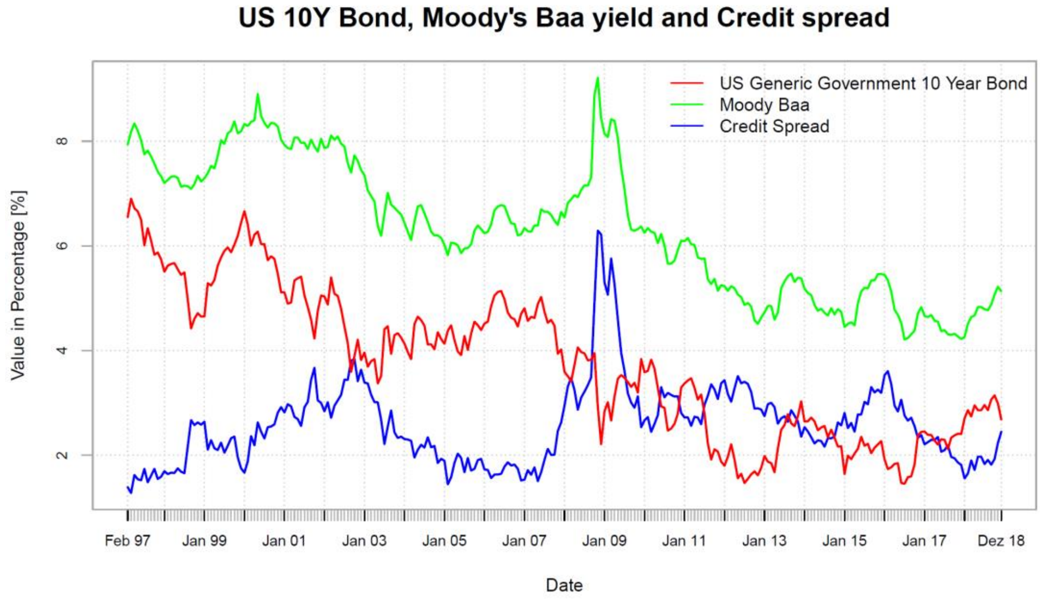

Figure 8: Developments of US 10Y Bond, Moody's Baa, and Credit Spread

Figure 9 shows the price development of the large and small cap stocks, where the large caps are represented by S&P 500 index and the small caps are shown by Russell 2000. The size spread factor is the difference between the Russell 2000 monthly total return and the S&P 500 monthly total return. The chart demonstrates a strong upward trend since the financial crisis in 2008. Thus, compared to 2009, Russell 2000 was able to almost quadruple its index volume by 2018. Furthermore, in general, 2018 was not a good year for the equity markets as a decline in prices can be observed for S&P 500 and Russell 2000.

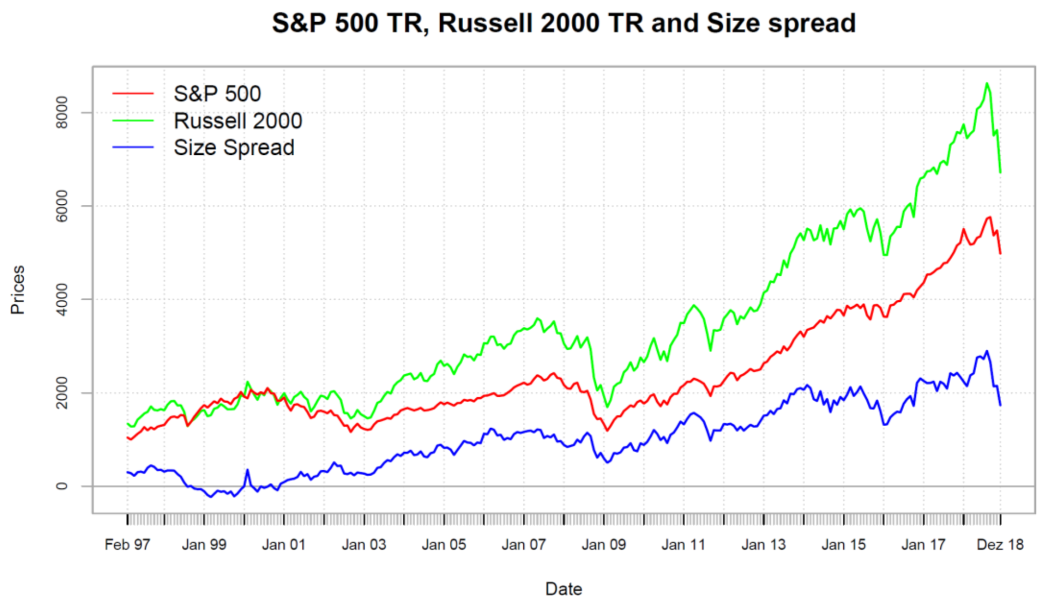

Figure 9: Price developments of S&P 500, Russell 2000 and Size spread

Figure 10 demonstrates that the SPI is showing an upward trend despite turbulent ups and downs over the 20-year time horizon. During the crisis period of 2007, the SPI suffered a sharp setback of approximately 50 percent. In addition, the price developments of FTSE and SPI are synchronous until 2013 .

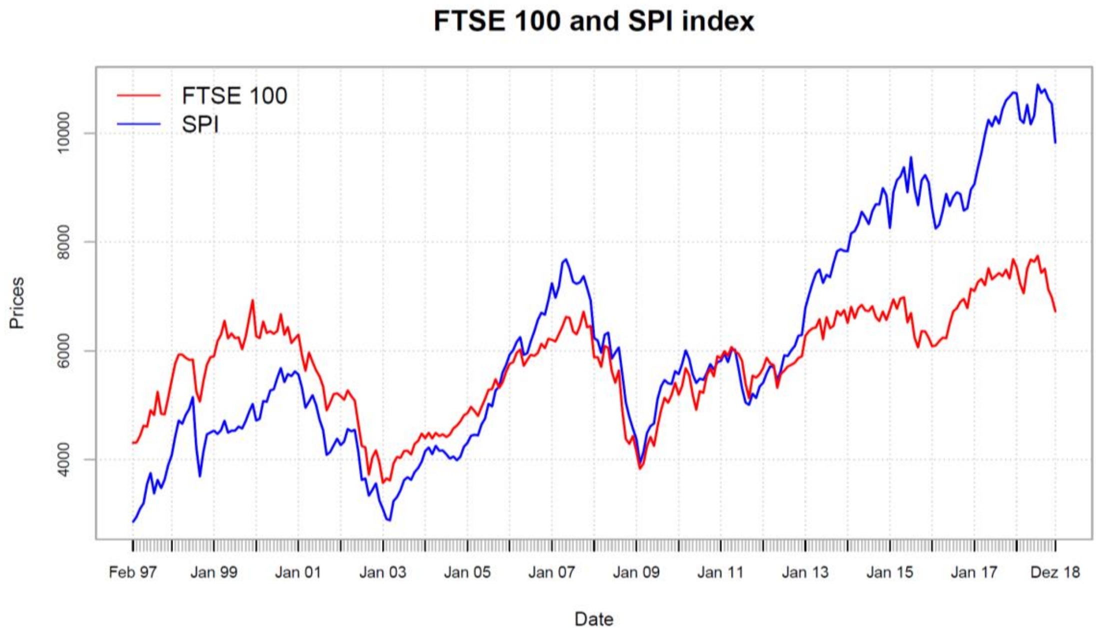

Figure 10: Price development FTSE 100 and SPI

Figure 11 presents the price developments of commodity and gold indices. Until the financial crisis in 2008, both indices were almost parallel. A strong upward trend followed from 2000 onwards. Compared to 1997, the price of gold almost quadrupled by 2012. The chart also demonstrates that during the subprime crisis in 2007, the gold price suffered a small relapse. However, gold was able to recover quickly and rose back to its all-time high of approximately 1800 in 2011. The commodity index dropped far more than gold during the financial crisis. However, it was able to recover and is currently moving in a sideways trend, as is also the case with gold. It should be mentioned that the commodity market is dependent on many factors. The OPEC group, among others, has been dominated in recent years by disagreements such as the dispute over the expansion of oil production.

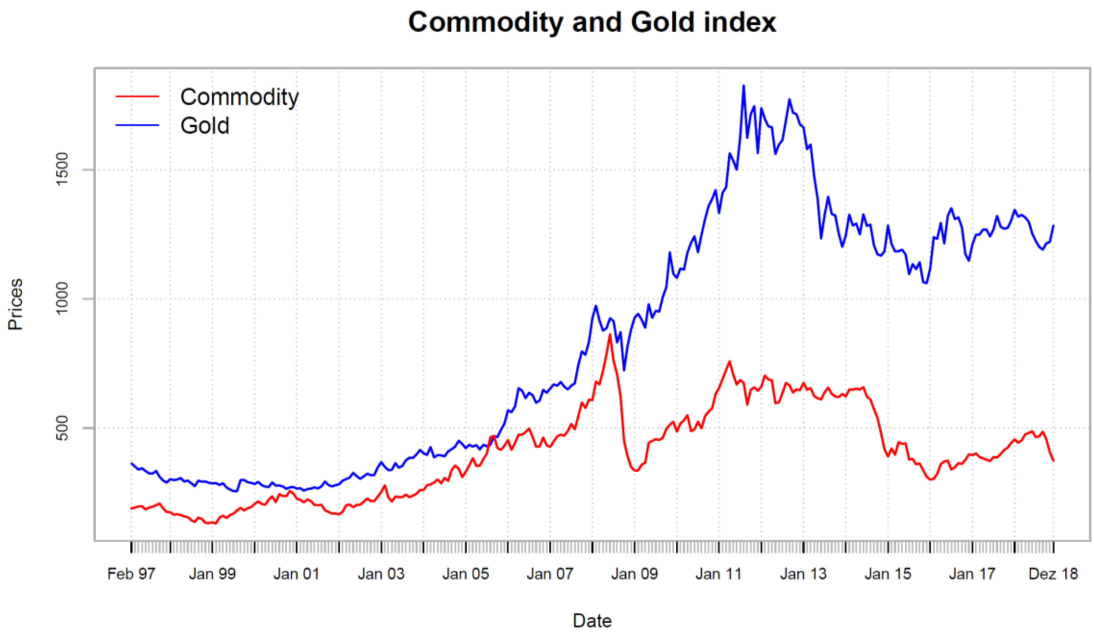

Figure 11: Price developments of Commodity and Gold index

5.1.2 Descriptive statistics

Descriptive statistics is an important and first step in any data analysis. On the one hand, it serves to describe the data based on individual characteristics and, on the other hand, it locates possible errors or outliers in the data. In the following, the results are summarized in tabular and visual form using statistical methods. The data is evaluated based on monthly returns for the full sample period from August 2007 to December 2018.

5.1.2.1 Histogram on hedge fund monthly simple returns

Figure 12 on the following page plots the histograms for each hedge fund strategy. In the chart of Progressive Capital (last chart), an extreme outlier causes a negative skewness (see also summary statistics from table 8 on page 30). This means that the tail of the left side of the distribution is longer than the tail on the right side. In other words, the distribution of Progressive Capital returns is not symmetric. In contrast, Global macro and CTA global seem to show nearly symmetrical distribution. Furthermore, Progressive Capital, convertible arbitrage, emerging markets, equity market neutral, fixed income arbitrage, and relative value returns clearly demonstrate the character of leptokurtic distribution, as demonstrated in their steep distribution form. A leptokurtic distribution is characterized by a large accumulation of returns close to the mean and some returns with large deviations from the mean. Compared to the normal distribution (shown by the red line), the leptokurtic distribution has a relatively larger percentage of small deviations as well as a larger percentage of extremely large deviations from the mean. Thus, an observed value is more likely to be either close to the mean or far from the mean. A distribution that is leptokurtic has a kurtosis that is greater than three and thus has an excess kurtosis greater than zero. High kurtosis is an indicator that data has heavy tails or outliers. The greater the excess kurtosis, the fatter the tails. These so-called fat tails are visible on all histograms by some outliers in the figure 12. The Q-Q-plot in figure 13 shows another view of the outliers in the Progressive Capital histogram.

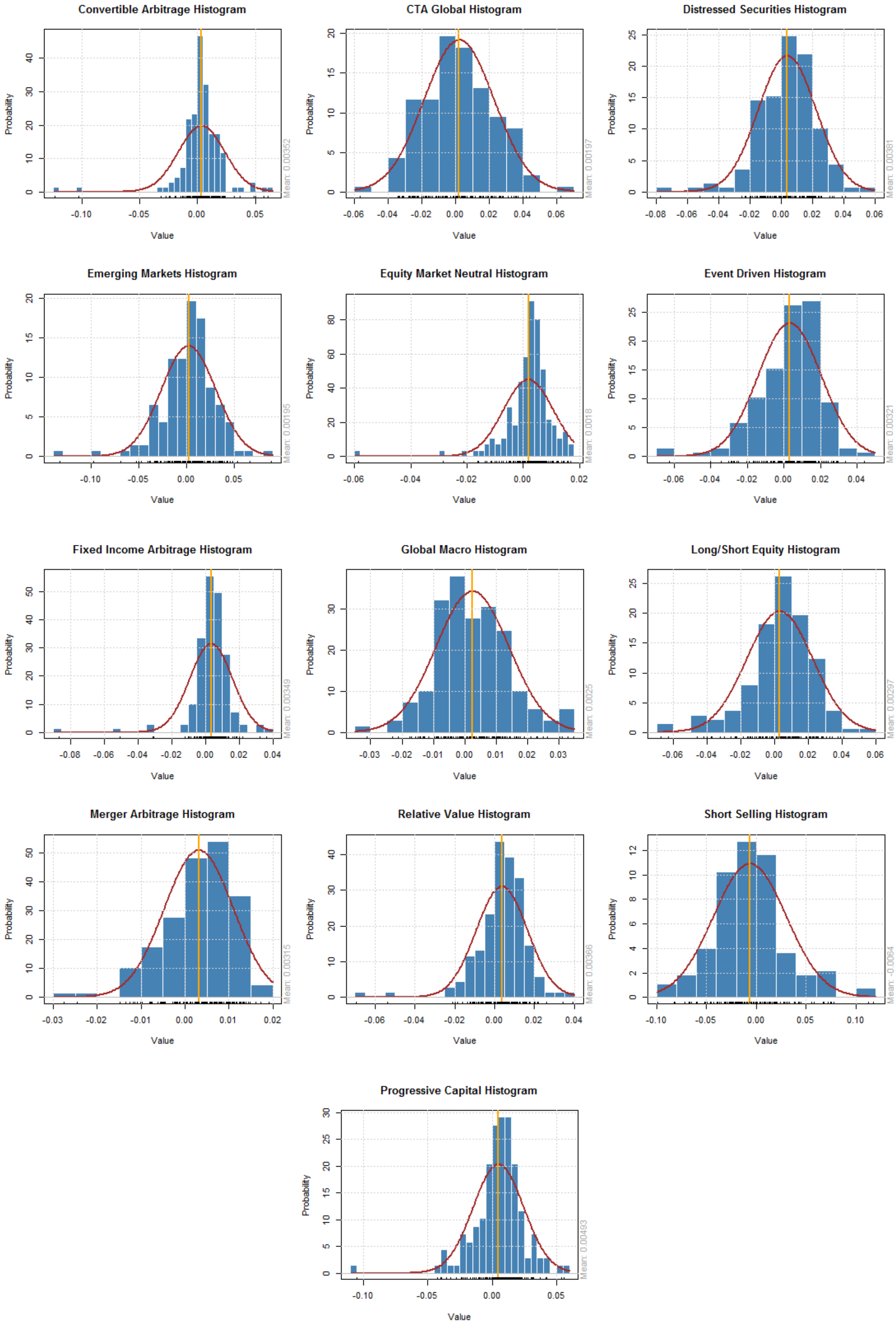

Figure 12: Histograms for hedge fund strategies

Figure 13 shows the distributions of Progressive Capital's monthly returns compared to the quantiles of the normal distribution. The thin black line represents the normal distribution line. On the lower left side, an outlier is clearly visible. Interestingly, with the exception of this outlier, the points line up quite closely along the normal distribution line. The returns of the niche alternatives of Progressive Capital seem to correspond to a normal distribution.

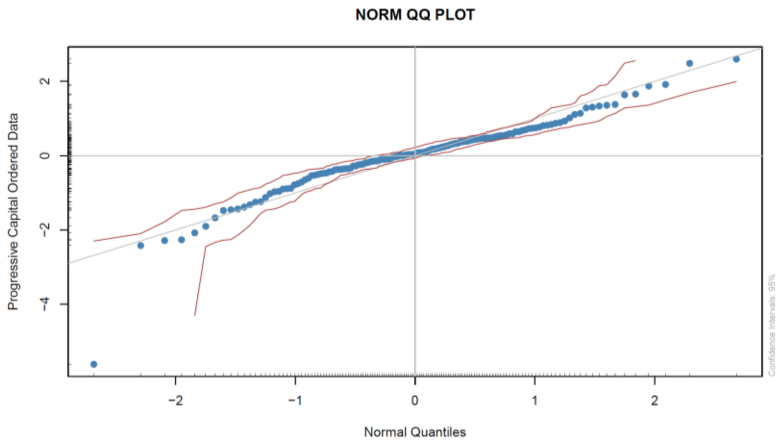

Figure 13: QQ-Plot of Progressive Capital returns

5.1.2.2 Cumulative Return

Figure 14 shows the normal cumulative returns for the EDHEC hedge fund strategies and Progressive Capital niche alternatives. The plot illustrates that Progressive Capital has the best performance, close to 200 %, during the sample period from August 2007 to December 2018. Due to a wealth index, the start point begins at 100 %. In contrast, short selling demonstrates a negative development over the years. All other strategies have similar cumulative returns ranging from 125 % to 175 %.

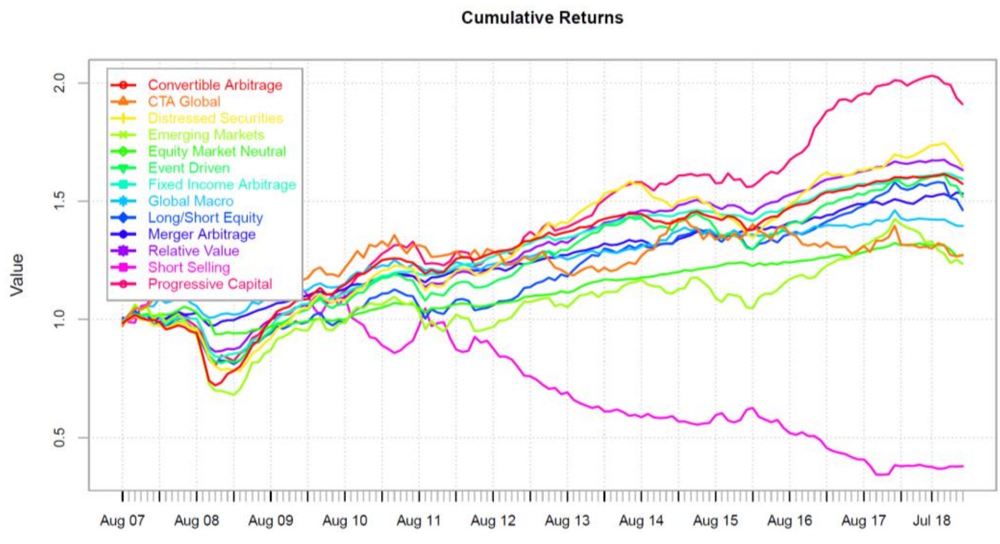

Figure 14: Cumulative returns of hedge fund strategies

Figure 15 on the following page visualizes a three-panel performance summary chart. The top chart is a normal cumulative return that shows the cumulative returns through time for Progressive Capital (black), HFRI index (red), S&P 500 (green), and SPI (blue). Progressive Capital performs significantly better than HFRI and SPI, but is slightly lower than the S&P 500.

The second chart presents the individual monthly returns overlaid with tail risk measurements referred to as Gaussian Value-at-Risk (VaR) and Gaussian Expected Shortfall (dotted line). The third chart in the series is a drawdown chart, which shows the level of losses from the last value of peak achieved. The drawdown is defined as any time the cumulative returns fall below the maximum cumulative returns. The drawdown of Progressive Capital is lowest compared to the others.

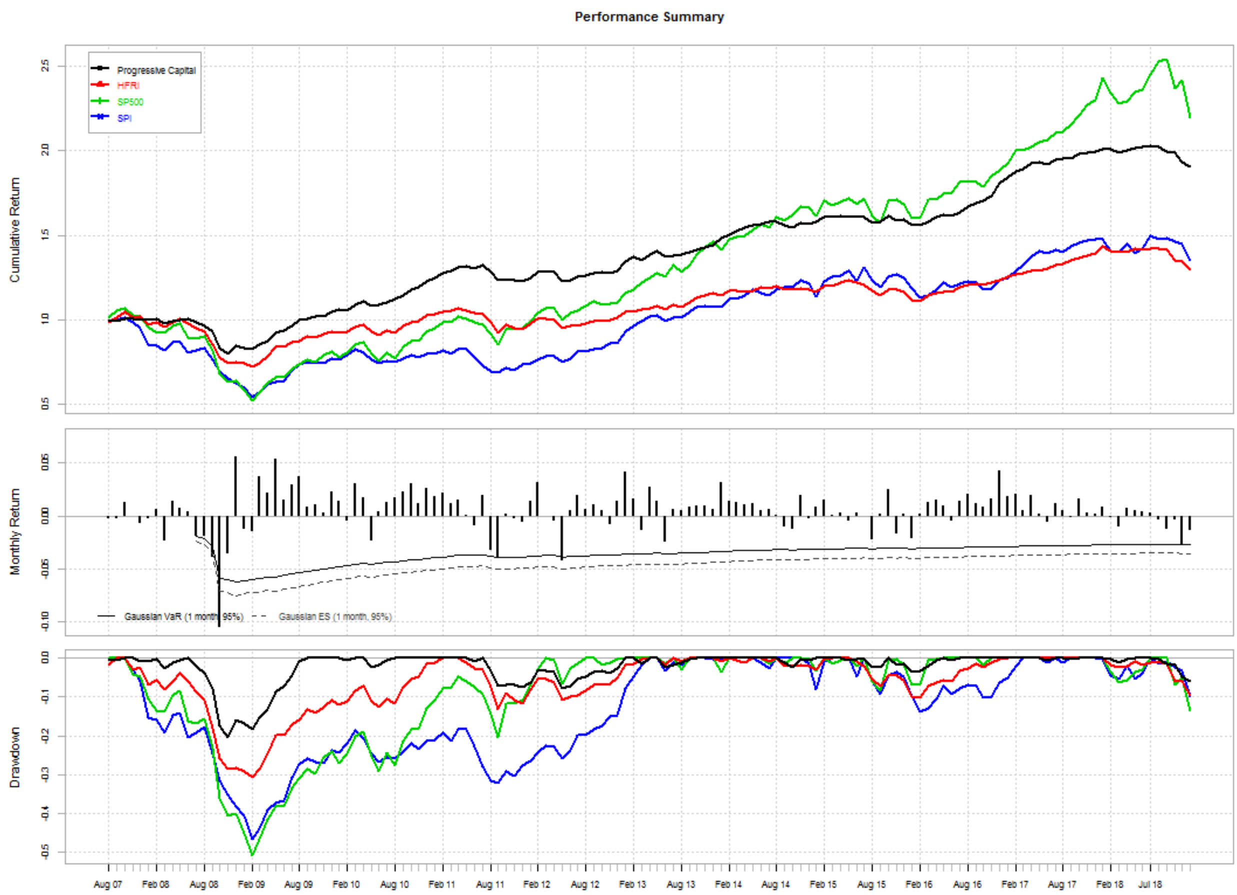

Figure 15: Performance summary of Progressive Capital, HFRI, S&P 500 and SPI

5.1.2.1 Correlation analysis

A correlation matrix is used to show the correlation between selected variables. Figure 16 indicates the correlation between Progressive Capital and other 17 risk factors for the sample period from August 2007 to December 2018. The data are based on monthly returns. The calculation of the correlation coefficients is based on Pearson and Spearman methods and range between -1 (red) and 1 (blue). The correlation of a variable with itself is always one (dark blue diagonal fields). HFRI and MSCI World ex USA show the highest correlation to Progressive Capital, each with 0.73. In addition, all government bonds such as the Switzerland 10Y Bond (CH_10Y), UK Gilt 10Y, and Germany Bond 10Y have a neutral behavior to Progressive Capital and thus are not correlated. VIX and trade weighted USD (TW_USD) are the only variables which negatively correlate (-0.38 and 0.59) to Progressive Capital returns. In addition, the Fama and French factors SMB and HML are low correlated to Progressive Capital with values of 0.2 and 0.14. Furthermore, the correlation matrix shows that equity-oriented risk factors have positive correlations to Progressive Capital and thus a linear relationship exists between these returns.

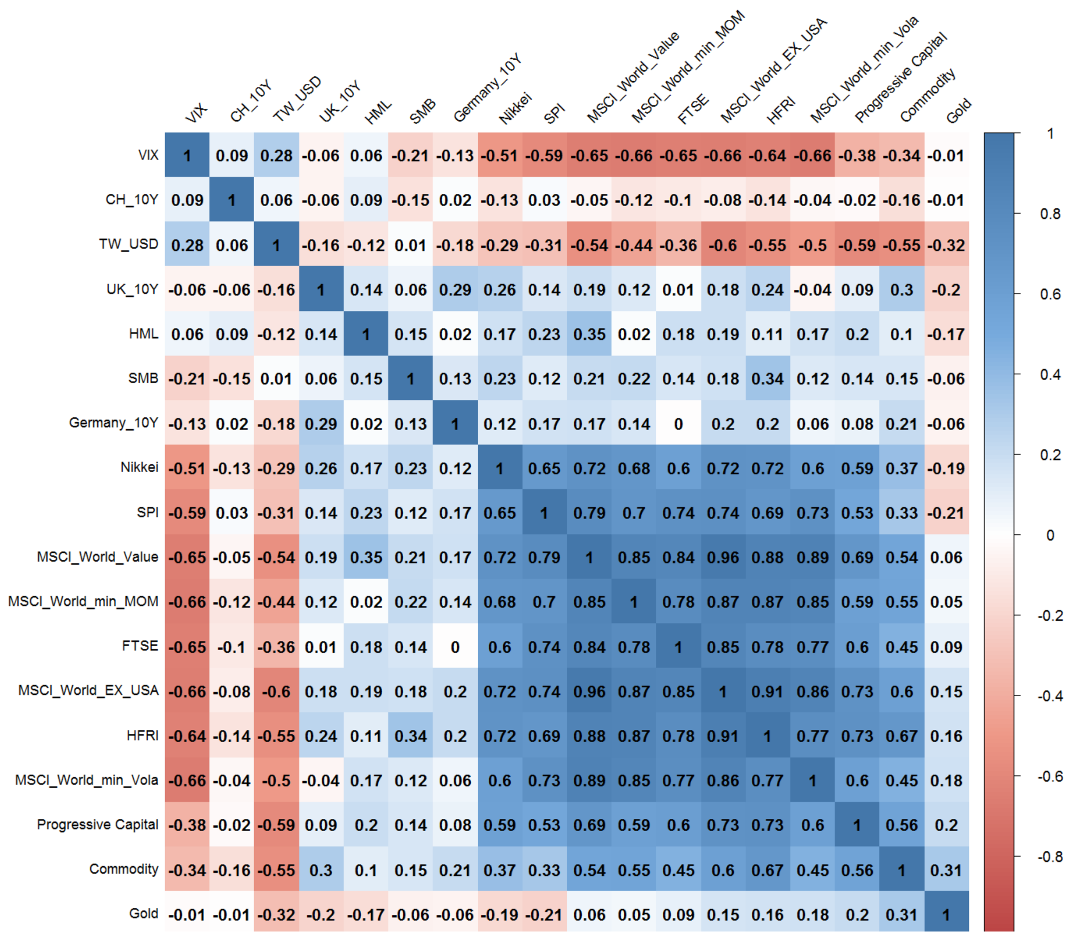

Figure 16: Correlation matrix of Progressive Capital and 17 risk factors

Figure 17 shows a pairwise scatterplot consisting of scatterplots for each variable combination of the data. Pairwise scatterplots are particularly useful for demonstrating the relationship and influence between two or more variables.
The pairwise scatterplot below indicates the relationships for five different variables, namely Progressive Capital, relative value, MSCI emerging markets, MSCI world ex USA, and HFRI monthly returns. The reason for choosing these four variables is their high correlation above 0.7 with Progressive Capital during the full sample period from August 2007 to December 2018. It becomes clear that all variables show a positive correlation and thus a linear relationship to Progressive Capital.

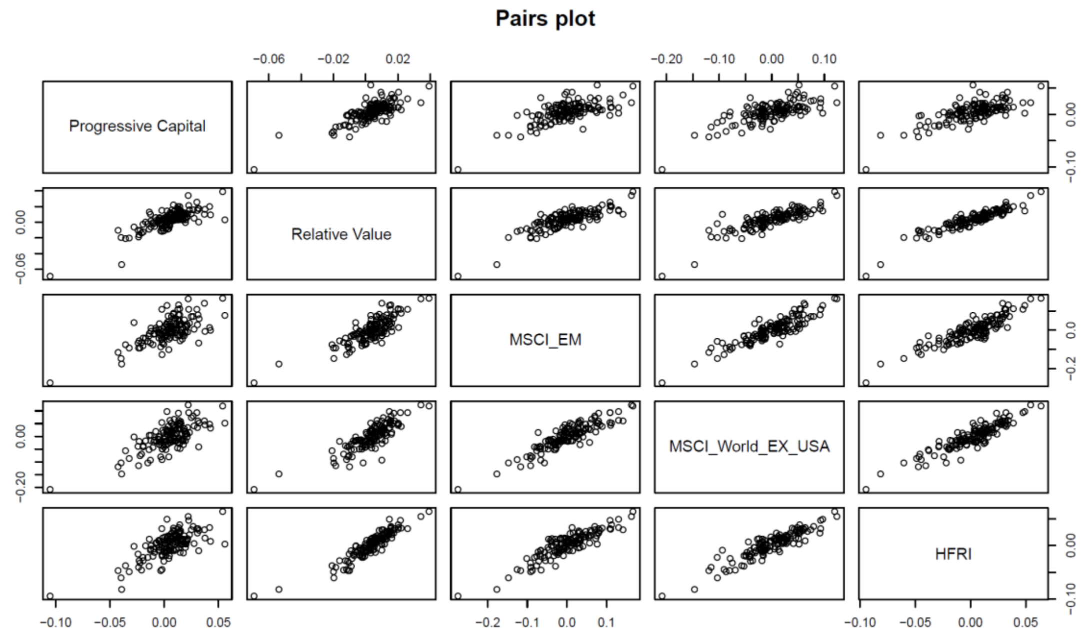

Figure 17: Pairwise scatterplot

5.1.2.2 Annualized risk-return profile

Figure 18 shows the annualized returns and risks to make a simple comparison over longer periods. The dotted three lines represent the Sharpe ratio levels from 1 to 3 (from right to the left). These lines are drawn with a y-intercept of the risk-free rate and the slope of the appropriate Sharpe ratio level. The chart demonstrates that emerging markets indicates the highest risk and, at the same time, the lowest return. In contrast, merger arbitrage shows the lowest risk and a proper return value. Thus, the Sharpe ratio of merger arbitrage is between the two and one levels. Short selling provides the worst risk-return profile of all hedge fund strategies. Finally, Progressive Capital indicates the highest return value above 5 % and, at the same time, an average risk value compared to the other strategies.

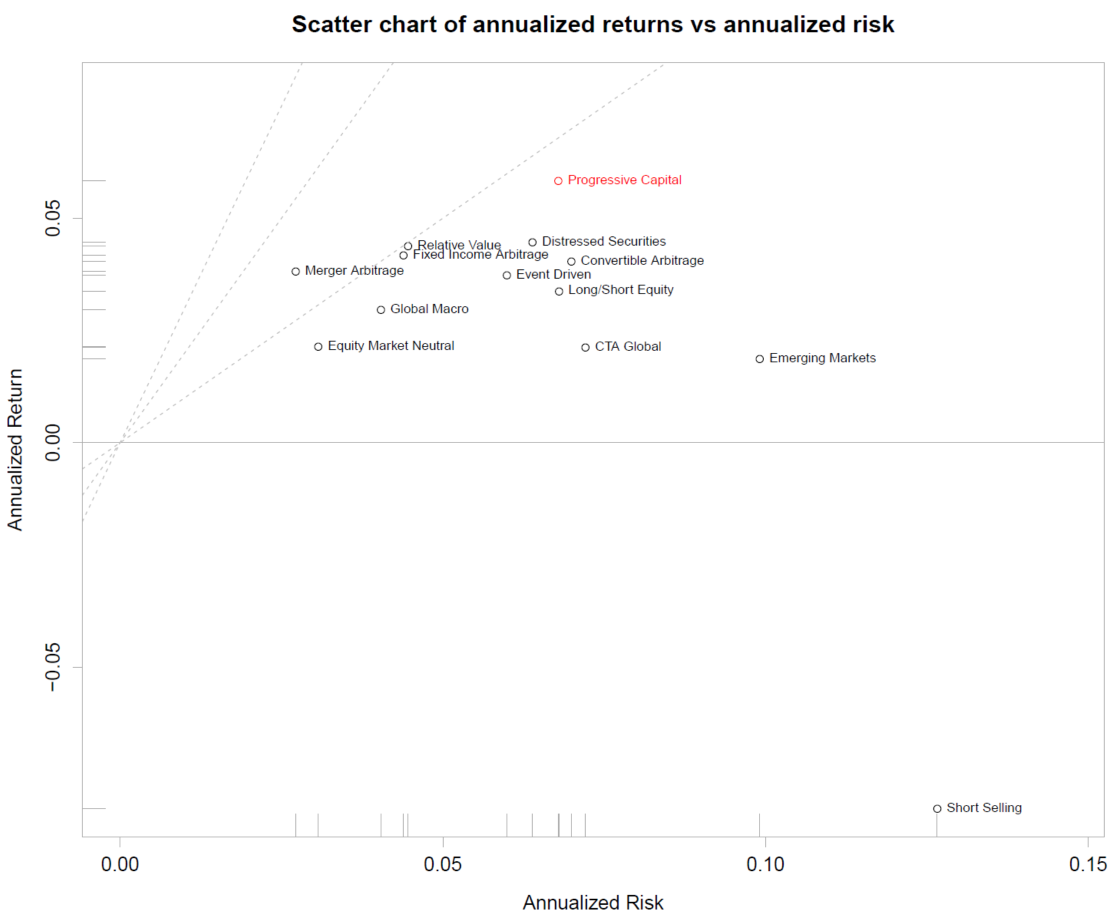

Figure 18: Scatterplot of annualized returns vs. annualized risks

Figure 19 shows box plots created for Progressive Capital and individual hedge fund strategy returns from the EDHEC database. A boxplot describes the distribution of a continuous variable by plotting its minimum, lower quartile (25th percentile), median (black line in the box), upper quartile (75th percentile), and maximum. It can also display observations that may be outliers, which are values outside the range of ± 1.5*IQR, where IQR is the interquartile range defined as the upper quartile minus the lower quartile. Values outside this range are depicted as dots. The red circles characterize the mean value for each hedge fund strategy. Progressive Capital demonstrates an extreme outlier at -0.10. In addition, the distribution of the box has a symmetrical form since the median is roughly in the center of the box. Short selling shows the greatest spread under all strategies and is skewed right. Furthermore, the boxes for fixed income arbitrage, merger arbitrage, and equity market neutral are very narrow, so the data are concentrated in the small range within the box that describes the mean 50 % of the data.

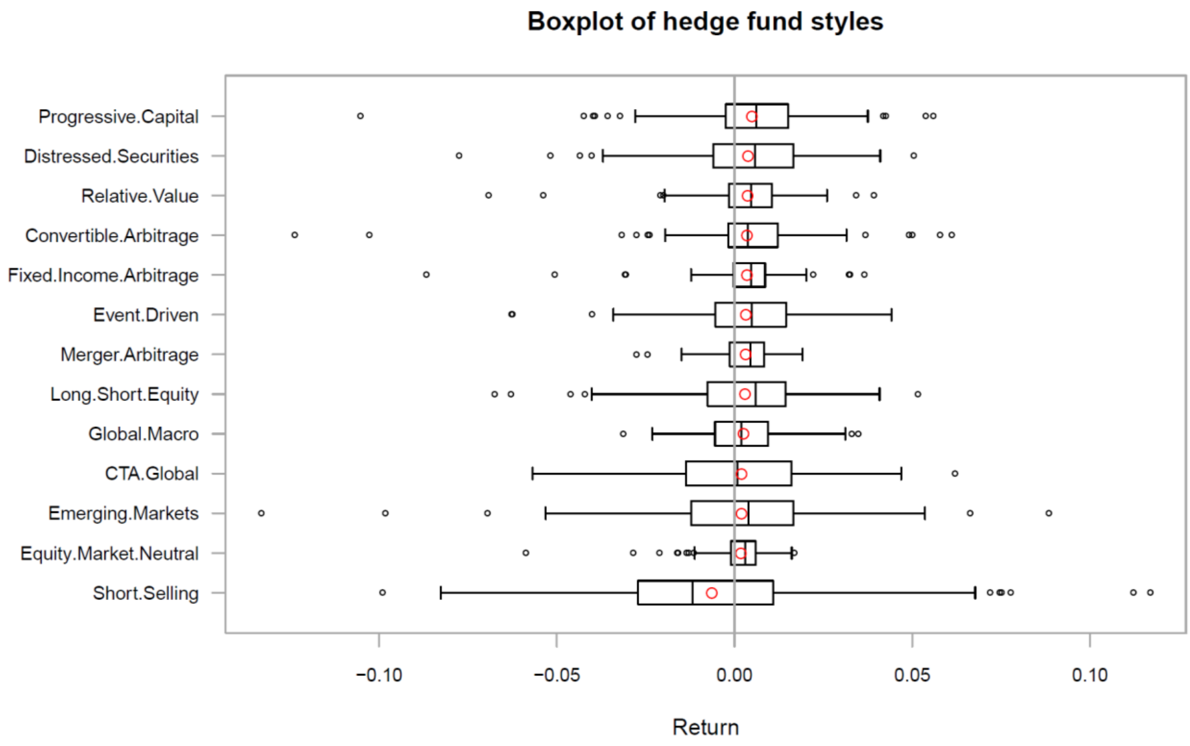

Figure 19: Boxplots of hedge fund strategies

5.2 Principal Component Analysis

The scatterplot matrix is often used to determine the relationship between the variables. The figure 20 below shows this representation with nine variables for the Fung and Hsieh eight-factor model and the niche alternatives of Progressive Capital. However, it becomes apparent that this representation reaches its limits, since the individual scatter plots are hardly readable. Therefore, the principal component analysis is used to determine a two-dimensional projection.

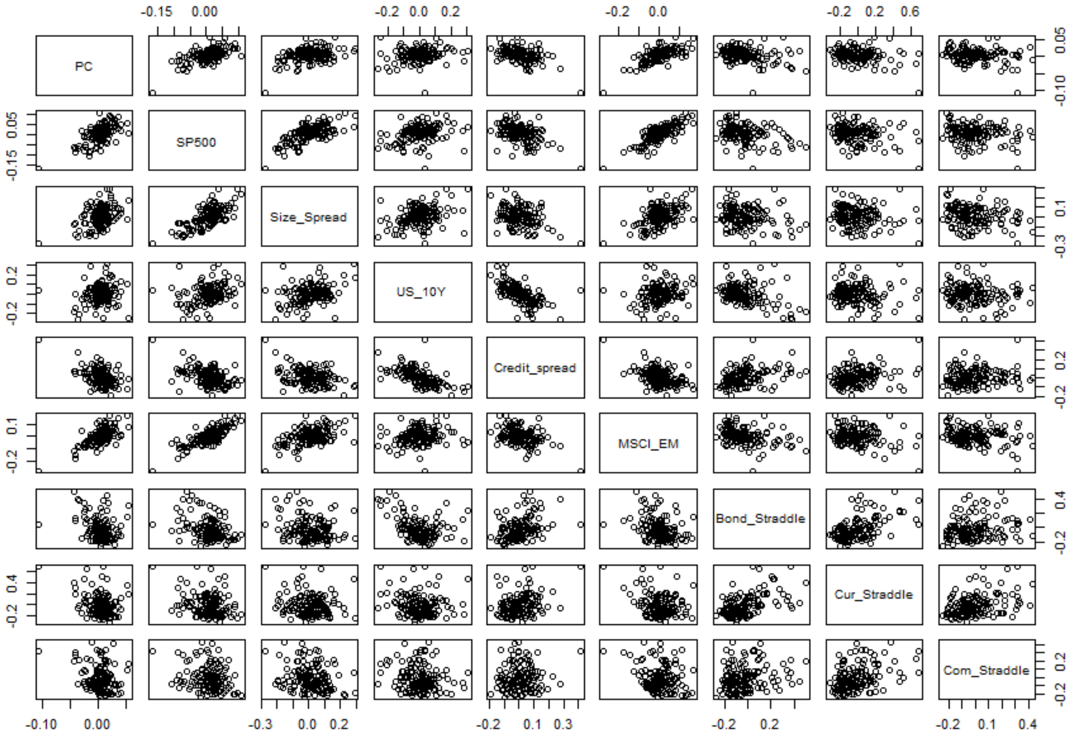

Figure 20: Scatterplot matrix. Relationship between Progressive Capital and Fung and Hsieh 8-factors

5.2.1 PCA applied on EDHEC and Progressive Capital returns

With regard to the principal component analysis, the biplot is often used. This is a two-dimensional scatter diagram of the principal components, which shows the data structure and the loadings of the first two components (relationship to the variables) on one graph. Figure 21 on the following page illustrates the biplot for the EDHEC and Progressive Capital hedge fund returns.

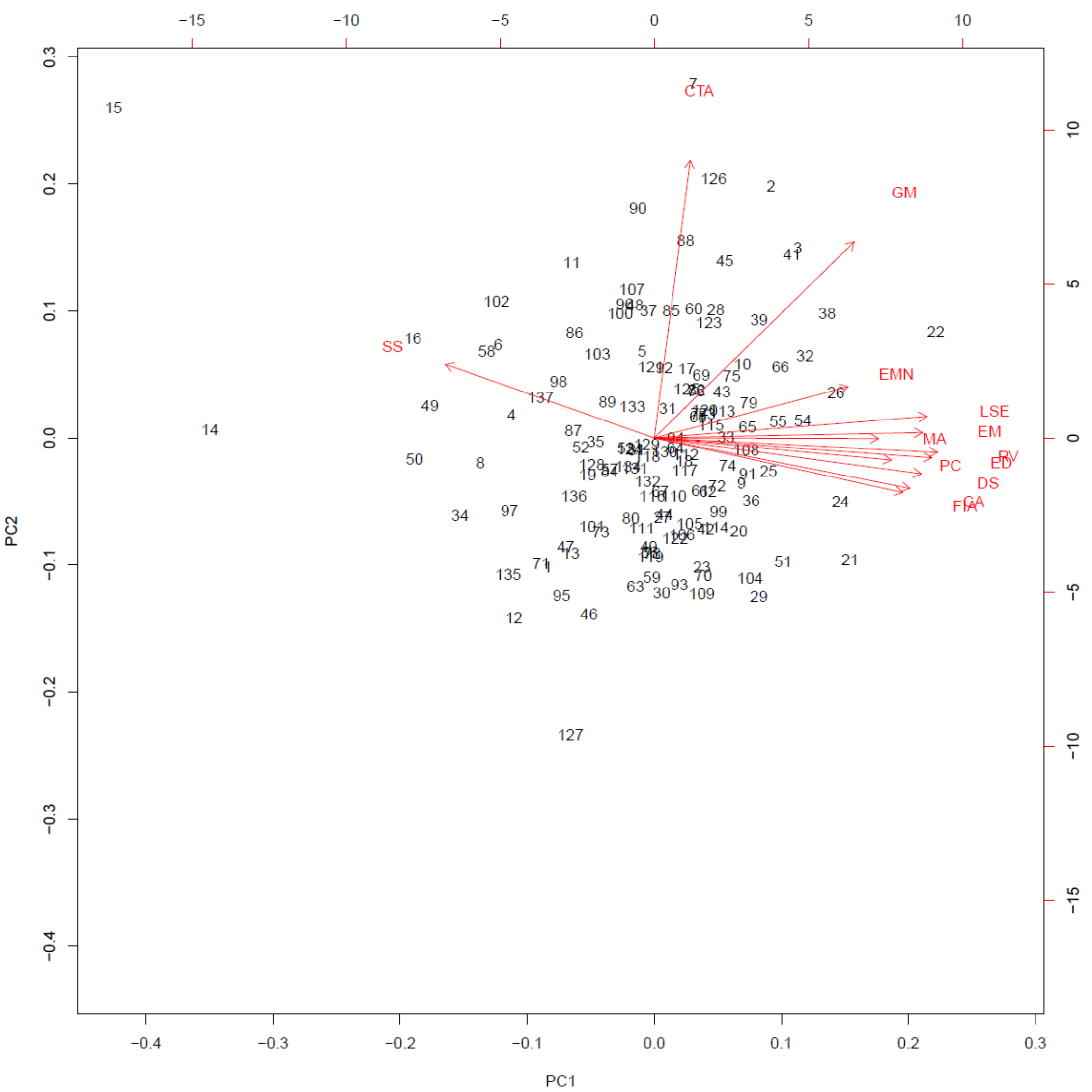

Figure 21: Biplot for EDHEC hedge fund investment strategies and Progressive Capital

The numbers represent the correlation matrix based on the returns for the period from August 2007 to December 2018. The biplot quickly shows which hedge funds are highly correlated with the respective principal components. Interestingly, almost all hedge fund styles, including Progressive Capital, are strongly positively correlated with the first principal component. Only the investment style SS (short selling) demonstrates a negative correlation. With regard to the second principal component, CA (convertible arbitrage) and FIA (fixed income arbitrage) show negative correlations whereas CTA and GM demonstrate strong positive correlations. In addition, it is noticeable that the observations are enclosed in a circular form and form a cluster within it. However, four outliers (7 = 29.02.2008, 14 = 30.09.2008, 15 = 31.10.2008, 22 = 29.05.2009, 127 = 28.02.2018) could be identified. It can be concluded that at least 9 of 13 hedge fund investment styles follow a similar trading strategy. This large number exhibits a homogeneous group of hedge fund strategies based on the statistical principal component analysis (PCA). In addition, five different strategies could be identified based on PCA, namely SS, CTA, GM, EMN, and the large group of nine strategies.

5.2.1.1 Optimal number of principal components

When using principal component analysis as a descriptive tool, the selected number of components should, as a rule of thumb, capture at least 75 % to 80 % of the variability in the data. Accordingly, an adequate representation of the projected data relative to the original data is ensured. In fact, the smallest number of components are selected so that the proportion of total variance explained by these principal components is at least 75 % or 80 % of the original variance. The requirement to cover at least 75 % to 80 % of the variance is somewhat arbitrary, but can be motivated by Pareto's 80/20 rule. In order to answer the question whether two principal components are sufficient to adequately represent the data according to these criteria or to reasonably approximate the variability of the data, some criteria have been applied. According to the Kaiser criterion, all components with an eigenvalue greater than one are taken into account to determine the optimum number of principal components.

The summary output in R, which summarizes the optimal number of principal components, is listed in table 12 below.

Importance of components					
	PC1	**PC2**	**PC3**	**PC4**	**PC5**
Eigenvalue (variance)	2.9627	1.2589	0.82603	0.78274	0.63293
Proportion of variance	0.6752	0.1219	0.05249	0.04713	0.03082
Cumulative proportion	0.6752	0.7971	0.84959	0.89672	0.92753

Table 12: Summary statistics for determination of the optimal number of principal components

The first component (PC1) covers 67.52% of the variability in the data. With the second component, 79.71 % of the variability is already covered, thus fulfilling the 75-25 rule.

According to the 80-20 rule of thumb for the eigenvalues, three principal components are sufficient, since their cumulative proportion is more than 80%. In these results, the first two principal components have eigenvalues greater than one. Thereby, these two components explain 79.71 % of the variability in the data.

Another popular criterion to determine the optimal number of principal components is the scree plot, which is displayed in figure 22. The rule of thumb is that the optimum number of principal components should be selected where the "elbow" appears in the screen diagram. The elbow is located at the start of the straight line near to the bottom of the right graph in figure 22. According to the scree plot, the eigenvalues start from a straight line after the second principal component, hence the optimal number of principal components is two. The same conclusion is reached with the criterion of Kaiser. Altogether, it becomes clear from all these considerations that two principal components are sufficient to adequately represent the variability in the data.

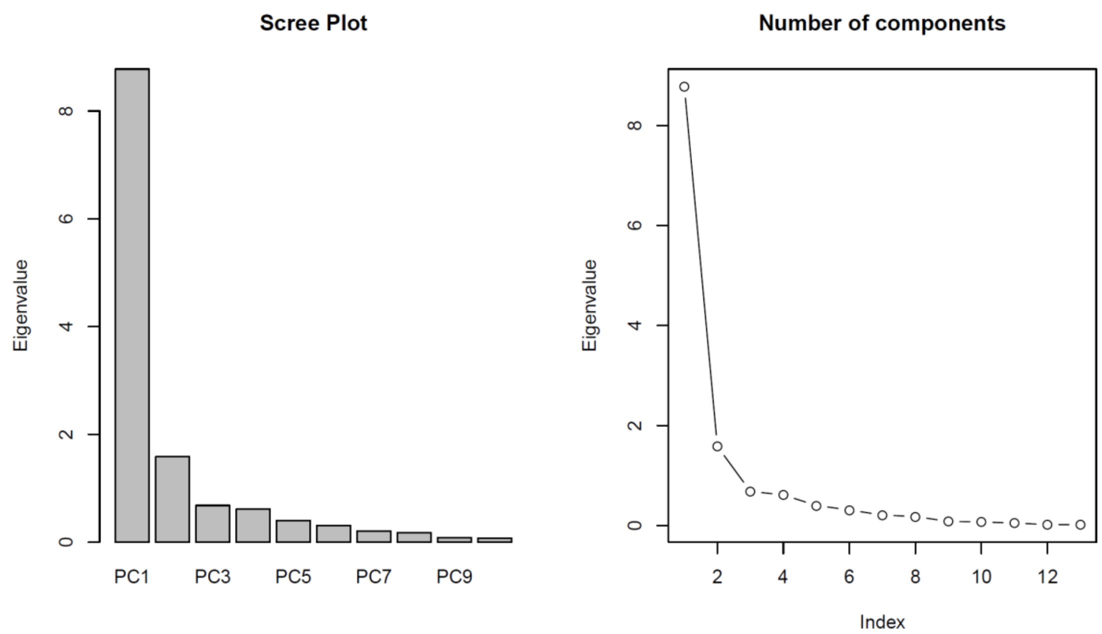

Figure 22: Screeplot

5.2.2 PCA applied on EDHEC and Progressive Capital returns with Fung and Hsieh eight-factor model

In this section, the principal component analysis is applied for all hedge fund strategies and niche alternatives of Progressive Capital returns associated with Fung and Hsieh eight-factor model. The aim is to categorize the individual hedge fund strategies and risk factors quantitatively in a two-dimensional space. Figure 23 shows the biplot for the mentioned factors.

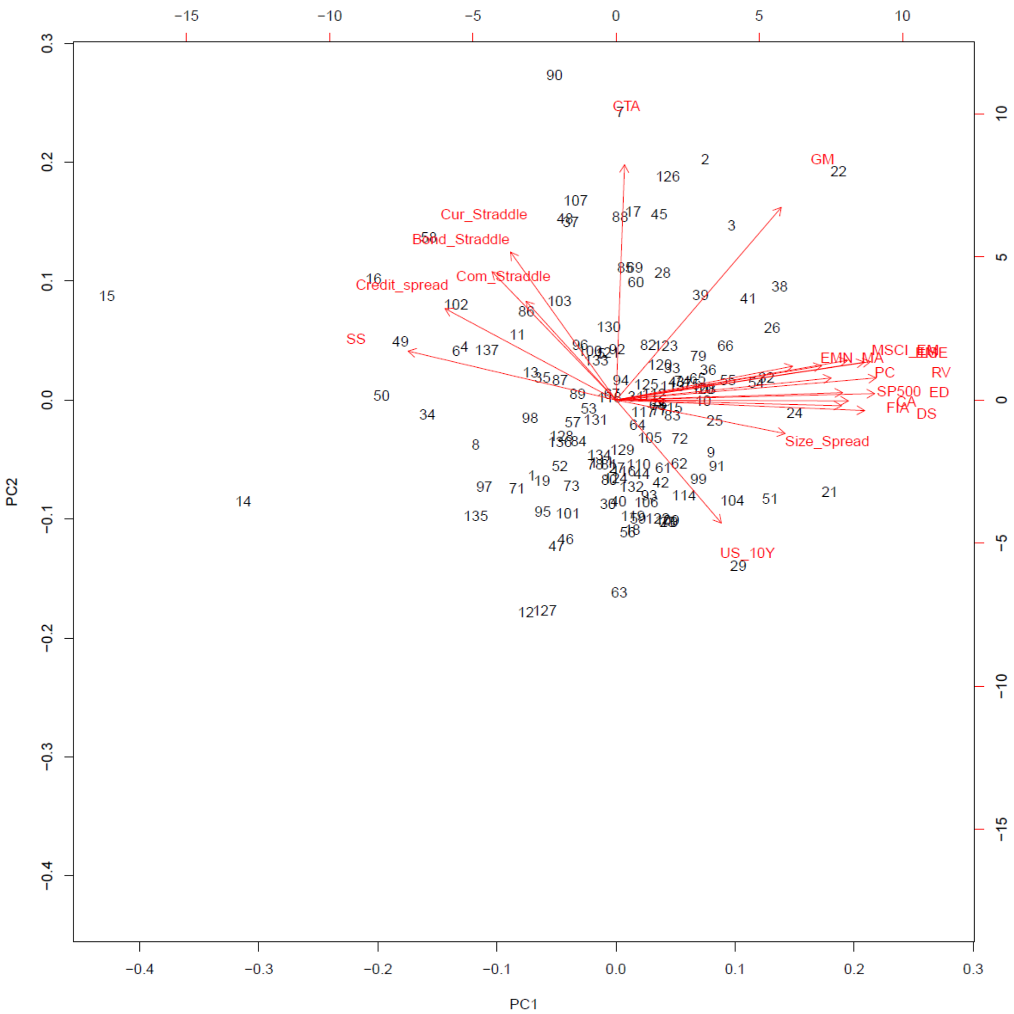

Figure 23: Biplot for EDHEC Hedge fund investment strategies and Progressive Capital with Fung and Hsieh eight-factor model

Figure 23 shows some clear patterns regarding the hedge fund strategies. On the right hand side, a large cluster depicts Progressive Capital, equity market neutral, long/short equity, merger arbitrage, relative value, event driven, distressed securities, fixed income arbitrage, and convertible arbitrage. In addition to those hedge fund strategies, there are also two risk factors, MSCI emerging markets and S&P 500, located in this cluster. These listed strategies and risk factors are positively correlated with the first principal component. In contrast, the primitive trend following strategies bond, currency, and commodity straddles are negatively correlated to the first principal component and positively correlated to the second principal component. The risk factor credit spread shows a similar characteristic. While size spread is close to the large group on the right hand side, US 10Y bond shows a unique character. Overall, Progressive Capital is in the middle of the large group and can be explained by the equity-oriented risk factors MSCI emerging markets and S&P 500. In total, four different hedge fund strategies could be identified, namely CTA global, global macro, short selling, and the remaining hedge fund strategies.

With regard to the optimal number of principal components, the summary output in table 13 provides important insights.

Importance of components					
	PC1	**PC2**	**PC3**	**PC4**	**PC5**
Eigenvalue (Variance)	3.389	1.5644	1.1347	1.0548	0.9442
Proportion of variance	0.547	0.1165	0.0613	0.0529	0.0424
Cumulative Proportion	0.547	0.6635	0.7248	0.7778	0.8203

Table 13: Summary statistics for determination of the optimal number of principal components

Table 13 presents the output summary. The first principal component with a proportion of 0.547 explains 54.7 % of the variability in the data. For assessing the total amount of variance that the continuous principal components explain, the cumulative proportion is used. In this case, two principal components explain 66.35 % of the data variability (see cumulative proportion). According to the 80-20 rule for eigenvalues, two principal components are not sufficient to present the variability in the data adequately. In agreement with this rule, five principal components are sufficient, since their cumulative proportion is over 80%. According to the Kaiser criterion, even four principal components are sufficient, since their eigenvalues are greater than one. Overall, it becomes clear from all these considerations that two principal components are not sufficient to present the variability in the data adequately.

5.2.3 PCA applied on Progressive Capital and risk factors

In this section, the same methods are applied as in the previous section 5.2.1 for the same sample period between August 2007 and December 2018. Only the data has changed. Now the principal component analyses are used for niche alternatives of Progressive Capital and the associated risk factors. The goal is again to categorize the individual variables quantitatively in a two-dimensional space. For the PCA, the biplot were used, as illustrated in figure 24.

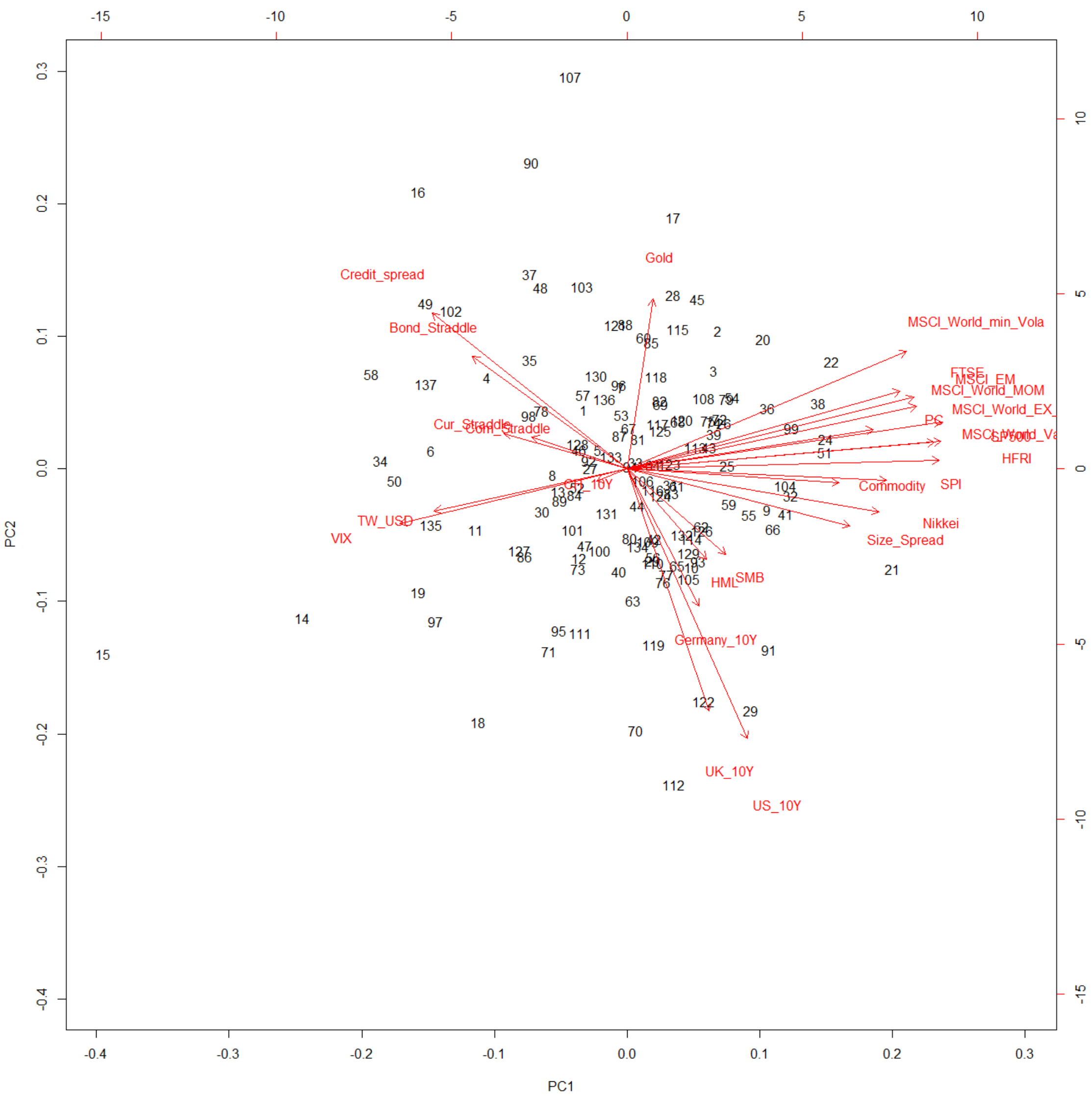

Figure 24: Biplot for Progressive Capital and risk factors

The biplot shows clear patterns in the implemented data. A large cluster of risk factors can be seen on the right side. This cluster contains the risk factors of HFRI, S&P 500, FTSE, MSCI value, MSCI momentum, MSCI EX USA, MSCI emerging markets, and Progressive Capital. All these variables are strongly positively correlated with the first

principal component. While the Germany 10Y, UK gilt, and US 10Y bonds show almost identical directions and are strongly negatively correlated with the second principal component, the CH 10Y Bond is somewhat uncorrelated with both principal components. For commodities, gold indicates a strong positive correlation to the second principal component, and the commodity index shows a positive correlation to the first principal component. Fama and French's risk factors SMB and HML form a separate cluster and are both negatively correlated with the second principal component. In conclusion, evidence suggests that the niche alternatives of Progressive Capital are characterized by equity-oriented assets. In total, approximately nine clusters are identified. Extreme outliers are the numbers **15** (31.10.2008) and **107** (30.06.2016).
With regard to the optimal number of principal components, the summary output in table 14 provides important insights.

Importance of components								
	PC1	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**	**PC8**
Eigenvalue (Variance)	3.3562	1.6092	1.3673	1.25273	1.14175	1.09423	0.97058	0.87027
Proportion of variance	0.4332	0.0996	0.0719	0.06036	0.05014	0.04605	0.03623	0.02913
Cumulative proportion	0.4332	0.5329	0.6048	0.66511	0.71524	0.76129	0.79753	0.8266

Table 14: Summary statistics for determination of the optimal number of principal components

The summary abstract indicates that the first principal component with a proportion of 0.4332 explains 43.32 % of the variability in the data. The second principal component has a smaller proportion of 0.0996 and thus explains only 9.96 % of the data variability.
Accordingly, two principal components explain 53.29 % of the data variability. However, this value does not conform to the 80-20 rule. According to the 80-20 rule for the eigenvalues, eight principal components are sufficient, since their cumulative proportion is more than 80%. According to the Kaiser criterion, six principal components are sufficient, since their eigenvalues are greater than one. Overall, it becomes clear from all these considerations that two principal components are not sufficient to present the variability in the data adequately.
In Appendix 8.1.5, the results of PCA applied on EDHEC and Progressive Capital returns with Fung and Hsieh eight-factor model are added.

5.3 Multi-factor models analysis

In the following chapter, the test statistics of the regression analyses for the assessment of the performance of hedge funds strategies and niche alternatives are presented for the full sample period from August 2007 to December 2018. The time series of the 13 hedge fund strategies are regarded as target variables. The first step is to test which explanatory (risk factors) variables have a significant influence on each hedge fund strategy. The second step is to measure the alpha of each hedge fund. The risk-free interest rate is 0 %. Finally, the question of the optimal choice of factor model is answered with the help of stepwise regression.

The models are based on monthly returns. The statistically significant values are marked with different levels of stars. The values with one star (*) are significant at the 5 % level, with two stars (**) at the 1 % level and with three stars (***) at the 0.1 % level. In table 17, the t-statistics are in parentheses.

This chapter is organized as follows. The first section explains the results of the Fung and Hsieh seven-factor model reported in Table 15. The second part discusses the results of the Fung and Hsieh eight-factor model, which are displayed in table 16. Thereafter, the third part explains the results of stepwise regression for EDHEC's hedge fund strategies in detail. The results are shown in Table 17. Finally, the fourth section presents the results of the Fund and Hsieh seven/eight-factor model and stepwise regression for niche alternatives of Progressive Capital reported in Table 18.

5.3.1 Results from Fung and Hsieh seven-factor model (EDHEC hedge fund strategies)

Table 15 reports the intercepts (alphas), coefficients (betas), t-statistics (t), the p-values (p), and the adjusted r-squares (R^2) for the twelve hedge fund strategy indices estimated by the Fung and Hsieh seven-factor model. Over all twelve hedge fund strategies, the average alpha is 0.0014 and the average adjusted R^2 is 0.53.

The estimated results show that all hedge fund strategies are significantly exposed to the risk factor S&P 500. Apart from the fact that S&P 500 is negative for short selling, it indicates a significant positive value for all other strategies. Thus, S&P 500 become a dominant risk factor in the multi factor model. The test statistics also indicate that six out of twelve hedge fund strategies provide a significant alpha. Fixed income arbitrage strategy has the highest alpha of 0.3 % (0.0030). In contrast, emerging markets and short selling provide negative insignificant alphas -0.07% (-0.0007) and -0.015 % (-00015) and thus are the smallest values.

For L/S equity and merger arbitrage strategies, only the risk factor S&P 500 is significant. With regard to performance, L/S equity has a positive insignificant alpha of 0.058 %, whereas merger arbitrage has a positive significant alpha of 0.24 %.

Distressed securities, emerging markets, event driven, and relative value show the same risk exposure. They are exposed to risk factors S&P 500, credit spread, and commodity straddle. These four strategies also have a similar adjusted R^2 value ranging between 0.61 and 0.71.

Only equity market and short selling are exposed to the risk factor bond straddle. This risk factor shows for both significant coefficients of -0.013 and 0.038.

CTA global is significantly exposed to S&P 500, size spread, US **b**ond 10Y, and currency straddle. It has an insignificant alpha of 0.0016 and the lowest adjusted R^2 of 0.24.

5.3.2 Results from the Fung and Hsieh eight-factor model (EDHEC hedge fund strategies)

Table 16 reports the results of the Fung and Hsieh eight-factor model. Over all twelve hedge fund strategies, the average alpha is 0.0020 and the average adjusted R^2 is 0.61. With regard to the significance of alphas, a total of nine out of twelve hedge fund strategies demonstrate a positive significant alpha ranging from 0.14 % to 0.37 %. Particularly high alphas are observed for the strategies convertible arbitrage, fixed income arbitrage, and relative value. Convertible arbitrage has the highest alpha of 0.37 %, while short selling shows a negative insignificant alpha of -0.20 %, which is at the same time the lowest.

Compared to the seven-factor model, there are now three more significant alphas identified, namely for equity market, event driven, and L/S equity strategies. However, the explanatory power of S&P 500 is not strong as in the seven-factor model. This could be related to the fact that the eighth factor MSCI emerging factor has been added. This risk factor exhibits significant coefficients to eleven hedge fund strategies.

Concerning adjusted R^2, the addition of the MSCI emerging market factor increased not only the adjusted R^2 of emerging markets strategy but also all eleven hedge fund strategies, which indicates that these strategies are involved by investing in emerging markets and thus higher adjusted R^2 for all strategies are observed. In fact, the highest increase in R^2 is observed for the strategies emerging markets (increased from 0.61 to 0.89) and global macro (from 0.30 to 0.45).

5.3.3 Results from stepwise regression on EDHEC hedge fund investment strategies

Table 17 shows the results of stepwise regression for twelve hedge fund investment strategies' monthly returns during the full sample period from August 2007 to December 2018. The table demonstrates the intercept (α) with t-statistics in parentheses, regression coefficients (β) on 25 risk factors, and adjusted R^2.

The overall results show that except for CTA global, equity market, and short selling, all other strategies have statistically significant intercepts (alphas), which range from 0.09 % (L/S equity) to 0.38 % (convertible arbitrage). Over all twelve hedge fund strategies, the average alpha is 0.17 %. The adjusted R^2 values are in general impressively high and range between 0.52 to 0.98. The average adjusted R^2 across all twelve hedge fund strategies is 0.78. Compared to the Fung and Hsieh 7/8-factor models, the adjusted R^2 values of the stepwise regression are higher for all hedge fund strategies. The high adjusted R^2 results indicate that these risk factors have significant explanatory power over returns of the hedge fund strategies. Furthermore, all risk factors have significant explanatory power to hedge fund strategies.

Equity market is exposed to a large number of 17 risk factors, in which the highest coefficients belong to HFRI (0.5) and MSCI ex USA (0.287). Thus, equity market possesses the greatest number of risk factors in the stepwise regression model to which it is exposed. Equity market has an insignificant alpha of 0.08 % and an adjusted R^2 of 0.6676

Merger arbitrage strategy is exposed to the least number of factors, namely six. It has the largest exposure to HFRI factor, next to MSCI value, and negative exposure to UK Bond 10Y, VIX, MSCI min Vola, and HML. The strategy has a significant alpha of 0.3 % and an adjusted R^2 of 0.5894.

Only CTA global and global macro are exposed to the risk factor commodity straddle. This risk factor results in a significant coefficient of 0.024 for the CTA global strategy, but is not significant in global macro strategy.

FTSE 100 and CH Bond 10Y significantly explain only for emerging markets, relative value, and short selling. The VIX index significantly explains only for CTA global

strategy. Thus, these risk factors do not belong to the dominant factors among all hedge fund strategies.
In contrast, the HFRI factor gains the most popularity for the hedge fund strategies. This factor has, in all strategies except short selling strategy, a significant exposure with highest coefficients.
With regard to the Fung and Hsieh factors, three out of eight factors have a strong explanatory power over many hedge fund strategies. These are the size spread, credit spread, and MSCI emerging markets factors. Moreover, 9 of 12 hedge fund strategies are exposed to the size spread factor. The MSCI emerging factor also explains for the most strategies (7 of 12), while the credit spread factor explains half of the strategies.
The five Fung and Hsieh factors S&P 500, US bond 10Y, bond straddle, currency straddle, and commodity straddle do not offer significant explanations to many strategies.

In terms of the Fama and French factors, the size factor SMB has significant coefficients for convertible arbitrage, CTA global, distressed securities, equity market, event driven, global macro, L/S equity, and short selling, and one insignificant coefficient for fixed income. The Fama and French value factor HML indicates an influence on CTA global, distressed securities, emerging markets, equity market, event driven, and merger arbitrage.

5.3.4 Results from the Fung and Hsieh 7/8-factor model and stepwise regression (Progressive Capital)

Table 18 presents the results of the Fung and Hsieh 7/8-factor models and stepwise regression of niche alternatives of Progressive Capital monthly returns on 25 risk factors. The results show that Progressive Capital has a statistically significant alpha of 0.47 % for the stepwise regression. This alpha is a slightly higher than the alpha from the Fung and Hsieh 7/8-factor model (0.37 % and 0.44 %). The value for the adjusted R^2 based on stepwise regression amounts to 0.666 and is therefore higher than the Fung and Hsieh 7/8-factor model (0.45 and 0.50). This high R^2 indicates that these risk factors have a significant explanatory power over Progressive Capital returns.
With regard to the Fung and Hsieh 7/8-factor models, none of the primitive trend following factors bond-, currency-, and commodity straddles influence the returns of Progressive Capital. All these factors have insignificant coefficients.

In the seven-factor model, Progressive Capital has the largest significant exposure to S&P 500 with a coefficient of 0.22. Furthermore, Progressive Capital has statistically significant negative exposure to US bond 10Y and credit spread.
With respect to the eight-factor model, Progressive Capital is significantly exposed to credit spread and MSCI emerging markets. While credit spread has a positive coefficient, MSCI emerging markets shows a negative coefficient.
Concerning the stepwise regression, Progressive Capital is significantly exposed to ten risk factors. It has the largest exposure to HFRI, next to MSCI ex USA, Nikkei 225, commodity index, VIX index, and negative exposure to credit spread, US government 10Y bond, MSCI emerging markets, MSCI momentum, and trade weighted USD index.
In terms of the Fama and French factors, both the SMB and HML factors do not influence the niche alternatives.

For comparison reasons, the selected models for all 13 hedge fund strategies based on the stepwise regression perform better than Fung and Hsieh models based on the adjusted R^2 indicator. The average adjusted R^2 is highest 0.77 for the stepwise regression model, 0.60 for the Fung and Hsieh eight-factor model and lowest with 0.53 for the Fung and Hsieh seven-factor model. This indicates that the risk factors that are used in the stepwise regression explain the variation of hedge fund returns better than the Fung and Hsieh factor models do. This argumentation can be explained by the fact that more than eight factors have been taken into account in stepwise regression.
Interestingly, the stepwise regression of all 13 hedge fund strategies demonstrates that Progressive Capital and equity market have the same adjusted R^2 of 0.66.
Most importantly, with regard to alpha, the results show that the average alpha is highest at 0.22 % for the Fung and Hsieh eight-factor model, 0.19 % for the stepwise regression model, and lowest with 0.16 % for the Fung and Hsieh seven-factor model. According to these results, Progressive Capital performs better in all three models than the average alphas of EDHEC hedge fund strategies. The highest alpha of 0.47 % was achieved by the stepwise regression approach. There is also an improvement of the alphas from the eight-factor model compared to the seven-factor model for all hedge fund strategies except short selling.

With regard to the explanatory power, there is also an enhancement of adjusted R^2 for all hedge fund strategies. The most significant gain was achieved by the strategies emerging markets (from 0.61 to 0.89) and global macro (from 0.30 to 0.45)
Overall, the larger set of risk factors used for stepwise regression seems to substantially increase the explanatory power for hedge fund strategies (e.g., niche alternatives from Progressive Capital, relative value, global macro etc.), while for others, the explanatory power of the three models is virtually identical (short selling).

Table 15: Summary Output of 7-factor model for EDHEC hedge fund strategies

Fung and Hsieh seven-factor model	Convertible Arbitrage			CTA Global			Distressed Securities			Emerging Markets			Equity mark. neutral			Event Driven		
	Coeff	***t***	***p***	***Coeff***	***t***	***p***	***Coeff***	***t***	***p***	***Coeff***	***t***	***p***	***Coeff***	***t***	***p***	***Coeff***	***t***	***p***
Intercept	0.0028	2.304	0.022*	0.0016	1.036	0.302	0.0023	2.433	0.016*	-0.0007	-0.497	0.620	0.0012	1.820	0.071.	0.0014	1.833	0.069
S&P 500	0.1891	4.514	0.00***	0.2066	3.764	0.0***	0.204	6.147	0.00***	0.451	8.397	0.00***	0.057	2.563	0.011*	0.240	8.650	0.00***
Size Spread	-0.006	-0.358	0.720	-0.050	-2.284	0.024*	0.008	0.663	0.508	-0.028	-1.308	0.193	0.006	0.687	0.493	0.008	0.786	0.433
US 10Y	-0.036	-2.177	0.031*	-0.052	-2.407	0.017*	0.007	0.587	0.558	-0.033	-1.572	0.118	0.007	0.849	0.397	0.011	1.046	0.297
Credit Spread	-0.110	-5.802	0.00***	0.014	0.573	0.567	-0.063	-4.222	0.00***	-0.085	-3.517	0.00***	-0.015	-1.514	0.132	-0.042	-3.334	0.001**
Bond Straddle	0.005	0.548	0.584	0.007	0.555	0.579	-0.009	-1.182	0.239	-0.015	-1.182	0.239	-0.013	-2.450	0.015*	-0.007	-1.193	0.235
Currency Straddle	-0.011	-1.470	0.144	0.027	2.777	0.006**	-0.003	-0.577	0.565	0.0023941	0.242	0.808830	0.008	1.998	0.047*	0.0004	0.094	0.925
Commodity Straddle	-0.021	-2.388	0.018*	0.022	1.913	0.057.	-0.014	-1.987	0.049*	-0.023	-2.078	0.039*	-0.006	-1.262	0.209	-0.013	-2.377	0.018*
	R^2: 0.5313			R^2: 0.2423			R^2: 0.6464			R^2: 0.6153			R^2: 0.2965			R^2: 0.7187		
	Fixed Income Arbit.			**Global Macro**			**L/S Equity**			**Merger Arbitrage**			**Relative Value**			**Short Selling**		
Intercept	0.0030	3.896	0.00***	0.0017	2.045	0.043*	0.00058	0.678	0.498	0.0024	4.767	0.00***	0.0026	4.112	0.00***	-0.0015	-0.855	0.394
S&P 500	0.115	4.385	0.00***	0.191	6.518	0.00**	0.339	11.430	0.00***	0.1047	5.859	0.00***	0.1837	8.423	0.00***	-0.373	-6.108	0.00***
Size Spread	-0.006	-0.639	0.523	-0.021	-1.774	0.078	0.007	0.617	0.538	0.0040	0.555	0.580	-0.0028	-0.320	0.749	-0.122	-4.931	0.00***
US 10Y	-0.031	-3.005	0.003**	-0.013	-1.197	0.233	0.016	1.436	0.153	-0.003	-0.524	0.601	-0.01353	-1.569	0.119	-0.00002	-0.001	0.999
Credit Spread	-0.074	-6.235	0.00**	-0.009	-0.678	0.498	-0.017	-1.290	0.199	-0.009	-1.164	0.247	-0.0508	-5.144	0.00***	0.0089	0.323	0.747
Bond Straddle	-0.002	-0.331	0.741	0.0029	0.418	0.676	-0.004	-0.603	0.547	0.003	0.711	0.478	-0.0019	-0.366	0.714	0.0389	2.669	0.008**
Currency Straddle	-0.007	-1.529	0.128	0.014	2.731	0.007**	0.001	0.297	0.767	-0.0019	-0.596	0.552	-0.0019	-0.481	0.631	0.0226	2.015	0.045*
Commodity Straddle	-0.008	-1.546	0.124	0.002	0.352	0.725	-0.010	-1.747	0.082	-0.005	-1.522	0.130	-0.0108	-2.361	0.019*	0.0036	0.282	0.778
	R^2: 0.5287			R^2: 0.3063			R^2: 0.7511			R^2: 0.4353			R^2: 0.6871			R^2: 0.6961		

Fung and Hsieh eight-factor model *Table 16: Summary Output of 8-factor model for EDHEC hedge fund strategies*

	Convertible Arbitrage			**CTA Global**			**Distressed Securities**			**Emerging Markets**			**Equity mark. neutral**			**Event Driven**		
	Coeff	***t***	***p***	***Coeff***	***t***	***p***	***Coeff***	***t***	***p***	***Coeff***	***t***	***p***	***Coeff***	***t***	***p***	***Coeff***	***t***	***p***
Intercept	0.0037	3.349	0.001**	0.0021	1.314	0.191	0.0029	3.213	0.001**	0.0016	1.957	0.052	0.0014	2.265	0.025*	0.0021	2.886	0.004**
S&P 500	0.0204	0.416	0.677	0.1251	1.779	0.077	0.0954	2.362	0.019*	0.0218	0.608	0.544	0.0083	0.292	0.770	0.1248	3.865	0.00***
Size Spread	-0.0019	-0.124	0.901	-0.0487	-2.210	0.028*	0.0116	0.917	0.360	-0.0178	-1.586	0.115	0.0075	0.840	0.402	0.0117	1.157	0.249
US 10Y	-0.0159	-1.035	0.302	-0.0425	-1.920	0.057	0.0206	1.626	0.106	0.0177	1.570	0.118	0.0134	1.502	0.135	0.0252	2.484	0.014*
Credit Spread	-0.0872	-4.923	0.00***	0.0253	0.999	0.319	-0.0487	-3.343	0.001**	-0.0271	-2.093	0.038*	-0.0087	-0.850	0.397	-0.0262	-2.251	0.026*
MSCI EM	0.1532	5.423	0.00***	0.0740	1.826	0.070	0.0989	4.251	0.00***	0.3905	18.896	0.00***	0.0449	2.743	0.006**	0.1051	5.649	0.00***
Bond Straddle	0.0109	1.202	0.231	0.00991	0.759	0.449	-0.0058	-0.780	0.437	-0.0012	-0.186	0.852	-0.0115	-2.192	0.030*	-0.0041	-0.695	0.488
Currency Straddle	-0.0118	-1.705	0.090.	0.0277	2.774	0.006**	-0.0038	-0.677	0.499	0.0009	0.188	0.850	0.0081	2.006	0.046*	0.00009	0.020	0.983
Commodity Straddle	-0.0169	-2.110	0.036*	0.0241	2.095	0.038*	-0.0112	-1.700	0.091	-0.0129	-2.212	0.0287*	-0.0047	-1.027	0.306	-0.0110	-2.097	0.037*
	R^2: 0.6159			R^2: 0.2558			R^2: 0.6878			R^2: 0.8977			R^2: 0.3304			R^2: 0.7731		
	Fixed Income Arbitrage			**Global Macro**			**L/S Equity**			**Merger Arbitrage**			**Relative Value**			**Short Selling**		
Intercept	0.0034	4.596	0.00***	0.0024	3.234	0.001**	0.0014	2.051	0.042*	0.0027	5.488	0.00***	0.0032	5.786	0.00***	-0.0020	-1.175	0.242
S&P 500	0.0398	1.224	0.223	0.0611	1.821	0.071	0.1794	5.708	0.00***	0.0538	2.436	0.016*	0.0784	3.240	0.001**	-0.2704	-3.467	0.00***
Size Spread	-0.0049	-0.485	0.628	-0.0179	-1.700	0.091	0.0113	1.154	0.250	0.0052	0.762	0.447	-0.0002	-0.029	0.976	-0.1245	-5.092	0.00***
US 10Y	-0.0223	-2.176	0.031*	0.0016	0.154	0.878	0.0358	3.621	0.00***	0.0023	0.339	0.735	-0.0010	-0.131	0.895	-0.0122	-0.499	0.618
Credit Spread	-0.0642	-5.460	0.00***	0.0087	0.724	0.470	0.0044	0.391	0.696	-0.0024	-0.311	0.755	-0.0365	-4.174	0.00***	-0.0050	-0.180	0.857
MSCI EM	0.0688	3.668	0.00***	0.1186	6.134	0.00***	0.1450	8.007	0.00***	0.0462	3.633	0.00***	0.0956	6.851	0.00***	-0.0932	-2.076	0.039*
Bond Straddle	0.0003	0.062	0.950	0.0071	1.150	0.252	0.0009	0.155	0.876	0.0046	1.141	0.255	0.0015	0.335	0.738	0.0355	2.457	0.015*
Currency Straddle	-0.0076	-1.656	0.100	0.0143	3.002	0.003**	0.0010	0.243	0.808	-0.0021	-0.678	0.498	-0.0022	-0.662	0.508	0.0229	2.072	0.040*
Commodity Straddle	-0.0067	-1.263	0.209	0.0053	0.981	0.328	-0.0070	-1.360	0.176	-0.0044	-1.239	0.217	-0.0082	-2.084	0.039*	0.0011	0.087	0.930
	R^2: 0.5702			R^2: 0.4598			R^2: 0.8329			R^2: 0.4841			R^2: 0.7692			R^2: 0.7037		

Stepwise Regression												
Strategy/ Risk factor	**Convertible Arbitrage**	**CTA Global**	**Distressed Securities**	**Emerging Markets**	**Equity Neutral**	**Event Driven**	**Fixed Income**	**Global Macro**	**L/S Equity**	**Merger Arbitrage**	**Relative Value**	**Short Selling**
Intercept	0.0038***	0.0019	0.0034***	0.0011***	0.0008	0.0021***	0.0025***	0.0017***	0.0009***	0.0030***	0.0031***	-0.0031
	(4.122)	(1.440)	(5.298)	(2.327)	(1.657)	(5.194)	(3.739)	(3.341)	(4.183)	(6.516)	(8.976)	(-1.827)
S&P 500		-0.390***		-0.229***				-0.217***				-0.241*
		(-4.192)		(-6.495)				(-4.300)				(-2.062)
Size Spread	-0.137***		-0.075**	-0.043***	0.066**	-0.070***	-0.047*	0.053*			-0.043***	-0.120***
	(-4.663)		(-2.836)	(-6.040)	(2.883)	(-3.933)	(-2.119)	(2.245)			(-3.813)	(-5.051)
US 10Y	-0.038**		-0.017				-0.043***				-0.023***	
	(-2.811)		(-1.641)				(-4.372)				(-4.438)	
Credit Spread	-0.076***		-0.038***		-0.014*	-0.021***	-0.053***				-0.030***	
	(-5.131)		(-3.823)		(-2.135)	(-3.427)	(-5.404)				(-5.395)	
MSCI EM		-0.169***	-0.097***	0.187***	-0.072***	-0.057***		-0.037	-0.058***		-0.035*	-0.070
		(-3.540)	(-3.809)	(10.211)	(-3.622)	(-3.541)		(-1.845)	(-6.174)		(-2.488)	(-1.593)
Bond Straddle	0.017*				-0.012**							0.028*
	(2.193)				(-3.272)							(2.163)
Currency Straddle	-0.012*	0.033***			0.004		-0.006	0.018***				0.026**
	(-2.270)	(4.707)			(1.678)		(-1.844)	(6.540)				(2.671)
Commodity Straddle		0.024*						0.006				
		(2.519)						(1.807)				
SMB	0.429***	-0.279***	0.208*		-0.246**	0.209***	0.111	-0.270***	-0.026*		0.115**	
	(4.103)	(-4.408)	(2.395)		(-3.268)	(3.572)	(1.409)	(-3.429)	(-2.454)		(2.803)	
HML		0.152*	0.090**	0.082***	0.090***	0.044*				-0.047*		
		(2.445)	(2.763)	(4.197)	(3.449)	(2.261)				(-2.143)		
MSCI EX USA				-0.144***	0.287***		-0.091*		0.107***			
				(-4.139)	(5.375)		(-2.330)		(5.140)			
MSCI Min Vola				0.115**		-0.048	0.080	-0.063	-0.053**	-0.076*		0.199
				(3.319)		(-1.741)	(1.561)	(-1.437)	(-2.881)	(-2.175)		(1.695)

MSCI Momentum	-0.0932* (-2.020)	0.317*** (3.959)	-0.081* (-2.349)		0.103*** (3.989)		-0.076 (-2.269)	0.188*** (3.814)	0.051*** (4.101)		-0.048** (-2.765)	
MSCI Value					-0.434*** (-7.032)				-0.081*** (-3.953)	0.076* (2.032)		
HFRI	0.7673*** (7.734)	0.795*** (4.221)	0.946*** (9.096)	1.045*** (15.757)	0.500*** (7.328)	0.834*** (15.900)	0.467*** (5.635)	0.542*** (6.840)	0.876*** (26.462)	0.178*** (4.097)	0.554*** (10.137)	
FTSE 100		-0.089 (-1.451)		0.063** (2.781)	-0.037 (-1.482)						0.026 (1.558)	-0.173* (-2.367)
Nikkei 225				0.036** (3.029)	-0.066*** (-4.983)		0.032 (1.921)				0.019* (2.077)	-0.083* (-2.058)
SPI	0.1121** (2.713)		0.054 (1.828)		-0.035 (-1.430)	0.080*** (4.393)	0.071* (2.530)	0.077** (2.938)	0.018 (1.662)		0.0375* (2.271)	
VIX		-0.023** (-2.996)					0.006 (1.871)			-0.004 (-1.796)		
Commodity			0.037* (2.523)				0.040** (2.982)		-0.020*** (-4.299)		0.015* (2.014)	
Gold		0.109*** (3.993)	-0.030 (-1.844)		-0.046*** (-3.980)			0.068*** (5.341)	0.010 (1.927)			
UK Bond 10Y		-0.055*** (-4.759)			-0.006 (-1.385)	-0.006 (-1.735)		-0.014** (-3.095)		-0.011** (-2.791)		
DE Bond 10Y	-0.0046 (-1.792)	-0.007* (-2.049)	-0.007*** (-4.401)		-0.002* (-2.056)	-0.002* (2.270)		-0.004** (-3.115)	-0.0009 (-1.557)		-0.003** (-3.238)	
CH Bond 10Y			0.0007 (1.683)	0.0008* (2.451)							0.0005* (2.093)	
Trade Weighted USD	-0.2035* (-2.261)		-0.185** (-2.896)	-0.266*** (-5.610)		-0.081* (-2.034)			0.063** (2.899)		-0.085* (-2.366)	
	R^2: 0.7381	R^2: 0.5205	R^2: 0.8548	R^2: 0.9685	R^2: 0.6676	R^2: 0.9297	R^2: 0.7027	R^2: 0.7595	R^2: 0.9847	R^2: 0.5894	R^2: 0.9106	R^2: 0.7308

Table 17: Summary output of stepwise regression for EDHEC hedge fund strategies

Progressive Capital (Niche Alternatives)									
	Fung and Hsieh 7-factor model			Fung and Hsieh 8-factor model			Stepwise Regression (including 25 risk factors)		
Risk factor	***Coeff***	***t***	***p***	***Coeff***	***t***	***p***	***Coeff***	***t***	***p***
Intercept	0.0037	2.920	0.004**	0.0044	3.595	0.00***	0.0047	4.503	0.00***
S&P 500	0.2200	5.015	0.00***	0.0927	1.713	0.0891			
Size Spread	-0.0001	-0.006	0.995	0.0030	0.180	0.857			
US 10Y	-0.0444	-2.559	0.011*	-0.0292	-1.715	0.088	-0.0643	-4.118	0.00***
Credit Spread	-0.0805	-4.048	0.00***	-0.0631	-3.231	0.001**	-0.0404	-2.468	0.014*
MSCI EM				0.1157	3.710	0.00***	-0.1227	-2.871	0.004**
Bond Straddle	-0.0022	-0.218	0.827	0.0018	0.183	0.855			
Currency Straddle	-0.0046	-0.583	0.560	-0.0051	-0.666	0.506			
Commodity Straddle	-0.0111	-1.207	0.229	-0.0080	-0.907	0.366			
SMB									
HML									
MSCI EX USA							0.1635	2.556	0.011*
MSCI Min Vola									
MSCI Momentum							-0.1539	-2.973	0.003**
MSCI Value									
HFRI							0.6486	4.456	0.00***
FTSE 100									
Nikkei 225							0.0657	2.360	0.019*
SPI									
VIX							0.0110	1.992	0.048*
Commodity							0.0474	2.128	0.035*
Gold									
UK Bond 10Y									
DE Bond 10Y							-0.004	-1.603	0.111
CH Bond 10Y							0.0013	1.842	0.067
Trade Weighted USD							-0.2382	-2.266	0.025*
	R^2: 0.4552			R^2: 0.5043			R^2: 0.666		

Table 18: Summary output of all regression models for Progressive Capital

5.4 Swiss pension fund portfolio

This section analyses the representative Swiss pension fund portfolio presented in Chapter 3.5.1. The main object is to analyze the asset allocation, in particular the part of the alternative asset classes of pension fund portfolio. The following questions are empirically investigated and analyzed:

- How did the Swiss pension fund portfolio perform?
- How did the Swiss pension fund portfolio perform with only Progressive Capital as alternative asset?

The first part of this section presents the performance of the individual assets, which occur in the Swiss pension fund asset allocation. In the second part, two slightly different portfolios are created and compared. Finally, in the third part, a portfolio optimization is applied to the two portfolios and conclusions are drawn.

5.4.1 Performance of assets in Swiss pension fund

Table 19 below provides an overview of the selected assets and their main performance measures (annualized), which were evaluated using CAPM. The sample period covers August 2007 to December 2018. The risk-free interest rate is set at -0.71 %, which is derived from the three-month Libor CHF (as at 31.12.2018). The SPI is defined as the market index.

Swiss pension fund portfolio						
	Return	**Vola**	**Beta**	**Jensen**	**Sharpe Ratio**	**Idio. risk**
Bonds CHF (SBR)	0.0290	0.0278	-0.0026	0.0362	1.2988	0.0008
Bonds foreign currency (LGC)	0.0394	0.0679	0.1921	0.0383	0.6849	0.0040
Foreign stocks (MXWO)	0.0296	0.1599	0.9601	-0.0042	0.2294	0.0101
Real estate CH (SWIIT)	0.0510	0.0671	0.1016	0.0538	0.8657	0.0043
Foreign real estate (ENGL)	0.0184	0.1747	0.8594	-0.0111	0.1458	0.0182
Mortgage CHF (SDA)	0.0109	0.0089	-0.0202	0.0189	2.0245	0.0001
Progressive Capital (PC)	0.0597	0.0682	0.2797	0.0549	0.9806	0.0033
Private equity (SPL)	0.0019	0.2633	1.5017	-0.0550	0.0341	0.0316
Hedge funds (HFR)	-0.0230	0.0578	0.2803	-0.0279	-0.2759	0.0020
Insurance linked secur. (SRC)	-0.0086	0.0354	0.0454	-0.0035	-0.0432	0.0012
Commodity (BCO)	-0.0734	0.1537	0.4220	-0.0843	-0.4316	0.0206

Table 19: Annualized performance values for each assets category in the Swiss pension fund

The Libor was deliberately omitted as it cannot be compared with the other asset categories. The niche alternatives of Progressive Capital shows the highest return of 5.97 % and ranks first ahead of real estate with 5.1 %. This return is therefore much higher than the other alternative investments such as private equity, hedge funds, insurance linked securities, and commodities. Three out of four alternative investments even show negative returns (HFR, SRC, and BCO). If we compare the volatility of alternative investments, Progressive Capital positions itself in the midfield at 6.82 %. The two assets commodity (BCO) and private equity (SPL) are significantly more volatile. In terms of beta values, private equity has the highest value at 1,5017 and is therefore more volatile than the market index SPI. Foreign stocks (MXWO) behave almost exactly as the market does. Progressive Capital and hedge funds (HFR) are characterized by a low volatility compared to the market due to their values of approximately 0.28.
While Progressive Capital shows a positive Jensen alpha, all other alternative investments indicate a negative alpha. A positive alpha indicates superior returns, while a negative alpha correspondingly indicates inferior returns. With regard to the Sharpe ratio, Progressive Capital provides the highest Sharpe ratio compared to the other alternative assets. Mortgage and bonds even have a higher Sharpe ratio than Progressive Capital. With regard to idiosyncratic risk, Progressive Capital shows an acceptable value of 0.0033 and thus is much lower than private equity and commodity.

Figure 25 on the following page shows the cumulative returns of the individual assets versus the time in the pension fund portfolio. For reasons of clarity, the assets have been divided into two groups. This indicates how the individual assets have developed over time. Some, such as Progressive Capital or Swiss real estate (SWIIT), have performed very well. Others, however, such as commodities (BCO) or private equity (SPL) show negative returns on average. In the case of equities (SPI, MXWO) and foreign real estate (ENGL), the financial crisis can be seen from 2007 to around 2009.
The Swiss National Bank's decision to lift the Euromind exchange rate in January 2015 is also noticeable in some assets. The return of LIBOR is still conspicuous. However, this is related to the construction of the Libor interest rate.

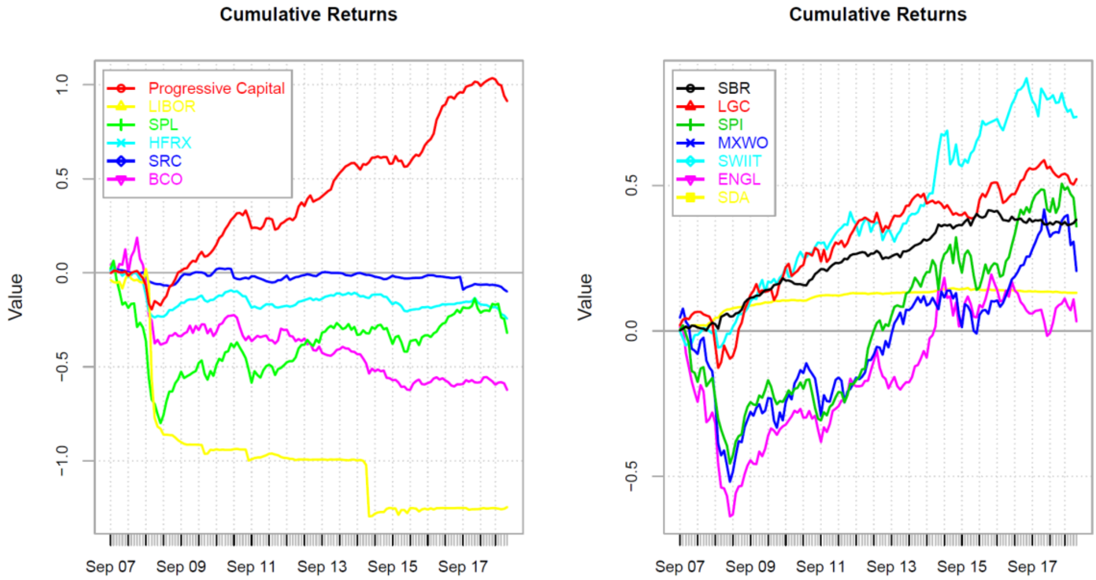

Figure 25: Cumulative returns of pension fund assets

5.4.2 Creation of the two pension fund portfolios

The portfolio analysis is conducted on two slightly different portfolios. The first portfolio includes Progressive Capital as an alternative asset in the Swiss pension fund asset allocation. The second portfolio contains the alternative assets hedge funds (HFRX), private equity (SPL), insurance linked securities (SRC), and commodity index (BCO) instead of Progressive Capital. All other asset classes remain unchanged for both portfolios. Thereafter, the two portfolios are compared based on their cumulative returns. Table 20 provides information on the asset allocations of the two portfolios with the respective asset weights. All the numbers are in percentage [%].

Portfolio 1												
Asset	Libor	SBR	LGC	SPI	MXWO	SWIIT	ENGL	SDA	PC			
Weight	6.3	20	10.4	14.2	18	20.7	2.1	1.3	6.2			
Portfolio 2												
Asset	Libor	SBR	LGC	SPI	MXWO	SWIIT	ENGL	SDA	SPL	HFR	SRC	BCO
Weight	6.3	20	10.4	14.2	18	20.7	2.1	1.3	1.6	2	0.9	1.7

Table 20: Construction of Portfolio 1 and 2

The two portfolios can be replicated using the asset allocation and the associated assets. The monthly returns on the assets in which the pension fund has invested are multiplied by the corresponding weighting and added up. This allows the creation of a chart to compare the two portfolios. The weights of the assets correspond to those of the Swisscanto study discussed in chapter 3.5.1 on page 21. The result is shown by cumulative returns for each portfolio in Figure 26.

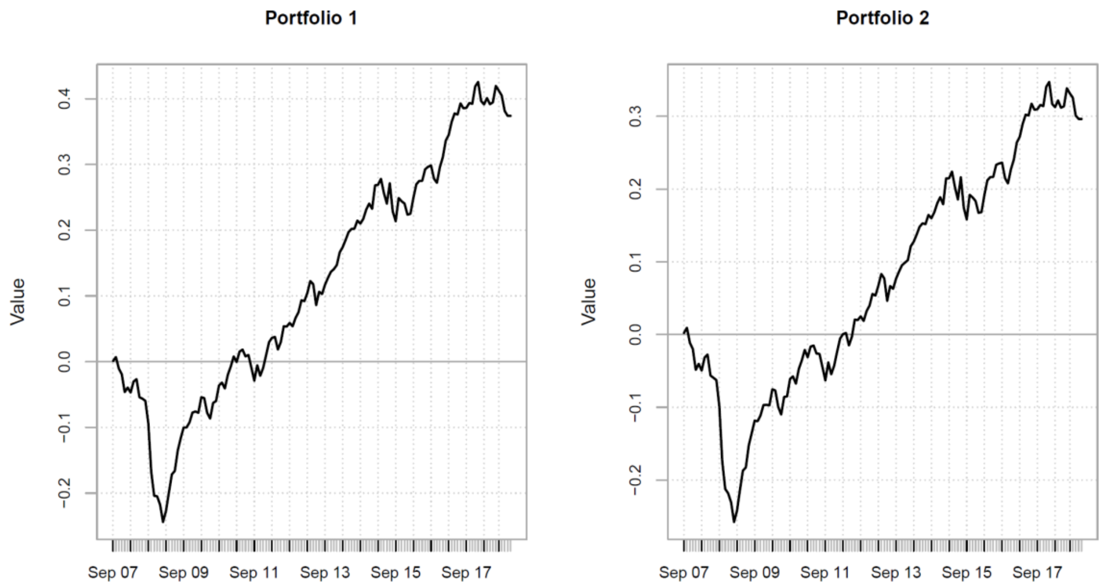

Figure 26: Cumulative returns of the two portfolios

In the case of the pension funds, the financial crisis is clearly visible. Almost 25% of assets were lost between the end of 2007 and mid-2009, and it took a few years to return to the pre-crisis level. The figure 26 demonstrates almost two identical developments of portfolio returns.

The difference lies in the return achieved over the period from August 2007 to December 2018. It is clear that the first portfolio generates a higher return than the second portfolio (40 % > 30 %). From this knowledge, it can be seen that Progressive Capital's niche alternatives has outperformed the four alternative assets in portfolio 2 by 10 %. This might support the argument that pension funds should include the niche alternatives as alternative assets in their portfolio to generate higher portfolio return.

5.4.3 Portfolio Optimization

The optimization problems are solved by using the R optimization infrastructure (ROI) solver with the PortfolioAnalytics package in R. For the analysis, the asset class Libor was deliberately omitted as it delivered a significantly negative return and thus distorted the results.

5.4.3.1 Portfolio 1

The first portfolio represents the Swiss pension fund portfolio with Progressive Capital as the only alternative asset category. The results of the first optimized portfolio are listed in the following table 21:

	Progressive Capital	**SBR**	**LGC**	**SPI**	**MXWO**	**SWIIT**	**ENGL**	**SDA**
Optimal weights	13.3	20	10.4	14.2	18	20.7	2.1	1.3
Mean return	0.003276							
Std.Dev.	0.0185							

Table 21: Summary of the optimized Portfolio 1

The calculated optimal weight for Progressive Capital is 13.3 %. The mean return is 0.32 % and the standard deviation is equal to 1.85 % of the optimum portfolio. The efficient frontier chart is shown in figure 27 below.

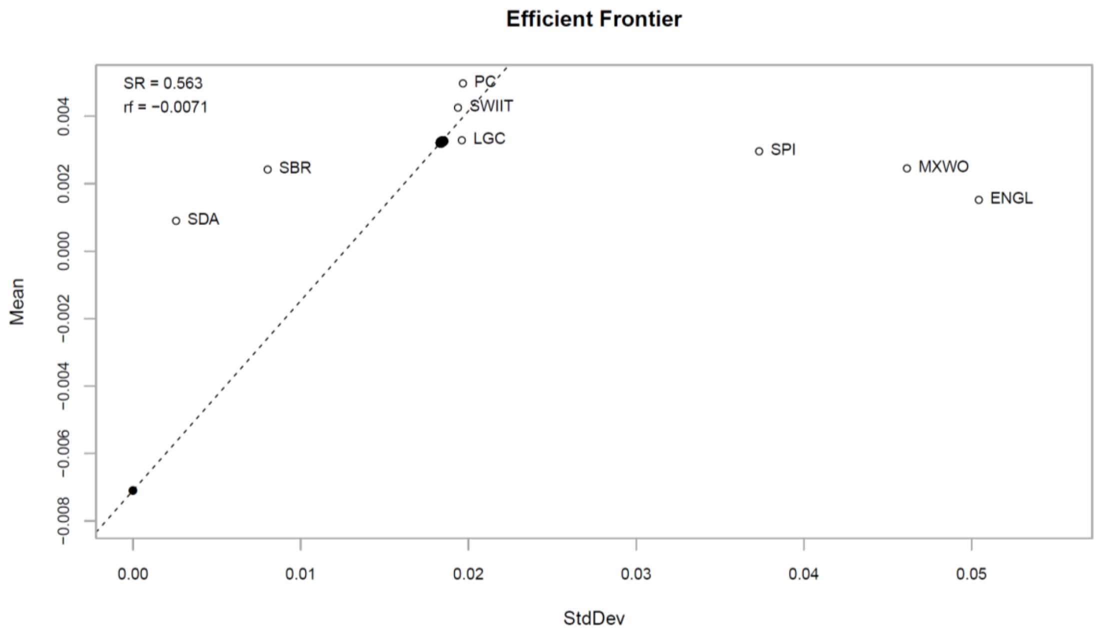

Figure 27: Efficient Frontier chart for Portfolio 1

Figure 27 shows the efficient frontier and risk-return scatter of the assets for the first optimized portfolio. The dotted line represents the capital allocation line. This model would help an investor who believes in efficient markets to construct an optimal portfolio that is exposed to the highest expected return at the lowest volatility. The lower black dot indicates the risk-free rate at -0.71 %. The upper black dots show the optimal portfolios. One of the portfolios, the tangency portfolio, demonstrates the highest possible Sharpe ratio of 0.563, which provides the best risk/reward trade-off.
With regard to the individual assets, Progressive Capital shows the highest return of all assets. In contrast, SPI, Foreign stocks (MXWO), and foreign real estate (ENGL) have high risks.

Figure 28 shows again the optimal portfolio based on the mean-variance optimization. The optimal portfolio (blue dot) is closely positioned to the bonds in foreign currency (LGC) asset. The lower plot indicates the optimal weights for each asset. It is clear that the weighting range for Progressive Capital (PC) is between 0.5 % and 15 %. This corresponds to the Swiss pension fund restrictions and was implemented with a constraint in R. All other weights remain unchanged. The optimal weight for Progressive Capital is 13.3 % and is marked with a blue dot.

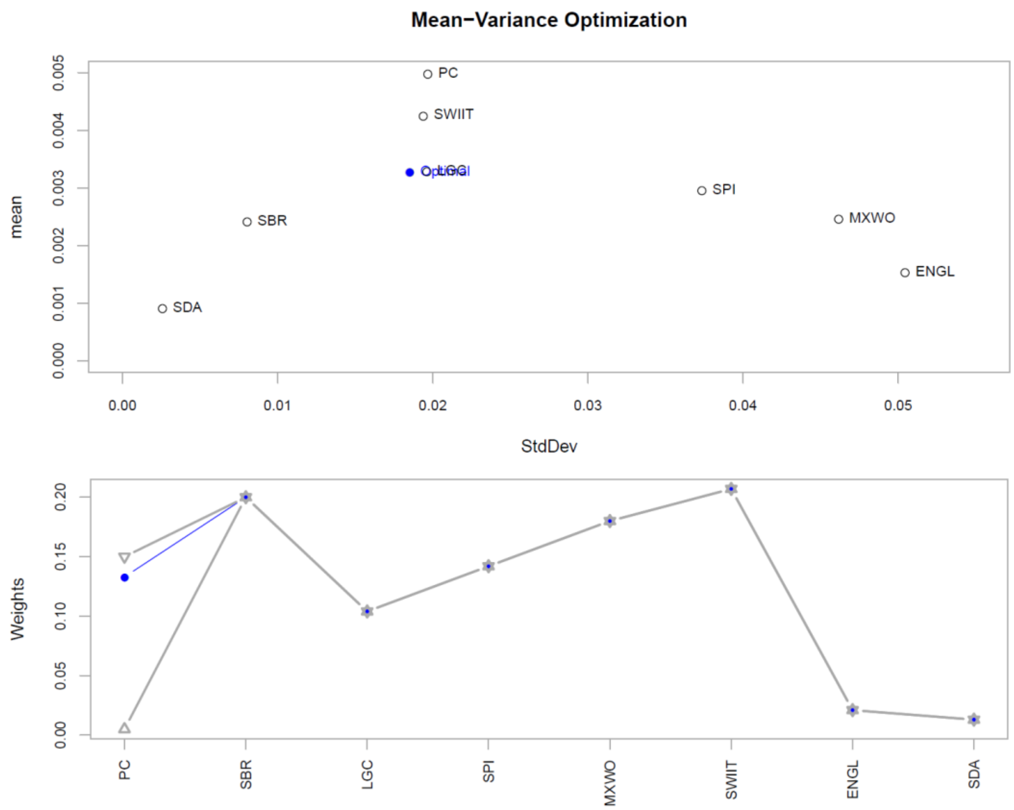

Figure 28: Mean-Variance optimization for Portfolio 1

5.4.3.2 Portfolio 2

The second portfolio comprises the asset categories hedge funds (HFRX), private equity (SPL), insurance linked securities (SRC), and commodity index (BCO) instead of Progressive Capital. These four alternative assets have been merged into a single alternative asset called "AltAssets". The results of the second optimized portfolio are listed in table 22 below.

	Alternative Assets From Swiss P.F.	SBR	LGC	SPI	MXWO	SWIIT	ENGL	SDA
Optimal weights	12.3	20	10.4	14.2	18	20.7	2.1	1.3
Mean return	0.001674							
Std.Dev.	0.02051							

Table 22: Summary of the optimized Portfolio 2

The optimum weight for the alternative assets is 12.3 %. In addition, the mean return is 0.16 % and the standard deviation shows a value of 2.05 %. The figure 29 below illustrates the optimal portfolio measured in Table 22. The upper dark dot shows the optimal portfolio with a Sharpe ratio value of 0.428. It is noticeable that the alternative investment "AltAssets" has the highest standard deviation while delivering the lowest return of all assets in the second portfolio.

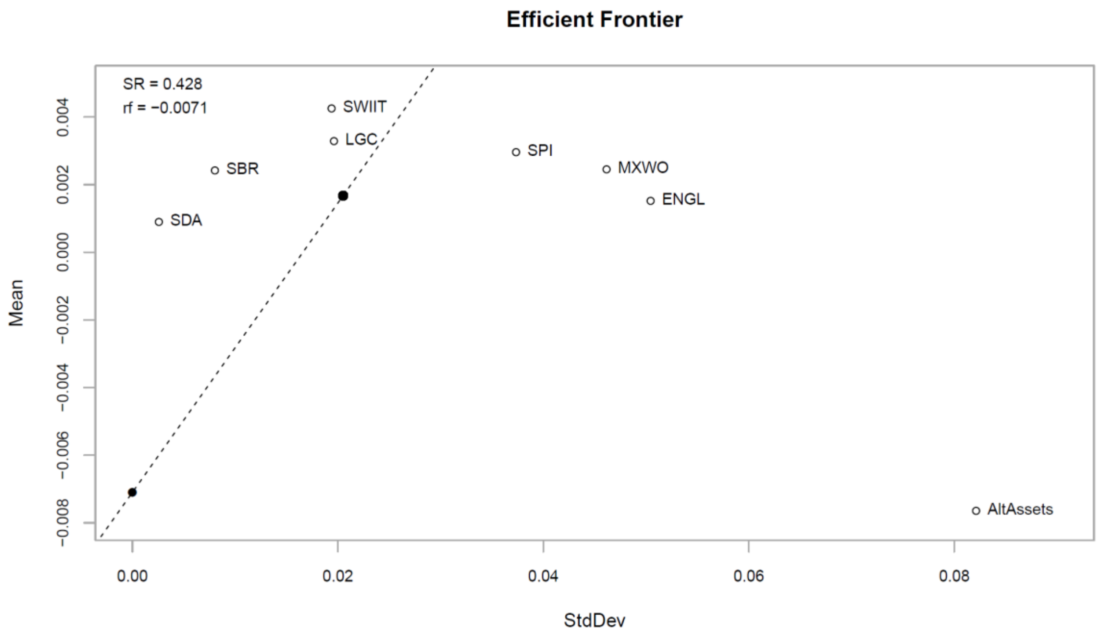

Figure 29: Efficient Frontier chart for Portfolio 2

In conclusion, based on similar weights of 12.3 % and 13.3 %, the first optimized portfolio with Progressive Capital as alternative asset provides a better performance due to the higher Sharpe ratio of 0.563. The second portfolio performs worse than the first portfolio in all respects, such as mean return and volatility values. Thus, the mean-variance optimization approach showed that Progressive Capital achieves a better performance through niche alternatives compared to traditional alternative investments. Based on these empirical results, it can be argued that the portfolio of a pension fund may well consider incorporating niche alternatives from Progressive Capital in order to achieve better performance.

6. Conclusion

This chapter concludes the present thesis. In the first section, the results of the empirical investigations are discussed in the conclusion and implications for practice. Thereafter, the discussion and appreciation of the results are presented. Finally, a brief outlook of the master thesis is explained.

6.1 Conclusion

The empirical study of the performance of hedge fund strategies and niche alternatives can be retrospectively described as successful. With the help of the comprehensive statistical analyses, important findings were obtained.

The purpose of this master thesis has been to investigate and analyze the performance of hedge fund strategies, in particular the specific niche alternatives of Progressive Capital. The methodology in this analysis is based on a combination of the quantitative classification method with different multi-factor models to explain the returns of hedge fund strategies.
In addition, a mean-variance analysis is used to evaluate the niche alternatives and traditional alternative assets in a representative Swiss pension fund.

This thesis used the principal component analysis to identify the minimum number of components that are necessary to describe the return on hedge funds. The results based on Progressive Capital and all risk factors showed that the optimal number of orthogonal components is eight to explain more than 80 % of the Progressive Capital return variation. In addition, based on all hedge fund strategies including Progressive Capital, the results of the Fung and Hsieh eight-factor model demonstrated, that five principal components are sufficient to adequately represent more than 80 % of the variability in the data. In addition, five different hedge fund strategies are identified.

For performance measurement of hedge fund strategies, three different multi-factor models are applied, which comprise a universe of risk factors: the widely used seven-factor model by Fung and Hsieh, the extended eight-factor model and a model based on a stepwise regression approach.

The results showed that S&P 500 is the most dominant risk factor for all thirteen hedge fund strategies in the seven-factor model. Compared to the eight-factor model, the MSCI emerging market risk factor plays an important role in explaining all hedge fund strategies except CTA global. In the stepwise regression model, the risk factor HFRI is significantly exposed to eleven hedge fund strategies, followed by size spread, which is exposed significantly to nine hedge fund strategies.

With regard to performance, there are few differences in the alphas resulting from the three different multi-factor models. The average monthly alpha is highest 0.22 % for the Fung and Hsieh eight-factor model, 0.19 % for the stepwise regression model, and lowest with 0.16 % for the Fung and Hsieh seven-factor model over all thirteen hedge fund strategies, including Progressive Capital. According to these results, Progressive Capital performs better in all three models than the average alphas do. The highest alpha of 0.47 % was gained by the stepwise regression, followed by 0.44 % in the Fung and Hsieh eight-factor model, and 0.37 % in the Fung and Hsieh seven-factor model.

In terms of the average adjusted R^2 for all thirteen hedge fund strategies, the stepwise regression model showed the highest value of 0.77, followed by the Fung and Hsieh eight-factor model with 0.60, and 0.53 for the Fung and Hsieh seven-factor model. This indicates that the risk factors, which are used in the stepwise regression, explain the variation of hedge fund returns better than the Fung and Hsieh factor models do.

The results of the portfolio analysis for the representative Swiss portfolio showed that the first portfolio comprising niche alternatives of Progressive Capital as alternative asset category outperformed the second portfolio containing the alternative assets hedge fund index, private equity, insurance linked securities, and commodity Index by 10 % over the full sample period from August 2007 to December 2018.

Based on the mean-variance optimization approach, in which both portfolios follow the pension fund investment restrictions, the results demonstrated that Progressive Capital achieves a better performance through higher Sharpe ratio and return, and at the same time a lower risk, compared to the four alternative assets from the second portfolio.

On the basis of these empirical results, this could be a strong argumentation that portfolio of a pension fund may consider including niche alternatives from Progressive Capital in their asset allocation in order to achieve a better risk-return profile.

6.2 Discussion and appreciation of the results

The methods used in this thesis, such as the principal component analysis or the stepwise regression method, have a high acceptance in the scientific literature, which confirms the high significance of the results.

With regard to the data, most scientific papers used the TASS database because of its suitability to the hedge fund industry and low biases. This database was not used in this paper as it was subject to a fee. However, scientific literature increasingly points out that an aggregated database such as the EDHEC is a better alternative for research analysis issue due to its higher representativeness.

Due to the different lengths of data series, earlier crises such as the dotcom bubble in 2000 could not be investigated. Similarly, no sub periods were defined for the investigation, since the full sample period runs from August 2007 to December 2018.

The results of the present thesis can be compared with those of Fung and Hsieh (1997) regarding the principal component analysis. They were able to extract five orthogonal principal components, which jointly explained approximately 43% of the cross-sectional variation in hedge fund returns (Fung and Hsieh, 1997, p. 284). In addition, they found five different hedge fund strategies, which provides the same result as in this thesis (Fung and Hsieh, 1997, p. 285).

According to the regression models, the results provided realistic adjusted R^2 values. Apart from this, to make a better comparison with Fung and Hsieh eight-factor model, one could reduce the stepwise regression to eight factors.

However, the results are significantly dependent on selected risk factors. Although stepwise regression has generated a higher adjusted R^2 in all three multi-factor models, it is possible that an even higher R^2 can be achieved with other factors. The search for matching risk factors proved to be a time-consuming procedure in this thesis. An attempt was made to develop the best possible model for the hedge funds strategies.

6.3 Recommendation and Implications for practice

Due to the limited availability of data, a more comprehensive analysis is recommended at a later stage. In particular, the part relating to the asset allocation of pension funds was significantly challenging. It was difficult to find the benchmark data from Bloomberg, which served as an approximation to replicate a pension fund portfolio as practically as possible. In addition, the results are dependent on the selected benchmark data. In practice, however, pension funds may include other assets in their portfolio, which may lead to small deviations.

Overall, a solid foundation has been created, based on widespread theoretical fundamentals. The implemented models can be easily adapted with the statistical tool R at any time, for example to change the data, so this work may be of great benefit for future extensions.

6.4 Outlook

This master thesis deals primarily with the performance of hedge fund strategies. Thus, methods have been applied that largely address this topic. Another research area of the hedge fund industry is liquidity risk. Liquidity risk is important for determining the performance of hedge funds and their impact on the market. Sadka (2009) found that the systematic liquidity risk, measured by the Sadka (2006) liquidity factor, has a strong significance when explaining the returns of hedge funds. Funds heavily exposed to liquidity risk outperform those with low liquidity risk. The hedge fund strategies are subdivided into various liquidity profiles. For example, CTA and macro strategies offer the highest liquidity and allow investors to, on average, access their capital more than once a month with the shortest redemption notice period of all hedge fund strategies. This research question is closely related to hedge fund share restrictions. However, specific data is required that are often not available in public databases, which means that these data are associated with costs.

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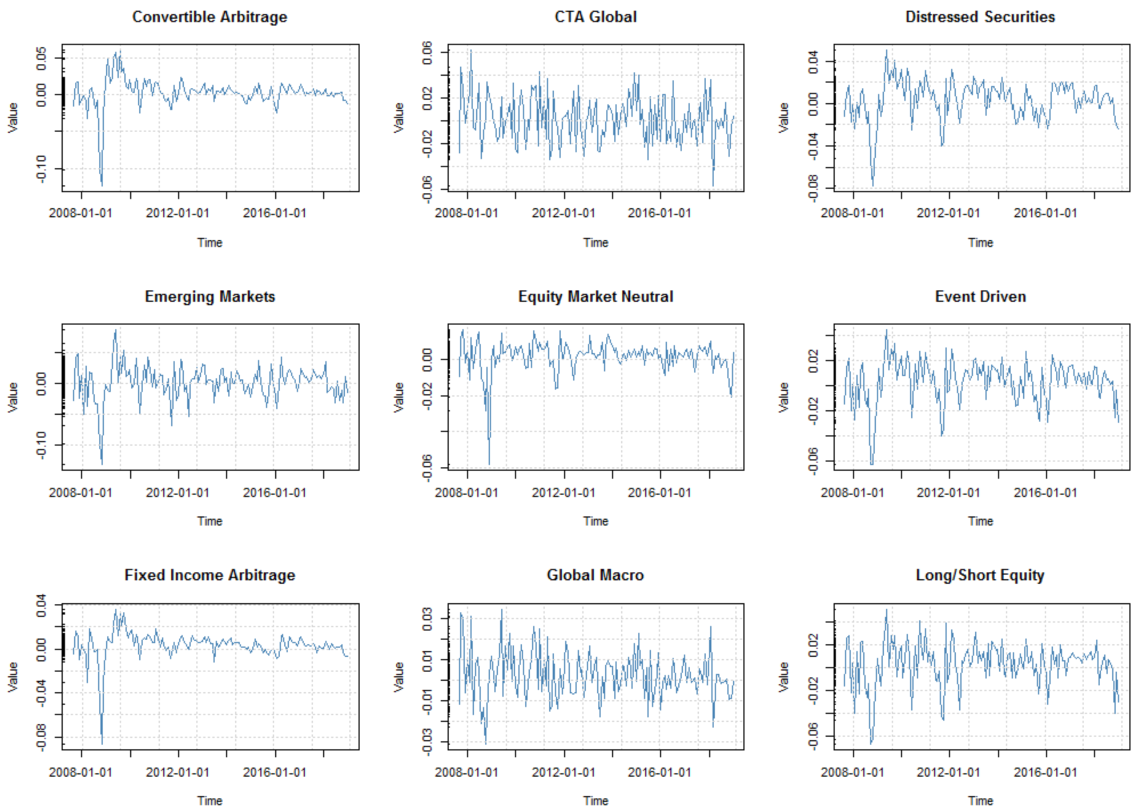
8. Appendix

8.1 Plots

In this thesis, all plots were generated with the statistics tool R-Studio. The R-code of the figures and methods are not shown but are available digitally as attached file to this thesis.

8.1.1 Progressive Capital and Hedge Fund Strategy returns



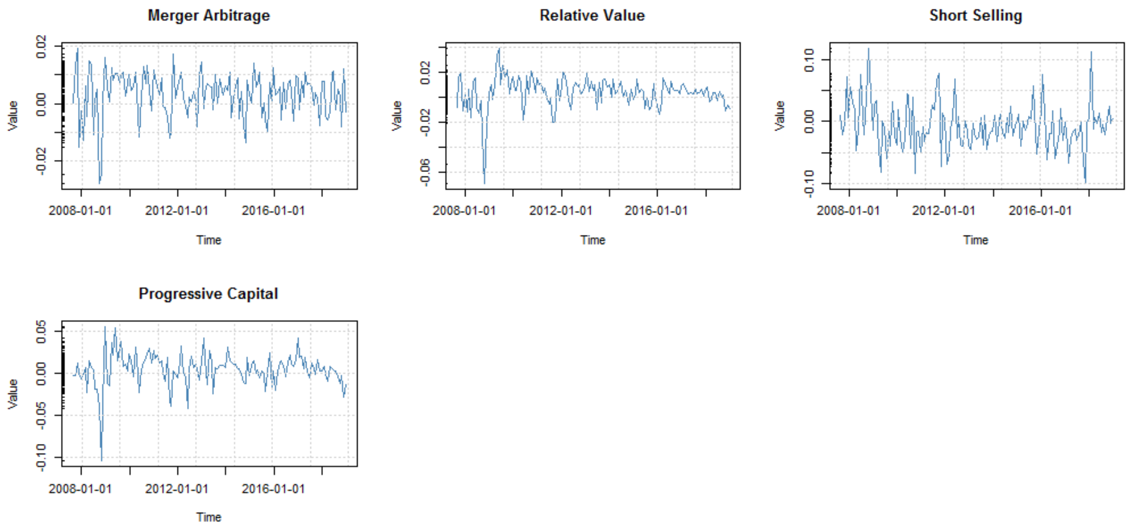


Figure 30: Returns of Progressive Capital and Hedge Fund Strategies

8.1.2 Fung and Hsieh eight-factor returns

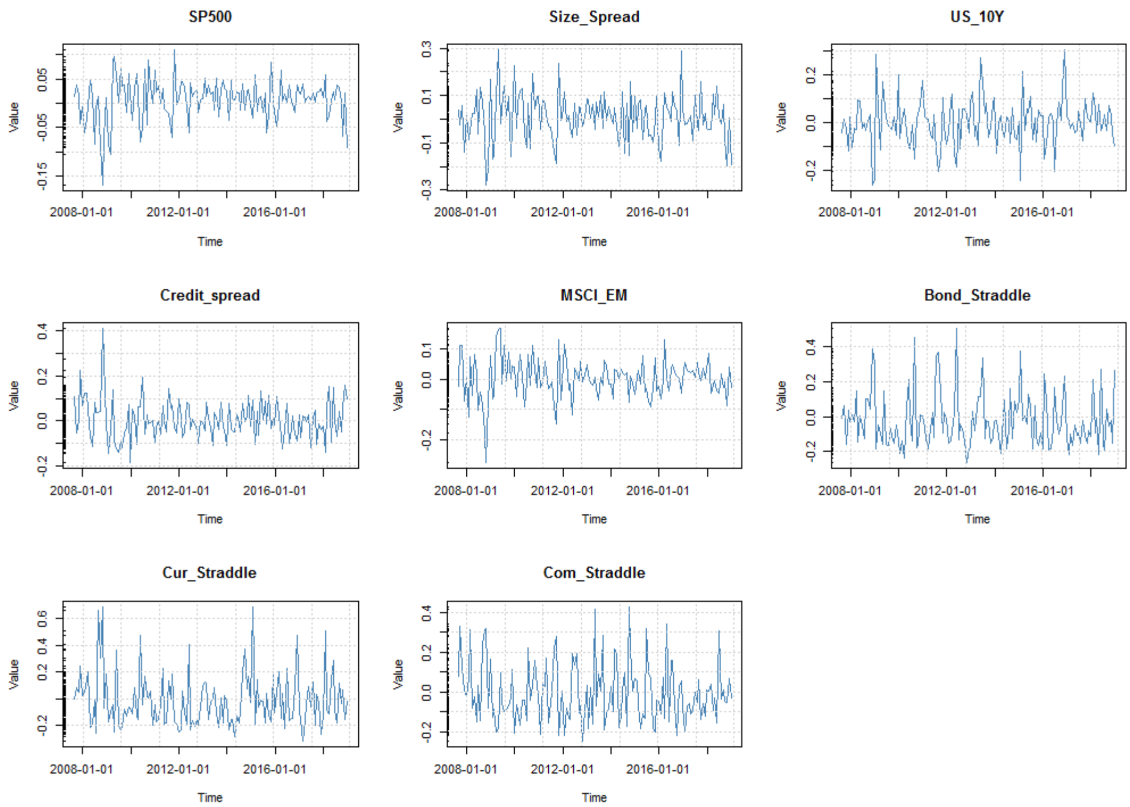


Figure 31: Returns of Fung and Hsieh eight-factor model

8.1.3 Risk factor returns

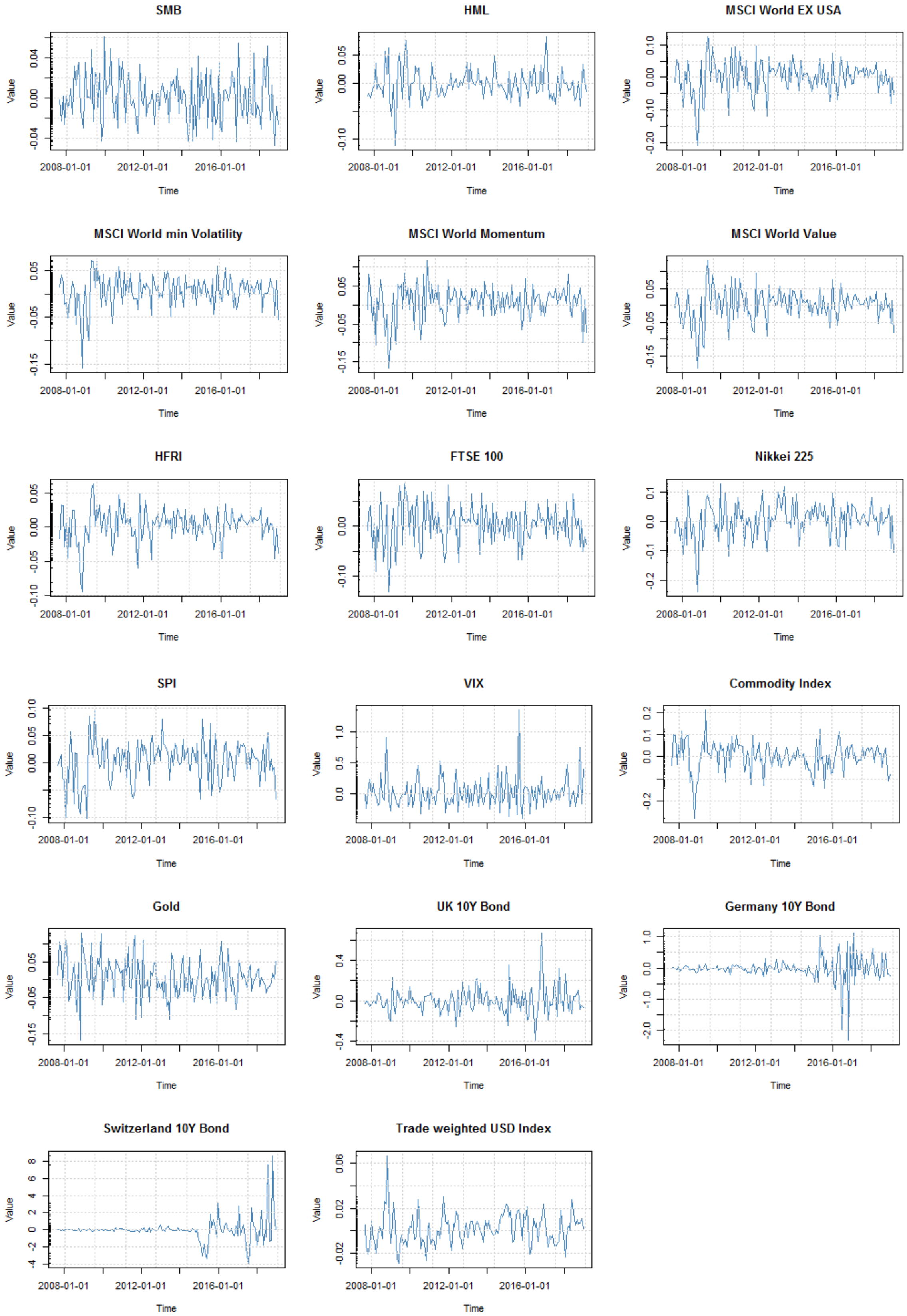


Figure 32: Returns of Risk factors

8.1.4 Asset returns in pension fund portfolio

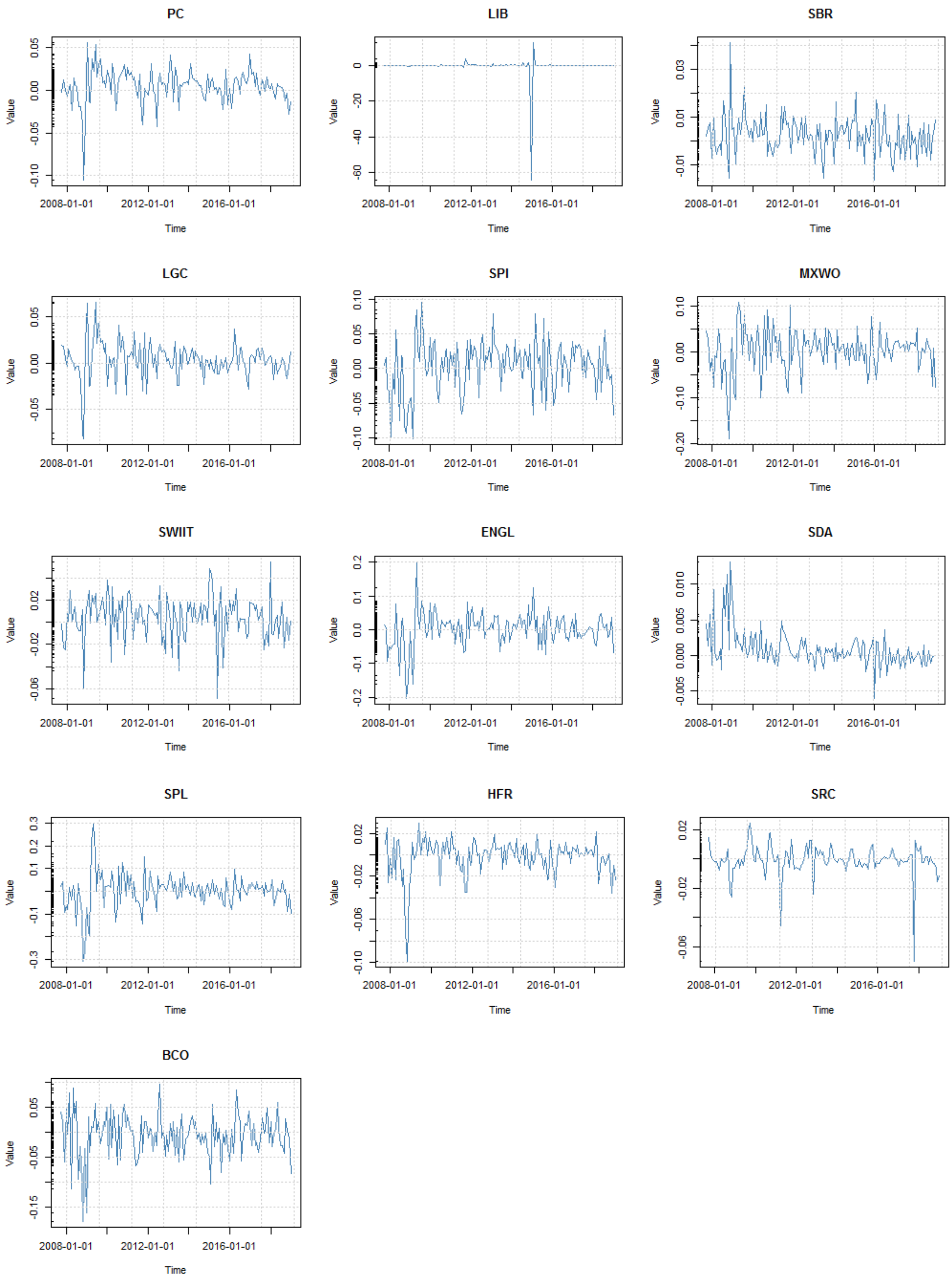


Figure 33: Returns of Assets in pension fund portfolio