MASTERARBEIT / MASTER'S THESIS

Titel der Masterarbeit / Title of the Master's Thesis

„Explaining Returns of Equity Focused Hedge Funds Through Factor Models"

verfasst von / submitted by

Tom Brentrup, B.A.

angestrebter akademischer Grad / in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien, 2021 / Vienna, 2021

Studienkennzahl lt. Studienblatt / degree programme code as it appears on the student record sheet:	UA 066 974
Studienrichtung lt. Studienblatt / degree programme as it appears on the student record sheet:	Masterstudium Banking and Finance
Betreut von / Supervisor:	Univ.-Prof. Dipl.-Vw. Thomas Gehrig, PhD
Mitbetreut von / Co-Supervisor	Dipl.-Inform. Dipl.-Volksw. Dr. Christian Westheide

Abstract

Hedge funds value the privacy of information, regarding their stock preferences and selection processes, greatly. However, they are obliged to disclose their equity holding reports in so-called Form 13F filings at each quarter end. This study explains the return composition of equity-focused hedge funds with respect to their factor premium exploitation as well as alpha generation. In this regard, I apply multifactor models in time- and cross-sectional regressions on a sample of 18 hedge funds, including four traditional as well as five novel factors. The data is retrieved from publicly avaiablabe Form 13F equity holding reports, comprising a sample period from January 2003 to December 2019. My results suggest that the applied multifactor models can explain hedge funds' return variability to a large extent. Of overall nine tested factors in different models over the observed sample period, five factor betas show highly significant results from which four are negative. The negative factor betas reveal that the interest in the systematic exploitation of those factor premia is limited. Besides low factor performances on average over the last 17 years, alpha emerges as the main return driver between performance-based hedge fund portfolios. Lasty, conducting a two-stage regression approach, I find that two variables contribute to the explanation of alpha.

Abstrakt

Die Diskretion von Informationen, vor allem für Aktienpräferenzen sowie deren Auswahlprozeduren, wird in der Hedge Fonds Branche geschätzt. Dennoch sind Hedge Fonds dazu verpflichtet, Einblicke in ihre Aktienportfolios in Form 13F Reports quartalsweise zu veröffentlichen. Meine Masterarbeit beschäftigt sich deshalb mit der Fragestellung, wie die Renditen von Hedge Fonds, im Hinblick auf die Generierung von Faktorprämien und abnormalen Renditen, zusammengesetzt sind. Hierzu wende ich Faktorenmodelle an, die die Zeitreihen- sowie Querschnittsdaten von 18 Hedge Fonds auswerten. Der Erhebungszeitraum umfasst die Zeitspanne von Januar 2003 bis Dezember 2019. Die Faktorauswahl bezieht sich auf Faktoren aus dem Carhart Vier-Faktoren Model und zusätzlich fünf weiteren Faktoren aus der jüngeren akademischen Forschung. Meine Ergebnisse zeigen, dass die Renditevariabilität der Hedge Fonds mit Hilfe meiner Faktorenmodelle zu einem hohen Teil erklärt werden kann. Mit Außnahme des Markt-Faktors, sind von insgesamt neun getesten Faktoren fünf Faktorladungen höchst signifikant, wovon widerum vier negativ sind. Die negativen Faktorladungen stellen die durchschnittliche Ausnutzung von Faktorprämien aus der jüngeren Forschung stark in Frage. Abgesehen von der niedrigen Renditeperformance von Faktorprämien während meines Untersuchungszeitraumes, kristallisiert sich die nicht-Faktor basierte Rendite als maßgeblicher Renditetreiber heraus. Zusätzlich finde ich mit Hilfe eines zwei-stufigen Regressionsansatzes zwei Variablen, die im Querschnitt zur abnormalen Rendite der Hedge Fonds beitragen.

Contents

I. List of Tables

II. List of Abbreviations

AIC	Akaike information criterion
AMEX	American Stock Exchange
AUM	Assets under management
BAB	Betting against beta factor
BE	Book equity
CAL	Capital allocation line
CAPM	Capital asset pricing model
CML	Capital market line
CRSP	Center of Research in Security Prices
GFC	Global Financial Crisis
HML	High minus low factor
I/A	Investment to assets factor
ME	Market capitalization
MGMT	Mispricing factor – management related anomaly cluster
MKT	Market factor in excess of the risk-free rate
MKT Square	Market factor variable squared
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
PERF	Mispricing factor – performance related anomaly cluster
QMJ	Quality minus junk factor
SEC	U.S. Securities and Exchange Commission
SER	Standard error of regression
SMB	Small minus big factor
SML	Security market line
SSR	Sum of squared residuals
TE	Tracking error
WML	Winner minus loser factor

1 Introduction

The linkage of expected returns and factor sensitives makes multifactor models a commonly used tool in active portfolio management. They can gauge to what extent hedge funds, mutual funds or equity portfolios are exposed to specific factors (Kritzman, 1997). As a major part in finance theory is based upon shareholder compensation for bearing risk, factors are frequently described as independent variables, which inherit some form of risk[12]. For having exposure to a factor, investors demand compensation in form of a factor premium. The size of a respective premium is dependent on the magnitude of exposure to a factor, also called factor loading or factor beta (Chincarini & Kim, 2010).

Next to the equity market risk premium, commonly mentioned in traditional capital asset pricing theory, which compensates investors for bearing risk of having exposure to the market factor, it is possible to capture other factor premia. As an example, managers with an incentive to capture *value* premia, hold stocks with high book-to-market ratios, also referred to as *value stocks*, whereas stocks, with low book-to-market ratios, are referred to as *growth stocks* (Fabozzi & Markowitz, 2011). Manser and Schmid (2016) report highly significant factor loadings when testing a sample of hedge funds in Carhart's (1997) Four-Factor model[3]. Consistent with these findings, Fung and Hsieh (2011) find that Carhart's (1997) Four-Factor model can explain up to 80 percent of return variation on long-short hedge funds, mutual funds and long-bias equity hedge funds.

While factor investing aims at delivering long-term positive returns in the form of factor premia, a portfolio’s abnormal return or non-factor-based return, frequently called alpha, is another performance driver in multifactor models. Alpha represents the part that cannot be explained by given factors in a model (Bodie et al., 2017). At the same time, alpha demonstrates

[1] Pedersen (2015) states that factor investeing is the approach to systematically apply investment *styles*. Fabozzi and Markowitz (2003) define investment style, as picking stocks that belong to a particular category based on similar charactaristics and a high return correlation among them. At the same time, those stocks are less correlated with other stock categories (Fabozzi & Markowitz, 2011).
[2] In my study I use the terms *factors* and *risk factors* interchangeably.
[3] Manser and Schmid (2016, p. 57) test the persistence of long-short equity hedge funds in the sample period from 1994 to 2005.

a manager's stock selection ability (Jensen, 1968). Since differences concerning stocks selection processes exist, a study conducted by Gregory-Allen et al. (2009) reveals that only a fundamental stock selecting approach contributes positively on actively managed equity fund alphas, whereas a quantitative approach had a the contrary effect, although not significant.

Hedge funds play an important part in the world of fund management and are actively managed, unrestricted investment vehicles, accessible mostly to institutional investors and high-net-worth individuals. Generally, the fee structure is considered high and managers of such vehicles value the privacy of information, specifically in terms of generating alpha and secret investment strategies (Goltz & Schroder, 2010).

Regarding trading strategies, hedge funds typically enjoy freedom in their approaches as they go short on specific securities, apply leverage, trade complex derivates and are less regulated than mutual funds. Therefore, applied strategies can become highly sophisticated but on a broad base can be divided up into equity strategies, macro strategies and arbitrage strategies (Pedersen, 2015). Equity strategies mainly subsume trading stocks and can further be subdivided into long-short, long-only-, market-neutral- or dedicated-short bias strategies from which long-short strategies make up 42 percent in the overall hedge fund universe (Fung & Hsieh, 2006).

Although the performance of hedge funds has widely been analyzed in past literature, my main contributions comprise (i) the determination of hedge fund's systematic exploitation of factor premia and alpha, using a unique set of traditional as well as novel factors, (ii) presenting factors that exert an impact on hedge fund portfolio alpha over time and in the cross-section. To this end, I take on a holistic view on the return composition of hedge funds instead on focusing solely on either factor betas or alphas.

This study builds on two sets of publicly available data. One comprises data on hedge funds and the other on data of factors. Regarding hedge fund data, it is a mandatory requirement for Institutional Investment Managers, with assets under management (AUM) equal or above $100 million in traded U.S. stocks, to file in reports to the Securities and Exchange Commission (SEC) on a quarterly basis. These reports are known as Form 13F reports. However, Form 13F reports inherit limitations. First, intra quarter trading is unobservable, since reports are released only once each per quarter end. Furthermore, only equity long-positions are required to be disclosed[4]. Nevertheless, in another study building upon hedge funds' Form 13F reports, Griffin and Xu (2009) consider the mere reliance on equity long positions as adequate. They argue that equity trading makes up an integral part of the hedge fund business. Factors used in this study comprise a *value*-, *size*- and *momentum* factor, which are more in line with the traditional literature on factors in general. In addition, more in line with novel research, a *betting against beta* factor, a *quality minus junk* factor, an *investment-to-assets* factor and two *mispricing* factors are successively introduced and tested.

The further outline of my thesis is as follows, starting with chapter 2: In order to conduct tests on hedge fund return data, I introduce an empirically testable version of the CAPM, which I deduce from the Single-Index model originating from Jensen (1968). Thereupon, I successively introduce the factors and explain the underlying theory as well as their construction and mechanics. Chapter 3 lays out the structure of data, shortcomings and assumptions followed by the construction of various factor models. Chapter 4 subsumes the description of hedge fund and factor statistics and gives a first taste on the further outcome. Chapter 5 focuses on the analysis and interpretation of regression results on factor betas, alpha and timely dynamics of the former two. Chapter 6 provides further tests on hedge fund portfolio alphas across time as well as in the cross-section of funds. Chapter 7 delivers an accurate summarization of results.

---

[4] See https://www.sec.gov/divisions/investment/13ffaq.htm for more detailed information on Form 13F reports.

2 Theoretical background

2.1 Single-Index model

As provided by Jensen (1968), assuming a single factor captures all systematic risk, the holding period return of security or portfolio *i* is given by:

$$\tilde{r}_i = E(\tilde{r}_i) + \beta_i \tilde{F} + \tilde{e}_i, \tag{1}$$
$$E(\tilde{F}) = 0,\ E(\tilde{e}_i) = 0,\ Cov(\tilde{F}, \tilde{e}_i) = 0,\ Cov(\tilde{e}_i, \tilde{e}_j)\ for\ i \neq j$$

where

$E(\tilde{r}_i)$ = Expected return on asset i.
$\beta_i\ \tilde{F}$ = Systematic risk component in which $\tilde{F}$ is a macroeconomic event impacting the overall market. β_i proxies an asset's sensitivity towards $\tilde{F}$. Each firm reacts differently to macroeconomic changes.
$\tilde{e}_i$ = Idiosyncratic risk or firm-specific risk.

When assuming that the single systematic risk factor, which affects all economic participants, is proxied by a broad market index, (1) is commonly referred to as Single-Index model[5]. Changes in the Market Index's return are expressed by $\tilde{r}_M - E(r_M)$, since

$$E(\tilde{r}_M) = \tilde{r}_M - \tilde{F} \tag{1.1}$$

Substituting (1.1) in (1), equation (1) becomes

$$\begin{aligned} \tilde{r}_i &= E(\tilde{r}_i) + \beta_i[\tilde{r}_M - E(\tilde{r}_M)] + \tilde{e}_i \\ \tilde{r}_i &= E(\tilde{r}_i - \beta_i \tilde{r}_M) + \beta_i \tilde{r}_M + \tilde{e}_i \\ \tilde{r}_i &= \alpha_i + \beta_i \tilde{r}_M + \tilde{e}_i \end{aligned} \tag{1.2}$$

Following from (1.2), security *i's* return is dependent on the risk measure β_i, the realized market return, $\tilde{r}_M$, a constant term, α_i, and a random error term, $\tilde{e}_i$, which has an expected value of zero (Midori, 2003, p. 90-92).

[5] The Single-Index model is comprehensively described in Bodie et al. (2017, pp. 248-271). Sharpe (1963) pioneered the Single-index model, which was first named diagonal model.

(1.2) shows an asset pricing model based on realized returns. Although a risk-free rate is missing, (1.2) builds the fundament for all further introduced factor models.

Alpha - The constant term, α_i, measures the return when the change in the market factor is zero. Therefore, α_i comprises an abnormal return measure that is not attributable to market performance or other risk factors and arises from prosperous security selection (Bodie et al., 2017). An investment manager with discretion over a stock portfolio, who possesses superior forecasting skills, will systematically choose securities with $\tilde{e}_i > 0$. Since $E(\tilde{e}_i)$ must be zero, the manager will earn positive α_i.[6] Consequently, he will earn more than the risk premium provided by the market portfolio. On the contrary, negative alpha values are possible as well. This happens when the random error term is chosen more poorly than by chance, also depending on a manager's stock selection process (Jensen, 1968, p. 7-8).

Which approach do managers undertake regarding the portfolio stock selection? Gregory-Allen *et al*. (2009) distinguishes between a *fundamental*- and a *quantitative* approach. The fundamental approach assesses a company's intrinsic valuation[7]. A thorough stock analysis on a qualitative as well as quantitative basis, however, can be time consuming and is therefore deployed on a manageable number of stocks. On the opposite, the *quantitative* approach makes use of different types of computer-based models that carry out systematical trading rules[8]. Algorithms apply strategies on large amounts of stocks, simultaneously lowering the portfolio risk through broad diversification (Gregory-Allen et al., 2009).

Risk Decomposition - As provided in (1.2), by assumption, macroeconomic shocks and firm-specific events are said to be independent from each other. Thus, as provided by (Kritzman, 1997, p.5; Midori, 2003, p. 98), total risk, measured by the variance of excess returns of security or portfolio i, σ_i^2, is the sum of a systematic- and an unsystematic part,

$$\sigma_i^2 = \beta_i^2 \sigma_M^2 + \sigma^2(e_i) \tag{1.3}$$

---

[6] Empirically speaking, I always allow for non-zero constant terms in linear regression. Specifically, the regression line is not forced to pass through the origin and $E(\tilde{e}_i) = 0$.

[7] Pedersen (2015) describes a fundamental stock selection approach as *discretionary long-short equity* for hedge funds.

[8] A quantitative stock selection procedure is also titled as *quant equity* (Pedersen, 2015).

where,

$\beta_i^2\sigma_M^2$= Systematic risk related to the variance of the market factor. If security or portfolio i's beta is proportionally high, it moves stronger with the market and vice versa.

$\sigma^2(e_i)$= Idiosyncratic risk due to firm specific events, also called unsystematic risk.

Focusing on the unsystematic part in (1.3), an increase in the number of securities held in a portfolio, decreases the unsystematic risk, because firm-specific events cancel each other out. For example, if a portfolio's security *i* profits from a positive announcement while portfolio's security *j* suffers from a shock by the same fictive extent, these two effects erase one another.

$$\sigma^2(e_P) = Var(\frac{1}{n}\sum_{i=1}^{n} e_i) = \frac{1}{n}\sum_{i=1}^{n}\frac{\sigma^2(e_i)}{n} = \frac{1}{n}\bar{\sigma}^2(e) \tag{1.4}$$

Formally written in (1.4), an increase in the number of portfolio positions, n, has a diversifiable effect on the portfolio's unsystematic risk because it will become inconsiderably small (Bodie et al., 2017, p. 254). In contrast, the same does not hold for a portfolio's systematic risk. It does not matter how many positions are included in a portfolio because each security is in some form exposed to the market. Consequently, the overall exposure to the market is the weighted average of all securities' exposures with the market. This does not only hold for the market factor, but for other factors as well (Fabozzi & Markowitz, 2011), as I will later demonstrate.

Also shown in (1), the assumption in the Single-Index model is that firm-specific events, for instance a positive earnings-announcement or a successful research break-through, are uncorrelated among each other. Looking at the covariance between any two securities *i* and *j*,

$$\begin{aligned} Cov\left[\tilde{R}_i, \tilde{R}_j\right] &= Cov[\alpha_i + \beta_i\tilde{R}_M + \tilde{e}_i,\ \alpha_j + \beta_j\tilde{R}_M + \tilde{e}_j] \\ &= E[\{\alpha_i + \beta_i\tilde{R}_M + \tilde{e}_i - E[\alpha_i + \beta_i\tilde{R}_M + \tilde{e}_i]\}\,\{\alpha_j + \beta_j\tilde{R}_M + \tilde{e}_j - E[\alpha_j + \beta_j\tilde{R}_M + \tilde{e}_j]\}] \\ &= E[\{\beta_i[\tilde{R}_M - \bar{R}_M] + \tilde{e}_i\}\{\beta_j[\tilde{R}_M - \bar{R}_M] + \tilde{e}_j\}] \\ &= \beta_i\beta_j Cov\left[E(\tilde{R}_M), E(\tilde{R}_M)\right] + \underbrace{\beta_j Cov\left[E(\tilde{R}_M), \tilde{e}_i\right]}_{=0} + \underbrace{\beta_i Cov\left[E(\tilde{R}_M), \tilde{e}_j\right]}_{=0} + \underbrace{Cov(\tilde{e}_i, \tilde{e}_j)}_{=0} \\ &= \beta_i\beta_j Var\left[E(\tilde{R}_M)\right] \end{aligned} \tag{1.5}$$

it becomes evident that it is only dependent on the securities' individual sensitivities with the market, measured by their respective beta coefficients (Bodie et al., 2017, p. 250; Koch, 2007, p. 3). Putting it differently, security covariances are only dependent on their betas with the market factor. Hence, it makes the calculation of covariances between security pairs redundant. The simplicity of the Single-Index model makes it an attractive asset pricing model (Bodie et al., 2017, p. 251-252).

2.2 CAPM

The capital asset pricing model, first released by William Sharpe (1964) and John Lintner (1965), is an equilibrium model, which predicts returns of risky assets. Under a variety of assumptions, a market risk premium is dependent on the exposure to systematic risk. Firm-specific risk is irrelevant, because its diversifiable and therefore not priced. On the contrary, the market factor resembles systematic risk to investors, which they can demand a premium for (Kritzman, 1997, p. 5).

Earlier to the publication of the CAPM, Markowitz (1952) showed how investors use portfolio optimization to arrive at an efficient portfolio in a risk-return framework. Each investor uses a combination of all risky assets and forms a concave positively sloped efficient frontier by expected returns and variances (Kritzman, 1997, p. 4). The tangency portfolio depicts the point where the CAL (capital allocation line) is tangent to the efficient frontier and has the highest reward-to-risk ratio, also called Sharpe ratio[9]. In Tobin's (1958) "Separation Theorem" he splits up an investor's investment process. First, investors find their optimal portfolio and second, they combine it with a risk-free investment. Investors then vary the weights of these two portfolios accordingly to their risk preferences (Tobin, 1958).

The CAPM extents Markowitz's (1952) and Tobin's (1958) academic work and inherits assumptions already made. More generally, the CAPM asks the question what prices should be in equilibrium given an identical universe of investable assets for all investors. Further,

[9] Sharpe ratio is a risk-adjusted return measure. It tells investors how much return they will receive for each unit of risk. The Sharpe ratio is denoted as $SR = \frac{E(r_i - r^f)}{\sigma(r_i - r^f)}$ (Pedersen, 2015, p. 29).

homogenous expected beliefs about expected returns, variances and covariances apply for all market participants (Berk & DeMarzo, 2017). With this insight, Sharpe (1964) concluded that investors, who form identical efficient frontiers and use the same risk-free rate, are also going to draw an identical CAL, which results in the same portfolio for everyone. This is called the Market Portfolio; the CAL is renamed to CML (capital market line) (Bodie et al., 2017, p. 286). A well-known expression of the CAPM, as given by Bodie et al. (2017), for a one-period expected return for a given asset or portfolio i is:

$$E(\tilde{r}_i) = r_f + \beta_i\left[E(\tilde{r}_M) - r_f\right], \quad (1.6)$$

where random variables are denoted by a tilde, and:

$\beta = \dfrac{cov(\tilde{r}_i, \tilde{r}_M)}{\sigma^2 \tilde{r}_M}$

r_f = One-period risk-free interest rate.

$\tilde{r}_M$ = One-period market portfolio return in which each stock's return contribution is dependent on its market value proportional to the sum of the market value of all other stocks.

Expression (1.6) says that expected returns are dependent on a risk-free rate plus a risk premium proportional to its systematic risk exposure, measured by beta. A risk premium is the expected market return minus the risk-free rate. Note that an asset's expected return is solely driven by its risk exposure towards the market portfolio. Therefore, a higher return can only be achieved by selecting assets that have a higher covariance with the market portfolio. In equilibrium, all assets should lie directly on the security market line (SML) (Jensen, 1968, p. 7). Notice that the alpha, which was already introduced in the Single-Index model, is not included in (1.6). If the CAPM is valid,

$$\alpha_i = E(\tilde{R}_i) - \beta_i E(\tilde{R}_M) = 0. \quad (1.7)$$

For each security or portfolio i, (1.7) states that alpha needs to be zero (Black et al., 1972, p. 2), where (1.7) is given in excess return format.

However, this is not always the case as was empirically underpinned by Jensen (1968, p. 17-20) and Black et al. (1972), who find that an expected asset's return is not exactly described by its exposure to the market portfolio. Further, betas must not be stationary over time but can vary (Black et al., 1972, p. 44). The authors noticed that, besides significantly negative intercept terms for high beta grouped portfolios of assets and significantly positive intercept terms for low beta grouped portfolios, this effect grew stronger in the analyzed time period from 1926 to 1966, with the strongest effect shown between 1947 to 1966.

While positive deviations from the SML are denoted by a positive alpha and vice versa, they should not occur following the traditional CAPM theory as stated in (1.7). To this end *Hypothesis (1)* of my study tests whether the former statement is true or not. *Hypothesis (2)* further investigates whether hedge fund portfolios do not systematically deviate from the market such that market betas are equal to one and exposures to other factors are, on average, zero.

Since the CAPM is an expectational model, meaning that the expected return on an asset *i*, $E(\tilde{r}_i)$, and the expected return on the market portfolio, $E(\tilde{r}_M)$, are unobservable, Jensen (1968) and Midori (2003) show how (1.6) can be transformed in usage of *ex post* realizations instead of *ex ante*.

A rearrangement of the Single-Index Model in (1.2), following the approach from Midori (2003, p. 93), sets (1.2) in expectation,

$$E(\tilde{r}_i) = \alpha_i + \beta_i E(\tilde{r}_M) \tag{1.8}$$

where α_i and β_i are constants and $\tilde{e}_i$ drops out of the equation because in expectation it becomes zero. When subtracting (1.2) from (1.8), expression (1.8) becomes

$$\begin{aligned} E(\tilde{r}_i) - \tilde{r}_i &= \beta_i E(\tilde{r}_M) - \beta_i \tilde{r}_M - \tilde{e}_i \\ E(\tilde{r}_i) &= \tilde{r}_i + \beta_i E(\tilde{r}_M) - \beta_i \tilde{r}_M - \tilde{e}_i. \end{aligned} \tag{1.9}$$

By substituting (1.9) into (1.6),

$$\tilde{r}_i + \beta_i E(\tilde{r}_M) - \beta_i \tilde{r}_M + \tilde{e}_i = r_f + \beta_i \left[E(\tilde{r}_M) - r_f \right]$$

$$\tilde{r}_i = r_f + \beta_i[\tilde{r}_M - r_f] + \tilde{e}_i \tag{2.0}$$

the famous CAPM relation is restated. Writing (2.0) in excess return format, (2.0) becomes

$$\tilde{R}_i = \beta_i (\tilde{R}_M) + \tilde{e}_i \tag{2.1}$$

and allows for *ex post* realizations.

Finally, the market factor in this study is proxied by the value-weighted return of all firms in the U.S. comprised in the CRSP database and trade either on the NYSE, AMEX or NASDAQ (Fama & French, 1993, p. 10). A risk-free rate is given by one-month T-bill rate.

2.3 Multifactor models

Including more than one factor into a model can be beneficial if assets are sensitive towards multiple sources of risk. Thus, the risk component changes from being one-dimensional to becoming multidimensional (Fama & French, 1993). Applying multifactor models in linear regression, coefficients report the exposure towards a specific factor and thus can play an important role in risk management. As most factors are mimicked by long-short portfolios in this study, positive and negative exposures are possible. When constructing a factor from a large pool of stocks, the factor constructor will choose stocks with common exposure to a variable or style (see Footnote 1 on investment style) and will separate the selected stocks into deciles, quintiles or any favorable quantile based on the magnitude of exposure. These variables can be based on, for instance, fundamental data of firms like price-ratios or leverage ratios. In a next step, the factor constructor will go long in stocks in the highest division and short stocks in the lowest, creating a long-short portfolio, which theoretically follows a zero-investment strategy (Chincarini & Kim, 2010, p. 120). The addition of equity is not needed at this point, leaving this strategy with zero cost (Alexander, 2000).

Out of an analyst's perspective, as it becomes evident to which factors a portfolio is exposed to, risks can be hedged if needed. However, if a factor bet is made, of course, there is no guarantee for a positive factor premium in the future. Analysts creating a portfolio, which follows a specific investment style, for instance *size*, bears the risk that no premium will be earned or worse, the factor performs negatively. A negative factor premium occurs when, for example, the short-leg appreciates in price while the long-leg decreases (Chincarini & Kim, 2010). The following factors are directly or indirectly based on fundamental firm data and therefore fall into the group of fundamental factors.

2.3.1 Size and Book-to-Market Ratio

A famous multifactor model by Fama and French (1993) includes three systematic risk factors. It is a demonstration that, next to a market factor, two additional risk factors add to the explanation of common variation in stock returns. These additional factors subsume a firm size variable, measured by the product of a stock's price times number of shares, *ME*, and a book-to-market variable, measured by the ratio of a firm's book value, *BE*, to its market value (Fama & French, 1993), *ME*. Banz (1981) first analyzed a size effect, which helps explain average returns in the cross-section of stocks. Rosenberg et al. (1985) laid the groundwork for a value factor, building on a 'book/price' strategy that gained abnormally high returns.

Thereafter, Fama and French (1993) conducted multiple time-series regression tests on the CAPM and added the two former introduced variables to the equation. In their study, monthly excess stock returns of 25 portfolios sorted on size and book-to-market equity are regressed against returns of a market factor and two factor mimicking-portfolios, related to *ME* and *BE/ME*. Regression slopes indicate the sensitivity towards a factor. Fama and French (1993) show that the *BE/ME* and *ME* variables proxy for risk factors that can explain common variation in stock returns. Regressions run using only the market factor as explanatory variable on stock portfolios ranked on size, showed that the smallest-size portfolio, controlling for *BE/ME*, earned 0.22 percent to 0.37 percent more alpha than the biggest-size portfolio, except for the lowest *BE/ME* quintile (Fama & French, 1993, p. 35). This result contradicts the CAPM, which states that in equilibrium all assets should lie on the SML, while alpha marks a deviation from the SML (Bodie et al., 2017, p. 286). Interestingly, when including *ME* and *BE/ME* in the asset pricing equation, alphas consistently shrank close to zero. As *ME* revealed a negative relation with average stocks returns[10], *BE/ME* functions in the opposite direction. If a firm's *BE/ME* ratio increases, higher abnormal returns are generated (Fama & French, 1993, p. 12).

[10] A size effect was first discovered by Banz (1981). He found a negative relation between stocks' market value and average returns.

Empirically tested by Fama and French (2004, p.42), the highest ranked stock portfolio by book-to-market ratio from 1963 to 2003 earned an annualized average return of 16.7 percent while the CAPM predicts a return of 11.8 percent on average.

What is the rationale behind a risk premium for holding on to high *BE/ME* stocks or stocks with *ME* and why should investors demand a risk premium for it? Answers to these questions are often diverse. However, as for the size effect, small firms possess less crisis resilience. The risk of default and insolvency for small firms in a crisis is higher than for big established firms. Investors can demand a premium for bearing this risk (Fama & French, 1993, p. 8). Regarding the *BE/ME* factor, a risk premium justification is given by Bondt and Thaler (1987). In their opinion a value premium occurs due to investors overreaction in volatile market phases. When investors categorize stocks in ranks of *BE/ME* they assign prices too high for growth stocks and prices too little for value stocks. Eventually, a price correction takes place that consequently pushes value stock returns up and growth stock returns down (Bondt & Thaler, 1987).

Factor Construction - In each year t from 1963 until 1991, Fama and French (1993) rank a universe of stocks, traded on exchanges like NYSE, AMEX and NASDAQ, on size by the NYSE median into categories small, S, and big, B. Independently of the split on size, they also assign stocks into three groups based on book-to-market equity ratio and use the breakpoints 30 percent for the bottom group, 40 percent for the middle group, and 30 percent for the top group. This division leads to six portfolios, two based on *ME* and three based on *BE/ME*. As an example, portfolio variants are S/L, S/M, S/H, B/L, B/M, B/H. In a next step, the HML factor is created as

$$HML = \frac{1}{2}(S/H + B/H) - \frac{1}{2}(S/L + B/L) \tag{2.2}$$

where *HML* stands for *high minus low* and is the average of the small and big size portfolios with high book-to-market ratios and subtracted by the average of the two small and big size portfolios with low book-to-market ratios. The size factor is created in the following way:

$$SMB = \frac{1}{3}(S/L + S/M + S/H) - \frac{1}{3}(B/L + B/M + B/H) \tag{2.3}$$

(2.3) stands for *small minus big*, *SMB*, and is the average of the three small-sized portfolios minus the average of the three big-sized portfolios, each weighted by their book-to-market ratio (Fama & French, 1993, p. 9-10).

2.3.2 Momentum

A momentum strategy is often characterized by buying recent winners and shorting recent losers. Stocks that have performed well (poorly) over a specific period of time are likely to continue to outperform (under-perform) (Pedersen, 2015, p. 138-139). In a study from 1993, Jegadeesh and Titman tested the momentum anomaly. Ten relative strength portfolios that rank stocks by their past returns over the prior three to twelve months, are then hold over a period varying from three to twelve months as well. Portfolios tested on this strategy earned significant abnormal returns during a sample period from 1965 to 1989 (Jegadeesh & Titman, 1993, p. 70). For instance, the 6-months formation/6-months holding period portfolio realized a compounded excess return of 12.01 percent annually on average (Jegadeesh & Titman, 1993, p. 89).

Factor Construction - In Jegadeesh and Titman's (1993) study, they create three strategies: Buying the best performing decile of stocks, shorting the worst performing decile of stocks and going long-short in the former two variants. They named these variants buy-portfolio, sell-portfolio and buy-sell portfolio. Carhart (1997) uses the buy- and sell-portfolios from Jegadeesh and Titman (1993) in his study on the performance of a mutual fund sample and further extends the equilibrium based Three-Factor model (Fama & French, 1993) with a momentum factor. In Carhart's (1997) study, he applies a 12-month formation period and a 12-month holding period momentum factor. Jegadeesh and Titman (1993, p. 71) formally state the momentum effect as

$$E(r_{it} - \bar{r}_t | r_{it-1} - \bar{r}_{t-1} > 0) > 0, \tag{2.4}$$

$$E(r_{it} - \bar{r}_t | r_{it-1} - \bar{r}_{t-1} < 0) < 0, \tag{2.5}$$

where $\bar{r}_t$ and $\bar{r}_{t-1}$ are denoted with a bar and stand for the cross-sectional average return in t and $t-1$, respectively. (2.4) and (2.5) represent the long and short side of a momentum strategy. In (2.4), stocks continue to perform above average in period t given a positive outperformance in period $t-1$. Likewise, stocks continue to perform below average in period t given an under-performance in period $t-1$. A positive momentum beta indicates that a portfolio holds momentum generating stocks. On the other side, a negative momentum beta is more difficult to interpret. It points out that more stocks in a portfolio performed poorly than well in terms of momentum (Jegadeesh & Titman, 1993).

This study assumes the factor construction as deployed by French's (n.d.) website, where the portfolio formation period is based on 2 to 12 months prior stock returns and is afterwards divided into three portfolios, taking the 30th and 70th percentiles of NYSE stocks as breakpoints. At the same time, all stocks are split into two size portfolios based on the NYSE median. As a result, six portfolios were created, which are adjusted on a daily basis. Lastly, momentum factor is termed *winner minus losers*, *WML*, and is the average of the two size portfolios with high prior returns minus the average of the two size portfolios with low prior returns (French, Kenneth, n.d.).

2.3.3 Betting against beta

In a dynamic model, Frazzini and Pedersen (2014) construct a portfolio that delivers high positive risk-adjusted returns by exploiting margin and leverage constraints of institutional investors. The so-called *betting against beta* factor, *BAB*, is a market neutral self-financing portfolio, which goes long levered low-beta stocks and shorts high-beta stocks. Five predictions, made by the authors, are fulfilled concerning their self-created model from which only a few are presented in this study.

Factor intuition - The specified model assumes a flatter SML than predicted by the CAPM, as suggested by Black et al. (1972). If unconstrained investors lever up their portfolio's long side with safe bets and shorting high beta stocks, they earn high risk-adjusted returns (Frazzini & Pedersen, 2014).

Proposition 1 claims that high-beta stocks are linked to low alpha values since leverage- and margin constrained investors bid up their prices. By ranking stocks by their respective beta estimates at the beginning of each calendar month from 1926 to 2012 into one of ten deciles, declining alpha estimates indeed show proposition 1 is valid. In the alpha estimation process, different asset pricing models in time-series regressions are applied, comprising the CAPM, Fama-French's (1993) Three-factor model and Carhart's (1997) Four-factor model. All models display a systematic decline in abnormal average return when beta increases. The same relation holds for Sharpe ratio estimates. They decline if portfolio market exposure inclines. A *BAB* factor goes long in the low-beta portfolio and shorts the high-beta portfolio. Out of a performance perspective, the factor states a monthly average excess return of 0.70 percent and an annualized Sharpe ratio of 0.78 (Frazzini & Pedersen, 2014).

Factor construction - *BAB* factor is a market neutral portfolio with a leveraged $\beta = 1$ on the long side and a de-leveraged $\beta = -1$ on the short side. On the portfolio basis, stocks are ranked by their respective beta estimate, where the lowest beta stocks on the long-side as well as the highest-beta stocks on the short-side get weighted the most. Formally provided by Frazzini and Pedersen (2014, p. 9),

$$R_{t+1}^{BAB} = \frac{1}{\beta_t^L}\left(r_{t+1}^L - r^f\right) - \frac{1}{\beta_t^H}\left(r_{t+1}^H - r^f\right) \tag{2.6}$$

where

$$r_{t+1}^L = r_{t+1}' w_L, r_{t+1}^H = r_{t+1}' w_H, \beta_{t+1}^L = \beta_{t+1}' w_L \; and \; \beta_{t+1}^H = \beta_{t+1}' w_H$$

For instance, the *BAB* factor, measured on the basis of U.S. stocks, is $1.4 dollars long in low-beta stocks and is on the contrary $0.7 dollars short in the high-beta stocks. The higher weight on the safe side is necessary because stocks that lie more to the left-side of the SML earn on average less than those to the right-side of the SML. Due to this disbalance, weighting the long side stronger than the short side is appropriate to be market neutral (Frazzini & Pedersen, 2014, p. 9).

2.3.4 Quality minus junk

The *quality minus junk* factor, QMJ, advocates stocks, with *quality* attributes, over stocks, with *junk* attributes. Established by Asness et al. in (2019), quality characteristics comprise *safety*, *profitability* and *growth* but come at a price. A high price, as recommended by the authors, is justified and investors accept it because high quality stocks practice what they preach. They earn high risk-adjusted returns compared to low-quality stocks. From June 1957 to December 2016, a factor constructed by going long in *quality* stocks and shorting *junk* stocks earned monthly excess returns of 0.29 percent and a Sharpe ratio of 0.47 on an annual basis (Asness et al., 2019, p. 55).

As presented by Damodaran (2002), the Gordon Growth Model states

$$P = \frac{Div_1}{r_e - g} \tag{2.7}$$

where

P = Price of the Stock.

Div_1 = The expected Dividend one year from now.

r_e = Required rate of return on investors equity.

g = Constant growth rate.

Scaling (2.7) by the book value of assets, (2.7) becomes

$$\frac{P}{B} = \frac{\frac{profit}{B} * \frac{Div_1}{profit}}{r_e - g} = \frac{profitability * payout-ratio}{r_e - g} \tag{2.8}$$

The price-to-book ratio sets the foundation on which firm quality characteristics rest: *Profitability*, *safety* and *growth*. For instance, a firm's price-to-book ratio will rise if profits in the numerator increase, the required rate of return decreases or the growth rate increases. Profitability is measured by a firm's profit scaled by its book value. All else equal, high profitability justifies higher stock prices. Profitable firms generate a constant income, which is acknowledged by investors. The quality attribute *growth* is calculated based on the last five-year growth, with respect to different profitability measures. Steady growth in profits demands a higher stock price. Lastly, *safety* is measured by a firm's required rate of return. All else equal, a stock requires a lower rate of return if its systematic risk exposure is modest. This means a stock is less sensitive to overall swings in the market (Asness et al., 2019, p. 36).

Since the Gordon Growth model is constant over time, Asness et al. (2019) create a dynamic model, which allows time- as well as cross-sectional variation in the quality variables. From 1957 to 2016 they assign a quality measure on each stock in a U.S. stock sample[11] based on the three quality attributes *profitability*, *growth* and *safety*. Afterwards they form ten decile portfolios, ranking the stocks by their respective quality measure. The portfolio with the highest quality score significantly outperforms the bottom quality score portfolio in terms of risk adjusted returns. Following the factor construction approach of Fama and French (1993, p. 8), a *QMJ* factor goes long in the top 30 percent of high-quality stocks and shorts the bottom 30 percent of junk stocks (Asness et al., 2019).

2.3.5 Investment-to-Assets

The *q*-factor model, by Hou et al. (2015), includes four factors that contribute to the explanation of average stock returns in the cross section. It is composed of a market factor, a size factor, an investment-to-assets factor, *I/A*, and a profitability factor, *ROE*. In their study they test 80 anomaly variables in the cross section and find that about half of them show insignificant average return estimates. The *q*-factor model is subsequently tested on the significant anomaly variables left and explains the majority of them. Hou et al. (2015, p. 685) add that many from the tested anomalies in their study are in some sort related to the investment and profitability effect, captured by their *I/A* and *ROE* factors. In the time span from 1972 to 2012 the *I/A* factor earned an average return of 0.45 percent per month (Hou et al., 2015, p. 685). My master thesis only incorporates the investment-to-assets factor, *I/A*, out of the *q*-factor model.

The *I/A* factor is based on a firm's investment channel and is negatively related towards stock returns in the cross-section (Hou et al., 2015). In the academic paper "The Investment CAPM", Zhang (2017, p. 545-547) elucidates the intuition behind the *I/A* in detail. All else equal, stocks with high investment spending should earn lower expected returns than stocks with low investment spending. Moreover, highly profitable stocks should earn higher returns in expectation than low profitable stocks (Zhang, 2017, p. 547). Formally expressed by Zhang (2017),

---

[11] Next to a U.S. stock sample, Asness et al. (2019) assign quality scores in 24 developed markets.

$$r^S_{it+1} = \frac{X_{it+1}}{1+a(\frac{I_{it}}{K_{it}})} \tag{2.9}$$

where

r^S_{it+1} = Stock return in $t + 1$, as the discount rate.

X_{it+1} = Marginal benefit of the investment at $t + 1$.

$1 + a\left(\frac{I_{it}}{K_{it}}\right)$ = Marginal cost of investment.

(2.9) suggests that, firm *i* invests as long as its marginal benefit from investment in t+1, X_{it+1}, discounted by the cost of capital, r^S_{it+1}, is equal to the marginal investment cost in t, $1 + a\left(\frac{I_{it}}{K_{it}}\right)$. Putting it differently, the ratio of firm i's expected profitability of investment in t+1, X_{it+1}, to the marginal cost of investment today, $1 + a\left(\frac{I_{it}}{K_{it}}\right)$, must be the equivalent to firm *i*'s expected return in t+1, r^S_{it+1}, (Zhang, 2017, p. 547).

Factor construction - Investment activity of a firm is defined as the ratio between total change in assets over a year divided by one year lagged total assets. Based on the negative relation between investment activity and average stock returns, Hou et al. (2015) risk factor is constructed in the following way: Accounting for size and ROE, *I/A* is long in the 30 percent lowest investment stocks and shorts the 30 percent highest investment stocks (Hou et al., 2015, p. 659-660), following the approach from Fama and French (1993).

2.3.6 Mispricing Factors

In their academic paper "Mispricing Factors", Stambaugh and Yuan (2017) construct a four-factor model including two mispricing factors, a market- and a size factor. Instead of establishing a risk factor, which corresponds towards a single anomaly, Stambaugh and Yuan (2017) follow a different procedure. They construct two risk factors that take the average of anomaly rankings in the cross-section of stocks. The idea behind this construction method is to more accurately assign stocks to the long- or short side of a respective factor.

Stambaugh and Yuan (2017) form two clusters of anomalies based on their return correlations. The first cluster comprises six of the eleven anomalies, namely: Stock issues, composite equity issues, accruals, net operating assets, asset growth and investment to assets. Since a firm's management has discretion over these anomaly variables, it is named *MGMT* and marks the first factor. The second anomaly cluster includes distress, O-score, momentum, gross profitability and return on assets. These anomalies can less likely be controlled by a firm's management and are more related with performance. Therefore, it is called *PERF* and marks the second factor (Stambaugh & Yuan, 2017, p. 1277).

Factor construction - Anomaly measures are generated in the following way: In a multivariate regression model, each stock's average abnormal return with respect to an anomaly is measured in the cross-section at a given time *t*. In this regard, a positive alphas signal buying a stock, where the stocks with the highest alphas are ranked the lowest on the anomaly scale. On the flipside, stocks with the smallest alphas signal shorting a stock and are in turn ranked the highest on the anomaly scale (Stambaugh et al., 2015, p. 1912; Stambaugh & Yuan, 2017).

As an example, firms in distress have a high probability of failure. However, their subsequent returns are much lower than expected (Campbell et al., 2008). As distressed firms earn negative abnormal returns, they rank accordingly high. Therefore, factors are constructed in a way to go long in low anomaly measured stocks and short high anomaly measured stocks (Stambaugh et al., 2015, p. 1912).

Stambaugh and Yuan (2017) adopt the factor construction approach from Fama and French (1993), but vary the breakpoints: Accounting for size, they use the 20th and 80th percent breakpoints when building their long and short leg. In the end, they take the simple average of the size related portfolios with low anomaly rankings and subtract the average of the two size portfolios with high anomaly rankings (Stambaugh & Yuan, 2017, p. 1275-1278). This study makes use of both mispricing factors.

2.4 Market Efficiency

An efficient market is determined by asset prices that entirely incorporate all available information at any given point in time. Hence, security prices would follow a random walk, meaning that stock prices fluctuate randomly, making stock price predictions irrelevant. If markets were completely efficient, no arbitrage opportunities would exist in financial markets. Active portfolio managers' search for inefficiencies would lead to unsuccessful results (Amenc & Sourd, 2005).

Fama (1970) distinguishes between three forms of market efficiency, namely *weak form*, *semi strong form* and *strong form*.

Weak form efficiency - In weak form efficient markets, trading on past trends would be fruitless, since today's stock prices reflect past stock prices (Amenc & Sourd, 2005). If data on past stock prices had the benefit of a solid prediction of stock performances, stock price signals would be implemented immediately. Therefore, a price appreciation would follow right away after a buy-signal and vice versa (Bodie et al., 2017). As an example, the momentum anomaly refutes the weak form efficiency hypothesis because autocorrelated stock returns may facilitate the profit generation from past prices (Chincarini & Kim, 2010, p. 58). Autocorrelation is frequently apparent in time-series data when returns are negatively or positively correlated from period to period (Greene, 2003, p. 279).

Semi strong form efficiency - Markets are said to be semi strong efficient if prices resemble information on companies that are available to all market participants. Besides past prices, this would have the consequence that information subsuming fundamental data on companies are also reflected in today's stock prices. Especially for active portfolio managers this form of market efficiency is not appealing since it would not be possible to find useful information from firms' fundamental data, for instance balance sheets, profit and loss statements. Stock selection approaches to gain abnormal returns would be a waste of time. For instance, if markets are truly efficient, *value*- as well as *size* investors could not earn abnormal returns, due to the availability of fundamental firm data to the general public (Chincarini & Kim, 2010, p. 54).

Strong form efficiency - Lastly, strong form efficient markets inherit all available information, even information that are explicitly known by firm insiders. This form of efficiency is quite extreme in its assumptions, as it runs counter to observed cases of abnormal profits made on insider information (Chincarini & Kim, 2010, p. 54).

Concluding from the former listed forms of market efficiency, semi-strong and strong form efficient markets would make the existence with respect to active portfolio management almost impossible. While market inefficiencies do occur and are exploited to gain high abnormal returns, markets cannot be completely efficient (Pedersen, 2015, p. 3).

In this regard, anomalies encompass market irregularities in asset prices and debunk the efficiency of markets. Academic literature has produced a vast amount of *factors* capturing anomalous return patterns (Harvey et al., 2016) that performed better than recognized asset pricing theory would have predicted (Schwert, 2002). Anomalies become evident in the empirical analysis of historical asset prices. Novy-Marx and Velikov (2016, p.105) state that hundreds of anomaly capturing factors have been created over the near past, which, however, commonly relate to the value-, momentum or size effect in the end. Further, anomalies can vanish or revert once they have been published, which can hamper their investigation process. Answering the question whether the applied asset pricing theory is wrong or if the markets are truly inefficient stays a challenge (Schwert, 2002). Nevertheless, managers in active portfolio management exert effort to improve their performance and consequently have an incentive to track recent factor publications in academic research (Novy-Marx & Velikov, 2016, p. 105).

2.5 Further measures

The *Information Ratio*, IR, takes a fund's annualized alpha and scales it by its respective tracking error, also called active risk. More generally, IR has the benefit of reporting a manager's ability of generating active return per unit of active risk, measured by the alpha volatility. An IR close to or above 1 is considered very good (Qian et al., 2007, p.82).

Tracking error, TE, measures the deviation of a portfolio's performance relative to a benchmark (Rasmussen, 2003, p. 318). Rey and Seiler (2001, p. 23) analyze different variants of tracking error in in- and out-of-sample tests on the Swiss Market Index and come to the conclusion that tracking error decreases in the number of assets in a portfolio. The decrease in tracking error is not as severe in in-of-sample test as in out-sample-test (Rey & Seiler, 2001, p 23). In linear regression, taking equation (1.2) from the Single-Index model as an example, the standard error of residuals provides an estimate how far asset or portfolio *i*'s return deviates from a benchmark, in this case the market index (Frino & Gallagher, 2001; Chu, 2013). Hence, the higher a portfolios residual volatility is, the less a model can explain the return variability of a fund because R^2 decreases in the sum of squared residuals (SSR)[12].

Factor Betas - Remember, a factor beta is nothing but the slope coefficient in linear regression, consisting of the sample covariance between x_i and y_i, scaled by the sample variance of y_i (Wooldridge, 2016, p. 26).

$$\hat{\beta} = \frac{Cov(x_i, y_i)}{Var(y_i)} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3.0}$$

In return-beta language, as stated in Fabozzi & Markowitz (2011, p. 94), a factor beta is an asset or portfolio *i*'s covariance with a particular risk factor, scaled by the risk factor's variance.

While a negative correlation between an asset's and risk factor return series may as well exist, let me use an example for inducing possible scenarios for an easier reading process later on. Assume an asset's return in the Single-Index model is given by a positive alpha and a positive market beta, where the market beta is close to one. Adding an additional risk factor to the equation, which is negatively correlated with asset *i*'s return. Since the average return of asset *i* stays constant, alpha must increase due to the negative exposure towards the additional risk factor. From an econometric point of view, the negative exposure increases the intercept variable because of a rotation in the regression line.

[12] See Appendix D for more detailed information on R^2, $adj.R^2$ and SER.

3 Method

3.1 Data

My sample comprises 9,493 stocks of 18 hedge funds in the U.S., with 4,279 daily observations from January 2003 to December 2019. Overall, 9,371,263 daily return estimates have been processed in Python.

Hedge fund Sample - The selection process of my equity-focused hedge fund sample is based on a report[13], ranking the top 200 hedge fund managers by gross AUM in the first quarter of 2019. From top to bottom, I select hedge fund names with an equity strategy, with 17 consecutive years of filing Form 13F reports and with headquarters in the United States[14].

Form 13F report - Hedge fund data is retrieved from the U.S. Securities and Exchange Commission[15] (SEC) and comprises quarterly filed Form 13F reports from institutional investment managers. Filings have to be made publicly available if investment managers hold equal or more than $100 million in traded securities in the United States. Holding reports must be submitted at least 45 days after each quarter end. Since holding reports reveal only a snapshot in time of a portfolio, I use return data from the Center of Research in Security Prices (CRSP)[16]. An equity strategy is a mandatory requirement in this study, since Form 13F reports encompass mainly equity holdings[17]. In this regard, funds that, for instance indicate a debt related strategy, holding mainly corporate- or government bonds, are consequently ignored. Short positions are not obliged to be disclosed and are thus not reported[18]. Thus, data of Form 13F-filings provide only one side of the coin. As a consequence, hedge fund managers are assessed solely on their

---

[13] The report was published from the website *HFAlert.com*, which changed to *greenstreet.com*. The report is not available anymore. *HFAlert.com* can still be found in the web archive. Information was retrieved mid-February 2020.

[14] Two additional equity-focused hedge funds were selected from *thehedgeefundlist.com*, which fulfill the above-mentioned selection criteria. *thehedgeefundlist.com* is not available anymore but can be found in the web archive. See https://web.archive.org/web/20190202121934/http://www.thehedgefundlist.com/ for further details. Information was retrieved mid-February 2020.

[15] See https://www.sec.gov/edgar/searchedgar/companysearch.html for more information on hedge funds' Form 13F reports.

[16] CRSP uses holding period total returns that reinvests all distributions to shareholders. See details on the return calculation: http://www.crsp.org/products/documentation/crsp-calculations

[17] See https://www.sec.gov/divisions/investment/13flists.htm for official lists of Section 13F securities.

[18] See https://www.sec.gov/divisions/investment/13ffaq.htm for more details on short positions.

respective long positions, which comes closest to a long-only strategy[19]. In this particular case, similarities in the trading strategy with respect to the mutual fund business are surely given. Mentioned by Fung and Hsieh (1999), next to hedge funds, mutual funds trading approach is considered as conservative, as they typically implement a buy-and-hold strategy. Lastly, I use the terms *hedge fund* and *fund* interchangeably. If I refer to mutual funds, I explicitly mention them.

Factor data - In general, all factors are based on U.S.'s listed stocks only. Data on risk factors are publicly available on each respective author's website. Specifically, Fama and French provide the majority of risk factors, namely a CAPM resembling market factor, a size factor, a value factor and a momentum factor.

When mentioning a specific hedge fund, I refer to the holding company, which reports their complete equity holdings of either one or more hedge funds to the SEC. Although the comparableness of hedge funds might be given through following a common strategy, my sample does not represent the general hedge fund population. Instead of a random selection process, I chose hedge funds by ranks of AUM. Hence, the sample resembles a successful fraction of the biggest hedge funds in size. In this regard, I use the terms size and market capitalization interchangeably.

Moreover, a survivor ship arises, if funds drop out of a database, which is caused by the incentive to hide poor performance (Pedersen, 2015). Since funds are obliged to report to the SEC, no fund can simply stop reporting based on its own accord. If, however, the AUM hurdle is not reached, funds will stop reporting and therefore will not appear in HFAlert's report[20]. Thus, for this study, funds need to have at least $100 million AUM in each quarter from the beginning of 2003 till the end of 2019.

---

[19] Long-only strategies refer to trading long-positions in equities, eventually in combination with leverage (Fung & Hsieh, 1999, p. 320)

[20] The report from *HFAlert.com* does not comment on the length of each fund's reporting horizon of Form 13F-reports. It simply states the first quarter AUM of 2018 and 2019 as well as the percentual change from quarter to quarter.

3.2 Methodology

Return Calculation - In order to calculate a given hedge fund's daily holding report's return, I calculate each position weight by dividing a given position value, measured by its market capitalization, by the total value of the portfolio of a given quarter (Chincarini & Kim, 2010, p. 243). Position weights will therefore not change over the course of a quarter. Multiplying each position weight with its corresponding return, yields a position's contribution. The daily return of a given hedge fund holding report is then the summation of all contribution of a given day (Fabozzi & Markowitz, 2011, p. 50). As an example, a given manager files her holding report on the 31st, December 2018. Then each position weight is multiplied with its corresponding return series in the first quarter of 2019. For this study, I assume the availability of holding report data at each quarter end with no time lag. This is obviously possible by looking at historical data.

Having calculated each funds' daily return series comprising 17 years in total, I create three hedge fund portfolios, in order to do robust inferences about my sample. The first portfolio weights hedge funds equally based on market capitalization, the second and third portfolio is created by selecting funds by performance in which each of the performance-based portfolios inherits five hedge funds.

The equal weighted portfolio, *Ew-Port*, provides a broader picture of the equity-focused hedge fund landscape. It is weighted equally for two reasons: On the one hand, I want to account for the differences in funds' market capitalization. Weighting funds equally, prevents a weight distortion within the portfolio and facilitates an even return comparison among funds. On the other hand, sample funds only make up a small successful fraction of the general hedge fund universe. Even if the sample is value-weighted, it would considerably neglect small to medium sized funds.

Further, the rationale behind two performance-based portfolios, *SR-high* and *SR-low*, follows two ideas as well: First, it points out differences in top versus low performing hedge funds, selected by their Sharpe ratios. Investors are concerned with their return on investment. It becomes intuitive to ask the question where differences in performance stem from. While arithmetic average returns and cumulative returns are not risk-adjusted, managers can take risky positions in order to achieve high returns. Nevertheless, this might not be in the best interest of investors. A Sharpe ratio close to or above one is an indication that a manager does generate a high performance relative to the risk taken. On the other hand, performance-based portfolios are less prone to biases and are more likely to reveal systematic differences than single funds (Qian et al., 2007).

The two performance-based portfolios consist of the following funds: *SR-high* includes Eminence Capital, Glenview Capital Management, Kensico Capital Management, Orbimed Advisors, Viking Global Investors. *SR-low* includes Adage Capital, Baupost Group, GMT Capital, Paradigm Capital and Steadfast Capital Management.

3.3 Model

In the following I list five separate factor models. Model names are abbreviated for convenience reasons. As an example, *3-F* model stands for 3-Factor model. All dependent variables, meaning all hedge funds and portfolios of hedge funds, including the market factor, *MKT*, are stated in excess of the risk-free rate in the further analysis.

CAPM: $R_t = \alpha + \beta_1 MKT_t + e_t$

3-F model[21]: $R_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + e_t$

4-F model[22]: $R_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 WML_t + e_t$

7-F model: $R_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 WML_t + \beta_5 BAB_t + \beta_6 QMJ_t + \beta_7 I/A_t + e_t$

4-F-mis model[23]: $R_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 MGMT_t + \beta_4 PERF_t + e_t$

[21] 3-*F* model stands for Three-Factor model as Fama-French (1993) first applied it.
[22] 4-*F* model stands for Four-Factor model and resembles the Carhart 4-Factor Model first applied it 1997.
[23] *4-F-mis* model stands for 4-Factor model with Mispricing Factors.

The *7-F* model is an extension of the Carhart (1997) Four-Factor model, with three additional factors, *BAB*, *QMJ* and *I/A*. The *4-F-mis* model resembles the Four-Factor model as constructed by Stambaugh and Yuan (2017), with two mispricing factors, a market- and a size factor[24].

The reason why both mispricing factors, *MGMT* and *PERF*, are not included in the *7-F* model and belong to a separate model, is due to high correlations between factors, which can lead to multicollinearity in linear regression[25]. The CAPM, the *3-F* model based on Fama-French's (1993) Three-Factor model and *4-F* model based on Carhart's (1997) Four-Factor model serve as auxiliary factor model variants.

Lastly, the following two hypotheses should answer whether my factor models help explain average hedge fund returns and if managers earn significant abnormal returns measured by alpha:

- H1a: Hedge fund portfolios do not systematically deviate from the market such that β_{MKT}= 1 and exposures to other factors are, on average, zero.
- H1b: Hedge fund portfolios exhibit systematic exposures to other risk factors.

- H2a: Hedge fund portfolios do not earn significant alpha after taking loadings on factors into account.
- H2b: Hedge fund portfolios earn positive alpha even after taking loadings on factors into account.

a: Nullhypothesis ($H0$)
b: Alternative Hypothesis ($H1$)

---

[24] Stambaugh and Yuan (2017) constructed a separate size factor in their paper. This study makes use of Fama-French's (1993) size factor.
[25] See Table A11 in Appendix A for a Variance Inflation Factor (VIF) test. VIF values above five can be a sign of collinearity (Hair et al., 2013, p. 201). As a result, estimation problems due to inflated standard errors can occur (Wooldridge, 2016, p. 86-87).

4 Descriptive statistics

Table 1 illustrates summary statistics of analyzed hedge funds, subsuming the time-series from January 2003 to December of 2019. The index to the left lists hedge fund names in alphabetical order. Some fund names are abbreviated for convenience. Columns (1) and (2) show average arithmetic annualized returns in excess of the 1-month T-Bill rate[26] and standard deviations, respectively. The Sharpe ratio is the ratio between (1) and (2). Columns (4) and (5) provide mean and median of the number of positions held during a quarter respectively.

Table 1
Summary statistics

Hedge Fund	(1) Excess Return in %	(2) Standard Deviation in %	(3) Sharpe Ratio	(4) Mean Position Quantity	(5) Median Position Quantity	(6) Median Dollar Value-per Quarter End ($Mil.)	(7) Mean Dollar Value-per Quarter End ($Mil.)
ADAGE CAPITAL PARTNERS	13.04	18.06	0.72	603.6	610.5	23,127.8	24,083.2
ARROWSTREET CAPITAL	14.06	19.32	0.73	603.8	430.0	5,205.9	11,375.6
BAUPOST GROUP	16.03	24.77	0.65	23.5	20.0	2,033.4	3,359.5
COATUE MANAGEMENT	19.15	23.04	0.83	47.8	39.5	3,036.2	4,440.7
EMINENCE CAPITAL	16.40	18.44	0.89	50.0	47.0	4,408.5	4,165.8
GLENVIEW CAPITAL MANAGEMENT	17.62	19.79	0.89	54.7	55.0	7,391.6	8,790.1
GMT CAPITAL	16.36	24.11	0.68	94.7	89.5	2,788.3	2,689.2
KENSICO CAPITAL MANAGEMENT	18.72	19.15	0.98	36.1	36.5	2,313.5	2,824.0
MAVERICK CAPITAL	14.10	19.27	0.73	96.9	76.0	7,764.8	7,735.7
ORBIMED ADVISORS	19.02	21.01	0.91	87.8	90.0	3,965.8	4,964.6
PAR CAPITAL MANAGEMENT	20.24	24.74	0.82	74.3	72.0	2,148.6	3,194.1
PARADIGM CAPITAL	10.79	19.93	0.54	206.5	224.5	1,438.8	1,391.8
RUANE CUNNIFF & GOLDFARB	14.30	19.49	0.73	130.6	129.5	9,418.3	9,717.7
SANDLER CAPITAL MANAGEMENT	17.96	20.97	0.86	83.1	81.0	519.2	698.8
SELECT EQUITY GROUP	15.22	19.01	0.80	73.1	72.5	5,503.5	6,662.7
STEADFAST CAPITAL MANAGEMENT	7.99	13.01	0.61	42.8	43.5	2,526.7	2,538.0
TIGER GLOBAL MANAGEMENT	20.72	23.56	0.88	42.8	42.5	4,272.2	5,488.6
VIKING GLOBAL INVESTORS	17.75	19.93	0.89	59.9	56.5	9,097.3	10,699.7

Columns (6) and (7) show median and mean dollar value in millions of a given holding report at each quarters end. A holding report's dollar value is the summation of each positions market capitalization.

Focusing on column (3), Sharpe ratio estimates vary quite drastically. Over 17 years Paradigm Capital achieved the lowest estimate of 0.54, whereas Kensico Capital Management generated the highest Sharpe ratio of 0.98. In terms of mean fund position quantity, estimates severely

[26] Data on 1-month Treasury Bill rates is provided by Kenneth French's website.

vary as well. As Baupost Group holds 23 portfolio positions on average, Adage Capital Partners and Arrowstreet Capital account for over 603 positions respectively.

Table 2 provides average annualized returns for all risk factors tested in this study. The market factor achieved the highest average return of 11.40 percent annually, followed by *BAB* with 7.99 percent. *WML*, *PERF* and *QMJ* yielded 3.97 percent, 4.40 percent and 3.22 percent respectively. Coming to the lower end of the return spectrum, *SMB*, *MGMT*, *I/A* and *HML* generated the lowest risk premia on an annual basis, with 1.50 percent, 1.21 percent, 0.07 percent and -0.27 percent listed in that order. Risk premia of *I/A* and *HML* are not statistically significant with t-statistics of 0.52 and -1.79 in each case.

Panel B of Table 2 displays a correlation matrix of factor returns. Leaving out *SMB* and *HML*, factor correlations with *MKT* are negative, ranging from -0.07 for *I/A* to -0.55 for *BAB*. *I/A* and *MGMT* show a moderate positive correlation of 0.57. Therefore, I assume both factors act as complements in time series regressions. A simple explanation for their correlation could be due to an *Investment-to-assets* anomaly that is also included in the *MGMT* factor. Further, *PERF* and *WML* also have a moderately strong correlation of 0.65 and could play a similar role in time series regressions. *PERF* inherits a momentum anomaly in its cluster as well, which makes a positive correlation not surprising, even if mispricing factors take the average of an anomaly cluster. *HML* and *PERF* show a strong negative correlation of -0.76, suggesting that both factors explain returns in inverse directions in regressions.

Table 2
Factor Means

Panel A

	MKT	SMB	HML	WML	BAB	QMJ	IA	MGMT	PERF
Return	**11.40**	**1.50**	-0.27	**3.97**	**7.99**	**3.22**	0.07	**1.21**	**3.40**
	(40.6)	(10.9)	(-1.79)	(-26.7)	(101.9)	(17.8)	(0.52)	(10.2)	(12.1)
2003-2005	15.58	7.80	6.28	4.99	19.89	-4.88	0.71	-1.75	-1.79
2006-2008	-8.77	-0.65	1.37	15.57	-11.07	12.82	-0.18	0.18	24.42
2009-2011	18.56	5.66	-4.07	-11.38	8.58	-0.59	2.73	-0.43	-2.32
2012-2014	22.34	-0.63	2.75	7.97	17.15	0.46	3.45	3.36	-4.94
2015-2017	12.58	-0.56	-0.67	3.94	11.47	8.39	-4.78	6.70	4.54
2018-2019	10.80	-4.07	-9.77	5.07	3.42	4.55	-1.94		
Annual Standard Dev.	18.35	9.00	9.84	9.73	5.13	11.18	8.81	7.74	18.44

Panel B

	MKT	SMB	HML	IA	WML	BAB	QMJ	MGMT	PERF
Mkt-RF	1.00	0.18	0.35	-0.07	-0.32	-0.55	-0.58	-0.23	-0.53
SMB		1.00	-0.09	-0.03	0.05	-0.26	-0.17	-0.19	-0.02
HML			1.00	0.29	-0.38	-0.42	-0.62	0.29	-0.76
IA				1.00	-0.01	-0.08	-0.04	0.57	-0.06
WML					1.00	0.45	0.37	-0.05	0.65
BAB						1.00	0.57	0.01	0.57
QMJ							1.00	0.23	0.75
MGMT								1.00	-0.09
PERF									1.00

Panel A provides average returns of risk factors measured on an annual basis. The first row comprises factor returns from January 2003 to December 2019, with *t*-statistics given in parenthesis. The index to the left lists three-year subperiod returns, where the last subperiod comprises two instead of three years. “Mispricing factors”, *MGMT* and *PERF*, have no estimates from 2017 to 2019, since their time-series is not further extended by the authors after 2016. The standard deviation comprises the complete time horizon and is also reported on an annual basis. Panel B reports the correlation matrix of risk factor returns from January 2003 to December 2016. All factor correlations shown are highly significant with p-values lower than 0.01. The correlation matrix uses Pearson’s Product-Moment Correlation.

5 Empirical results

5.1 Factor betas

Table 1 shows factor loading results in time-series regressions. In the ongoing analysis, the focus lays on the *7-F* model and *4-F-mis* model, because they report the highest R^2 estimates of 0.98, respectively. Therefore, they explain most of the variation in average returns for all hedge fund portfolios. As differences in R^2 and adjusted $Adj.R^2$ are negligible small (see Table A11 Appendix A), I choose the Akaike Information Criterion (AIC) as an additional model selection criterion. Next to R^2 values that are equal or higher than in the case for the *4-F-mis* model, the *7-F* model demonstrates the lowest AIC estimates compared to all models. As the AIC compares models on a relative basis, absolute values are negligible. The model with the lowest AIC is superior because it penalizes a model for additional regressors, as opposed to R^2 (Greene, 2003, p. 573).[27]

Shown in the left index, *Beta* comprises the *7-F* model market exposure, *MKT*, and is highly significant for all hedge fund portfolios. A beta close to one signals a one-to-one movement with the market. This is unsurprising and should be considered with caution as hedge funds solely report their long positions. Their true market beta could vary due to short positions. While negative and positive market exposures cancel each other out, hedge funds could also be market neutral, meaning a $\beta_{MKT} = 0$, although their long-position portfolio shows differently (Fabozzi & Markowitz, 2011).

Starting off with results of the *Ew-Port*, equity focused hedge funds capture the size effect, measured by a highly significant *SMB* exposure, ranging from 0.22 to 0.24 for all applied models. *SMB* exposures mark the highest estimates economic wise and are highly significant, which indicates a favor for small firms.

---

[27] $\mathrm{A}dj.R^2$ measures also penalize the addition of regressors to a model, but the effect can be irrelevant if the sample size is large (Greene, 2003, p. 84).

Table 3
Factor Loadings (2003-2019)

	Ew-Port					SR high					SR low				
	CAPM	*3-F* M.	*4-F* M.	*7-F* M.	*4-F-mis* M.	CAPM	*3-F M.*	*4-F M.*	*7-F M.*	*4-F-mis* M.	CAPM	*3-F M.*	*4-F M.*	*7-F* M.	*4-F-m*
Excess return	16.01				16.11	17.9				17.77	12.8				13.2
Alpha	**4.00**	**3.71**	**3.73**	**4.46**	**4.74**	**6.13**	**5.72**	**5.58**	**6.02**	**6.63**	1.39	1.31	1.55	**2.13**	**2.9**
	(4.05)	(4.69)	(4.65)	(6.00)	(5.34)	(4.66)	(4.96)	(4.83)	(5.45)	(5.12)	(1.11)	(1.24)	(1.46)	(2.12)	(2.5
MKT	**1.01**	**1.00**	**1.00**	**0.97**	**0.97**	**0.97**	**0.98**	**0.99**	**0.96**	**0.94**	**0.99**	**0.95**	**0.95**	**0.92**	**0.9**
	(186.14)	(187.8)	(189.9)	(170.2)	(171.63)	(117.8)	(141.9)	(142.1)	(137.7)	(102.19)	(121.8)	(104.9)	(114.08)	(82.8)	(140.
SMB		**0.24**	**0.24**	**0.22**	**0.23**		**0.18**	**0.18**	**0.17**			**0.31**	**0.31**	**0.3**	**0.2**
		(19.22)	(19.20)	(19.27)	(19.99)		(11.06)	(10.76)	(12.14)			(18.55)	(19.36)	(22.51)	(19.7
HML		**-0.07**	**-0.07**	**-0.10**			**-0.16**	**-0.15**	**-0.20**			**0.05**	**0.04**	0.00	
		(-5.27)	(-5.68)	(-7.03)			(-8.55)	(-8.62)	(-9.80)			(3.20)	(2.08)	(0.06)	
WML			0.00	0.01				0.02	0.02				**-0.05**	**-0.04**	
			(-0.09)	(0.92)				(1.71)	(1.42)				(-2.75)	(-2.61)	
IA				**-0.09**					**-0.06**					**-0.09**	
				(-4.91)					(-2.35)					(-4.73)	
BAB				0.01					**0.08**					**0.04**	
				(0.98)					(4.92)					(3.19)	
QMJ				**-0.15**					**-0.22**					**-0.19**	
				(-13.31)					(-12.15)					(-16.11)	
MGMT					**-0.15**					**-0.15**					**-0.2**
					(-8.54)					(-5.90)					(-12.
PERF					**-0.02**					**0.01**					**-0.0**
					(-1.39)					(0.62)					(-8.3
R-squared	0.96	0.97	0.97	0.98	0.98	0.93	0.94	0.94	0.95	0.94	0.93	0.94	0.95	0.96	0.9
Adj. R Square	0.96	0.97	0.97	0.98		0.93	0.94	0.94	0.95		0.93	0.94	0.95	0.96	
AIC	-209.0	-2082.7	-2080.7	-2625.6	-1729.8	2106.6	1082.5	1074.8	593.7	1086.8	2131.2	617.1	576.6	152.7	163.

This table reports results from linear time-series regressions. Top column headers are abbreviations for different hedge fund portfolios, where *Ew-Port* stands for equally weighted hedge fund portfolio and *SR high* and *SR low* stand for the top and bottom five hedge funds selected by their respective Sharpe ratios. The portfolios' excess returns serve as the dependent variables and are run against different factor models, shown in the lower column headers. The CAPM, *3-F* model, *4-F* model and *7-F* model comprise the time period is from January 2003 to December 2019. *4-F-mis* model comprises the time period from January 2003 to December 2016, since "Mispricing Factors" are no longer provided after 2016. Return stands for the average arithmetic excess return on an annual basis. Observation frequency of returns is daily, whereas excess returns and alpha estimates are given on an annual basis. *t*-statistics are given in parenthesis and heteroscedasticity and autocorrelation robust standard errors were used in the estimation process (Newey-West). Bold figures signal significance at or below the 5 percent level.

On the contrary, *Ew-Port* loads negatively on *HML*, significant on the one percent level, signaling a preference for growth stocks and less for value stocks. Thus, capturing value premia seems to be out of favor for equity focused hedge funds. A negative exposure towards *QMJ*, with a loading of -0.15 ($t = -13.31$), discloses that hedge funds have an incentive for holding *junk* stocks than *quality* stocks on average.

Further, the *Ew-Port* is negatively correlated with the mispricing factor *MGMT*, exhibiting an exposure of -0.15 (t = -8.54) on. Specifically, the negative loading on *MGMT* is in line with the negative loading on *I/A*, -0.09 ($t = -4.91$), since *MGMT* also incorporates an *investment-to-assets* anomaly. This result further advocates the fact that equity focused hedge funds tend to pick high-investment stocks and therefore do not earn an investment premium on average.

The investment premium also corresponds with the value premium from *HML*. As growth stocks have a higher market capitalization due to higher prices, they have more investment possibilities than value stocks. Consequently they invest more and therefore earn lower expected returns (Zhang, 2017, p. 550). Moreover, *asset growth* makes up a separate anomaly in the *MGMT* cluster. As the factor loadings on *MGMT* and *HML* are both negative, this further supports that there is a tendency for hedge funds to hold more growth stocks than value stocks.

In sum, based on results of the *Ew-Port*, Table 3 demonstrates nine separate risk factor loadings (seven from the *7-F* model; two from the *4-F-mis* model) of which five are highly significant. From these five factor loadings, four are negative, including *HML*, *I/A*, *QMJ* and *MGMT*. This result reveals that hedge fund managers do not exert effort to capture these factor premia on average. However, this could be caused due to the non-existence of a factor at a given point in time. As an example, while the observed time horizon in my study dates back to the beginning of 2003, the research paper *Quality minus junk* was published in 2019, which is evidence that *QMJ* as factor was not available to this time. Other reasons for inverse factor correlations could be strategy related. When managers anticipate poor risk factor returns on average, they might want to hedge that particular source of risk (Bodie et al., 2017, p. 311).

Tests on the *SR-high* and the *SR-low* in Table 3 reveal further that the *SR-high* substantially deviates from the *SR-low* portfolio in terms of *HML* exposure. This factor beta difference of

0.2 is the biggest economic wise. Interpretation wise, *SR-high* managers bet more heavily on growth stocks relative *SR-low* managers, capturing price appreciations if investors overreact and consequently bid up prices consistent with the behavioral finance perspective of the value effect (Bondt & Thaler, 1987)[28]. The *SR-high*'s *HML* loading is also twice the size as that of the *Ew-Port.*

A negative loading of -0.07 on *PERF* for the *SR-low* is in line with a negative loading on *WML*, since the anomaly cluster of *PERF* includes a separate momentum effect. It seems that the *SR-high* is indifferent towards the momentum effect.

In a nutshell, differences in both performance-based portfolios are given through the value- and momentum factor, whereas *QMJ*, *BAB* and *I/A* only provide minor differences. In addition, these factor loadings differences become more negligible considering the low impact on the return contribution. Over the specified time horizon, the *SR-high* and *SR-low* achieved an average excess return of 17.9 and 12.8 percent respectively. Taking the return contribution of *MKT* and alpha into account, the return attributable to risk factors left in the model is 0.94 percent for the *SR-high* and 0.18 percent for the *SR-low* in the *7-F* model. The *SR-high* clearly outperforms the *SR-low* in systematically capturing risk premia by a factor of almost 5. However, the return contribution of risk factor marks only a fraction of the profits those portfolios earn on average. From a return contribution standpoint, it is irrelevant whether managers tilt portfolios with respect to a given risk factor if risk premia are on average low.

Over the time period from 2003 to 2019, *SMB* returned 1.5 percent on average. As a consequence, the annual return contribution of *SMB* for the *SR-high* and *SR-low* makes up 0.26 percent and 0.45 percent respectively. The *SR-high*'s average return contribution from *HML* is merely 0.05 percent on an annual basis, which is even less than for *SMB*. While HML performed negatively on average, it makes intuitively sense holding growth stocks rather than value stocks for the *SR-high*.

[28] See Chen and Zhao (2009) for a comprehensive discussion on value and size premia.

Lastly, besides the market factor, five factor betas show significance on the one percent level and thus help to explain average returns over time. Thus, I reject H1a of *Hypothesis (1)*. The market beta is not the single determinant for risk, which refutes the CAPM in its statement that expected returns solely depend on the exposure to the market portfolio. Although the market factor is a systematic risk factor, not every factor introduced in this study captures systematic risk per se. It is correct that factors can explain fund returns in a systematic way. Fama and French (1993) state that *SMB* and *HML* proxy for systematic risk factors, whereas Stambaugh and Yuan (2017) argue that factors capture common market mispricing in the form of anomalies that drive expected returns. However, the question whether factor risks originate from a systematic or mispricing background lies beyond the scope of this study.

5.2 Alpha

Table 5 reports alpha estimates already included in Table 4 but extends it by providing Information ratios as well as Sharpe ratios of the hedge fund portfolios *Ew-Port*, *SR-high* and *SR-low*.

Taking the *7-F* model as a benchmark model, the equal-weighted portfolio delivers an alpha of 4.46 percent in the with ($t = 6.00$). The *SR-high* delivers an alpha estimate even greater than the *Ew-Port*, with 6.02 percent on average, whereas the *SR-low*'s alpha is only 2.13 percent on average

This difference in alpha marks a severe disbalance in the abnormal return generation process between the performance-based portfolios. In addition, the gap even widens when considering the CAPM, *3-F* and *4-F* model estimates. *SR-low*'s alphas do not pass the 2.0 percent mark and are insignificant for all three models. Only in the *7-F* and *4-F-mis* models, alpha is significantly different from zero, which is mainly caused by negative factor loadings (see *2.4 Further measures* for an example). Therefore, it is not safe to assume that alpha is achieved by managerial skill. The poor t-statistics points out luck in achieving alpha because it could also just be zero. Coming back to the disbalance in alpha of the performance-based portfolios, what stays hidden, is how alpha is produced. Whether alpha is attributable to a new strategy in the form of a systematic factor or if managers simply trade on trends and bet on the outcome of events. Although omitted variable bias can be present in a model, even if R^2 values are high, studies suggest that in a standard Four-Factor model, factors comprise systematic risk to a large extent, reducing the scope of further unknown risk factors (Novy-Marx & Velikov, 2016, p. 105; Fung & Hsieh, 2011, p. 84).

Table 4
Alpha Evolvement of Hedge Fund Portfolios

Portfolio	Ew-Port	SR high	SR low
Excess return	16.01	17.90	12.80
CAPM Alpha	**4.00**	**6.13**	1.39
	(4.05)	(4.66)	(1.13)
3-F Model Alpha	**3.71**	**5.72**	1.31
	(4.69)	(4.96)	(1.29)
4-F Model Alpha	**3.73**	**5.58**	1.55
	(4.65)	(4.83)	(1.47)
7-F Model Alpha	**4.46**	**6.02**	**2.13**
	(6.00)	(5.45)	(2.09)
4-F-mis Model-Alpha	**4.74**	**6.63**	**2.93**
	(5.34)	(5.12)	(2.49)
Sharpe ratio	0.84	0.96	0.68
Information ratio	1.40	1.47	0.35
R-squared	0.98	0.95	0.95

This table depicts results from linear time-series regressions. The time period is from January 2003 to December 2019. Column headers are abbreviations and stand for different hedge fund portfolios, where *Ew-Port* stands for equally weighted hedge fund portfolio and *SR high* and *SR low* stand for the top and bottom five hedge funds selected by their respective Sharpe ratios. The portfolios' excess returns serve as the dependent variables and are run against different factor models, shown in the left index. In time-series regressions, alpha is the intercept of the regression line. *4-F-mis* model estimates comprise a time span from January 2003 until December 2016, due to a reporting stop of the mispricing factors. *Beta* and *R*-squared estimates are based on the *7-F* model results. Sharpe ratios and Information ratios comprise the whole time period. Observation frequency of returns is daily, whereas excess returns, alphas, Sharpe- and Information ratios are given on an annual basis. *t*-statistics are given in parenthesis and heteroscedasticity and autocorrelation robust standard errors were used in the estimation process (Newey-

Taking the average over all applied model's alpha estimates makes the estimate more robust for inferential purposes. In this regard, the *Ew-Port*, *SR-high* and *SR-low* generate alpha terms of 4.13 percent, 6.02 percent and 1.86 percent respectively. Elaborating further on the alpha difference, the ratio between average alpha and excess return makes up around 25.8 percent and 33.6 percent of annual excess returns for the *Ew-Port* and *SR-high*. Hence top performing hedge fund's alpha makes up more than one-third of its average return, which leaves managers with a risk-less gain on top of the factor premia. For the *SR-low* average alpha makes up only 15.0 percent of total excess return.

Regardless of a specific model, managers of the *SR-low* clearly generate the least alpha over 17 years, leaving it with an annual alpha of roughly 2 percent on average. This result marks a distinction between the two performance-based portfolios, because hedge fund managers of the *SR-high* earn severely more alpha than managers of the *SR-low*. This result might seem obvious, but differences in the *SR-high* and *SR-low* could have also stemmed from systematic differences in factor premia exploitation. As my former analysis demonstrates, this is not the case.

Lastly, since alpha estimates are significantly different from 0 for all model variations of the *Ew-Port* and *SR-high* after accounting for factor loadings, H2a from *Hypothesis (2)* can be rejected. Following the CAPM theory, in equilibrium all assets should lie on the security market line, where alphas signify deviations from the SML (Bodie et al., 2017). In my investigation alphas are significant on the one percent level for at least two hedge fund portfolios. Thus, managers prove the possibility of achieving abnormal profits.

Before diving into the dynamics of factor betas, one comment regarding the ongoing factor model choice. From now on, the *7-F* model is my preferred choice over the *4-F-mis* model when reporting my results. The reasons for this are as follows: Besides the superiority of *7-F* model compared to the *4-F-mis* model with regards to R^2 and AIC estimates, a spanning test of Carhart's (1997) Four-Factor model (*4-F* model) on *PERF* and *MGMT* as dependent variables, discloses that the *4-F* model can accommodate the anomalies captured in *MGMT*, leaving an alpha of 2.29 and insignificant in statistical terms (t = 1.19). In addition, the *4-F* explains a large part of the return variability of *PERF*, $R^2 = 0.77$[29] (see Table A10 in Appendix A). This result is coherent with my factor correlation results from Table 2. *PERF* is

[29] In academic literature, spanning tests commonly aim at explaining away the alpha term of fundamental risk factors as response variable (Gokten, 2018).

strongly inversely correlated with HML ($\rho_{(PERF,HML)} = -0.76$) and positively correlated with *WML* ($\rho_{(PERF,WML)} = 0.65$).

5.3 Time dynamics

As the CAPM theory assumes portfolio risk is stationary over time (Amenc & Sourd, 2005, p. 123) this does not have be the case in general. Manser and Schmid (2016, p. 55) also argue that hedge funds are more prone to dynamic strategies, suggesting that the CAPM is not an appropriate benchmark due to the stationarity of betas. In my observed time-series from January 2003 to December 2019, risk parameters might as well be changing. Moreover, it would be interesting to know whether managers try to time the market through increasing or decreasing their market betas.

Table 5 reports factor loadings of the *7-F* model comprising three-year subperiods of the time-series, allowing for more dynamic movement of factor betas. Subperiods are not overlapping, where the last period, 2018 till 2019, comprises two instead of three years. In addition, I include a squared market factor variable, *MKT Square*, to account for market timing activity, which stems from the Treynor and Mazuy model (1966)[30]. *MKT Square* tests whether a fund's market exposure is non-linear. Market timing ability would then conclude that a fund's market exposure should be reduced in market downturns and be increased it in market upturns, resulting in a curvature of beta. If the factor beta of *MKT Square* is positive, a manager demonstrates market timing ability. A negative factor beta, on the contrary, signals timing the market worse than if not participate in timing at all. For instance, increasing the market exposure in downturns and decreasing market exposure in upturns (Amenc & Sourd, 2005). Surely, the validity of a market timing test when exploring solely the long side of hedge fund holdings can be misleading. Hedge fund managers could still time the market via short positions

[30] The original Treynor and Mazuy model inherits two factors, one market factor and the squared market factor. Both factors are in excess of the risk-free rate. In my study, I add a squared market factor to the 7-F model.

Table 5

7-F Model Factor Loadings in Three-Year Subperiods

Subperiod	*(1)*			*(2)*			*(3)*		
Years	*2003-2005*			*2006-2008*			*2009-2011*		
Portfolio	Ew-Port.	SR high	SR low	Ew-Port.	SR high	SR low	Ew-Port.	SR high	SR low
Return	27.45	29.16	25.61	-5.77	-2.25	-7.95	26.38	24.87	25.05
Alpha	**8.42**	**10.41**	3.95	**7.05**	**10.55**	5.86	**5.45**	4.63	**4.06**
	(5.32)	(4.23)	(1.58)	(3.35)	(3.76)	(1.58)	(3.17)	(1.93)	(2.26)
MKT	**0.93**	**0.91**	**0.87**	**0.98**	**0.95**	**0.93**	**0.99**	**0.99**	**0.95**
	(84.55)	(60.41)	(58.77)	(80.05)	(55.73)	(43.44)	(118.13)	(77.17)	(111.1)
MKT Square	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
	(1.43)	(0.74)	(1.40)	(2.37)	(1.39)	(0.75)	(0.73)	(-0.48)	(0.78)
SMB	**0.29**	**0.22**	**0.38**	**0.25**	**0.19**	**0.23**	**0.20**	**0.12**	**0.29**
	(17.81)	(10.48)	(13.08)	(9.33)	(5.37)	(8.32)	(12.05)	(5.33)	(17.21)
HML	**0.06**	**-0.17**	**0.26**	-0.09	-0.08	**-0.11**	**-0.09**	**-0.09**	**-0.07**
	(2.51)	(-3.92)	(5.5)	(-1.95)	(-1.4)	(-2.3)	(-3.74)	(-4.29)	(-3.11)
WML	0.02	0.05	0.00	**-0.07**	**-0.06**	**-0.09**	0.01	**0.07**	**-0.05**
	(1.16)	(1.94)	(-0.13)	(-2.92)	(-2.08)	(-2.54)	(0.58)	(3.76)	(-3.4)
IA	**-0.12**	**-0.28**	**-0.11**	**-0.13**	-0.04	**-0.21**	**-0.10**	**-0.09**	**-0.09**
	(-3.89)	(-5.14)	(-2.32)	(-2.34)	(-0.54)	(-3.74)	(-3.52)	(-2.26)	(-2.76)
BAB	**-0.06**	-0.01	**0.06**	0.04	**0.10**	**0.11**	0.01	**0.10**	-0.02
	(-3.08)	(-0.44)	(2.01)	(1.86)	(3.56)	(3.36)	(0.44)	(4.66)	(-1.17)
QMJ	**-0.22**	**-0.41**	**-0.18**	**-0.17**	**-0.11**	**-0.21**	**-0.06**	-0.02	**-0.14**
	(-7.36)	(-8.68)	(-3.92)	(-4.85)	(-2.78)	(-4.56)	(-2.15)	(-0.63)	(-6.89)
R-squared	0.97	0.93	0.90	0.98	0.97	0.97	0.99	0.97	0.99

Subperiod	*(4)*			*(5)*			*(6)*		
Years	*2012-2014*			*2015-2017*			*2018-2019*		
Portfolio	Ew-Port.	SR high	SR low	Ew-Port.	SR high	SR low	Ew-Port.	SR high	SR low
Return	28.06	33.04	21.50	11.36	11.28	8.39	10.96	13.65	5.90
Alpha	**5.78**	**7.83**	3.20	0.42	0.70	-0.29	1.49	4.14	-0.21
	(3.68)	(3.76)	(1.15)	(0.32)	(0.37)	(-0.15)	(0.92)	(1.25)	(-0.1)
MKT	**1.01**	**1.02**	**0.93**	**0.96**	**0.99**	**0.95**	**0.93**	**0.98**	**0.89**
	(106.36)	(86.49)	(67.5)	(91.66)	(63.06)	(89.18)	(124.36)	(77.13)	(82.25)
MKT Square	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00
	(-1.46)	(-0.62)	(-1.23)	(-1.65)	(-0.39)	(-0.78)	(0.19)	(-0.64)	(0.00)
SMB	**0.16**	**0.08**	**0.30**	**0.15**	**0.14**	**0.25**	**0.18**	**0.19**	**0.22**
	(9.61)	(4.09)	(9.87)	(9.44)	(7.13)	(9.87)	(13.76)	(7.1)	(12.69)
HML	**-0.19**	**-0.25**	**-0.01**	**-0.12**	**-0.22**	0.01	**-0.07**	**-0.11**	**0.09**
	(-8.09)	(-8.13)	(-3.11)	(-8.37)	(-8.03)	(0.36)	(-3.36)	(-3.2)	(3.75)
WML	**0.14**	**0.17**	0.05	0.03	0.03	-0.01	0.01	-0.03	0.01
	(6.61)	(6.49)	(1.95)	(1.83)	(1.04)	(-0.47)	(0.63)	(-0.83)	(0.24)
IA	**-0.08**	-0.01	**-0.09**	**-0.11**	**-0.18**	-0.00	**-0.09**	-0.05	0.02
	(-2.61)	(-0.32)	(-2.46)	(-4.02)	(-4.16)	(-0.02)	(-3.58)	(-1.08)	(0.45)
BAB	**-0.09**	-0.00	**-0.14**	**-0.05**	-0.05	**-0.09**	**-0.04**	0.04	**-0.11**
	(-3.65)	(-0.07)	(-3.9)	(-3.13)	(-1.92)	(-4.72)	(-2.61)	(1.22)	(-4.88)
QMJ	**-0.18**	**-0.23**	**-0.23**	**-0.15**	**-0.28**	**-0.22**	**-0.15**	**-0.40**	**-0.20**
	(-7.99)	(-6.68)	(-7.29)	(-9.21)	(-10.73)	(-12.95)	(-8.44)	(-10.01)	(-6.72)
R-squared	0.97	0.94	0.92	0.97	0.94	0.96	0.98	0.95	0.96

This Table reports factor loadings of the 7-F model using linear time-series regression. As dependent variables, excess returns from three different hedge fund portfolios over the time horizon from 2003 till 2019 were used, in which the first, Ew-Port, is weighted equally and the second and third portfolios, SR high and SR low, are composed of the top and bottom five hedge funds ranked by their Sharpe ratios respectively and weighted equally on a portfolio basis. Factors in the left index serve as independent variables and are mimicking portfolios, which hold common sources of risk. Observation frequency of returns is daily, whereas excess returns and alpha estimates are given on an annual basis. *t*-statistics are given in parenthesis and heteroscedasticity and autocorrelation robust standard errors were used in the estimation process (Newey-West). Bold figures during downturns, which stay hidden as short positions are not reported. Nevertheless, the idea behind a market timing factor in my model is to analyze whether managers still try to time the market solely concentrating on the long side.

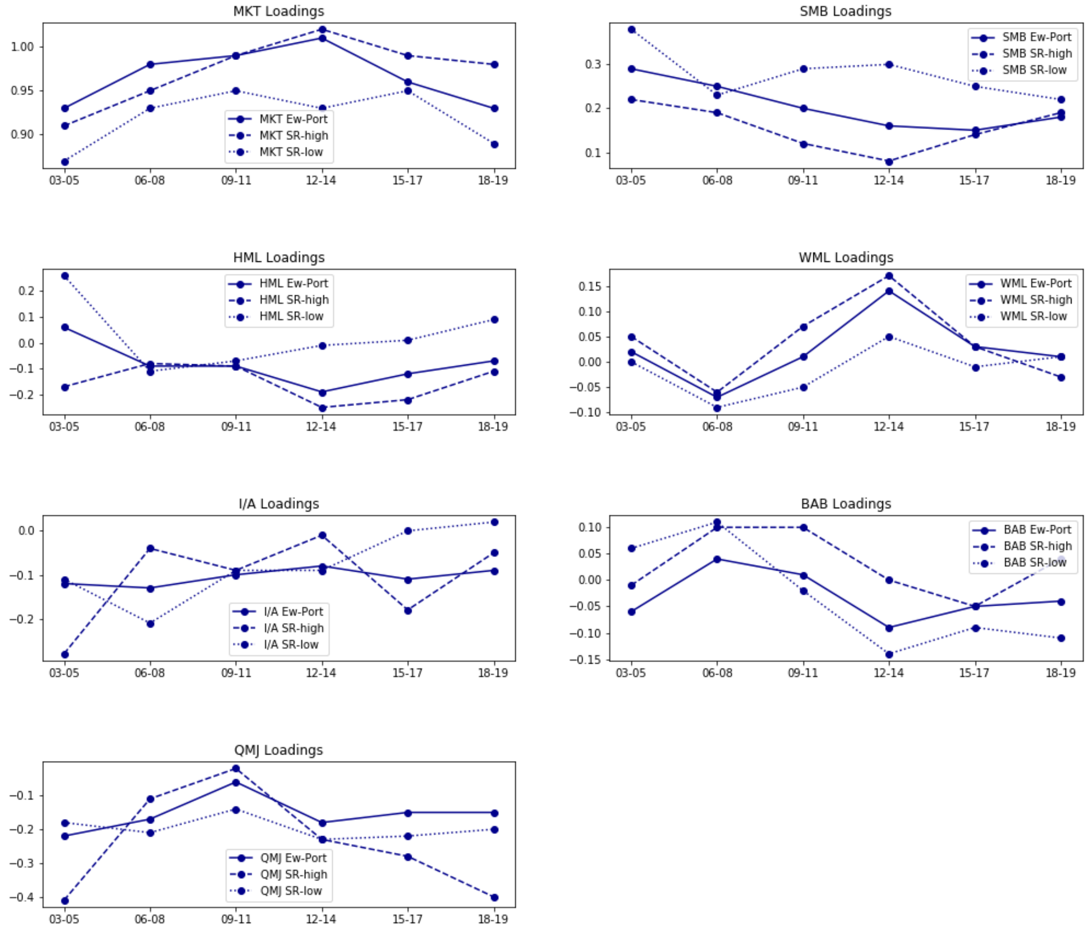
Starting off, the *Ew-Port* earns significant alpha in four out six subperiods, ranging from 0.42 to 8.42 percent on average. The *SR-high* reports three periods with significant alpha, whereas the *SR-low* accounts for only one period with significant alpha. Except in subperiod 2, subsuming the beginning and climax of the Global Financial Crisis (GFC)[31], *2006 - 2008*, the *SR-high* earned the highest alpha during each subperiod compared with the rest, ranging from 0.70 to 10.55 percent. Interestingly, the most alpha it gained was during the subperiod 2. This gain, however, is set off against a severe market contraction, as formerly displayed in Table 2, where *MKT* returned -8.77 percent. Not only did the *SR-high* performed badly, but all portfolios also suffered losses between *2006* to *2008*, but the *SR-high* managed the crisis best, by stating a loss of -2.25 percent on average. The last two subperiods mark the end in returning alpha to investors. From 2015 onwards, no portfolio earned significant alpha. It is possible that after 2015 markets became more efficient to some degree, meaning that exploitable inefficiencies could have ceased. Thus, chances of choosing high abnormal returning stocks shrank.

Regarding the market timing ability of managers, except for one, all loadings on *MKT Square* are not significant and negligible low economic wise, suggesting managers do not participate in market timing on their portfolio long side.

Facilitating the time aspect, Figure 1 illustrates the dynamics of factor betas over subperiods in line charts, where subperiods are equivalent to those shown in Table 5. Starting with *SMB* loadings, the *Ew-Port* and *SR-high* start monotonically lowering their exposure from the beginning of 2003, reaching a low point in subperiod 4 for the *SR-high* and a low point for the *Ew-Port* in subperiod 5. The *SR-low*'s *SMB* exposure drops to a first low during subperiod 2, *2006 to 2008*, and its second low point is in subperiod 6. *QMJ* exposures are highest for all portfolios in subperiod 3, shortly after the Global Financial Crisis, marking a subperiod in which all portfolios proportionally had the least exposure to *junk* stocks.

[31] The Global Financial Crisis, abbreviated to GFC, covers the period between 2007 to 2008 (Olson & Zoubi, 2017).

Figure 1
Hedge fund portfolio loadings on risk factors in three-year subperiods



Note: Figure 1 is based on own calculations using Form 13F report data

WML and *BAB* loadings mostly move in tandem for all three portfolios. Interestingly, *SR-high* and *SR-low* managers present very distinctive factor timing bets on *I/A* during subperiod 2 and subperiod 5. As *SR-high* managers increase the amount of low-investment stocks in contrast to high-investment stocks in subperiod 2, *SR-low* managers bet on the reverse by lowering their *I/A* exposure and buying more high-investment stocks. Lastly, loadings on *HML* converge to around -0.1 for all portfolios in subperiod 2 and subperiod 3, separate afterwards for the *SR-high* and *SR-low*, where the *SR-high* lays the focus on *growth stocks* with negative loadings peaking below -0.2. The *SR-low* becomes factor neutral in subperiod 4 and subperiod 5 and increases its exposure slightly towards value stocks afterwards.

6 Inferences

In chapter 5 I disclosed what returns of equity-focused hedge funds are composed of. Specifically, I showed which type of stocks portfolios of hedge funds generally hold, how betas dynamically move over time and how alpha plays a predominant role in the performance distinction. Since I have answered the question what returns are composed of, I now ask what does determine alpha?

6.1 Number of positions

Focusing on the number of positions of the two performance-based portfolios, the *SR-high* has an average quarterly position number of nearly 58, whereas the *SR-low* accounts for over 194. This divergence demands another test. Does the number of positions have an impact on alpha?

Table 6 reports three portfolios ranked by the average number of stocks hold during a quarter, *High-number*, *Medium-number* and *Low-number* (see Portfolio Formation
in Appendix A). *Medium-number* and *Low-number* portfolios end up with the best results, both in terms of excess returns and alpha. For the *7-F* model, *Medium-number*'s and *Low-number*'s alphas are on average 5.64 ($t = 4.97$) and 5.80 ($t = 4.6$) respectively. The *High-number* performs worst. Although the *Medium-number* earns an average alpha and excess return slightly higher than the *Low-number*, their average position quantity is not far from one another. The *Low-number* accounts for 41 positions, the *Medium-number* for 72 while the *High-number* reaches 289 on average.

The data suggests that holding a large number of stocks harms the generation of alpha, which makes intuitively sense when considering equation (3) from the Single-Index model. The unsystematic part of portfolio risk is decreasing in the number of positions a portfolio incorporates. Nevertheless, the diversification of risk comes at the expense of alpha. With an increase in the number of stocks, the possibility of continually picking positive abnormal returning stocks could vanish.

My result points out that a fundamental approach outperforms a quantitative approach in terms of alpha and is in line with Gregory-Allen et al. (2009, p. 48), who reveal that only a fundamental stock selection approach adds value with regards to alpha. A computer-based approach fails to do so. The analyzed funds from Gregory-Allen et al.'s (2009)'s study comprise mutual fund returns and are integrated into a two-stage regression test. First, they determine each funds' alpha and second, they examine which investment processes contributes to the explanation of alpha.

Table 6
Alpha estimates of position-quantity based portfolios in factor models.

Portfolio	High-number	Medium-number	Low-number
Excess return	13.77	17.96	16.43
CAPM Alpha	1.63	**5.61**	**4.85**
	(1.93)	(4.09)	(3.35)
3-factor Alpha	**1.57**	**5.20**	**4.46**
	(2.22)	(4.46)	(3.43)
4-factor Alpha	**1.81**	**5.01**	**4.44**
	(2.52)	(4.26)	(3.39)
7-factor Alpha	**2.02**	**5.64**	**5.80**
	(2.80)	(4.97)	(4.60)
4-factor Alpha mis	**2.71**	**5.89**	**5.61**
	(3.46)	(4.32)	(3.81)
Beta	**1.01**	**0.99**	**0.92**
	(188.05)	(125.35)	(107.39)
R-squared	0.98	0.95	0.93
Mean Num. of Pos.	289.35	72.15	40.50

This table reports alpha estimates of different factor models in time series regressions. Top column headers are abbreviations for different hedge fund portfolios, where portfolios, *High-number*, *Medium-number* and *Low-number*, are based on the position quantity hold during a given quarter on average. Each portfolio includes six hedge funds, where the *High-number* incorporates the highest position quantities, and the *Low-number* incorporates the lowest position quantities. The exact portfolio formation can be found in Appendix A on page 51. The portfolios' excess returns serve as the dependent variables and are run against different factor models, shown in the index. The CAPM, *3-F*, *4-F* and *7-F* model comprise the time period from January 2003 to December 2019. The *4-F-mis* model comprises the time period from January 2003 to December 2016, since 'Mispricing Factors' are no longer provided after the year of 2016. In the last row of the index, 'Mean Num. of Pos..' stands for the average number of positions per quarter over the 17 years. Alphas and excess returns are provided on an annual basis. Observation frequency of returns is daily, *t*-statistics are given in parenthesis and heteroscedasticity and autocorrelation robust standard errors were used in the estimation process (Newey-West). Bold figures signal significance at or below the 5 percent level.

Since my study concentrates solely on the portfolio long-side of equity-focused hedge funds, parallels to the mutual fund industry are given. However, my result from Table 6 is not based on a two-stage regression approach but a demonstration of how funds' abnormal performance differs over time when ranking hedge fund portfolios by number of positions.

Considering merely a portfolio's average number of positions over a specified period of time as an indicator for performance might be misleading. If the number of positions would have a global impact on a fund's abnormal performance, then the *SR-low* (see page 35 for portfolio formation) should rather include hedge funds with a high number of stocks than fund with a low number of stocks on average. The contrary should appeal to the *SR-high*. Thus, high number of position hedge funds should earn lower expected returns as alpha marks a main distinction between *SR-high* and *SR-low* portfolios. Baupost Group, with an average position number of 23, and Steadfast Capital Management, with an average position number of 43, clearly reject this statement, because both hedge funds hold the lowest number of positions on average (see Table 1) and still belong to the *SR-low*.

This leads me to the following question: As alpha is a main distinguishing part between top and bottom risk-adjusted portfolios, why are Baupost Group and Steadfast Capital Management included in the *SR-low* but when ranked by number of positions appear in the *Low-number* portfolio? First of all, as the SR is a risk-adjusted performance measure, next to a fund's absolute return, the standard deviation of returns is also decisive. It is not enough by earning high absolute returns in order to achieve a high SR. Risk plays a key role as well. Second, obviously, the number of positions has an impact on alpha over time but is no guarantee for achieving it. Even if holding only a manageable number of positions in a portfolio, consistently picking stocks that underperform will harm the overall performs drastically.

Notice, the *Low-number* portfolio has a *7-F* alpha of 5.80 percent (t = 4.60), whereas Baupost Group's alpha is 5.20 (t = 1.41) and Steadfast Capital Management's alpha is 1.44 (t = 0.98). Both hedge funds report below-average alpha estimates while insignificantly far away from zero. To answer the question above, let me first analyze Baupost Group. By ignoring the fact that Baupost Group's *7-F* alpha is insignificant, it is economic wise close to the average of the *Low-number* portfolio's alpha and therefore fits well in this particular portfolio. The reason why it is not included in the *SR-high* is due to total risk. As the Sharpe ratio measures the excess return for each unit of risk, Baupost Group clearly underperforms, with a SR=0.65. It has the highest annualized standard deviation, $\sigma_{Baupost} = 24.77$, of the sample. In this particular regard, the return generation of Baupost Group is much riskier than for example OrbiMed Advisors, with a SR = 0.91. Steadfast Capital Management on the other hand earns low alpha, while holding a small number of positions and can therefore count as an outlier. As mentioned above, low number of positions is no performance guarantee, because the ability of forecasting outperforming stocks is crucial.

6.2 Impact of TE and QMJ loadings on performance

Apart from the analysis of section 5, I apply another test to examine if specific variables have an impact on hedge fund alphas in the cross-section. For this reason, I test whether TE or QMJ loadings exert an influence on alpha[32]. Notice, constant terms in the following regression outputs have not been annualized. Instead, they are based on daily return data to ensure estimates are more accurate. Before continuing with the regression analysis, I briefly mention the intuition behind TE and QMJ loadings as independent variables.

If a portfolio deviates strongly from its benchmark, it demonstrates a high TE and vice versa (Rasmussen, 2003, p. 279). How can managers deviate strongly from their benchmark? Leading back to findings from Rey and Seiler (2001), the less positions a portfolio inherits, the more likely it deviates strongly from it, given that the stocks are part of the index. As an example, considering the case of hedge funds against the market portfolio, where the market portfolio is proxied by all U.S. traded stocks weighted by market capitalization. Hedge funds with relatively few positions will deviate more strongly from the market portfolio than a portfolio with a couple of hundred positions. For this reason, I mainly use TE in two ways: On the one hand, I let TE proxy for a fund’s number of positions, because a higher number of stocks in a portfolio will track a benchmark better than a portfolio with a low number of stocks (Vardharaj et al., 2004, p. 1-2). On the other hand, TE measures the extent a manager concentrates on stock selection rather than systematic factor investing. As an example, if a fund’s return variability

[32] Due to the fact that this testing approach relies on time-series regression results from my former analysis, I am actually applying a two-stage regression procedure.

can be explained to 95 percent, $R^2 = 0.95$, then 5 percent are attributable to stocks selection processes and 95 percent to factor investing choices (Bodie et al., 2017, p. 824). Regarding the TE calculation, my benchmark portfolio is not resembled by a single risk factor but by factors of the *7-F* model. Therefore, I follow the approach from Bodie et al. (2017) and call the set of risk factors given in the *7-F* model *tracking portfolio* from now on. TE is therefore determined by the standard deviations of residuals of a particular hedge fund after taking into account the standard deviation of my tracking portfolio[33].

In addition to TE, I test if factor exposures of *QMJ*, have an impact on funds' abnormal performances. More specifically, if negative *QMJ loadings* are attributable to high alpha and positive *QMJ loadings* are attributable to low alpha. The intuition behind this variable stems from the fact that 4 out of 18 hedge fund loadings, with respect to QMJ, are negative[34]. Although a general trend for holding *junk* stocks was yet indicated through *Ew-Port*'s negative *QMJ* loading, separate hedge fund exposures highly vary. Moreover, some funds show a better risk adjusted performances if loadings on *QMJ* are negative. Kensico Capital and OrbiMed Advisors achieve the highest SR estimates of the sample, with 0.98 and 0.91, respectively. Simultaneously their loadings on *QMJ* are negative, with -0.56 for OrbiMed and -0.19 for Kensico. Contrary, Paradigm Capital and Ruane, Cunniff and Goldfarb have low SR estimates, 0.54 and 0.73, but positive *QMJ* loadings of 0.05 and 0.17, respectively.

Looking at Panel A of Table 7, it reports cross-sectional regression results of TE on hedge fund alphas and cumulative returns[35] using estimating equation (3.1). Each funds' TE values comprise the complete sample period from January 2003 to December 2019[36].

Looking at columns (1) and (2), with TE as the single explanatory variable, TE has a positive and highly significant influence on alphas, $\beta_{TE} = 0.03$, and cumulative returns, $\beta_{TE} = 843.55$. In case of alpha, all else equal, if a fund's TE increases by one unit, the daily alpha estimate appreciates by 0.03 percent on average. This test reveals that those funds are rewarded, who

[33] See Appendix B for more details on SER.
[34] Separate hedge fund loadings on QMJ are given Table A11 in Appendix A.
[35] Cumulative returns are in excess of the risk-free rate and are calculated by linking the discrete daily returns of each fund geometrically.
[36] TE values are provided in Table A9 in Appendix A.

put more emphasis on security selection instead of factor investing. As pointed out earlier, TE can be interpreted in a different manner. In line with my result from chapter 6.1, a higher tracking error, which is influenced by the number of positions a portfolio inherits, adds value. On the other side, a lower TE would decrease alpha, all else equal, and simultaneously resembles a portfolio with a relatively large number of positions.

Panel B further provides regression estimates in the cross-section, where *QMJ loadings* serves as explanatory variable and alpha and cumulative returns serve as dependent variables[37]. Each funds' *QMJ loading* comprise the complete sample period from January 2003 to December 2019.

Table 7

Cross-sectional regressions of TE and QMJ loadings on alpha and cumulative returns

$$\alpha_i = const + \beta_1 TE_i + e_i, \tag{3.1}$$

$$\alpha_i = const + \beta_1 QMJ_i + e_i \tag{3.2}$$

	Panel A		**Panel B**	
	(1) Alpha	(2) Cum. Return	(3) Alpha	(4) Cum. Return
Const	0.00	**351.65**	**0.01**	**668.62**
	(0.08)	(2.35)	(5.57)	(9.64)
TE	**0.03**	**843.55**		
	(4.55)	(2.71)		
QMJ			**-0.03**	**-656.87**
			(-3.44)	(-2.19)
R-squared	0.53	0.32	0.27	0.15

Panel A of this table reports results from cross-sectional regressions. TE serves as independent variable and stands for the tracking error. The TE is based on the deviations from the 7-F model tracking portfolio, which measures each fund firm-specific volatility after taking risk factors into account. Panel B of this table reports results from cross-sectional regressions. QMJ serves as independent variable, where QMJ stands for each funds Quality minus junk exposure in the 7-F model. Applying for Panel A and B, alpha values and cumulative returns serve as dependent variables, where alpha marks each funds' daily abnormal excess return in the 7-F model. Cumulative returns are in excess of the risk-free rate and comprise the time period from January 2003 to December 2019. *t*-statistics are shown in parenthesis and are adjusted for heteroscedasticity (Newey-West). Bold figures signal significance at or below the 5 percent level.

[37] Due to the fact that the inclusion of both independent variables, TE and QMJ, leave no coefficient significant, a complete regression output can be found in Table A13 of Appendix A for an interested reader.

Observing columns (3) and (4), the variable QMJ loadings as a single regressor, reveals a negative correlation with alphas, likewise in the case for cumulative returns. All else equal, for each unit of exposure with *QMJ*, alpha and cumulative returns are negatively affected. The more *quality* stocks are included in a portfolio, the less alpha and cumulative returns are generated.

6.3 Impact of lagged TE and QMJ loadings on performance

Table 8 reports regression results of lagged TE and *QMJ loadings* on hedge fund alphas in the cross-section of funds. The time series is divided into non-overlapping three-year subperiods to account for time-varying regression coefficients. The purpose regarding lagged variables is to examine if hedge fund investors could utilize signals from publicly available data to predict alpha.

Table 8
Predictive cross-sectional Tests of TE and QMJ on Hedge Fund Portfolios.

$$R_{i,t} = \alpha_1 + \beta_1 TE_{t-1} + e_i \tag{3.3}$$

$$R_{i,t} = \alpha_1 + \beta_1 QMJ_{t-1} + e_i \tag{3.4}$$

Period *Ew-Port*	(1) Alp0608	(2) Alp0911	(3) Alp1214	(4) Alp1517	(5) Alp1819
TE(t-1)	**0.05**	**0.08**	**0.16**	**-0.03**	0.03
	(2.11)	(3.48)	(5.80)	(-2.48)	(0.34)
QMJ(t-1)	**-0.02**	-0.05	-0.02	0.02	-0.03
	(-2.89)	(-1.61)	(-0.56)	(1.69)	(-0.86)

This table reports factor loadings from cross-sectional regression for non-overlapping three-year time periods. 7-F model alphas of the *Ew-Port*, *SR-high* and *SR-low* serve as dependent variables. Tracking error, TE, and the Quality minus junk loadings, QMJ loadings, serve as independent variables. The dependent variable is given by the average of daily alpha estimates. Each row shows the regression betas (slope coefficients) of the one-period lagged Tracking error, TE_{t-1}, and QMJ factor loading, QMJ_{t-1}. Notice, each regression coefficients stems from a one-factor regression model, thus TE(t-1) and QMJ(t-1) are not part in the same equation as shown in (3.3) and (3.4). *t*-statistics are given in parenthesis and are adjusted for heteroscedasticity. Bold figures signal significance at or below the 5 percent level.

Starting with results from regression equation (3.3) corresponding to the first row of Table 8, TE helps in the prediction of alpha until subperiod (4), with four significant slope coefficients. However, as the coefficient sign becomes negative in subperiod (4), $\beta_{TE(t-1)} = -0.03$, the signal reverts and thus loses its meaning. After period (4), TE's predictive ability vanishes, with a *t*-statistic of merely 0.34, which is consistent with the result that alpha generally decays after 2015. Switching to *QMJ loadings*, except for period 1, none of the slope coefficients are indistinguishably far away from zero, exerting no predictive power.

7 Conclusion

Investigating a sample of 18 hedge funds in multifactor models with respect to their factor betas and alpha based on publicly available 13F equity holding reports, rigorously lays out what returns of these actively managed vehicles are composed of.

Considering time-series regression results over the sample period from January 2003 to December 2019, five significant factor loadings in the *7-F* model demonstrate that, besides the market factor, fundamental factors help explaining average stock returns. However, the result comes at a surprise as four out of five factor betas show negative loadings, significant on the one percent level. Apart from a common preference for small firms, equity strategy hedge fund managers exhibit low interest on the subsequent factor premia on average, comprising *HML*, *I/A*, *QMJ* and *MGMT*. Differences in factor loadings for performance-based portfolios mainly exists in *HML* and *WML*. The top five hedge funds ranked by Sharpe ratios hold more growth stocks and are indifferent to the momentum effect, while hedge funds with low Sharpe ratios are indifferent to *HML* and more akin to negative momentum. However, results on this issue could deviate, considering a broader sample of hedge funds also accounting for small and medium sized funds. A larger hedge fund sample, representing the broad hedge fund industry, would allow for more accurate estimates on capturing factor premia.

Looking at betas over subperiods, all hedge fund portfolios lower their exposure with respect to *junk* stocks during subperiod 2, *2006 to 2008*, and increase it afterwards. Large factor timing bets can be narrowed down on the investment-to-asset anomaly, *I/A*, for the two performance-based portfolios, as managers of the *SR-high* tilt their portfolios to low-investment stocks during the GFC, whereas managers of the *SR-low* bet on the opposite. In the following subperiods, *I/A* bets diverge again, with an increase in *I/A* exposure for the *SR-low* and a decrease in exposure for the *SR-high*. In general, hedge fund managers exert no market timing ability when considering solely the portfolio long side. With further inside on hedge fund short positions this result might differ. Interestingly, no hedge fund achieves an abnormal return after the beginning of 2015.

Nevertheless, alpha materializes as the main return driver between top and bottom hedge funds portfolios, ranked on a risk-adjusted basis. Due to largely poor factor performances over the observed sample period, except for the market factor, hedge fund managers cannot distinguish themselves through profitable exploitation of factor premia.

Creating three tercile hedge fund portfolios ranked on their average number of positions during a quarter, time-series regression estimates display that a *low-number* and a *middle-number* portfolio clearly outperform a *high-number* portfolio with respect to alpha. Further, I apply a two-stage regression approach in a second test, where TE contributes significantly positive to alpha. Simultaneously, *QMJ loadings* reveal a negative correlation with hedge fund alphas. Lastly, TE can predict alpha in three out of six subperiods but eventually the signal reverts in subperiod 4, which is consistent with my former result that alpha is generally decays after 2015.

III. Bibliography

Alexander, G. J. (2000). On Back-Testing "Zero-Investment" Strategies. *The Journal of Business*, *73*(2), 255–278. https://doi.org/10.1086/209642

Amenc, N., & Sourd, V. L. (2005). *Portfolio Theory and Performance Analysis*. Wiley. https://books.google.de/books?id=3iWkFIkdkxkC

Asness, C. S., Frazzini, A., & Pedersen, L. H. (2019). Quality minus junk. *Review of Accounting Studies*, *24*(1), 34–112. https://doi.org/10.1007/s11142-018-9470-2

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18. https://doi.org/https://doi.org/10.1016/0304-405X(81)90018-0

Berk, J. B., & DeMarzo, P. M. (2017). Corporate finance. In P. E. Limited (Ed.), *2018* (Fourth edi). Pearson. https://ubdata.univie.ac.at/AC13351588

Black, F., Jensen, M. C., & Scholes, M. (1972). *The Capital Asset Pricing Model: Some Empirical Tests*. Praeger Publishers Inc. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=908569

Bodie, Z., Kane, A., & Marcus, A. J. (2017). *Investments*. McGraw-Hill Education. https://books.google.de/books?id=uVVEvgAACAAJ

Bondt, W. F. M. De, & Thaler, R. H. (1987). Further Evidence on Investor Overreaction and Stock Market Seasonality. *The Journal of Finance*, *42*(3), 557–581. https://doi.org/10.2307/2328371

Campbell, J., Hilscher, J., & SZILAGYI, J. A. N. (2008). In Search of Distress Risk. *Journal of Finance*, *63*, 2899–2939. https://doi.org/10.2139/ssrn.770805

Carhart, M. M. . (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, *52*, 57–82. https://www.jstor.org/stable/2329556

Chen, L., & Zhao, X. (2009). Understanding the Value and Size Premia: What Can We Learn from Stock Migrations? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1360382

Chincarini, L. B., & Kim, D. (2010). *Quantitative Equity Portfolio Management: An Active Approach to Portfolio Construction and Management*. McGraw-Hill Education. https://books.google.de/books?id=CpPEYzvonCEC

Damodaran, A. (2002). *Investment Valuation: Tools and Techniques for Determining the Value of Any Asset*. Wiley. https://books.google.de/books?id=sLQhYjndgwEC

Fabozzi, F. J., & Markowitz, H. M. (2011). *The Theory and Practice of Investment Management (a review)*. https://doi.org/https://doi.org/10.1002/9781118267028.ch1

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance (New York)*, *25*, 417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2004). The Capital Asset Pricing Model: Theory and evidence. *Journal of Economic Perspectives*, *18*(3), 25–46. https://doi.org/10.1257/0895330042162430

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1–25. https://doi.org/10.1016/j.jfineco.2013.10.005

French, Kenneth, R. (n.d.). *Detail for Daily Momentum Factor (Mom)*. Detail for Daily Momentum Factor (Mom). https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor_daily.html

Frino, A., & Gallagher, D. R. (2001). Tracking S&P 500 Index Funds. *Journal of Portfolio Management*, *28*, 55. https://doi.org/10.3905/jpm.2001.319822

Fung, W., & Hsieh, D. (2006). Hedge Funds: An Industry in Its Adolescence. *Economic Review*, *91*, 1–34.

Fung, W., & Hsieh, D. A. (1999). A primer on hedge funds. *Journal of Empirical Finance*, *6*(3), 309–331. https://doi.org/https://doi.org/10.1016/S0927-5398(99)00006-7

Fung, W., & Hsieh, D. A. (2011). The risk in hedge fund strategies: Theory and evidence from long/short equity hedge funds. *Journal of Empirical Finance*, *18*(4), 547–569. https://doi.org/https://doi.org/10.1016/j.jempfin.2011.04.001

Gokten, Y. E. E.-G. K. E.-S. (2018). *Comparison of CAPM, Three-Factor Fama-French Model and Five-Factor Fama-French Model for the Turkish Stock Market* (p. Ch. 4). IntechOpen. https://doi.org/10.5772/intechopen.70867

Goltz, F., & Schroder, D. (2010). Hedge fund transparency: Where do we stand? *Journal of Alternative Investments*, *12*(4), 20–35. https://doi.org/10.3905/JAI.2010.12.4.020

Greene, W. H. (2003). *Econometric Analysis*. Prentice Hall. https://books.google.de/books?id=JJkWAQAAMAAJ

Gregory-Allen, R. B., Shawky, H. A., & Stangl, J. (2009). Quantitative vs. Fundamental Analysis in Institutional Money Management: Where's the Beef? *The Journal of Investing*, *18*(4), 42–52. https://doi.org/10.3905/joi.2009.18.4.042

Griffin, J. M., & Xu, J. (2009). How smart are the smart guys? A unique view from hedge fund stock holdings. *Review of Financial Studies*, *22*(7), 2531–2570. https://doi.org/10.1093/rfs/hhp026

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2013). *Multivariate Data Analysis*. Pearson Education Limited. https://books.google.de/books?id=VvXZnQEACAAJ

Harvey, C. R., Liu, Y., & Zhu, H. (2016). ..and the Cross-Section of Expected Returns. *The Review of Financial Studies*, *29*, 68. https://doi.org/10.1093/rfs/hhv059

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, *28*(3), 650–705. https://doi.org/10.1093/rfs/hhu068

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers : Implications for Stock Market. *The Journal of Finance*, *48*(1), 65–91.

Jensen, M. C. (1968). The Performance Of Mutual Funds In The Period 1945-1964. *The Journal of Finance*, *23*(2), 389–416. https://doi.org/10.1111/j.1540-6261.1968.tb00815.x

Koch, A. K. (2007). *Factor Models and Arbitrage Pricing Theory (APT) [Pdf slides]*. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.619.376&rep=rep1&type=pdf

Kritzman, M. P. (1997). *The Portable Financial Analyst: What Practitioners Need to Know*. Irwin. https://books.google.de/books?id=WfiHswEACAAJ

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, *47*, 37. https://doi.org/10.2307/1924119

Manser, S., & Schmid, M. M. (2016). *The Performance Persistence of Equity Long/Short Hedge Funds BT - Derivatives and Hedge Funds* (S. Satchell (ed.); pp. 218–239). Palgrave Macmillan UK. https://doi.org/10.1057/9781137554178_11

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Midori, M. (2003). The CAPM and the Single-Index Model-Ex-ante Expectaitons and Ex-post Tests. *The Economic Review of Toyo University*, *29*(1), 83–101. http://id.nii.ac.jp/1060/00005366/

Novy-Marx, R., & Velikov, M. (2016). A Taxonomy of Anomalies and Their Trading Costs. *The Review of Financial Studies*, *29*, 147. https://doi.org/10.1093/rfs/hhv063

Olson, D., & Zoubi, T. (2017). Convergence in bank performance for commercial and Islamic banks during and after the Global Financial Crisis. *The Quarterly Review of Economics and Finance*, *65*, 71–87. https://doi.org/https://doi.org/10.1016/j.qref.2016.06.013

Pedersen, L. H. (2015). Efficiently inefficient: How smart money invests and market prices are determined. *Efficiently Inefficient: How Smart Money Invests and Market Prices Are Determined*, 1–348.

Qian, E. E., Hua, R. H., & Sorensen, E. H. (2007). *Quantitative Equity Portfolio Management: Modern Techniques and Applications*. CRC Press. https://books.google.de/books?id=_NjLBQAAQBAJ

Rasmussen, M. (2003). Quantitative Portfolio Optimisation, Asset Allocation and Risk Management. In *Hampshire, U.K.: Palgrave Macmillan*.

Rey, D. M., & Seiler, D. (2001). Indexation and Tracking Errors. *WWZ/Department of Finance*, *2*(1). http://www.econbiz.de/archiv1/2009/95490_indexation_trackingerrors.pdf

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive Evidence of Market Inefficiency. *The Journal of Portfolio Management*, *11*, 9–16.

Schwert, G. W. (2002). Analomies and Market Efficiency. *National Bureau of Economic Research, Working Pa*. http://www.nber.org/papers/w9277

Sharpe, W. F. (1963). A Simplified Model for Portfolio Analysis. *Management Science*, *9*(2), 277–293. https://www.jstor.org/stable/2627407

Sharpe, William F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance (New York)*, *19*, 442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Stambaugh, R. F., Yu, Jj., & Yuan, Y. U. (2015). Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle. *The Journal of Finance*, *70*(5), 1903–1948. https://doi.org/https://doi.org/10.1111/jofi.12286

Stambaugh, R., & Yuan, Y. (2017). Mispricing Factors. *Review of Financial Studies*, *30*(4), 1270–1315. https://econpapers.repec.org/RePEc:oup:rfinst:v:30:y:2017:i:4:p:1270-1315.

Tobin, J. (1958). Liquidity Preference as Behavior Towards Risk. *The Review of Economic Studies*, *25*(2), 65–86. https://doi.org/10.2307/2296205

Treynor, J. L., & Mazuy, K. (1966). Can Mutual Funds Outguess the Market? *Harvard*

Business Review, *44*, 131–136.

Vardharaj, R., Fabozzi, F. J., & Jones, F. J. (2004). Determinants of Tracking Error for Equity Portfolios. *The Journal of Investing*, *13*, 47. https://doi.org/10.3905/joi.2004.412305

Wooldridge, J. M. (2016). *Introductory econometrics: a modern approach* (Sixth edit). Cengage Learning. https://ebookcentral.proquest.com/lib/londonschoolecons/detail.action?docID=5133150

Zhang, L. (2017). The Investment CAPM. *European Financial Management*, *23*(4), 545–603. https://doi.org/10.1111/eufm.12129

IV. Appendix A

Table A9 Hedge fund factor alphas

	Adage Capital	Arrow-street Capi-tal	Baupost Group	Coatue Man-age-ment	Emi-nence Capi-tal	Glen-view Capi-tal	GMT Capi-tal	Kensico Capi-tal	Mave-rick Capi-tal	Orbimed Advi-sors	Par Capi-tal	Para-digm Capi-tal	Ruane Cun-niff & Gold	Sandler Capi-tal	Select Equity	Stead-fast Capi-tal	Tiger Global	Viking Global
Excess Return	13.04	14.06	16.03	19.15	16.40	17.62	16.36	18.72	14.10	19.02	20.24	10.79	14.30	17.96	15.22	7.99	20.72	17.75
CAPM Alpha	**1.55**	1.94	3.14	6.33	**4.90**	**5.53**	2.00	**6.77**	2.21	**8.08**	6.36	-0.60	2.66	**4.85**	**3.49**	0.86	**7.13**	**5.45**
	(3.02)	(1.77)	(0.80)	(1.81)	(3.23)	(2.60)	(0.84)	(3.72)	(1.48)	(2.13)	(1.78)	(-0.3)	(1.42)	(2.78)	(2.22)	(0.58)	(2.22)	(2.90)
3-F Model Alpha	**1.52**	2.08	3.03	5.69	**4.60**	**5.39**	2.13	**6.60**	1.92	**6.83**	6.11	-0.73	2.63	**4.46**	**3.36**	0.63	**6.30**	**5.15**
	(3.00)	(1.90)	(0.81)	(1.71)	(3.18)	(2.59)	(0.91)	(3.67)	(1.37)	(3.00)	(1.81)	(-0.5)	(1.41)	(2.71)	(2.27)	(0.42)	(2.09)	(2.84)
4-F Model Alpha	**1.65**	2.10	3.76	5.28	**4.93**	**5.56**	2.18	**6.41**	2.21	6.49	6.13	-0.44	3.17	**3.52**	**3.79**	0.57	5.78	**4.55**
	(3.33)	(1.86)	(1.00)	(1.58)	(3.42)	(2.67)	(0.93)	(3.54)	(1.57)	(1.91)	(1.81)	(-0.3)	(1.69)	(2.16)	(2.56)	(0.38)	(1.91)	(2.57)
7-F Model Alpha	**1.76**	2.08	5.20	**8.76**	**4.44**	**5.09**	2.85	**6.72**	2.58	**7.83**	**6.88**	-0.49	3.38	**4.27**	**3.65**	1.44	**8.51**	**6.11**
	(3.47)	(1.90)	(1.41)	(2.60)	(3.06)	(2.50)	(1.26)	(3.73)	(1.84)	(2.35)	(2.04)	(-0.4)	(1.79)	(2.61)	(2.48)	(0.98)	(2.84)	(3.50)
4-F-mis Model Alpha	**2.15**	**2.79**	7.16	7.27	**4.41**	**6.55**	**6.27**	**9.07**	2.71	6.13	**9.07**	-0.60	3.09	3.46	3.12	-0.08	6.13	**7.13**
	(3.73)	(2.19)	(1.60)	(1.90)	(2.71)	(2.82)	(2.45)	(4.50)	(1.76)	(1.62)	(2.32)	(-0.4)	(1.42)	(1.93)	(1.87)	(-0.1)	(1.77)	(3.53)
Beta	**0.99**	**1.02**	**0.95**	**0.98**	**0.98**	**1.00**	**1.13**	**0.96**	**1.00**	**0.99**	**1.06**	**0.92**	**0.97**	**1.08**	**0.97**	**0.60**	**1.06**	**0.98**
	(227.19)	(124.58)	(38.02)	(38.17)	(102.99)	(57.14)	(40.31)	(49.00)	(109.06)	(47.88)	(60.13)	(66.92)	(95.40)	(80.37)	(93.12)	(37.39)	(52.68)	(65.60)
Sharpe ratio	0.72	0.73	0.65	0.83	0.89	0.89	0.68	0.98	0.73	0.91	0.82	0.54	0.73	0.86	0.80	0.61	0.88	0.89
Information ratio	0.91	0.47	0.37	0.71	0.76	0.66	0.30	0.95	0.47	0.67	0.52	-0.09	0.46	0.65	0.63	0.24	0.73	0.87
Tracking error	1.93	4.47	14.10	12.40	5.84	7.75	9.36	7.06	5.46	11.65	13.14	5.35	7.41	6.56	5.84	5.98	11.70	7.09
QMJ 7-F Loadings	-0.07	-0.10	-0.47	-0.19	0.09	-0.16	-0.25	-0.19	-0.05	-0.56	-0.10	0.05	0.17	-0.17	0.06	-0.20	-0.30	-0.27
R-squared	0.99	0.95	0.69	0.72	0.90	0.85	0.85	0.87	0.92	0.70	0.73	0.93	0.86	0.91	0.91	0.80	0.76	0.88
R-squared Adj.	0.99	0.95	0.69	0.72	0.90	0.85	0.85	0.87	0.92	0.70	0.73	0.93	0.86	0.91	0.91	0.79	0.76	0.88

This table depicts excess returns and intercept estimates from linear regression. Column headers depict the individual hedge funds in the sample. Excess returns of the individual funds serve as the dependent variables in the linear regression and are run against different factors, shown in the left index. Factors are mimicking portfolios and hold common sources of risk. In time-series regressions, alpha is the intercept of the regression line. In this table, five separate factor models were used, generating five intercept estimates for each fund over the course of 17 years, specifically from January 2003 to December 2019. *Beta, Sharpe ratio, Information ratio, Tracking error* and *R-squared* in the index are based on the 7-F model. All estimates shown are provided on an annual basis. *t*-statistics are given in parenthesis. Newey-West standard errors are used in the estimation process. Bold figures signal significance at or below the 5 percent level.

Table A10
Factor Spanning Test

Index	BAB	QMJ	IA	PERF	MGMT
Const	**9.67**	**5.06**	0.65	**5.45**	2.26
	(4.40)	(3.11)	0.57	(2.23)	(1.19)
MKT	**-0.22**	**-0.18**	**-0.06**	**-0.20**	**-0.14**
	(-12.91)	(-17.84)	(-9.14)	(-13.64)	(-12.55)
SMB	**-0.28**	**-0.15**	0.02	**-0.10**	**-0.07**
	(-10.25)	(-8.83)	(1.86)	(-3.58)	(-3.08)
HML	**-0.22**	**-0.36**	**0.23**	**-1.00**	**0.31**
	(-6.43)	(-19.38)	(16.17)	(-28.13)	(13.22)
WML	**0.31**	**0.08**	**0.03**	**0.69**	0.00
	(11.53)	(4.63)	(2.56)	(29.49)	(-0.05)
R squared	0.44	0.48	0.18	0.77	0.21

This table displays a factor spanning test in which BAB, QMJ, IA, PERF and MGMT are run against Carhart (1997) Four-Factor model in time-series regression. The regression time horizon for BAB, QMJ and I/A is from January 2003 to December 2019 whereas regressions run on PERF and MGMT are from January 2003 to December 2016. Alpha estimates are given on an annual basis. *t*-statistics are given in parenthesis and are adjusted for autocorrelation and heteroscedasticity (Newey-West). Bold figures signal significance at or below the 5 percent level.

Table A11
Variance Inflation Factor (VIF) Test

	9-F model	VIF	7-F model	VIF
0	Mkt-RF	1.80	Mkt-RF	1.64
1	SMB	1.21	SMB	1.17
2	HML	3.24	HML	1.87
3	IA	1.76	IA	1.23
4	WML	2.08	WML	1.37
5	BAB	1.98	BAB	1.91
6	QMJ	4.03	QMJ	2.08
7	MGMT	2.41	Mkt-RF_s	1.03
8	PERF	**6.31**		

Table A12
4-F-mis Model Factor Loadings in Three-Year Subperiods

Subperiod	*(1)*			*(2)*			*(3)*		
Years	*2003-2005*			*2006-2008*			*2009-2011*		
Portfolio	Ew-Port	SR high	SR low	Ew-Port	SR high	SR low	Ew-Port	SR high	SR low
Excess return	27.45	29.16	25.61	-5.77	-2.25	-7.95	26.38	24.87	25.05
Const	**7.49**	**8.82**	**7.44**	**4.46**	**7.10**	1.70	**5.67**	**5.64**	**4.44**
	(4.4)	(3.53)	(2.79)	(2.18)	(2.53)	(0.66)	(3.27)	(2.14)	(2.4)
Mkt-RF	**0.97**	**0.96**	**0.86**	**0.95**	**0.92**	**0.87**	**0.99**	**0.96**	**0.95**
	(90.32)	(83.9)	(63.92)	(86.11)	(48.26)	(74.34)	(118.25)	(60.65)	(119.24)
SMB	**0.33**	**0.30**	**0.38**	**0.23**	**0.15**	**0.19**	**0.21**	**0.10**	**0.30**
	(18.95)	(15.16)	(13.42)	(10.07)	(3.79)	(7.69)	(14.24)	(5.12)	(21.79)
MGMT	**-0.18**	**-0.37**	**-0.19**	**-0.18**	**-0.12**	**-0.34**	**-0.08**	-0.02	**-0.15**
	(-6.31)	(-9.44)	(-3.94)	(-6.54)	(-2.68)	(-3.94)	(-2.9)	(-0.53)	(-6.57)
PERF	**-0.06**	**-0.18**	-0.04	**-0.06**	-0.03	**-0.08**	**0.03**	**0.09**	**-0.05**
	(-3.8)	(-6.33)	(-1.14)	(-3.47)	(-0.83)	(-4.8)	(2.89)	(6.59)	(-6.02)
R-squared	0.96	0.93	0.89	0.98	0.97	0.98	0.99	0.97	0.99

Subperiod	*(4)*			*(5)*		
Years	*2012-2014*			*2015-2016*		
Portfolio	Ew.-Port	SR high	SR low	Ew.-Port	SR high	SR low
Excess return	28.06	33.04	21.50	4.99	3.45	2.27
Const	**5.06**	**8.53**	0.44	-0.91	-1.03	-3.37
	(2.82)	(3.41)	(0.17)	(-0.46)	(-0.35)	(-1.41)
Mkt-RF	**1.03**	**1.04**	**0.95**	**0.96**	**0.98**	**0.91**
	(84.94)	(68.89)	(64.36)	(83.39)	(54.7)	(79.61)
SMB	**0.22**	**0.14**	**0.32**	**0.15**	**0.14**	**0.22**
	(11.31)	(6.05)	(10.22)	(6.83)	(4.65)	(10.25)
MGMT	**-0.16**	**-0.09**	**-0.15**	**-0.24**	**-0.45**	**-0.12**
	(-5.97)	(-2.72)	(-4.42)	(-7.15)	(-10.38)	(-4.49)
PERF	**0.04**	0.04	**-0.10**	-0.01	**-0.04**	**-0.15**
	(2.72)	(1.7)	(-4.31)	(-1.31)	(-2.32)	(-12.25)
R-squared	0.96	0.92	0.92	0.97	0.93	0.96

This Table reports factor loadings of the 4-F-mis model using linear time-series regression. As dependent variables, excess returns from three different hedge fund portfolios over the time horizon from 2003 till 2016 were used, in which the first, Ew-Port, is weighted equally and the second and third portfolios, SR high and SR low, are composed of the top and bottom five hedge funds ranked by their Sharpe ratios respectively and weighted equally on a portfolio basis. Factors in the left index serve as independent variables and are mimicking portfolios, which hold common sources of risk. Observation frequency of returns is daily, whereas excess returns and alpha estimates are provided on an annual basis. *t*-statistics are given in parenthesis and heteroscedasticity and autocorrelation robust standard errors were used in the estimation process (Newey-West). Bold figures

Table A13

Influence of TE and QMJ loadings on performance measures

	(1) SR	(2) Cum Ret	(3) Alpha	(4) IR	(5) SR	(6) Cum Ret	(7) Alpha	(8) IR
Const	**0.72**	**367.3**	0.00	**0.00**	**0.51**	-34.88	-0.01	**0.00**
	(12.01)	(2.47)	(0.30)	(3.91)	(4.19)	(-0.11)	(-0.71)	(2.03)
TE	0.06	**768.9**	**0.03**	0.00	0.97	2480.3	0.06	-0.00
	(0.56)	(2.56)	(4.34)	(-0.90)	(1.87)	(1.87)	(1.72)	(-0.44)
TE Square					-0.86	-1565.4	-0.03	0.00
					(-1.73)	(-1.21)	(-0.82)	(0.30)
QMJ	-0.08	-140.3	-0.01	0.00	-0.19	-670.2	-0.02	-0.00
	(-0.58)	(-0.43)	(-0.84)	(-1.16)	(-0.82)	(-1.32)	(-1.16)	(-1.06)
QMJ Square					-0.23	-1387.0	-0.02	-0.00
					(-0.50)	(-1.21)	(-0.80)	(-0.83)
R-squared	0.05	0.32	0.54	0.05	0.16	0.41	0.57	0.07

This table reports results from cross-sectional regressions. TE, TE Square, QMJ and QMJ Square serve as independent variables, where TE stands for the tracking error and QMJ stands for each funds' QMJ exposure. TE Square and QMJ Square stands for each variable's squared term. SR, Cum Ret, Alpha and IR stand for each funds' Sharpe ratio, cumulative excess returns, 7-F model alpha and 7-F model Information ratio. The TE is based on the Standard Error of Residuals (SER) from the 7-F model tracking portfolio, which measures each fund firm-specific volatility over the complete time horizon from January 2003 to December 2019. QMJ stands for hedge funds' QMJ exposure over the complete time horizon. *t*-statistics are shown in parenthesis and are adjusted for heteroscedasticity (Newey-West). Bold figures signal significance at or below the 5 percent level.

Portfolio Formation

High-number		Medium-number		Low-number	
Adage Capital Partners	603.6	OrbiMed Advisors	87.8	Coatue Management	47.8
Arrowstreet Capital	603.8	Sandler Capital Management	83.1	Eminence Capital	50.0
Paradigm Capital Management	206.5	PAR Capital	74.3	Tiger Global Management	42.8
Ruane, Cunniff & Goldfarb	130.6	Select Equity Group	73.1	Kensico Capital	42.8
Maverick Capital	96.9	Viking Global Investors	59.9	Steadfast Capital Management	36.1
GMT Capital	94.7	Glenview Capital Management	54.7	Baupost Group	23.5

This table reports the fund selection for different hedge fund portfolios ranked on number of positions. Top column headers are abbreviations for different hedge fund portfolios, where portfolios, *High-number*, *Medium-number* and *Low-number*, are based on the position quantity hold during a given quarter on average. Each portfolio includes six hedge funds, where the *High-number* incorporates funds with the highest number of positions, and the *Low-number* incorporates fund with the lowest number of positions. Hedge fund names can be abbreviated for convenience.

(See page **51**)

V. Appendix B

R-square, R^2, also called the coefficient of determination, measures how well a model fits the data at hand, by determining what percentage of total variability can be explained through the applied model.

$$R^2 = 1 - \frac{SSR}{SST}\ , \tag{3.4}$$

$$SSR\ =\ \sum_{i=1}^{n}(y_i - \hat{y})^2 = \sum_{i=1}^{n} \hat{e}_i{}^2\ , SST\ =\ \sum_{i=1}^{n}(y_i - \bar{y})^2$$

SSR stands for residual sum of squares and represents the part that cannot be explained in the regression equation. SST stands for the total sum of squares and measures the sum of squared deviations of the dependent variable, y_i, from its average, $\bar{y}$. The higher the SSR term is, the lower is the explanation extent of the model, which is hence expressed in a low R^2 estimate (Wooldridge, 2016, p. 34-35).

Adjusted R-squared has the same function as the R^2 has but due to the fact that R^2 always increases when a new variable is added to the equation, it penalizes to addition of new variables (Wooldridge, 2016, p. 181).

$$R^2\ adj. = 1 - \frac{SSR/(1-k-n)}{SST/(1-n)}, \tag{3.5}$$

where n = sample size, $k\ =\$ degrees of freedom.

According to Wooldridge (2016, p. 88) the *Standard Error of Regression*, SER, is an estimator of the error term's standard deviation.

$$SER\ =\ \frac{\sum_{i=1}^{n}\widehat{u_i}^2}{(n-k-1)} = \frac{SSR}{(n-k-1)}, \tag{3.6}$$

where n = sample size and $k\ =\$ degrees of freedom.