Diploma Thesis

„MULTI FACTOR MODELS IN HEDGE FUND AND FUND OF FUNDS MANAGEMENT“

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ABS	Asset-Based Style Factor
ABSA	Asset Based Style Analysis
APCA	Asymptotic Principle Component Analysis
AR	Autoregressive
AWJ	Alfred Winslow Jones
BAI	Bundesverband Alternative Investments e.V.
CAPM	Capital Asset Pricing Model
CTA	Commodity Trading Advisor
FH	Fung and Hsieh
FMP	Factor mimicking Portfolio
FoF	Fund of Funds
HF	Hedge Fund
HFR	Hedge Fund Research
LTCM	Long Term Capital Management
MA	Moving Average
MSCI	Morgan Stanley Commodity Index
PBS	Peer Group-Based Style Factor
PC	Principle Component
PCA	Principle Component Analysis
PTFS	Primitive Trend Following Strategy
RBS	Return-Based Style Factor
RBSA	Return Based Style Analysis
S&P	Standard and Poors
SF	Style Factor
TSA	Time Series Analysis.
VAN	VAN Hedge Advisory Inc.

ABSTRACT

Hedge funds and fund of funds, as alternative investment vehicles, have enjoyed healthy growth in recent years. These investments became popular for their extraordinary performance characteristics that differ from returns of traditional asset classes. This is due to their capability to deliver positive returns when equity markets are both up and down. That is an attractive return profile for portfolio diversification and optimization purposes, in order to reduce risk and increase return.

Because fund investment is primarily based on expected performance, theoretical or empirical based return expectation models are required. Particularly the special characteristics of these alternative investments lead to difficulties in modeling their returns.

The objective of this diploma thesis is to explore different areas of hedge fund and fund of funds research. This work will present a general overview of the models that are used to describe these unusual return characteristics. Special focus is directed to the multi factor model approach developed by Fung and Hsieh (2001).

The final part covers an empirical analysis of monthly hedge fund return data. By the use of the principal component analysis and the application of an ARIMA-model the author develops a multi factor model in order to forecast the returns of hedge funds.

1 INTRODUCTION

1.1 Motivation

In general, money is a limited resource. Hence, the use of money is related to costs, like the input of any other restricted resource too. These costs are determined by the worldwide operating capital markets, which forces all of the market participants to deploy money efficiently. On principle, money can be deployed in three different purposes:

- It can be used for consumption purposes, in order to satisfy both essential as well as luxury requirements
- Money can also be saved to establish reserves, which will prevent from difficult economic situations
- Investment decisions present opportunities to enhance the amount of capital, if invested successfully

Usually, every single participant in the capital markets, i.e. institutional as well as private players, has to decide, which amount of money he wants to allocate in consumption, reserves, and investment. The overall objective of this decision process is to obtain the highest individual utility. Consequently, the enhancement of efficient capital allocation makes a general contribution to higher utility.

In this sense, the thesis contributes to the enhancement of efficient investment decisions. The primary task confronting investors is to form an educated opinion about the value of a certain investment object. Then, the investment decisions are based on this opinion. Usually, business analysts develop these opinions to allocate capital efficiently.

The focus of this diploma thesis is directed to the investments among hedge funds (HF) and fund of funds (FoF). Especially, in the case of these investment vehicles the decision making process turns out to be very complex. The development of models, which are able to describe the return generating process of this investment class, is a fundamental part of the analyst’s job. The models used to support the decision making process are often multi factor models. Although there already exist statistical models, which can describe the returns of traditional investment vehicles, empirical studies have proved that these are not suitable for the description of hedge fund returns. On the one hand, this implicates a deeper analysis of hedge funds and fund of funds. On the hand, this poses the question of how to model the special return behavior of hedge funds.

1.2 Core Question of the Thesis

Unlike traditional investment vehicles, HF’s are less restricted in the choice of instruments used and in the way they take advantage of these. For example, HF’s are able to gain from both positive and negative price developments by taking long as well as short positions. Additionally, hedge funds are allowed to utilize large amounts of debt capital in order to lever-up returns. These possibilities enable hedge fund managers to apply investment styles, which are completely different from those of traditional investment vehicles. Due to these special treatments of HF’s, also their performance characteristics differ heavily from those of traditional investment classes such as bonds, ordinary shares and commodities. This characteristic complicates the application of traditional multi factor models to the returns of HF’s. Consequently, new approaches are needed in order to capture the special return behavior of HF’s. Compared to the long history of the mutual fund industry, the hedge fund industry is still in its infancy. Therefore, problems of data biases additionally arise, which have also to be solved within the model building process.

The core question of this thesis is to point out why traditional approaches exactly fail in modeling the returns of HF’s and how methodologies are developed nowadays, so that the performance characteristics of HF’s can be successfully described. Thereby, the focus is directed to the particular approach by William Fung and David A. Hsieh[1], published in 2001. [14] During the last decade, the authors Fung and Hsieh (in the following referred to as FH) intensively dealt with

[1] William Fung is Visiting Research Professor of Finance, Centre for Hedge Fund Research and Education, London Business School

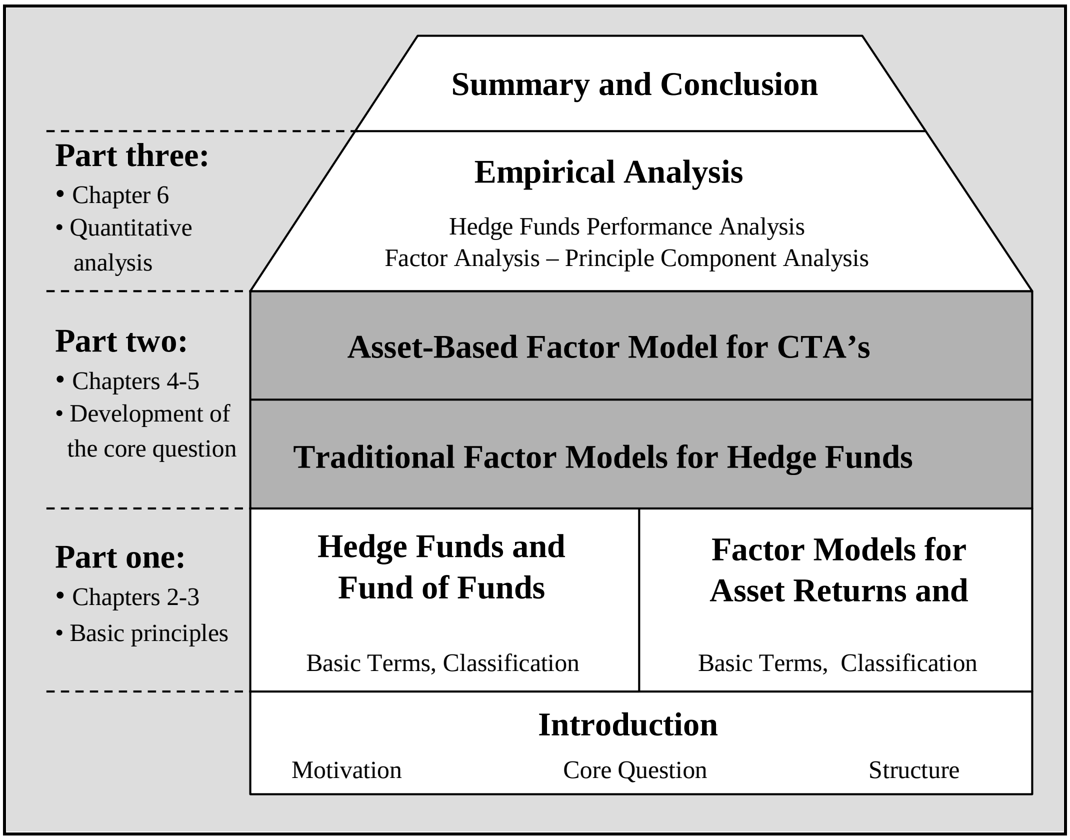
the problems of characterizing the performance of HF's in general and the problems of modeling the returns of particular major hedge fund strategies. Within their work Fung and Hsieh successfully developed benchmarks for the non-linear investment strategies applied by HF's. The basis principle of this methodology was established in their work of 1997. [8] On this basis FH were able to develop a multi factor model using look-back options, which is able to capture the performance characteristics of a particular hedge fund category. The major group of hedge funds that belongs to this category is called Commodity Trading Advisors (CTA's). These funds usually apply trend following strategies. In the work of 2001 FH developed a multi factor model that successfully described the returns generating process of hedge funds applying trend following strategies.

David A. Hsieh is Professor of Finance, Fuqua School of Business, Duke University

1.3 Structure of the Thesis

Basically, the work can be divided into three major parts. The following figure illustrates the general procedure within this thesis.

Fig. 1: Overview – Structure of the Thesis



Source: Self-made figure.

The first part, comprising chapters two and three, clarifies basic concepts and provides a common understanding of facts, which are relevant to the problem. The section serves as basic principle to understand the further development of modeling the returns of hedge funds. The core of the first paragraph composes the classification of both hedge funds and approaches to build multi factor models.

The second part is made up of the chapters four and five. In chapter four the attention is turned to the application of traditional factor models in the matter of modeling hedge fund returns. Special focus is directed to the asset class factor model, developed by William Sharpe (1992). Considering this example, the suitability of traditional factor models is examined at first. It turns out that traditional factor models are not bale to capture the special performance characteristics of hedge funds. The problems related to the weak explanatory power of traditional factor models gives motivation for the second part of this section. For further developments the author suggests an asset based approach. Chapter five deals with a particular asset based approach, developed by Fung and Hsieh (2001), to model the returns of trend following hedge fund strategies. At first the proceeding within their work is described. Finally, the capability of their developed model to capture the hedge fund return characteristics is analyzed.

The third part forms chapter six. The core of this paragraph composes a quantitative analysis of hedge fund return data. The data, provided publicly by the VAN Company[2], consists of monthly hedge fund return data in the period of January 1995 to December 2004. This paragraph is divided into two sections. The first section deals with the performance analysis of the data. The second part contains the elaboration of a forecasting model for hedge fund returns.

At the end of the thesis, the author provides a summary in form of the insights achieved by his work. The insights presented in chapter seven, are differentiated into general perceptions and personal insights achieved by the author during this work.

[2] VAN Hedge Fund Advisors International, LLC. http://www.vanhedge.com.

2 HEDGE FUNDS AND FUNDS OF FUNDS

2.1 History

Many perceive the hedge fund industry as a fairly new phenomenon, but its roots are found in the 1940's. The birth of hedge funds dates back to the 1st January 1949, when the American Alfred Winslow Jones (in the following referred to as AWJ) issued his first private equity fund. Due to his work as a financially specialized journalist, Jones observed that nobody not even the Wall Street professionals was able to predict the trend of security prices. Consequently, AWJ realized that new strategies should own the ability to generate positive returns regardless of the direction of the overall market movements. Therefore, AWJ implemented an investment strategy to construct a portfolio, which was long in presumably undervalued stocks and on the opposite short in presumably overvalued stocks. Unlike other investment managers, who followed buy and hold strategies only, AWJ was the first manager to combine a leveraged long stock position with a portfolio that consisted of short stock positions. In the end, Jones financed his long positions of undervalued stocks through selling presumably undervalued stocks short. [21]

This special strategy enables managers to offset the market exposure associated with owning stocks and bonds by the corresponding short positions. This means, managers are able to gain profits independently from the overall market movement, as long as anticipated overvalued and undervalued stocks are estimated correctly. Hence, Jones swapped market risk for manager risk and in turn he demanded high performance based fees for his managers. The following example explains the root of AWJ's strategy once more.

For example:

- The manager sells one stock of company A at a price of € 100 short, in order to finance the purchase of two stocks of company B at a price of € 50, hence no equity has been used
- For reasons of simplification we do not consider transaction costs and lending fees for short-selling

Fig. 2: Long-Short Strategy

	Price of Stock A	**Price of Stock B (in €)**						
		35	**40**	**45**	**50**	**55**	**60**	**65**
(+/- in %)	(in €)	*-30%*	*-20%*	*-10%*	*0%*	*10%*	*20%*	*30%*
-30%	**70**	**0**	10	20	30	40	50	60
-20%	**80**	-10	**0**	10	20	30	40	50
-10%	**90**	-20	-10	**0**	10	20	30	40
0%	**100**	-30	-20	-10	**0**	10	20	30
10%	**110**	-40	-30	-20	-10	**0**	10	20
20%	**120**	-50	-40	-30	-20	-10	**0**	10
30%	**130**	-60	-50	-40	-30	-20	-10	**0**

Source: Self-made table.

As one may see in the example, the manager gains from price developments only, if presumably undervalued stocks perform relatively better than the presumably overvalued stocks. The profit is realized independently of the price direction (area above diagonal of zeros). For this reason, the strategy is nowadays also called relative value strategy.

This relative value approach often leads to small return margins, so that Jones additionally established the use of a high percentage of debt capital within his transaction. In doing so, AWJ was able to raise fund returns by the appearing leverage effect. [5]

AWJ organized his fund as a general partnership. This corporate form provided a high flexibility in terms of little restrictions regarding portfolio construction, so that he was able to put his strategy into practice. 1952 his fund was converted into a limited partnership, which is to date a common structure in business. Within such limited partnerships the investors are limited partners and the managers are general partners. As general partners, the fund managers usually invest a significant portion of their personal wealth into the partnership. This ensures the alignment of economic interests among the partners. Investors to this partnership are charged a performance based fee to successful managers. [9] The incentive fee is usually benchmarked at 0% return each year, or against an index such as the U.S. or U.K. treasury rate.

One can summarize that unlike traditional investments, such as mutual funds, AWJ established three important characteristics of investment strategies[1] that are still part of the industry today:

- The combination of long and short positions
- The use of a significant part of leverage
- The incentive management fees

1966 an article[2] in the Fortune magazine focused on Jones fund and presented that his fund had outperformed all mutual funds of that era. The prospect of better returns naturally increased the number of funds during the 1960's. Consequently, also top money managers were drawn to the hedge fund industry because of the unique fee structure.

With a greater popularity, hedge fund managers changed their approach. Managers were taking more risk by leveraging instead of hedging their positions. But using a "*leveraged-long-only*" strategy made these funds highly susceptible to market volatility. In consequence of the market downturn beginning at the end of the 60's, these riskier strategies did not pay off. Due to the 1973-1974 bear market, large hedge fund losses were registered. This led many investor turn away from hedge funds, so that the industry hit a difficult period.

With the arrival of derivates in the 1980's new investment styles could be developed. In turn, hedge funds became a more heterogeneous group of investment vehicles. This was the beginning of a growth industry and hedge fund

[1] A.W. Jones wrote an article about his investment style *"Fashion in Forecasting"* in Fortune, March 1949, 88, 186.
[2] Loomis, Carol, 1966, *"The Jones Nobody Keeps Up With"*, Fortune April, 237-247.

returns found its record highs during the great tech bubble from 1994 to 1999. As a result of the burst in 2000, true hedge fund managers were separated from the improvised managers. One has to recall that generating absolute returns through shifting market conditions should be the core business of the hedge fund managers. But still, many funds were positioned too directional, which finally led to their downfall.

After 2000 the investment industry had changed tremendously. More sophisticated investors demand profound financial products from their managers, so that hedge funds had to change their approach to attract capital. Nowadays the industry acquires customers by explaining clearly their investment strategies to their investors and by continuously providing performance data for benchmark purposes. Additionally, managers can fall back on newer and more efficient financial tools today. This is mainly caused by the rapid progression of information technologies during the last years.

All these aspects contribute to a sustainable development among the hedge fund industry, so that both the market efficiency and customer satisfaction were improved.

2.2 Situation of Hedge Funds in Germany

Until the end of 2003 it was not permitted to establish German hedge funds. Consequently, foreign hedge funds formed the only possibility for the investors to make use of these investment vehicles. But in fact the tax provisions, according to the Foreign Investment Act (Ausland-Investment-Gesetz), effectively prevented the public distribution of foreign hedge funds in Germany. The increasing demand for investment alternatives and the German investment act (Investmentgesetz) adjustment regarding the European guideline (OGAW) gave reason to modify the German wording of the law.

2.2.1 Establishment

At 1st January 2004 the German Investment Modernization Act (Investmentmodernisierungsgesetz) became operative. This legislation allows the establishment of hedge funds in Germany and additionally facilitates the public distribution of foreign hedge funds under conditions comparable to those of German hedge funds.

The establishment of hedge funds as an investment fund is now permitted in form of a so-called investment fund with additional risks (Sondervermögen mit zusätzlichen Risiken). These funds can either be managed by a domestic investment management company (Kapitalanlagegesellschaft) or as an investment stock corporation (Investmentaktiengesellschaft). The new legislation eases the hedge fund restrictions in Germany. But still, the actual legal environment holds limitations. In fact the establishment of German hedge funds is permitted but due to the distinction between single hedge funds and fund of hedge funds, the access to them is still restricted. Finally, only fund of hedge funds may be distributed publicly in Germany. [3]

While institutional investors may directly invest in hedge funds now, private investors only have an indirect access to these financial instruments. Private

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[3] SHEARMAN & STERLING LLP; 599 Lexington Avenue, New York, NY 10022;Client Publication; 10/2003 "*New German Rules for Hedge Funds and Foreign Funds,*"

investors are only allowed to invest in mutual funds and funds of funds, which also include the funds of hedge funds. According to this forced diversification of risk, the German Federal Ministry of Finance wants to protect private investors against essential capital loss.[4]

2.2.2 Taxation

Generally, HF's are taxed comparable to the taxation of German investors in foreign HF's and foreign funds of hedge funds. Unlike HF's, funds of hedge funds are basically taxed like German investors in domestic HF's and domestic funds of hedge funds. Under the new Investment Tax Act (Investmentsteuergesetz), three different types of funds and corresponding types of taxation can be distinguished, irrespective of whether the fund is foreign or domestic. According to a paper of the BAI[5] the actual situation can be summarized as follows:

1. **Transparent Funds**
   - Funds that fulfill all information requirements
   - Transparent funds enjoy optimal taxation of their investors
   - Investors will basically be taxed as if they had directly invested in the assets held by the fund ("transparency principle")
   - Investors will not be taxed on undistributed capital gains from securities and derivative transactions
2. **Semi-transparent funds**
   - Funds that do not fulfill certain information requirements
   - Investors in semi-transparent funds lose the tax benefits which are tied to certain income components not disclosed by the fund (capital gains from shares and dividends; foreign tax credit amounts)

[4] http://www.uni-leipzig.de/bankinstitut/dokumente/2003-07-08-01.pdf (March 2005)

[5] The Bundesverband Alternative Investments e.V. (BAI) is the lobby association for the alternative investment industry in Germany. Ist main goal is to higher the reach and deepen the public understanding for the asset class. Online: http://www.bvai.de

3. **Non-transparent funds** (all other funds)

- Investors in non-transparent funds face punitive taxation
- Taxable income is the higher of:
  - All distributions received plus 70 % of the increase between the first and the last redemption price of the calendar year
  - 6 % of the last redemption price of the calendar year

According to Sec. 5 I of the German Investment Tax Act, the most important information to be disclosed by foreign and domestic funds to achieve optimal tax treatment for its investors is:

- Overall amount of the retained income and gains after costs, calculated on the basis of cash flow accounting
- Capital gains from disposing of securities as well as from derivative transactions
- Dividend income
- Capital gains from disposing of shares in companies
- Earnings from disposal of subscription rights with respect to bonus shares
- Taxable foreign income from which a tax credit in Germany is granted as well as the amount of the credited tax[6]

[6] BAI e.V.; Achim Pütz; BAI Chairman and Partner at SJBerwin; "*Hedge Fund Opportunities in Germany – Practical Guidance Q&A*"

2.3 Basic Terms

2.3.1 Leverage

In the financial context, the term leverage is defined as the borrowing of money, in order to gain the expected return on investment via debt capital. In addition to the equity E, the investment manager applies debt capital D at an interest rate of r_i. Without considering debt capital, the expected return on investment is denoted by r_E, the so-called return on equity. According to this, the total expected return on investment (including debt capital) is denoted by r_{E+D}, and results as follows:

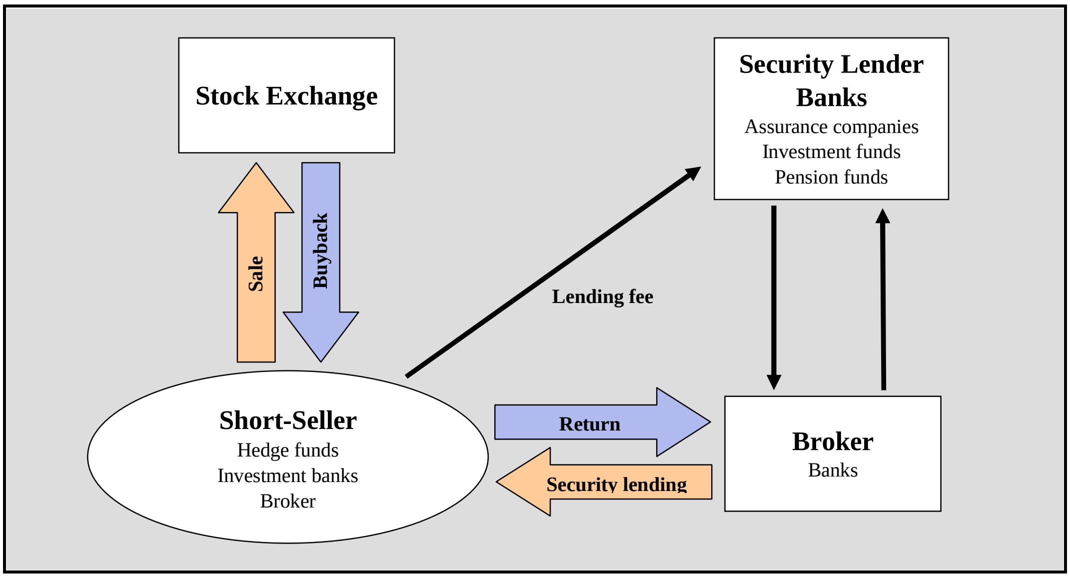
$$r_{E+D} = r_E + D/E * (r_E - r_i)$$

As long as the return on equity is greater than the costs of debt capital ($r_E \geq r_i$), the total return on investment r_{E+D} increases simultaneously with the enhancement of debt capital D. The greater the part of debt capital the more intensive is the leverage effect. Here, it has to be pointed out that we are dealing with expected returns. In consequence of this speculation, risk is involved within the transaction. Therefore, a possibility of capital losses arises. This is the case, if the return on equity is smaller than the cost of debt capital ($r_E \leq r_i$).

2.3.2 Short selling

In practice short selling is perceived as the disposition of securities, which are not owned by the seller. The overall goal is to buyback these securities in future at a lower price. From a legal point of view this process consists of four single transactions, which are illustrated in figure three. At first, the short seller borrows securities from the security lender for a certain period of time. In return, the lender receives interest payments from this particular short seller. Additionally, the lender often demands a financial security. This security is normally called "*collateral*". Furthermore, a leverage effect will occur, if the short seller has to provide a security less than 100% of the short-selling volume. Subsequently, the short seller sells the securities at the market. At a later date, at the latest on maturity, the short seller has to buyback the securities at the market, in order to give these back to the lender.

Fig. 3: Short Selling



Source: Diagram based on: Kaiser, Dieter G.: Hedgefonds, Wiesbaden 2004; Hedgefonds (1): Assetklasse, http://www.dit.de/data/pdf/research/05_04_aa_hedgefonds_1_assetklasse.pdf (April 05)

The motivation for this transaction is to gain from falling prices of the underlying stock. The short seller achieves profits, if he is able to buyback the security at a lower price than the purchase price of the security. In addition, the short seller has to consider the interest payments on the one hand side. On the opposite, he is able to invest the capital, gained from short selling, in order to yield interest by the purchase of bonds or other securities. The risk of capital loss taken by the short seller emerges, if the stock price increases during the short selling procedure or at the later date of purchase of the underlying security. In this case he has to buyback the security at a higher market price. The following table provides information about the use of leverage regarding different hedge fund classes, defined by Van Hedge Fund Advisors International, LLC.[7]

[7] http://www.hedgefund.com/van/contact/contact.htm

Fig. 4: Global Hedge Funds - Use of Leverage

Hedge Fund Style	No Leverage	Leverage Low (<2:1)	Leverage High (>2:1)	Total
Aggressive Growth	30.7%	55.0%	14.3%	69.3%
Distressed Securities	46.3%	42.6%	11.1%	53.7%
Emerging Markets	39.5%	40.9%	19.5%	60.5%
Income	40.0%	31.8%	28.2%	60.0%
Macro	16.2%	29.3%	54.5%	83.8%
Market Neutral-Arbitrage	20.5%	19.5%	60.0%	79.5%
Market Neutral-Securities Hedging	28.6%	26.1%	45.4%	71.4%
Market Timing	36.9%	24.3%	38.7%	63.1%
Opportunistic	22.9%	45.5%	31.6%	77.1%
Several Strategies	29.2%	38.3%	32.5%	70.8%
Short Selling	31.8%	45.5%	22.7%	68.2%
Special Situations	22.2%	57.6%	20.2%	77.8%
Value	30.1%	52.3%	17.6%	69.9%
Total Sample	***28.8%***	***41.4%***	***29.8%***	***71.2%***

Source: 2003 by Van Hedge Fund Advisors International, Inc. and/or its licensors, Nashville, TN, USA.

The table shows that the use of leverage differs among the hedge fund categories. In general, almost one third of the registered hedge funds abandon the use of debt capital within their investment strategies and 40% declare to only use leverage in a relation smaller than 2:1. The remaining hedge funds (29,8%) declare to use high leverage. Consequently, the deployment of debt capital only concentrates on a relative small range of hedge funds. In particular hedge fund managers applying the "*Macro*-" and "*Market Neutral*-" strategy make an extensive use of leverage in order to reproduce favored risk-return profiles among their funds.

2.3.3 Incentive fee structure

Besides the use of short-selling and leverage, AWJ also established a compensation structure, which was different from traditional fee structures. AWJ introduced a compensation structure within the hedge fund industry, which is mainly based on the performance of the fund managers. Typically, hedge fund managers charge a fixed annual fee of 1% to 2%, which is calculated on the basis of the amount of managed assets. Additionally, the managers charge an incentive fee of 5% to 25%, which is calculated on the basis of the annual return. This incentive fee is usually a percentage of the profit above the asset value at the end of each year. Generally, this incentive fee is subject to a high water mark provision. This means, if the fund loses money, then the manager must take up the loss in the next year before the incentive fee becomes applicable.

Here, the author wants to point to a structure immanent problem. This kind of asymmetric payoff to the manager affects the manager's performance as well as the fund's survival. For example, the more the manager is "*out of the money*"[8], the more he may agree to transactions that are more risky.

2.3.4 Hedging

The term hedging refers to an investment strategy with the objective to protect investments against various types of market risks. For example, AWJ[9] used short selling of overvalued stocks in order to safeguard the long position of undervalued stocks against price losses. Today, also options and futures are utilized to hedge positions within a portfolio, due to their capability of adverse price movements.

A distinction is drawn between static and dynamic hedge strategies. In the case of a static strategy a long position is only hedged once during the investment duration by a corresponding short position or option. The application of dynamic hedge strategies demands at best a continuous adjustment at run time regarding changes in price rates of each long position. In the following two explicit definitions of hedging are given:

> *"A hedging transaction is a purchase or sale of a financial product, having as its purpose the elimination of loss arising from price fluctuations. With regards to currency transactions it would protect one against fluctuations in the foreign exchange rate."* [10]

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[8] A call option whose strike price is higher than the market price of the underlying security, or a put option whose strike price is lower than the market price of the underlying security. http://www.investorwords.com/3529/out_of_the_money.html (July 05)

[9] A.W. Jones wrote an article about his investment style *"Fashion in Forecasting"* in Fortune, March 1949, 88, 186

[10] www.cambridgefx.com/currency-exchange/forex-directory.html (Feb. 2005)

“A strategy designed to reduce investment risk using call options, put options, short-selling, or futures contracts. A hedge can help lock in profits. Its purpose is to reduce the volatility of a portfolio by reducing the risk of loss.” [11]

2.4 Traditional and Alternative Investments

Traditional as well as alternative investments are often used as abstract concepts these days. Additionally, not even literature presents a clear and differentiating statement of these terms. It is clear that these two terms are in relationship with each other. For investment managers alternative investments represent an alternative to traditional investments. Alternative investments are often newer instruments than the traditional option, because they provide modern features that differ from older investment vehicles. Consequently, the following question arises: What kind of investment can be denoted as “*new investments*”? For example, some ultra conservative investors would consider stocks and mutual funds to be alternative investments when compared to fixed-income investments such as certificates of deposit or fixed annuities. On the opposite, very sophisticated investors may not consider such instruments as alternative investment vehicles, since they deal with them all the time.

In practice, institutional investors consider alternative investments to be investments, which either due to their complexity or to their structure are not actively traded in the public markets. But what kind of real financial products hides behind these investments in common use? For a clear differentiation between these two terms the definition of the Bundesverband Alternative Investments e.V. (BAI) shall serve.

According to the BAI, the term traditional investment includes:

- Fixed-interest securities (e.g. bonds, marketable debt instruments)
- Shares, traded on the stock exchange
- Special forms (e.g. profit certificates, zero coupon bonds)
- Mutual funds

[11] Campbell R. Harvey; www.duke.edu/~charvey/Classes/wpg/bfglosh.htm (Feb. 2005)

Besides these traditional forms other investment offers exist that differ in their return and risk performance characteristics. The term “alternative investment” has become a catch-all for these investments, which include:

- Commodities
- Precious metals
- Works of art
- Hedge funds
- Private equity

The term “*mutual fund*”, referred to as traditional investment and the terms “*hedge fund*” as well as “*fund of funds*”, referred to as representatives of the alternative investment class are explicitly singled out in the following.

2.4.1 Mutual Fund

A fund is a portfolio, which consists of different securities such as real estates, fixed-interest securities or investments in other traditional asset classes. All these assets added together deliver a monetary value, which is divided in single shares. In turn these constructed shares are then available for capital investors. Owners of shares within a fund do not own directly the original underlying assets of a fund. They participate in joint property. For this reason shares in a fund are derivates.

In Germany funds are managed by investment management companies in form of “Sondervermögen” according to the German investment act.

Mutual funds are so-called open-ended funds. Basically, funds can be classified either as open-ended or as closed funds. Unlike closed funds, open-ended funds are daily traded on the stock exchange and open to the public. Consequently, mutual funds are liquid instruments since the investor is able to sell them at any time for share market price. On the contrary, closed funds are normally established on the basis of an explicit defined duration and can not be prematurely sold. Hence these instruments are generally illiquid investment vehicles. In addition, closed funds are often over the counter products and are therefore usually not open to the public.

The following definition of mutual funds will serve through this thesis:

> *"A pool of money from a number of investors that is invested by professional money managers according to stated investment objectives. Shares of the fund are offered, usually on a continuous basis, and can be sold back to the fund anytime at that day's share price."* [12]

The advantage of fund investment compared to direct security investments is a higher degree of risk diversification. Although fund investors do not have to invest large amounts of money, they still benefit from the size advantage of joint equity.

[12] http://atwork.harvard.edu/benefits/retirement/glossary.shtml (Feb. 2005)

2.4.2 Hedge Fund

One might think that the term hedge fund defines a “hedged fund”. This means an investment vehicle that reduces its risk by some kind of insurance strategy. But this conclusion is not correct. Hedge funds are similar to mutual funds. They are also actively managed investment portfolios holding positions in publicly traded securities. But unlike mutual funds, they own a broader flexibility in:

- Types of securities they may hold
- Types of positions they may take (long AND short positions)
- Use of leverage [5]

According to AWJ, who only used a long-short strategy, it was appropriate to call his fund at least partly “hedged”. But in consequence of the emerged investment strategies, this term is very misleading today. The term strategy tells us how long and short security positions are combined to reflect the strategy’s objective and how these positions are levered and managed. The large variety of strategies and financial instruments used today result in hedge funds that differ completely in performance and risk from the return characteristics of Jones’ fund. In fact nowadays many hedge funds use strategies, which are not at all “hedged” or riskless. For these reasons a definition of hedge funds is not easy to state and that’s why they are often defined by an enumeration of their special characteristics:

> *“Broadly defined, hedge funds are private partnerships wherein the manager/general partner has a significant personal stake in the hedge fund and is free to operate in a variety of markets and to utilize investments and strategies with variable long/short exposures and degrees of leverage.”* [23]

> *“Hedge funds are considered alternative investments since they employ an investment strategy that differs from conventional, long only, money management. … It encompasses a greater variety of investment instruments (options and futures) and a greater variety of investment techniques (short selling, hedging arbitrage, etc.) than conventional money management.”* [24]

> *"A hedge fund constitutes an investment program whereby the managers or partners seek absolute returns by exploiting investment opportunities while protecting principal from potential loss."* [26]

The following definition will serve throughout this thesis for the term "hedge fund":

> *"All forms of investment funds, companies and private partnerships that*
>
> 1. *use derivates for directional investing*
> 2. *and/or are allowed to go short*
> 3. *and/or use significant leverage through borrowing*
>
> *Borrowing includes margin borrowing against securities, foreign exchange credit lines, and loans. The term significant refers to borrowing in excess of 25%."* [22]

Hedge fund managers take advantage of eased restrictions by developing their own investment strategies (detailed explanation later) that aim at positive returns independently from market movements. For this reason, hedge fund performance is not measured relative to a benchmark. Hedge fund managers are only measured by absolute returns. That's why hedge fund managers are often called "*absolute return managers*".

2.4.3 Fund of Funds

FoF's are investment funds, which exclusively invest their pooled capital in other funds. For example, FoF's do not directly invest in corporate shares; they rather hold shares of equity funds. The individual funds within a FoF's are called subfunds. The fund of hedge funds is a special fund of funds that only invests in other hedge funds. Funds of hedge funds play a special role according to the German financial market. Unlike single hedge funds, funds of hedge funds can be publicly distributed, according to the German investment act. Hence, private investors can indirectly invest in hedge funds through buying shares of FoF's. That's why especially in Germany this investment form attracted a lot of attention.[13]

In comparison with direct investments, FoF's provide an exclusive advantage for the investors. The financial risk of the investors can be reduced, due to the appearing diversification effect obtained by the investment in funds that are:

- Managed by different fund managers
- Issued by different investment management or investment stock corporations

On the other hand, FoF's own a special fee structure. Since fees are paid in every subfund as well as in the FoF's itself, the total sum of charged fees cuts returns disproportional heavily.[14]

Additionally, funds of hedge funds are subject to restrictions according to the German Investment Modernization Act. The manager has to consider:

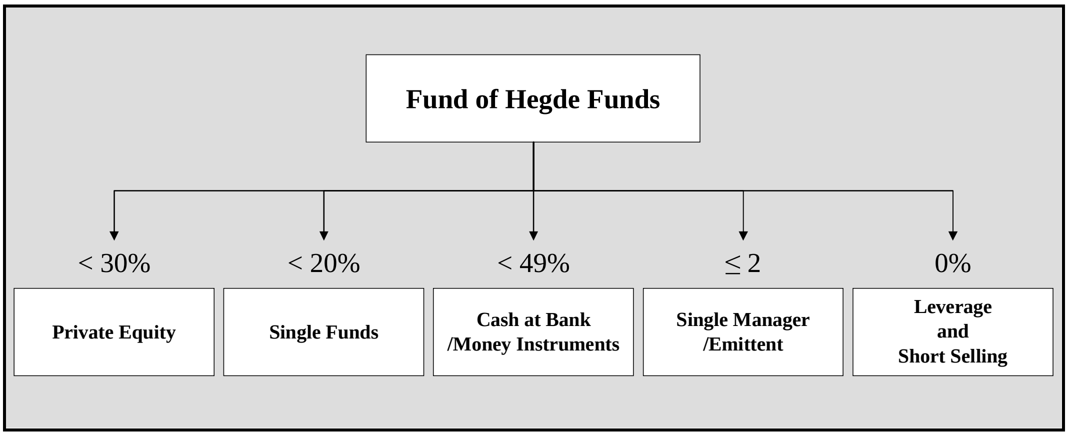
- The maximum investment in single funds may not exceed 20% of the total assets of the fund of funds
- The cash at bank and investments in money operations may not exceed 49% of the total assets of the fund of funds

[13] http://de.wikipedia.org/wiki/Hedgedachfonds
[14] http://de.wikipedia.org/wiki/Dachfonds

- The maximum investment in private equity may not exceed 30% of the total assets of the fund of funds
- Funds of hedge funds managers may not invest in more than two single funds of the same fund manager or emitter
- The use of both leverage and short selling is forbidden
- The use of derivates is only permitted in order to safeguard against currency risks

The following figure illustrates the restrictions, to which funds of hedge funds are subject to:

Fig. 5: Fund of Hedge Funds - Restrictions



Source: Self-made figure.

2.4.4 Summary

Fig. 6: Hedge Funds vs. Traditional Investments

Alternative Investments	Traditional Investments
• Incentive management fees • Skill based strategies - Market risk is removed by manager risk • Not subject to strict regulations (exception: Germany) • Absolute return approach • Aim at positive returns independently from overall market movements • Hedge fund managers do not try to reproduce benchmarks	• Fees depend on managed asset volumes • Market based strategies → market risk exposure • Traditional investments are subject to strict regulations • Relative returns approach – manager performance is relatively measured to benchmarks (market) • Try to reproduce benchmarks

Source: Self-made figure.

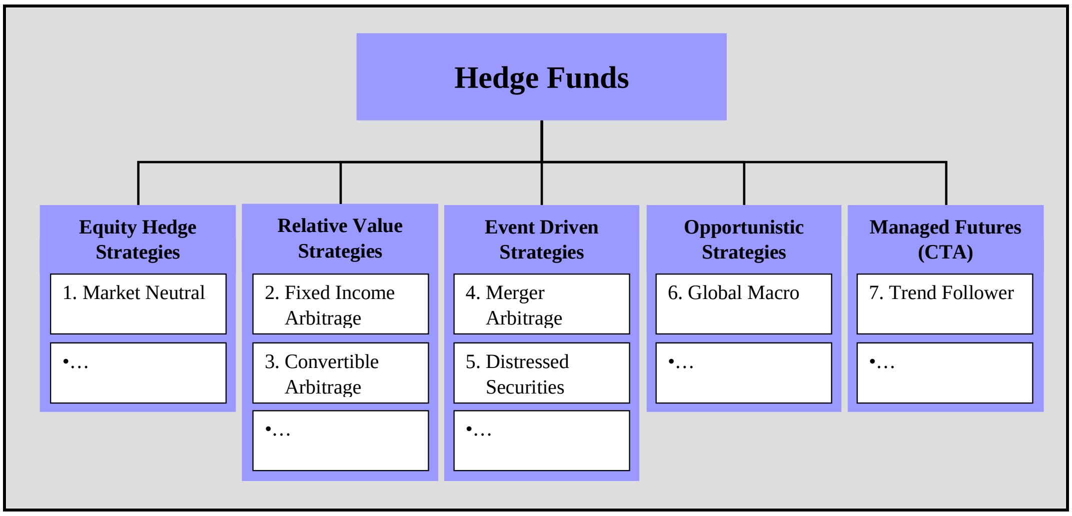
2.5 Hedge Fund Classification

The enormous amount of hedge fund strategies and the wide range of different instruments used within the HF's make it difficult to get a general idea of the hedge fund industry. The specific underlying investments utilized and also the investment strategies employed lead to a large variety of defined hedge fund strategies. Generally, all strategies can be assigned to the following six classes:

- Equity hedge strategy
- Relative value strategy
- Event driven strategy
- Opportunistic strategy
- Managed futures strategy
- Multi strategies strategy

The class of HF's applying multi strategies covers the combinations of strategies, which are part of the other classes. Hence, this category does not need to be explained in more detail. The following diagram gives a general overview about the classification of hedge fund strategies:

Fig. 7: Classification - Hedge Funds



Source: Partners Group; http://www.premier-hedgefund.com

Here, the author wants to point out that there are many other hedge fund strategies in practice. But these six classes should be sufficient for representative purposes. In the following the aforementioned strategies are explained in detail.

2.5.1 Equity Hedge Strategies

The source of return within these strategies is similar to traditional investments. The aim is to gain from increasing stock prices via the long positions within the portfolio. Additionally, equity hedge managers use short selling and hedging to attempt to limit the risk exposure of the purchased long positions. Hence, equity hedge portfolios may be anywhere from net long to net short, depending on the market conditions. A trading advisor typically combines core long holdings of equities or derivates with either short sales of stocks, stock index options or other derivatives.

2.5.1.1 Market neutral

Market neutral funds refer to funds that actively seek to avoid major risk factors. They are the forerunners of all other types of hedge funds. Market neutral strategies refer to the classic model of hedge funds, developed by AWJ.

The aim is to eliminate the influence of the overall stock market on each position within the fund. This objective is achieved by selling expected overvalued stocks and buying expected undervalued stocks. If this strategy is applied within a certain industry to remove the possibility of a particular industry risk from the holdings, managers apply the so called “*pairs-trading*” strategy. This means long and short positions stem from the same industry.

The risk and also the success of this strategy are based on the correct valuation of stocks. This challenges the analyst to decide which stocks are overvalued and which are undervalued.

2.5.2 Relative Value Strategies

Relative-value hedge funds seek profit by exploiting irregularities or discrepancies in the pricing of stocks, bonds or derivatives. They take a position on forward interest rates, on the spread between different yields and also on the price differences between related securities. They are also called "arbitrage" funds.[15]

2.5.2.1 Fixed-Income arbitrage

The first transactions in the bond arbitrage business corresponded to the basics of share arbitrage. In this case the manager wants to take advantage of price differences at different exchange places.

In the case of fixed income arbitrage the instruments applied are bonds only. But unlike shares, bonds own two fundamental differences: they have a determined maturity and secondly they offer fixed payments of interest during the maturity.

[15] FINANCIAL POLICY FORUM, DERIVATIVES STUDY CENTER, Washington http://www.financialpolicy.org (April 05)

Consequently, managers try to take advantage of these characteristics when they apply fixed income arbitrage strategies.

Fixed income arbitrage strategies aim at the generation of capital gain due to the change of security spreads. The difference between the interest rates of two financial instruments is called spread. Managers usually utilize corporate and government bonds of comparable characteristics. But in general, the available instruments include government bonds, corporate bonds, municipal bonds, options on bonds, bond futures and other bond derivates. Through the combination of fixed-income instruments, the managers want to remove the market risk of the interest rates. The basic assumption for the selection process of fund positions is that one particular interest-bearing instrument will go up more and respectively down less than another interest-bearing instrument. That’s why this strategy also belongs to the class of relative value strategies. Thereby no specific assumption about the general direction of interest is made. Only the spread change between two instruments is important. The manager succeeds if the chosen bond performs “relatively” better than another one.

Almost any combination of fixed-income instruments forms substrategies of the fixed-income arbitrage category. In the following a few examples of substrategies are given:

- Buying long-term government bond and selling a short-term government bond is called a “*term spread*”.
- Buying a corporate bond and selling a government bond of the same duration is called a “*default spread*”.
- Buying a government bond and selling a futures contract on the same bond is called a “*basis spread*”.

The risks associated with fixed-income arbitrage funds include the risk that the spread moves in the opposite direction to the one assumed. Other factor, such as the risk of default of the underlying company, country, etc. or the general movements and levels of interest rates at the worldwide capital markets, additionally influence the values of fixed-income arbitrage funds.

2.5.2.2 CONVERTIBLE ARBITRAGE

This strategy is the most complex strategy of all relative value strategies. The convertible bond is a hybrid security, partly a traditional bond and partly a stock. Consequently, also the value of a convertible bond consists of two parts. On the one hand side, the fixed interest rate and the terminal value form the largest part of the convertible bond's price. But on the opposite, also the right to swap the bond for a share at the end of maturity contributes to the price of a convertible bond. Hence, the value of the underlying stock influences the price of the convertible bond as well as the risk of default and the general interest level, as in the case of traditional bonds.

For these reasons the manager has three different possibilities to gain from arbitrage activities, by applying the convertible arbitrage strategy:

1. One possibility is to gain from pricing discrepancies between the convertible and other comparable bonds. For example, if another traditional bond with comparable maturity and higher yield exists, the manager sells the convertible bond short, which owns a lower yield, and takes long positions in the traditional bond.

2. Another way to achieve arbitrage profits can be realized via the embedded option in these bonds. Normally, these embedded options are lower priced than options traded at the OTC-market. Consequently, the manager sells high priced options at the OTC-market short and takes long positions in the lower priced embedded options via the convertible bond. Additionally, the manager usually immunizes his portfolio against bond yield fluctuations by concurrently selling similar corporate bonds that are favorable priced.

3. The third alternative is to achieve capital gain from convertible securities that have pricing discrepancies relative to the company's stock. The value of a convertible security also depends on the price of the underlying stock. This price dependency between convertible bond and underlying stock avails the manager for arbitrage activities. Since the option only forms part of the total price of a convertible bond, the price dependency generally lies

between 0 and 1. For example, if the price dependency equals 0,5 and the price of the underlying stock increases by 1%, the price of the convertible bond will only increase by 0,5%.

Due to the fact that the option forms a bigger or a smaller value component regarding the stock price movement, this level of dependency simultaneously changes. Additionally, the price dependency does not change proportionally, which leads to the fact that convertible bonds perform “relatively” better independently of the direction of stock price movements. It has to be noted that this strategy only pays, if the stock price volatility is high. In the end, this strategy can be interpreted as a bet on the change in the price dependency as a result of high stock price fluctuations.

All of the three possibilities are far less risky than the purchase of naked convertible bonds. Consequently, these strategies carry a lower expected return than the convertible bond itself. For this reason hedge fund managers usually employ high amounts of leverage to amplify the performance of this investment vehicle.

Since convertible arbitrage hedge funds “indirectly” deal with traditional bonds and the underlying stock, funds of this category are exposed to the interest rate risk and the risk of corporate default. These risks may be hedged with appropriate instruments. In turn, this leads to lower return margins, which again increases the utilization of debt capital. Due to the intensive use of leverage even credit risk forms part of the total risk exposure.

2.5.3 Event Driven Strategies

Managers applying this strategy try to identify special events that affect corporate valuations. Thereupon, they construct trades in order to extract value when these events occur. The predominant strategies are “*distressed securities*” and “*merger arbitrage*”, which are explained in the two following sections.

2.5.3.1 DISTRESSED SECURITIES

Event driven funds refer to funds, which take positions on corporate events in two basic ways. Funds that actively take positions[16] in the equity of companies, whose security's price is expected to be affected by situations such as:

- Corporate bankruptcies
- Reorganizations
- Distressed sales
- Corporate restructurings

are referred to as *"Distressed Securities"*. Depending on the manager's style, the positions are normally acquired through bank debt or high yield corporate bonds. Only sometimes managers use company stocks within this strategy.

2.5.3.2 MERGER ARBITRAGE

Another well known event-driven strategy is called: *"merger arbitrage strategy"*. This strategy is also known as *"risk arbitrage strategy"*. Managers following this strategy take advantage of corporate events that are often publicly announced months before they actually take place. The situations, managers want to gain from, include:

- Mergers and acquisitions
- Spin offs
- Recapitalizations
- Share buy-backs
- Exchange offers
- Leveraged buy-outs

[16] Such strategies may invest or sell short

The most common strategy of these is the merger and acquisition strategy. Therefore, this strategy is subject to further examinations.

Funds that belong to this style category usually invest in companies, which participate in announced mergers and acquisitions. Assuming an announced deal will be completed; managers want to gain from this situation by usually going long the equities of target companies and going short the equities of the acquirer. If this deal comes true, managers want to take advantage of the fact that the acquirer has to make a bid, which is above the actual stock price of the target. Otherwise the shareholders will not sell their equity. Consequently, the stock price increases towards the acquirers offer. By an increasing probability of a successful merger the stock price of the target simultaneously increases towards the offered bid price. For example, if the bid is in form of a share deal, the target stock price would move towards the stock price of the acquiring company. Therefore, the investor anticipates a better development of target shares in relation to the acquirers stocks. In this case the manager is able to gain arbitrage profits if he finances long positions in the targets' stock through short sells of the acquirers' stock. This strategy is applied in reverse based on the assumption that the deal will fail.

Normally, these event driven strategies do not implement hedging, although this is possible through simultaneously buying and selling two instruments of the same company.

2.5.4 Opportunistic Strategies

Rather than consistently selecting securities according to the same strategy over time, some managers change their investment approach in order to adapt to changing market conditions. In doing so, managers are able to take advantage of currently opening investment opportunities. Consequently, characteristics of the portfolio, such as asset classes, market capitalization, etc. are likely to vary significantly from time to time. Additionally, the manager may employ a combination of different approaches at a certain point in time.[17]

2.5.4.1 GLOBAL/MACRO

Global/Macro funds commonly refer to those funds that rely on macroeconomic analysis in order to take bets on expected market movements. Hence, the manager seeks to profit from changes in the value of an entire asset class. The movements may result from forecasted shifts in:

- The world economies
- The political fortunes
- The global supply and demand for physical and financial resources

The risk that managers of global/macro funds have to consider is that the anticipated situation will not materialize at all or that the anticipated situation will not have the designated effect on the taken positions.

The manager constructs his portfolio based on a top-down view of global economic trends instead of considering individual corporate securities. Therefore, a wide range of investment vehicles are utilized of the managers. In order to take advantage of the perceived situation, positions are taken in stocks, bonds, currencies, commodities or any other liquid investment vehicle.

Finally, one can say that global/macro funds follow the most liberal of all hedge fund management styles, since the investment approach may change over time and the applied range of financial products is extremely wide.

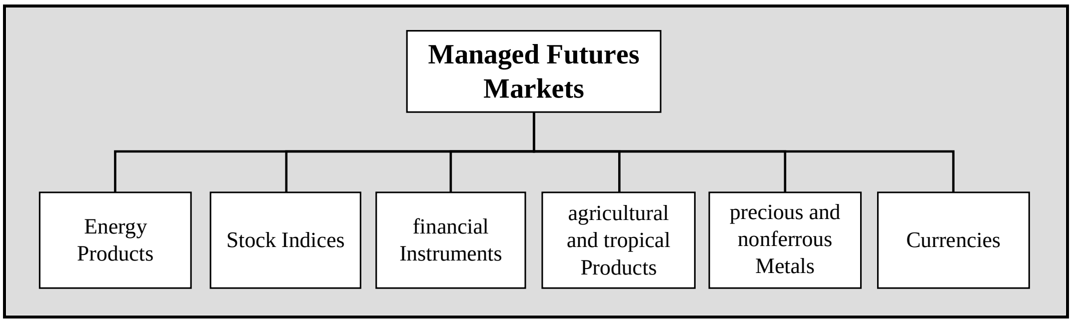
2.5.5 Managed Futures

The term managed futures describes an industry made up by professional money managers that are known as commodity trading advisors, in the following referred to as CTA's. Usually, trading advisors invest on the basis of mathematical models.

[17] Van Hedge Fund Advisors International, LLC, Nashville, Tennessee;

The trading may occur at any time horizon (short, medium, or long term timeframes). The establishment of global futures exchanges and the accompanying increase in actively traded contract offerings allow trading advisors to diversify their portfolios by geography as well as by product. Nowadays, managed futures accounts can participate in at least 150 different markets worldwide. These markets include:

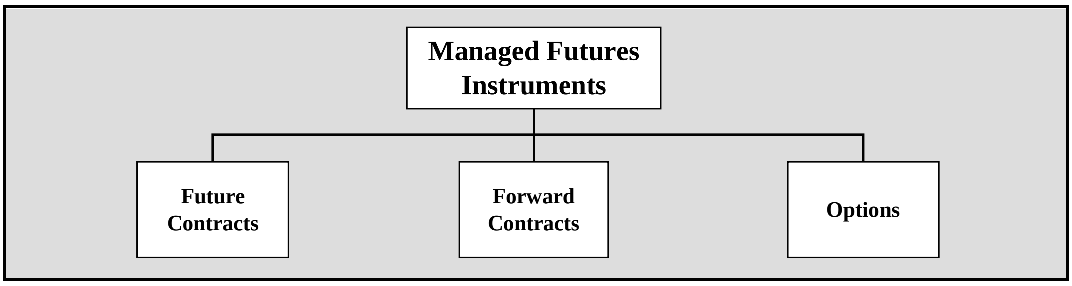
Fig. 8: Managed Futures - Markets



Source: Self-made figure.

Consequently, most CTA's are globally diversified and trade a portfolio of many markets. This is one of the reasons why managed futures are so interesting for investors as they provide diversified exposures to a wide range of markets. Typically, CTA's apply derivative instruments within their investment strategies, which include:

Fig. 9: Managed Futures – Instruments



Source: Self-made figure.

http://www.hedgefund.com/abouthfs/strategysector/strategysector.htm (April 05)

These investment vehicles are financial contracts for the buying and selling of an index, stock, bond, or commodity at some future date. In the sense of portfolio theory these financial contracts are used as following:

- Contracts for buying a certain asset act as long positions
- On the opposite managers may hedge a portfolio or take advantage of negative price movements by contracts for selling an asset in the future

In doing so, managed futures trading advisors can take advantage of any kind of price trend. CTA's that take advantage of anticipated price trends by applying future contracts are called *"trend followers"*. This category, which belongs to the class managed futures, is explained next.

2.5.5.1 Trend Follower

The primary trading strategy employed by CTA's is the systematic trend-following strategy. The objective of systematic trend followers is to gain from the maintenance of positions through any kind of[18] long term trends,[19] which take place in the markets. As we already know, managed futures trading advisors are able to take advantage of price trends, irrespective of the direction of price movements. They can buy futures positions in anticipation of a rising market or sell futures positions in order to anticipate in falling markets. For example, hard commodities such as gold, silver, oil, grains, and livestock tend to do well during periods of hyperinflation. Therefore, CTA's purchase contracts to buy these assets in the case of hyperinflation, so that the managers may gain from the increasing prices. On the contrary, futures provide the opportunity to gain profits by selling into a declining market with the expectation of buying or closing out the position at a lower price during deflationary times.

The trading itself is based on the systematic application of quantitative models that produce "reliable" forecasts of the contracts underlying. The models are

[18] negative as well as positive price movements

[19] In this case, trends that last longer than one month are usually denoted as long term trends.

responsible for the generation of “buy” as well as “sell” signals for a set of markets.

2.6 Assignment of Hedge Funds

As we have seen, hedge funds themselves are not a homogeneous group of investment vehicles. In practice, there is some disagreement about how to classify hedge funds and about how to assign a single hedge fund to a certain predefined category.

Combining single funds to one category not only serves for simplification purposes. In practice, one important issue considers the special arrangement of hedge funds, so that hedge fund indices can be formed. This enables investors to observe performance characteristics of different investment alternatives, in order to provide benchmarks as an additional basis for investment decisions and to track selected strategies. Hence, an assignment methodology delivers best results if interclass correlations are low and hedge fund return correlations within each class are high. From this it follows that each class should include the “*correct*” single hedge funds. One distinguishes between two possible assignment techniques, which are explained in the following:

- The *qualitative* approach
- The *quantitative* approach

Detailed descriptions of these two different approaches to group hedge funds are given in the following sections.

2.6.1 Qualitative Assignment of Hedge Funds

The application of the qualitative approach means that we assign hedge funds according to their qualitative characteristics. In this case, the assignment of a fund to a certain class of funds is based on their self-described investment styles. This so called *self-description* is usually published by the fund manager, who wants to attract many investors to pool fund capital. According to Richard E. Oberuc, a single fund can be assigned according to the following three factors:

- The overall goal
- The instruments employed
- The investment procedures applied

If the qualitative assignment of single hedge funds leads to categories, which are fundamentally and statistically uncorrelated with each other and if the funds within each class show high correlation has to be proved. Within an analysis of Richard E. Overuc, he employed indices defined by Hedge Fund Research[20] (HFR) and accepted their assignment of individual funds to hedge fund categories. Other organizations tracking the performance of hedge funds use different overall classification schemes. The following table summarizes all mentioned hedge fund strategies regarding the classification factors of Richard E. Overuc:

[20] Hedge Fund Research Inc. is a research company, which provides investors with up-to-the-moment quantitative data and two-page state-of-the-art analytical reports on over 1500 Global Fund of Funds from HFR Database. http://www.hedgefundresearch.com (06/2005)

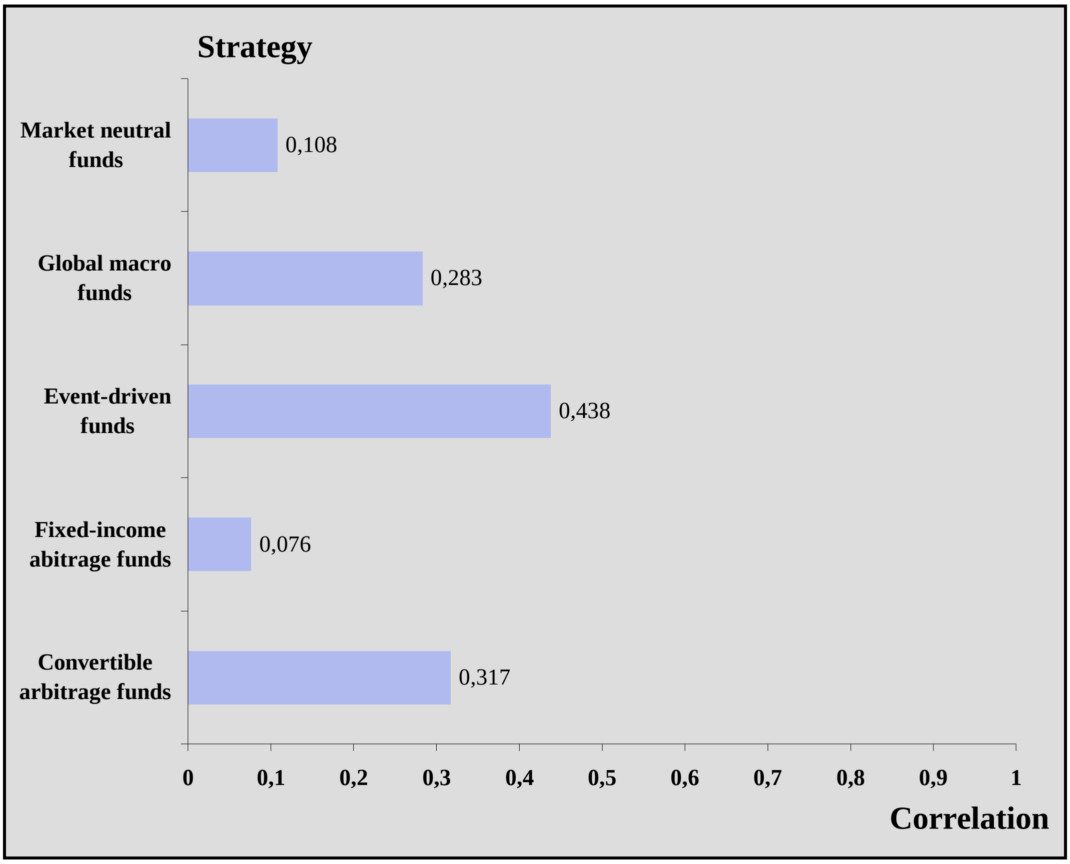
Fig. 10: Qualitative factors for the class assignment of hedge funds

	Gain by	Instruments	Procedures	Risks
Convertible Arbitrage	Pricing differnce: convertable security ↔ stock	• Convertable bonds • Undelying stocks • Corporate bonds	• Buying convertible bonds • Short selling of stocks and corporate bond	• Interest rate risk • Credit risk • Risk of default
Fixed-Income Arb.	Difference between bond spreads	• Bonds: governement, corporate, municipal • Options on bonds • Bond futures	• Term spread • Default spread • Basis spread	• Interest rate risk • Risk of default
Event Driven	Anticipated corporate events	• Company shares • Corporate bonds • Bank debt	• Distressed securities • Reorganisation	• Risk of default • Deal failure
Global Macro	Anticipated economic and political events	• Stocks • Bonds • Currencies • Commodities	• Free investment concepts	• Risk of default • Anticipated event does nor occur
Market Neutral	Avoidance of major risk factors	• Stocks	• Long/short strategies • Pairs trading	• Correct valuation of stocks
Managed Futures	Anticipated price developments of stocks, bonds, and commodities	• Future contracts • Forward contracts • Options	generating trade signals based on quantitative methods, e.g.: • moving averages • time series analysis	• Correct valuation of price movements

Source: Self-made figure.

The correlations between hedge fund indices and single funds within each index are represented in figure 11. The table shows that the average correlation among funds within each hedge fund strategy tends to be low. From this it follows that hedge funds applying the same strategy generally have independent performances.

Fig. 11: Correlation between indices and their single funds



Source: Hedge Fund Correlation Coefficients among single hedge funds (January 1990 – December 2001)

In the following a table of hedge fund index correlation coefficients provided by the HFR is given. Also the assignment of each fund to a particular category is made by HRF. [28] Via the hedge fund index correlation coefficients regarding each category we can prove if the classes are statistically uncorrelated. The statistics for these hedge fund indices, shown in the table below, represent the performance of a portfolio of all funds constituting each index.

Fig. 12: Index correlation coefficients

Strategies	Convert. Arb. Correl.	Fixed-Income Arb. Correl.	Event-Driven Correl.	Global Macro Correl.	Market Neutral Correl.	S&P 500 Stock Correl.	Govt. Bond Correl.
Convertible arbitrage funds	1	0,13	0,62	0,4	0,14	0,33	0,14
Fixed-income abitrage funds	0,13	1	0,2	0,12	0,06	-0,04	-0,28
Event-driven funds	0,62	0,2	1	0,57	0,17	0,6	0,06
Global macro funds	0,4	0,12	0,57	1	0,21	0,43	0,33
Market neutral funds	0,14	0,06	0,17	0,21	1	0,11	0,23
S&P 500 stock index	0,33	-0,04	0,6	0,43	0,11	1	0,21
U.S. government bond index	0,14	-0,28	0,06	0,33	0,23	0,21	1

Source: Hedge Fund Index Correlation Coefficients (January 1990 – December 2001)

Table 12 shows that each of the five hedge fund categories is substantially independent of the others. One can also observe that the examined funds tend to be independent from traditional asset classes, such as stock and bond markets. Only event-driven funds and global macro funds have a modest correlation with the stock market.

2.6.2 Quantitative Assignment of Hedge Funds

The problem related to a qualitative hedge fund classification is that there is often a difference between what managers say they do and what they really do. In order to solve this problem Fung and Hsieh (1997) (in the following referred to as FH) provided a quantitative classification scheme. This serves as an assignment basis alternative to the qualitative style descriptions. [9] This scheme is based on fund returns only. FH argued that two hedge funds should deliver correlating returns, if their managers apply the same strategy in the same market. In order to group funds based on their return correlation with each other, FH used the principle component analysis (PCA; explained in section 3.6) in order to find common factors, which explain the cross sectional variation in hedge fund returns. The result from this was that the first five principle components (PC), each representing a certain strategy, were able to explain 45% of the variation among the underlying dataset.

The basic idea of the qualitative assignment is that hedge funds can be grouped by the correlation between their returns and these five PC's. The correlation with one of the five PC's denotes that this particular fund applies a certain strategy. The fact that there are different principal components implicates that fund returns have low correlations to each other. In turn, this tells us that a different type of risk is associated with these investment styles. The assignment is as follows:

- Funds, which returns correlate with the first PC apply a "*trend following*" strategy
- The second PC represents "*global/macro*" funds
- The third component is made up of "*long only*" funds
- The fourth component corresponds to funds, which apply a "*trend following*" strategy with emphasis on major currencies
- The fifth PC represents "*distressed securities*" funds

2.7 Critical Approach of alternative Investments

According to a paper, published by the Reserve Bank of Australia[21] [18], critics can generally be grouped into three major statements:

2.7.1 Hedge funds put at risk the integrity of markets

Over the 1990s hedge funds have emerged as major financial players, by taking very large positions in particular markets. This has led to concerns that hedge funds are contributing to financial instability and impairing the efficient operation of markets. One of the main arguments against hedge funds is the reproach of economics destabilization. Critics accuse hedge fund managers of manipulating markets and currencies by their aggressive trading strategies. This means, the

[21] Reserve Bank of Australia, Sydney, March 1999; "*Hedge Funds, financial Stability and Market Integrity*"; Paper submitted to House of Representatives Standing Committee on Economics, Finance and Public Administration's Inquiry into the International Financial Markets Effects on Government Policy, June 1999; http://www.rba.gov.au/PublicationsAndResearch/OccasionalPapersAndOtherReports (April 05)

expectations of major market participants may cause negative influences on interest and monetary politics. For example, politicians consider George Soros to be responsible for the rapid currency devaluation, due to his famous attack on the British Pound in 1992. George Soros anticipated the Pound to be overvalued. He found out that the British bank of issue bought large amounts of British devices in order to keep the price up on an “artificial” high level in situations of the shortfall of a certain mark. Consequently, the price did not reflect the weak economic situation of the country. Therefore, Soros took a notably bet, associated with a high portion of leverage, on falling exchange rates. Over time, the reserves of the British bank of issue were not sufficient to stop the devaluation, so that the British pound fell rapidly, additionally strengthened by Soros speculations. Soros extracted from this transaction about $ 1billion and in consequence of the intense inflation the UK left the European Monetary Union. If the British Pound would have gone down anyway sooner or later or if Soros has been the only responsible is still material of discussion these days.

2.7.2 Hedge funds offer little protection to investors

Another often discussed critical argument against hedge funds is the lack of supervision through an institution. Due to the unique organizational structure of hedge funds, they are subject to little restrictions. Therefore, they do not have to publish information unlike mutual funds. The organizational structure leads to the fact that investors in hedge funds are typically both sophisticated and wealthy. Additionally, they have the resources to monitor and assess the risk they take. Consequently, such investors should be able to manage their investments without government regulation. If they are dissatisfied with the amount of information they are receiving, they should either put pressure on the fund manager to provide more information or they can place their capital elsewhere. This is the major reason why hedge funds have been subject to minimal regulation in the past. But still, critics demand public-policy response in order to enhance the stability of the financial system. If critical situations, as in the case of Long Term Capital Management, can be avoided by disclosures there is a strong and legitimate case for this to reduce and contain those risks.

2.7.3 Hedge funds endanger the stability of the financial system

The extensive use of leverage in combination with hedge funds is also often criticized. The part of leverage is determined by the amount of borrowed debt capital and the application of derivatives and short selling. Leverage is principally used by investment managers to gear up the performance of hedge fund strategies, whose margins are very small. A high leverage ratio additionally raises the risk of hedge funds. For example, the debacle of the well known hedge fund, Long-Term Capital Management LP (LTCM), highlights the risks of leverage. LTCM was formed in February 1994. One of the reasons for LTCM's near failure was its high leverage ratio and the lack of adequate capital to back its portfolio positions. LTCM got into difficulties when it thought that the high spread between prices on long term treasury bonds and long term corporate bonds was too high, and bet that this spread would narrow. [7] Due to the Russian debt default in 1998 and its impact on financial markets around the world, LTCM lost majority of its assets and faced numerous margin calls from different investment banks. Not having enough equity to cover these calls, LTCM was on the brink of bankruptcy. [13]

3 FACTOR MODELS FOR ASSET RETURNS AND RETURN VARIABILITY

3.1 Introduction

The objective of modern portfolio theory is to provide the investment managers with an optimal portfolio according to the investor's requirements. The manager's objectives are measured in terms of expected return at minimal risk, while he has to face an infinite number of possible securities. Consequently, the investor needs a statistical model that describes how the return on a security is produced, the so-called return-generating process. In order to meet the investor's expectations, this framework has to consider expected returns as well as standard deviations of securities and covariances between securities. Factor models can be used to predict returns, to generate estimates of return and also to estimate the variability and covariability of returns. [33] Additionally, factor models are simple as well as intuitive and they offer the researcher parsimony. These characteristics strengthen the utility of model type at both a theoretical and an empirical level. Hence, factor models are a popular and widely used approach to model security returns[1]. [27]

Factor models assume that the return on a security is sensitive to the movements of various factors. In the sense of the return-generating process, a factor model attempts to capture factors and their impact that systematically move prices of securities. These common factors are often interpreted as fundamental risk components. The model itself finally isolates the assets sensitivities to these risk factors. Therefore, a primary goal of security analysis is to determine these factors and the sensitivities of the security to the determined factors.

[1] Peter Zangari (2003), *"Modern Investment Management"*, Goldman Sachs Asset Management, p. 334

3.1.1 Structure of this Chapter

His chapter is arranged in three parts. The first part covers the sections one to three. Within this part the basic terms, which are necessary for a general understanding of factor models, are defined. These definitions are made on the basis of a general multi factor model specification, given at first. The second part covers the sections four and five. This part deals with the differentiation of factor returns and the possible approaches to evaluate these. Thereby, special attention is directed to the principle component analysis. The third part includes the sections six and seven. Here, a factor classification is given as well as a classification of multi factor models itself.

3.2 Equity Factor Model Specification

The fundamental assumption of equity factor models is a risk return relationship that can be led back to a group of economic risk factors. Consequently, a model structure is needed, which differentiates between these different factors. Factor models can be used to describe both the security returns and the variability of security returns. Each type of multifactor model for asset returns has the general form:

$$R_{it} = \alpha_i + \beta_{1i} f_{1t} + \beta_{2i} f_{2t} + \cdots + \beta_{ki} f_{kt} + \varepsilon_{it} \tag{3.1}$$

Where:

R_{it}	Return (real or in excess of the risk free rate) on asset i (i = 1,…,N) in time period t (t = 1,…,T)
α_i	The intercept (i = 1,…,N)
f_{kt}	The k^{th} *common factor* (k = 1,...,K) in time period t
β_{ki}	The *factor loading* or *factor beta* for asset i on the k^{th} factor
ε_{it}	The *specific factor* of asset i in time period t

Assumptions:

1. The factor realizations, f_{kt} go with unconditional moments:

$$E[f_t] = \mu_f$$
$$\operatorname{cov}(f_t) = E\left[(f_t - \mu_f) \times (f_t - \mu_f)'\right] = \Omega_f$$

2. The asset specific error terms, ε_{it} are uncorrelated with each of the common factors, f_{kt} This means that the outcome of the factor has no bearing on the random error term, so that:

$$\operatorname{cov}(f_{kt}, \varepsilon_{it}) = 0, \qquad \textit{for all } k, i \textit{ and } t$$

3. It is also assumed that the error terms, ε_{it} are serially uncorrelated and contemporaneously uncorrelated across assets. This means that the outcome of the random error term of one security has no bearing on the outcome of the random error term of any other security.

$$\begin{array}{l} \operatorname{cov}(\varepsilon_{it}, \varepsilon_{js}) = \sigma_i^2 \ \textit{for all } i = j \textit{ and } t = s \\ \\ \operatorname{cov}(\varepsilon_{it}, \varepsilon_{js}) = 0, \textit{ otherwise} \end{array} \Leftrightarrow \begin{pmatrix} \sigma_{\varepsilon_{11}}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{\varepsilon_{22}}^2 & & \vdots \\ \vdots & & \ddots & \\ 0 & \cdots & & \sigma_{\varepsilon_{NN}}^2 \end{pmatrix}$$

If these assumptions are valid, it is guaranteed that the returns of the securities will be correlated only through the responses to the common factors. Hence, reality is perfectly reproduced through the model.

In the case of invalid assumptions, the factors are not able to exactly anticipate expected returns, so that a difference between estimated and observed returns occurs. Therefore, the model just becomes an approximation of the truly realized security returns. In this case, a different factor model will probably deliver a more accurate reproduction of the return-generating process. [31]

Consequently, variance and covariance of asset returns are modeled as follows:

$$\sigma^2(R_{it}) = \beta_{1i}^2\sigma^2(f_{1t}) + \beta_{2i}^2\sigma^2(f_{2t}) + \cdots + \beta_{ki}^2\sigma^2(f_{kt}) + \sigma^2(\varepsilon_{it})$$

$$\sigma^2(R_{it}) = \sum_{j=1}^{K}\beta_{ji}^2\sigma^2(f_{1t}) + \sigma^2(\varepsilon_{it}) \tag{3.2}$$

$$\operatorname{cov}(R_{it}, R_{jt}) = \beta_{1i}\beta_{1j}\sigma^2(f_{1t}) + \beta_{2i}\beta_{2j}\sigma^2(f_{2t}) + \cdots + \beta_{ki}\beta_{kj}\sigma^2(f_{kt}) \tag{3.3}$$

Where:

$\sigma^2(R_{it})$	Variance on asset i (i =1,…,N) in time period t (t =1,…,T)
$\beta_{ki}^2\sigma^2(f_{kt})$	Variance influence through the k^{th} *common factor* (k=1,...,K) on asset i (i =1,…,N) in time period t (t =1,…,T)
$\sigma^2(\varepsilon_{it})$	The asset specific variance (idiosyncratic risk) on asset i (i =1,…,N) in time period t (t =1,…,T)

According to portfolio theory, the variance as well as the standard deviation of security returns can be interpreted as measures of financial risk. As shown in equation (3.2), the total risk of a particular security is composed of two parts. One part covers the sum of all single variances related to each factor and another part consists of asset specific risk. This differentiation of risk is explained in the section 3.3.

3.2.1 Matrix Notion of Factor Models

Multifactor models can be rewritten in two ways by using matrix notion:

- Either as a *cross-sectional regression* at time t by stacking the equations for each asset
- Or as a *time-series regression* model for asset i by stacking the observations for a given asset.

These two approaches are explained next.

3.2.1.1 CROSS-SECTIONAL REGRESSION

Multifactor model for asset returns in matrix notion as a *cross-sectional regression* at time t:

$$R_t = \alpha + B\ f_t + \varepsilon_t \qquad ,t = 1,\ldots,T \tag{3.4}$$

Where:

R_t	Is the (N×1) vector of asset returns i (i=1,…,N) at time t
α	Is the (N×1) vector of intercepts
B	Is the (N×K) matrix of factor loadings (factor betas)
f_t	Is the (K×1) vector of factor returns (factor realizations) at time t
ε_t	Is the (K×1) vector of asset specific error terms at time t

3.2.1.2 TIME-SERIES REGRESSION

Multifactor model for asset returns in matrix notion as a *time-series regression* model for asset i:

$$R_i = 1_T \alpha_i + F\ \beta_i + \varepsilon_i \quad ,i = 1,\ldots,N \tag{3.5}$$

Where:

R_i	Is the (T×1) vector of asset return i at time t (t=1,…,T)
1_T	Is a (T×1) vector of ones
α_i	Is the intercept of asset i
F	Is the (T×K) matrix of factor returns (factor realizations)
β_i	Is the (K×1) vector of factor loadings of asset i
ε_i	Is a (T×1) vector of error terms of asset i

3.2.1.3 MULTIVARIATE REGRESSION

Finally, we can bring the cross-sectional and the time-series regression together. This can be done .if we collect the data from t=1,…, T and rewrite equation (3.1) in a more condensed format.

Multifactor model for asset returns in matrix notion as a multivariate regression model for asset i at time t:

$$R = \alpha + B\,F + E \tag{3.6}$$

Where:

R	Is the (N×T) matrix of n=1,…N asset returns at time t=1,…,T
α	Is a (N×1) vector of intercepts related to n=1,…,N assets
B	Is the (N×K) matrix of n=1,…,N factor loadings related to the k=1,…,K factors
F	Is the (K×T) matrix of factor returns related to the k=1,…,K factors at time t=1,…,T
E	Is the (N×T) matrix of error terms of asset n=1,…N at time t=1,…,T

3.3 Risk Partition

The partitioning of risk is based on the portfolio theory by Harry M. Markowitz (1952). The fundamental assumption of his theory was that the risk of an individual investment object could be partly eliminated through the efficient mixture with other assets. In terms of securities this part consists of the risk, which is related to a specific asset, the so-called idiosyncratic risk. Therefore, the idiosyncratic risk should not be important to an investor and the manager should not demand a higher return in the case of increasing idiosyncratic risk. [25] Hence, only the risk that is common to all assets remains, the so-called systematic risk. The systematic risk can not be eliminated through diversification. Consequently, the investor demands higher returns in the event of higher systematic risk regarding a certain investment.

According to this, William F. Sharpe[1] divided the security risk within his market model (CAPM) into two parts:

- Securities sensitivity to the movements of the market portfolio as the systematic risk
- The asset specific risk

Although Sharpe's market model still enjoys popularity in practice, statistical tests[2] proved that the CAPM is not able to describe the return generating process properly. Consequently, the partition of risk needs a more general explanation these days.

3.3.1 Systematic Risk

In the sense of security returns, the objective of multi factor modeling is to create a theoretical construct, which is able to reproduce the real return-generating process. This aim is very ambitious and real processes are often too complex, so that they can not be reproduced exactly. For this reason, model builder must abstract from the full complexity of the situation and consequently simplify the reality by only focusing on the most important features. Hence, the systematic risk can be defined as the influence of all significant factors regarding their loadings on the security return, which the model builder has chosen to be representative for the real situation. According to the factor model specification, given in equation (3.1), the systematic risk consists of:

$$R_{it} = \alpha_i + \underbrace{\beta_{1i} f_{1t} + \beta_{2i} f_{2t} + \cdots + \beta_{ki} f_{kt}}_{systematic\ risk} + \varepsilon_{it}$$

[1] William F. Sharpe is the STANCO 25 Professor of Finance, Emeritus at Stanford University's Graduate School of Business. He has published articles in a number of professional journals, is past President of the American Finance Association and in 1990 he received the Nobel Prize in Economic Sciences.

[2] Survey of Black, Jensen and Scholes (1972); Survey of Fama and MacBeth (1974); Survey of Fama and French (1992)

3.3.2 Idiosyncratic Risk

In return, models are not able to reproduce the reality perfectly and an error term consequently occurs. Since the model will not cover all factors that influence the real process, there will always be a distance between model and reality. This difference is attributed to the effect of a random error term. This term is defined as the idiosyncratic risk, which simply shows that the significant factors, chosen by the model builder, do not perfectly explain the security returns. The random error term can be viewed as a random variable that has a probability distribution with a mean of zero and a standard deviation $\sigma_{\varepsilon i}$. The outcome of the random error term can be interpreted as the result from the spin of a special kind of roulette wheel. [31] According to the factor model specification, given in equation (3.1), the systematic risk in consists of:

$$R_{it} = \alpha_i + \beta_{1i} f_{1t} + \beta_{2i} f_{2t} + \cdots + \beta_{ki} f_{kt} + \underbrace{\varepsilon_{it}}_{\textit{idiosyncratic risk}}$$

3.4 Basic Terms

Thus far, the terms factor, factor return and factor loading have been treated as abstract concepts. This section provides definitions and explanations of these terms, so that they become more precise.

3.4.1 The utilized Factors

In order to understand a factor model, one has to begin with the meaning of the factors used within such model. For this reason, a definition of the term *factor* will be given in this section.

Factor models assume that the return on a certain variable is sensitive to the movements of various factors. In terms of the return-generating process, a factor model attempts to capture both common factors among a set of securities and their impact on this set. This impact lets security prices move systematically. The function of common factors can be interpreted as *capturing fundamental risk* *components*. Later, the factor model isolates the assets sensitivities to these risk factors. Therefore, a primary goal of security analysis is:

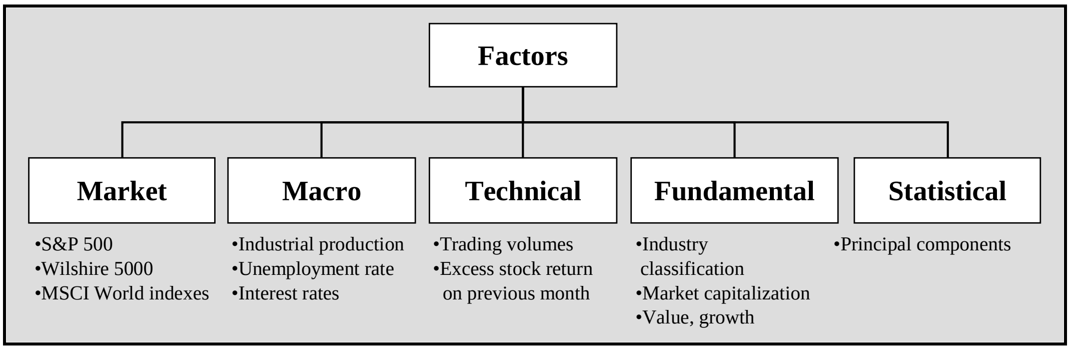
- The determination of the common factors among a set of securities
- The determination of the securities' sensibilities to the predetermined common factors

We begin with a definition of factors that will serve through this thesis:

> *"A factor is a random variable that, at a particular point in time, can explain or account for the variation among a set of security returns*[3]*. Put another way, a factor is a variable that is common to a set of security returns, influencing each return through its factor loading."* [4] [27]

Some examples according to the factor classification by Chan, Karceski and Lakonishok (1998) are given below:

Fig. 13: Factor classification overview



Source: Self-made figure.

[3] This set contains one or more security returns.

[4] Modern Investment Management, Goldman Sachs Asset Management, Peter Zangari (2003), p. 334

3.4.2 Factor Returns

Once the pervasive factors of a model are elected, the model builder has to decide about the values of the factors. These values are defined as factor returns or factor realizations; see f_{kt} in equation (3.1). For example, if the model builder decides a particular index to be the return determining variable of a security, than its realization, the index return equals the factor realization.

3.4.3 Factor Loading

It is a well known fact that the value of securities varies over time. This volatility is based on the fact that assets are exposed to certain risk factors. In terms of factor models, these asset exposures are related to the pervasive factors within a model. Ideally, these elected factors are able to describe the return-generating process of securities. For example, an asset can have exposures to:

- Itself
- An industry or sector
- A currency
- A country
- Investment styles
- Risk factors

To put a factor model into practice it is not sufficient to only determine the pervasive factors and their factor realizations. In addition, one needs to evaluate the impact of a certain factor on the return-generating process. In literature the measure of sensitivity of a securities return to a certain factor is defined as the factor loading or factor beta; see β_{ki} in equation (3.1). Factor loadings can be interpreted as an individualization of factor returns regarding a certain security.

Thereby, the value of a certain factor loading depends on the type of exposure we are dealing with. For example, the asset exposure to an industry can either be zero or one. In the case of being in that industry the certain asset exposure is one and otherwise it equals to zero.

3.5 Observable and unobservable Factor Returns

In practice, factors are classified by observable and unobservable factor returns. Factors, whose returns are observable, appear in the form of time series'. Their values are common to all securities at a particular point in time. Consequently, the model builder directly knows the factor realizations once the factors are elected. On the contrary, the model builder knows neither the factor realizations nor the securities sensitivities to those factors in the case of unobservable factor returns. The assignment of factors to the different groups and the problems related to each type of factor return are presented in the following.

3.5.1 Macroeconomic and Market Factors

In the case of macroeconomic factors and market factors, their realizations f_t in equation (3.1) are observable variables. Additionally, they are common to all securities at period t=1,…, T. Once these factors are specified and constructed, the manager has to only estimate their factor loadings, β_{ki}, regarding each asset i (i= 1,…,N). This econometric problem can be solved by applying N time series regression techniques for each security.

3.5.2 Fundamental and Technical Factors

These factors are also observable variables in some way. But unlike macroeconomic and market factors, observations describe asset specific characteristics. According to this, the data provides a cross section of observations (at time t=1,…, T) that are not common to all assets. For this reason, these factors belong to the class of unobservable factors. In consequence, "general" risk factors have to be estimated first, so that they can be used for modeling the return generating process of all underlying securities. In practice, two ways of estimating these "general" risk factors exist. One way was developed by Bar Rosenberg, the founder of the BARRA Inc.[5], hereafter defined as the "BARRA approach". Another possibility is the approach pioneered by Eugene Fama and Kenneth French (1992). Both ways are explained in the next two sections.

3.5.2.1 BARRA APPROACH

Within this approach the observable security specific observations are treated like factor loadings. Consequently, the factor returns, which are not observable, have to be estimated. Basically, the manager needs a time series of factor returns that correspond to the already known asset specific factor loadings. This is an econometric problem. Therefore, it can be solved through cross-sectional regressions. This means that returns on individual securities have to be cross-sectionally regressed on the factor exposures. If the manager runs in total T of these cross-sectional regressions, he is able to generate a time series consisting of T values that can be interpreted as factor returns. Finally, these generated realizations are common to all assets.[6]

3.5.2.2 FAMA-FRENCH APPROACH

This procedure was introduced by Eugene Fama and Kenneth French (1992). They defined factor returns by constructing a so called factor-mimicking portfolio (FMP). This means, the FMP emulates the behavior of the underlying factor. Consequently, the return on this portfolio can be interpreted as the "observed" factor realization for the asset specific characteristic.

The procedure itself is explained in the following. It consists of the following steps [33]:

- First the cross-section of assets is sorted by their values of their specific characteristic

[5] Barra Inc. is the market leader in delivering innovative, financial risk management solutions worldwide. Since 1975, our products and services have combined advanced technology, superior analytics, research, models and proprietary data to empower investment professionals to make strategic investment decisions. http://www.barra.com

[6] Grinold and Kahn (2000) for deeper insight

- The sorted assets are split into two groups. The first group contains the top half and the second group contains all assets that fall in the bottom half
- Then the manager forms a hedge portfolio (FMP), which is long in the top quintile and short in the bottom quintile of the sorted assets of nearly equal amounts. Together these positions have the ability to mimic the particular factor
- The observed return on this hedge portfolio is the taken as the observed factor realization at time t
- By repeating this process for each asset specific characteristic at each period (t=1,…,T) the model builder achieves a time series for each factor. On this basis, factor loadings can be estimated for each asset using N time series regressions.

3.5.3 Statistical Factors

The factor realizations of statistical factors, see f_{kt} in equation (3.1), are not directly observable. Model builders, which use this type of factors to describe the return-generating process, have to extract the factor returns from the historical observable asset returns, R_t in (3.1). The primary techniques for the extraction of factors influencing security returns are:

- Principle component analysis (in the following also referred to as PCA)
- Asymptotic principle component analysis (in the following also referred to as APCA)

These techniques are explained in more detail in section 3.6. Once the factors are determined and their realizations are estimated, the manager has to estimate the factor loadings β_i for each asset and the asset specific error term ε_i. These can then be estimated via time series regression.

3.6 Principal Component Analysis

In the case of multifactor models for security returns, one of the decisive managerial functions is to estimate the pervasive factors that describe the return-generating process. At the same time, managers want to keep the number of necessary factors to a minimum, in order to achieve parsimony of the model and to avoid the problem of overfitting[7]. The PCA is a mathematical tool, which can be used to examine a set of data points, which are provided in a matrix form. It has been used in disciplines as diverse as chemistry, sociology, economics and psychology. If factor models are used to reproduce the return generating process of securities, the input set of data is represented through the covariance matrix of observed asset returns.

Fundamentally, the PCA is a data reduction method. It is designed to capture the variance in a data set through principle components. The procedure usually generates a lot of insights into the data generating process. It can be interpreted as a process of searching for factors. In terms of factor models for security returns, these factors describe the return-generating process. In the following is given an example[8], which explains the basic idea of the PCA.

Suppose we want to measure people's satisfaction with their lives by the two factors:

- Satisfaction with their hobbies
- Intensity of pursuing a hobby

It is very likely that responses to these factors are highly correlated with each other. If this is the case, we can conclude that they are quite redundant. In turn, the question arises if both factors are really needed to decide about the people's satisfaction.

The relationship between the two factors can be summarized through a regression. If we define a variable that approximates this regression line in form of a linear

[7] Overfitting is the phenomenon that a model adapts so well to a historical data set that the random disturbances in the training set are included in the model as being meaningful.
[8] http://www.statsoft.com/textbook/stfacan.html (3/11/2005)

combination of the two variables, this single variable would capture most of the "essence" of the two items. In effect, we have reduced the dimensionality of the given data from two to one dimension. Simultaneously, we summarized the "most important" parts by combining two variables into a single factor, the so-called principal component.

If we extend this example from two to multiple variables, the extraction of principal components amounts to an iterative process, so that the principle components are ordered by their ability to explain the variation within a certain dataset. Hence, the first principle component describes the maximum amount of variance in this data set respectively the second component, third component and so on. The principle components have to be constructed in such way that they are orthogonal to each other and normalized to have the unit length.

We begin with a definition of the term *"principle component"*. Then the author reviews the standard principle component procedure. Finally, an alternative method, known as the asymptotic principle component analysis, is roughly discussed at the end of this section.[9] [27]

3.6.1 Principal Components

In order to understand the principle component analysis, a definition of principle components is necessary:

> *"Principle Components are a set of variables that define a projection that encapsulates the maximum amount of variation in a dataset and is orthogonal (and therefore uncorrelated) to the previous principle component of the same dataset."*[10]

In terms of asset return factor models, principle components are factors, which are used to describe the return-generating process. Hence, PC represent f_{kt}, see equation (3.1). In addition, the factors are linear combinations of observed asset returns.

[9] Modern Investment Management, Peter Zangari (2003), p. 345
[10] www.ucl.ac.uk/oncology/MicroCore/HTML_resource/PCA_1.htm (3/11/2005)

3.6.2 Traditional Principal Component Analysis

The PCA is a statistical technique that is used to extract one or more statistically significant unobservable factors from an underlying data set. These extracted factors are called principle components, in the following also referred to as PC. The traditional PCA extracts these PC from the (N×N) sample covariance matrix $\hat{\Omega}_N$ of observed security returns. A typical application of the PCA, which serves as basis for later factor modeling procedures, is presented next[11]:

Step 1: Data collection

We suppose that the number of securities totals N. With N assets, there are N possible PC's. Consequently, we face an N-dimensional data set that consists of security returns. At each period t (t=1,…,T) these dimensions are expressed in terms of cross sectional asset return data sets. Consequently, the (N×T) matrix R (according to equation (3.6)) is known.

Step 2: Subtract the mean

The PCA bases on the cross-sectional regression model for asset returns, according to equation (3.4)

$$R_t = \alpha + B\ f_t + \varepsilon_t$$

To make the PCA work properly we need asset returns, whose means equal to zero. Hence, we have to subtract the mean return across each time series. The remaining time series is called a time series of excess asset returns. According to this, equation (3.4) can be written as follows:

$$R_t = B\ f_t + \varepsilon_t \tag{3.7}$$

[11] http://kybele.psych.cornell.edu/%7Eedelman/Psych-465-Spring-2003/PCA-tutorial.pdf (3/11/2005)

Step 3: Calculate the return covariance matrix

Since the (N×N) sample covariance matrix $\hat{\Omega}_N$ of asset returns serves as input data for the factor extracting procedure, one has to estimate this matrix according to the following equation:

$$\hat{\Omega}_N = \frac{1}{T} RR' \quad \text{, where R is the (N×T) matrix of observed returns}$$

Step 4: Choosing the k principle components

After the determination of the squared (N×N) sample covariance matrix, one can estimate their eigenvectors, in the following defined as x_i, and their eigenvalues. The eigenvectors have to be estimated at unit length, as earlier mentioned. The results of the PCA are demonstrated as follows:

An eigenvector that solves the equation

$$\max_{x_1} \quad x_1' \hat{\Omega}_N \, x_1 \quad s.t.\, x_1' x_1 = 1$$

is denoted as the first principle component, $\hat{f}_1$. The eigenvector that solves the equation

$$\max_{x_2} \quad x_2' \hat{\Omega}_N \, x_2 \quad s.t.\, x_2' x_2 = 1 \quad and \quad x_2 \neq x_1$$

is denoted as the second principle component, $\hat{f}_2$. This process is repeated until K principle components are estimated.

Step 5: factor realization estimation

In practice, factor realizations are estimated over time, to generate a time series of factor returns according to the following equation:

$$f_{kt} = x_k' R_t \quad , k = 1,\ldots,K$$

3.6.3 Asymptotic Principal Component Analysis

Connor and Koracyk (1986) proposed and developed the asymptotic PCA based on the analysis in Chamberlain and Rothschild (1983). The asymptotic principal component analysis is similar to the traditional PCA procedure. But, unlike the PCA, which is based on the (N×N) sample covariance matrix $\hat{\Omega}_N$, the APCA uses the (T×T) matrix $\hat{\Omega}_T$ as a basis to extract principle components.

$$\hat{\Omega}_T = \frac{1}{N} R'R \qquad \text{, where R is the (N×T) matrix of observed returns}$$

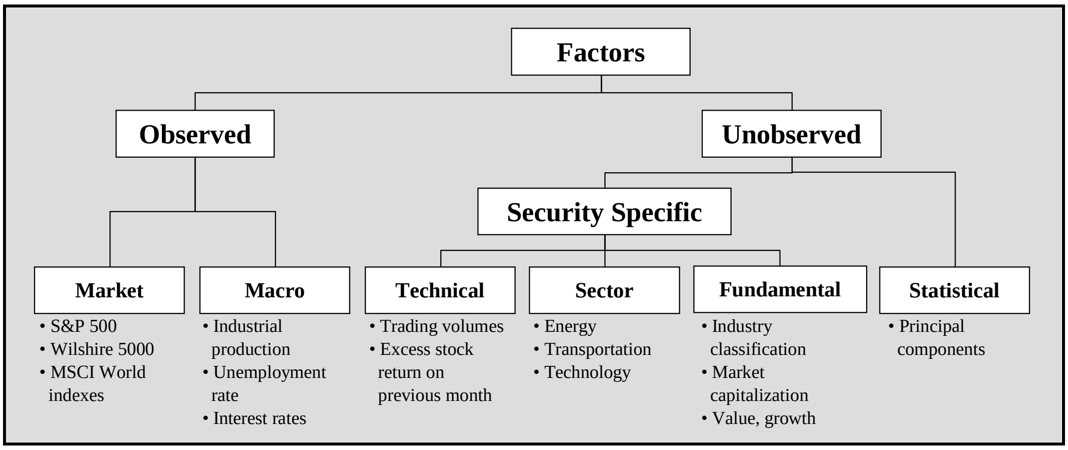
The application of the APCA makes sense in situations, where the number of assets grows large, so that N is much greater than the number of periods T. In practice, one may typically have many more securities than historical observations. In this case, the advantage of APCA consists of the fact that the computational complexity can be reduced. This is realized by estimating the eigenvectors of the smaller (T×T) matrix $\hat{\Omega}_T$, whereas PCA estimates eigenvalues on the basis of the larger (N×N) matrix $\hat{\Omega}_N$. In turn, the APCA relies on large asymptotic results as the number of cross section grows large. Consequently, the APCA obtains an approximated factor structure, whereas the traditional PCA delivers exact factor values.

3.7 Factor classification

The term factor has become a catch all for variables influencing the return-generating process. Given the wide application of factor models and the variety of ways factors can be defined it is not surprising that factors can take various shapes. This makes it difficult to keep a clear overview. The factor classification according to Peter Zangari (2003) gives a manageable survey of common factors. His developed classification is illustrated in section 3.7.1.

3.7.1 Hierarchy of Factors

Fig. 14: Factor classification

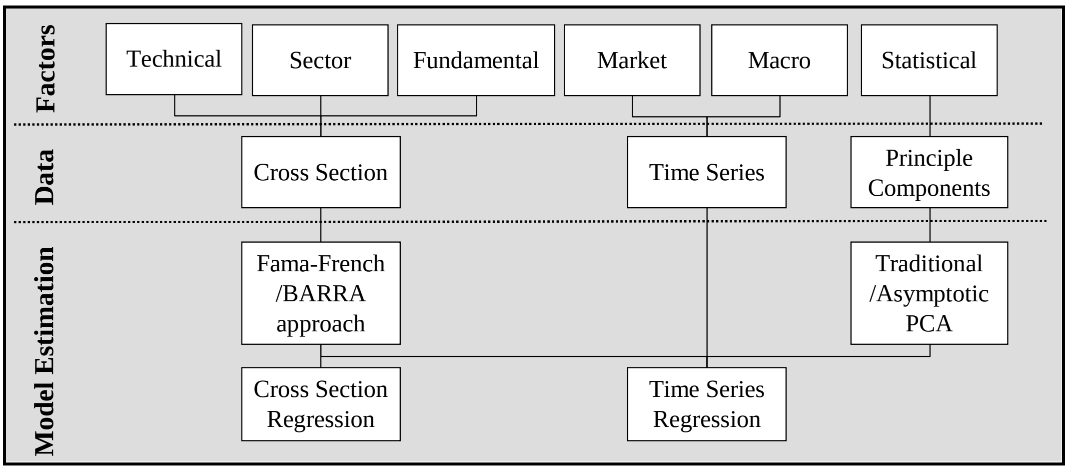


Source: Modern Investment Management, Goldman Sachs Asset Management

Here, the author wants to point out that each set of factors includes different variables in order to capture a particular feature of the individual security returns. [27]

3.7.2 Relationship between Factors, Data and Model Estimations

Fig. 15: Relationship: Factors – Data - Models Estimation Techniques



Source: Self-made figure.

3.8 Factor Model Classification

Factor models can take a variety of shapes, depending on the different type and number of factors applied within a certain model. Hence, it makes sense to classify factor models by the included factors. Consequently, one can categorize factor models based on whether the model implies factor returns that are either observable or unobservable. The following classification bases on this distinction of factors.

3.8.1 Observed Factor Returns

In this section, the author provides a few examples of factor models applied in practice. The following models contain factors, whose realizations are observable.

3.8.1.1 Market Factor Model

Sharpe's single factor model (introduced 1964) is the most common model of all market factor models. This model has the following form:

$$R_{it} = \alpha_t + \beta_i R_{Mt} + \varepsilon_{it} \qquad , i = 1,\dots,N; \quad t = 1,\dots,T \tag{3.8}$$

Where:

R_{Mt}	Denotes the return excess relative to the risk-free rate on a market index in period t. According to equation (3.1) $R_{Mt} = f_{1t}$, while $f_{it} = 0, \quad for\, i > 1$.
α_t	Represents the risk-free rate at period t
β_i	Market beta, which measures the covariation between the market index and securities return
ε_{it}	Is the asset specific error term

The market index is meant to capture economy-wide risk, while ε_{it} is capturing the non market risk. Typically, value weighted indices like S&P 500, Wilshire 5000 or the MSCI World Index are used as factor realizations, whereas long term government bond yields often form the realizations of the interception factor α_t.

The interception factor can be interpreted as the risk free rate of return. Since R_{Mt} and α_t are observable factors, the parameters β_i and ε_{it} have to be estimated using time series regression for each asset.

3.8.1.2 Macroeconomic Factor Model

In the general form, macroeconomic factor models consider K macroeconomic variables as factor realizations, f_{kt}. All of these factors are observable. Consequently, factor loadings as well as the asset specific error terms can be estimated via time series regressions.

The most popular model of this category was developed by Chen, Roll and Ross (1986). They investigated whether macroeconomic factors can explain security returns. Within their elementary study of the American capital market, they identified four macroeconomic factors, which are meant to explain the return-generating process of securities. The identified factors are as follows:

- Monthly and annual growth rate of industrial production
- Expected and unexpected inflation rate
- Default risk premium as difference between corporate and government bonds
- Maturity premium, represented by the difference between long and short term government bond returns

The fundamental conclusion of their study was that the ability of Sharpe's market model can be improved by additionally considering these identified factors. Hence, they enlarged Sharp's single index model to a multifactor model, which just considers further macroeconomic factors. [3] One way to additionally incorporate macroeconomic factors into the market model is described in the following. [27]

The market model takes the known form:

$$R_{it} = \alpha_t + \beta_i R_{Mt} + \varepsilon_{it}, \quad i = 1,\ldots,N; \quad t = 1,\ldots,T$$

But in this case ε_{it} is modeled as follows:

$$\varepsilon_{it} = \beta_{1i} f_{1t} + \beta_{2i} f_{2t} + \cdots + \beta_{ki} f_{kt} + \delta_{it} \tag{3.9}$$

Where:

f_{kt}	Is the realization of the kth macroeconomic factor at time t
β_{ki}	Is the factor loading of the kth macroeconomic factor on the asset i
δ_{it}	Is the idiosyncratic return on asset i at time t

3.8.2 Unobserved Factor Returns

This section includes the fundamental as well as the statistical factor model. These models use factors, which realizations are not directly observable. Consequently, these models need a larger computational effort to reproduce the return-generating process. In addition, examples of models that use unobservable factor returns are given within this paragraph.

3.8.2.1 Fundamental Factor Model

As representatives for fundamental factor models serve the well known BARRA models. The first BARRA model is based on the work of Barr Rosenberg, an econometrician. In the early 1970's , he formed a firm, now called BARRA Inc., to enhance and to sell the factor model to institutional investors. All factor models, which are estimated by the BARRA Inc., are based on the assumption that securities with similar exposures to fundamental factors will achieve similar return behaviors. Hence, factor returns have to be estimated that are common to all securities (see section 3.5.2). [31]

Observable asset specific characteristics are used within fundamental factor models to describe the return-generating process of a security. For example, the prices of securities in the same industry or economic sector often move together in response to changes in prospects for that sector. As an example of a BARRA-type fundamental factor model, the author considers the industry factor model with K mutually exclusive industries. This model assumes that the return on a certain security depends on the fact that the underlying asset acts in or does not act in a particular industry. The model has the general form according to equation (3.1):

$$R_{it} = \alpha_i + \beta_{1i} f_{1t} + \beta_{2i} f_{2t} + \cdots + \beta_{ki} f_{kt} + \varepsilon_{it}$$

Where:

f_{kt}	Represents the factor returns for the k^{th} industry in time period t
β_{ki}	Are observable asset specific factor sensitivities that are time invariant and have the form: $\beta_{ki} = 1 \quad if\ \ asset\ i\ is\ in\ industry\ k$ $\beta_{ki} = 0 \quad otherwise$

3.9 Summary

- A factor model bases on the assumption that the returns on securities respond to one or more common factors
- Equity factor models reproduce the return-generating process, which relates security returns to the movements of the common factors
- The total risk of a security is composed of systematic risk and idiosyncratic risk
- Any aspect of a security's return, which is left unexplained by the factors is assumed to be idiosyncratic risk
- The idiosyncratic risk is assumed to be unique to the certain security and is therefore uncorrelated with any other idiosyncratic risk of another security
- Three basic methods are used to estimate factor models: the time series approach, the cross-sectional approach, and the factor analytic approach
- Factors can be differentiated whether their returns are observable or not observable
- Factor models can be classified by the kind of factors used within the model: macroeconomic factors, market factors, technical factors, fundamental factors, statistical factors, etc.
- Equity factor models can be used to estimate the returns, covariance and variance of securities

4 TRADITIONAL FACTOR MODELS FOR HEDGE FUNDS

4.1 Introduction

Although hedge fund managers typically transact in asset markets similar to those of traditional managers, it is a well known fact that hedge fund returns differ from those of traditional investment vehicles. This fact is regularly exploited by investors who look for diversification opportunities.[1] To go beyond just relying on historical hedge fund performance repeating itself, one needs to answer the question: How are hedge fund returns generated? Many people believe that the reason for the different return characteristics of hedge funds is based on the special investment style applied by the managers. Hedge fund managers use derivatives, follow dynamic trading strategies and take long as well as short positions. [19] Therefore, a widespread approach to explain hedge fund returns is to model certain hedge fund strategies. In doing so, model builders reproduce the applied investment style rather than the realized returns of single hedge funds. Finally, factor models are one possibility to model investment styles. Factor models that are used to model a certain investment style apply so-called style factors. Therefore, the estimation of these style factors is part of the actual model building procedure too. Style analysis generally is used to determine style factors. The term style analysis dates back to the mutual fund industry. This means that many hedge fund models base on models that were originally developed to explain mutual fund returns.

Therefore, this chapter is organized as follows: at first, this section provides an introduction to factor models that are designed for describing the styles of traditional investments. The starting point of the introduction is the asset class factor model, which was developed by William Sharpe in 1988. Then the basic terms used within these models are defined. The last part deals with the examination of traditional approaches in the aspect of suitability for hedge fund returns.

[1] For benefits of alternative investments in portfolios see Schneeweis; Karvas; Georgiev (2002)

4.2 Traditional Factor Models

Since the hedge fund industry is still in its infancy compared to the long history of mutual funds, it is not surprising that the majority of equity factor models have been developed in order to explain traditional return characteristics. These factor models are referred to as *"traditional factor models"*. Many approaches to model the returns of hedge funds and funds of funds are based on traditional factor models. Since hedge funds possess return characteristics that are generally different to those of traditional investment vehicles, it has to be proved, if traditional factor models are additionally suitable to model the returns of hedge funds.

In the following section the author introduces a certain traditional factor model, the so called "*Asset Class Model*", developed by William Sharpe.

4.2.1 Sharpe's Asset Class Factor Model

An asset class factor model can be considered as a special case of the generic type for asset returns (3.1), introduced in the previous chapter:

$$R_{it} = \alpha_i + \beta_{1i} SF_{1t} + \beta_{2i} SF_{2t} + \cdots + \beta_{ki} SF_{kt} + \varepsilon_{it} \tag{5.1}$$

$$R_t = \alpha + \sum_k \beta_k SF_{kt} + \varepsilon_{it} \quad , for\ i = 1, \ldots, N \tag{5.2}$$

Where:

R_{it}	Return on asset i
α_i	Value of the intercept
SF_{kt}	Value of the k^{th} *common Style Factor*
β_{ki}	The *factor loading* for asset i on the k^{th} factor
ε_{it}	Non-factor component of the return

Additional assumption:

1. $\sum_k \beta_{ki} = 1$

Within such a model, the factors are called style factors. Each style factor of Sharpe's model represents the return on an asset class k (k = 1,…,K). Additionally, the sum of the sensitivities (β_{ki} values) is required to total 1. This is an additional assumption to the generic factor model (3.1).

In effect, the return on an asset is represented as the return on a portfolio invested in the n asset classes plus a residual component ε_i. The improvement within this factor model consists in the choice of factors (SF_{kt}). In doing so, Sharpe provides an explicit link between investment styles and traditional asset classes. The advantage of this link is that the returns of a single asset and portfolio respectively can directly be assigned to a class of assets, whose return characteristics are observable. Additionally, the return data for these kinds of assets usually dates back to many decades, so that there is sufficient data to achieve an acceptable statistical significance among the necessary estimations.

4.2.1.1 Sharpe's Style Factors

In his model, Sharpe (1992) [20] used twelve asset classes as factors in order to describe the return generating process. Each asset class is represented by an index. The average return of each index represents the factor realization (value of SF_{kt}). The asset classes utilized by Sharpe and the corresponding indices he applied are shown in the following figure:

Fig. 16: Definition - Asset Classes

SF_1	**Bills**	
		Cash-equivalents with less than 3 months to maturity
		Index: Salomon Brothers' 90-day Treasury bill index
SF_2	**Intermediate-term Government Bonds**	
		Government bonds with less than 10 years to maturity
		Index: Lehman Brothers' Intermediate-term Government Bond Index
SF_3	**Long-term Government Bonds**	
		Government bonds with more than 10 years to maturity
		Index: Lehman Brothers' Long-term Government Bond Index
SF_4	**Corporate Bonds**	
		Corporate bonds with ratings of at least Baa by Moody's or BBB by Standard & Poor's
		Index: Lehman Brothers' Corporate Bond Index

SF 5	**Mortgage-Related Securities**	
		Mortgage-backed and related securities
		Index: Lehman Brothers' Mortgage-Backed Securities Index
SF 6	**Large-Capitalization Value Stocks**	
		Stocks in Standard and Poor's 500-stock index with high book-to-price ratios
		Index: Sharpe/BARRA Value Stock Index
SF 7	**Large-Capitalization Growth Stocks**	
		Stocks in Standard and Poor's 500-stock index with low book-to-price ratios
		Index: Sharpe/BARRA Growth Stock Index
SF 8	**Medium-Capitalization Stocks**	
		Stocks in the top 80% of capitalization in the U.S. equity universe after the exclusion of stocks in Standard and Poor's 500 stock index
		Index: Sharpe/BARRA Medium Capitalization Stock Index
SF 9	**Small-Capitalization Stocks**	
		Stocks in the bottom 20% of capitalization in the U.S. equity universe after the exclusion of stocks in Standard and Poor's 500 stock index
		Index: Sharpe/BARRA Small Capitalization Stock Index
SF 10	**Non-U.S. Bonds**	
		Bonds outside the U.S. and Canada
		Index: Salomon Brothers' Non-U.S. Government Bond Index
SF 11	**European Stocks**	
		European and non-Japanese Pacific Basin stocks
		Index: FTA Euro-Pacific Ex Japan Index
SF 12	**Japanese Stocks**	
		Japanese Stocks
		Index: FTA Japan Index

Source: Sharpe, William (1992);"Asset Allocation: Management Style and Performance Measurement"

One has to note that the combination of indices represents a certain investment style, which is only determined by the location variable. Regarding these defined asset classes or rather style factors SF_{kt}, Sharpe's asset class model has the following form according to equation (5.1):

$$R_{it} = \alpha_i + \beta_{1i}SF_{1t} + \beta_{2i}SF_{2t} + \beta_{3i}SF_{3t} + \beta_{4i}SF_{4t} + \beta_{5i}SF_{5t} + \beta_{6i}SF_{6t} +$$

$$\beta_{7i}SF_{7t} + \beta_{8i}SF_{8t} + \beta_{9i}SF_{9t} + \beta_{10i}SF_{10t} + \beta_{11i}SF_{11t} + \beta_{12i}SF_{12t} + \varepsilon_{it}$$

$$R_t = \alpha_i + \left(\sum_{j=1}^{12} \beta_j SF_{jt} \right) + \varepsilon_{it} \qquad (5.3)$$

4.2.1.2 Sharpe's Style Factor Exposures

The traditional view of asset allocation assumes that an investor allocates assets among the asset classes. Ultimately, one is interested in the investor's exposures to these key asset classes. The investor's exposures generally depend on:

- The amounts invested in the various securities
- The exposures of each security to the asset classes

It is possible to determine a fund's exposure, β_{ki} from the analysis of securities held by the fund. On the basis of the detailed breakdown of assets the invested amounts, relative to market capitalization, can be estimated. These amounts then serve as the fund's exposure regarding the predefined asset classes. This method relies on detailed information about the fund itself. Generally, this data is only available from sources internal to the fund. Therefore, this method is usually finds into practice within internal investigations.

On the contrary, public sources only provide more superficial information about a fund. Consequently, another approach is elected for external analysis. Such a method only uses the realized fund returns to infer the typical exposures, β_{ki} of the fund to each asset class. For example: Given monthly returns on a fund, along with comparable returns for a selected set of asset classes, one could simply employ a multiple regression analysis. Within this analysis fund returns would act as the dependent variable and asset class returns as the independent variables. The resulting slope coefficients could then be interpreted as the historic exposures of the examined fund to the asset class returns. [20] In the end, there are two approaches to determine theses exposures:

- Asset-based style analysis ("*internal approach*")
- Return-based style analysis ("*external approach*")

These two methods are explained in more detail during the following section.

4.3 Basic Terms

4.3.1 Style Factors

According to factor model theory, style factors are variables that explain the variation among a set of security returns. They are sources of correlation among observable as well as unobservable characteristics, which explain the return generating process of securities. In the special case of an asset class model, Sharpe defined:

> "*Style factors are sources of correlation among returns of indices, each representing a certain segment or asset class.*"

Literature differentiates between three kinds of style factors, which are applied within factor model theory: *"peer-group-based"*, *"return-based"* and *"asset-based"* style factors. These are explained below:

4.3.1.1 Peer-Group-Based Style Factors

In practice, funds are often grouped into categories based on the managers self disclosed strategies and locations of invested capital. The strength of this method lies in its simplicity and little data input. Style factors that constructed this way are denoted as peer-group-based style factors (in the following also referred to as PGS).

The objective of peer-group style factors is to capture the performance of funds, which operate "*similar*" strategies. In this context the term similar means similar sounding self disclosures of the managers. The idea behind this approach of forming style factors is that managers, who apply similar sounding strategies, should obtain similar performance characteristics. Thereby, the average return of a fund within a certain group is reported as the regarding peer-group-based style factor.

4.3.1.2 RETURN BASED STYLE FACTORS

Qualitative style categorization of a fund's strategy typically depends on the fund managers' self-descriptions. Additionally, there is no standard format in which historical hedge fund performance has to be reported. When we come to practice, there is often a difference between what a manager says he does and what he actually realizes. Due to the mentioned problems, there is a lack of controlling methods for this gap. These difficulties especially arise, if one wants to determine the investment style of a particular manager using PGS.

Fung and Hsieh suggest an alternative method to avoid these problems. Instead of relying on what managers tell us what they do; FH look at the actual return patterns to see what managers actually do. By running statistical analysis' on historical performance using mathematical techniques, they group funds with similar return characteristics together. The techniques applied are:

- Cluster analysis
- Principal component analysis

The principle components, which are the basis for this kind of grouping funds together, are denoted as "return-based style factors" (RBS). [11] The average return of funds within a certain group serves as return-based style factor return.

4.3.1.3 ASSET BASED STYLE FACTORS

The third group of style factors is called asset-based style factors, in the following referred to as ABS. The basic idea behind ABS is to define style factors from underlying portfolios, whose returns can be replicated by observable asset prices. The following example will simplify the understanding of this term:

A typical mutual fund style is named "*small-capitalization (small-cap) / value stocks*" [1]. This means, managers that apply this style exclusively invest in stocks that own suitable parameter values regarding:

[1] Value stocks → stocks, which own a low price to book ratio and low price to earnings ratio

- Capitalization
- Price-to-book ratio
- Price-to-earnings ratio

In this case, an asset-based style factor could be defined as an index, which represents stocks that own suitable parameter values. Defining styles this way offers the opportunity to model also investment strategies that apply different styles at the same time by combining indices that represent these strategies. For example, defining the first style as "*long-short / value*" and the second style as "*long-short / growth*" [2], a linear combination would represent a fund applying a value-growth strategy. In effect, a link between strategy and observable securities has been created.

4.3.2 Investment Style

These days, investment style is the dominant principle used to classify, to analyze, and to deploy equity portfolios. From a qualitative point of view style refers to the investment philosophy of an investor, money manager, mutual fund and especially of hedge fund managers. According to Fung and Hsieh (2001) [15], the concept of "*investment style*" should be thought of in two dimensions:

- Investment strategy
- Location

The dimension location refers to the various asset classes, in which the managers invest. On the other hand, the investment strategy dimension tells us how long / short security positions are combined. Additionally, strategy refers to how these positions are levered and managed. This means that the term investment style finally refers to a combination of these two elements.

[2] Growth stocks → stocks that own a high price to book ratio and high price to earnings ratio

By the way managers take advantage of the strategy dimension investment styles can be grouped in two parts:

- *static* trading strategies
- *dynamic* trading strategies

These terms are explained in the next section. But first, the definition of the term "*investment style*" is given from a more quantitative point of view. A more analytical definition rises from asset class factor model theory. Regarding the equation (5.1), the generic model has the following form:

$$R_{it} = \alpha_i + \beta_{1i}SF_{1t} + \beta_{2i}SF_{2t} + \cdots + \beta_{ki}SF_{kt} + \varepsilon_{it}$$

Once the asset classes or style factors (SF_{kt}) respectively are chosen, the combination of all exposures regarding a portfolio and set of securities can be referred to as an investment style. On the basis of these exposures, one may identify and describe the characteristics of a certain investment portfolio. In the special case of an asset class model, Sharpe defined:

> "*Investment style is a set of asset class exposures regarding a certain asset portfolio.*"

According to this definition, the investment style of a particular manager can be described by the correlation of the purchased assets to predefined asset classes. In the end, the location dimension of the underlying portfolio is examined. This means, if a mutual fund only correlates with one style factor, e.g. long term bond index, one can conclude that the manager follows a pure long term bond investment style. Consequently, if a portfolio correlates with more than one style factor (or index) the investment style becomes more complex. In addition, the parameter values of β_{ki} provide the information about the combination of long and short positions[3], so that both style dimensions can be captured

[3] This is possible if the exposures are not restricted to take only values between zero and one.

4.3.2.1 Static Trading Strategies

Since mutual funds are legally restricted within the utilization of the strategy parameter, assets among these funds are passively held as long positions for a substantial length of time. The concept is also referred to as a "*buy-and-hold long-only strategy*". This denotation rises from the fact that mutual fund returns are usually gained by positive price developments of the purchased assets. For this reason, mutual funds generally own positive correlations on asset classes. In addition, these correlations own regression coefficients, which lie between zero and one and con not have negative values.

As we have seen, stylistic differences especially involve the location variable comparing traditional investments and hedge funds. But "*where*" can assets be located? Typical segments in which mutual fund manager invest are the following:

- Value stocks - (low price/earnings and price/book ratio)
- Growth stocks - (high price/earnings and price/book ratio)
- Large stocks - (market capitalization is greater than $5 billion)
- Long term bonds - (average bond duration is greater than 6 years)
- High quality bonds - (average bond rating is at least AA)

According to the objectives of a fund manager, he may invest in one certain segment but also in different segments at the same time. Consequently, the investment in both one single segment and in combinations of different segments could be referred to as particular investment styles.

4.3.2.2 Dynamic Trading Strategies

On the contrary, hedge fund managers are not restricted to the location variable. The following example by Fung and Hsieh (1997a) illustrates how return is a function of the location choice and trading strategy in the case of hedge funds:

"Consider a manager trading S&P futures contracts. Without leverage, a fully invested position of being consistently long one futures contract (i.e., buy and hold) will result in a regression coefficient of one on the S&P 500 index. If the manager leverages up to two futures contract, the regression coefficient will be two. Conversely, if he is short one futures contract, the regression coefficient will equal -1. However, if he alternates between long and short each month, the regression coefficient will be close to zero. In this example, the location is the U.S. stock market in all cases. The returns, on the other hand, are very different depending on the trading strategy. In the first two cases, the returns are positively correlated with U.S. stocks. In the third case, the returns are negatively correlated with U.S. stocks. In the fourth case, the returns are uncorrelated with U.S. stocks." [8]

By means of this example, one may see that the combination of asset location, long as well as short positions can lead to completely different return behaviors than those static trading strategies. Figure 17 summarizes the gained information:

4.3.2.3 SUMMARY

Fig. 17: Investment Style - Static vs. Dynamic Strategies

Static **Trading Strategies**	***Dynamic*** **Trading Strategies**
• Funds only differ in the asset classes in which they invest • Managers do not change rapidly trading strategies • Buy-and-hold long-only strategies • Gain profits via positive price developments of the purchased assets • Asset exposures lie between 0 and 1 due to limited leverage and no use of short sells	• Funds differ in both asset classes in which they invest and investment strategy • Managers do change rapidly trading strategies • Due to the use of options, profits are gained independently from price developments • Asset exposures can take values greater than one due to an extensive use of leverage • Asset exposures can also take negative values due to short selling

Source: Self-made figure.

4.3.3 Style Analysis

Equity style analysis is a method, which is used to identify and describe the characteristics of an investment portfolio. On the basis of the identified characteristics, style analysis reveals that a portfolio manager follows a certain investment style. Examples for the application of style analysis in practice are the following:

- Individual investors use style analysis to independently determine a portfolio’s style, so that they are able to understand what type of investments they actually buy and how these fit into their portfolio
- Financial advisors and money managers use style analysis to monitor investments, so that they can verify whether the investment manager remain true to their intended style
- Additionally, style analysis is used for:
    1. The Creation of custom benchmarks either by fund-specific combinations or portfolios that consist of different indexes
    2. The Construction of peer groups

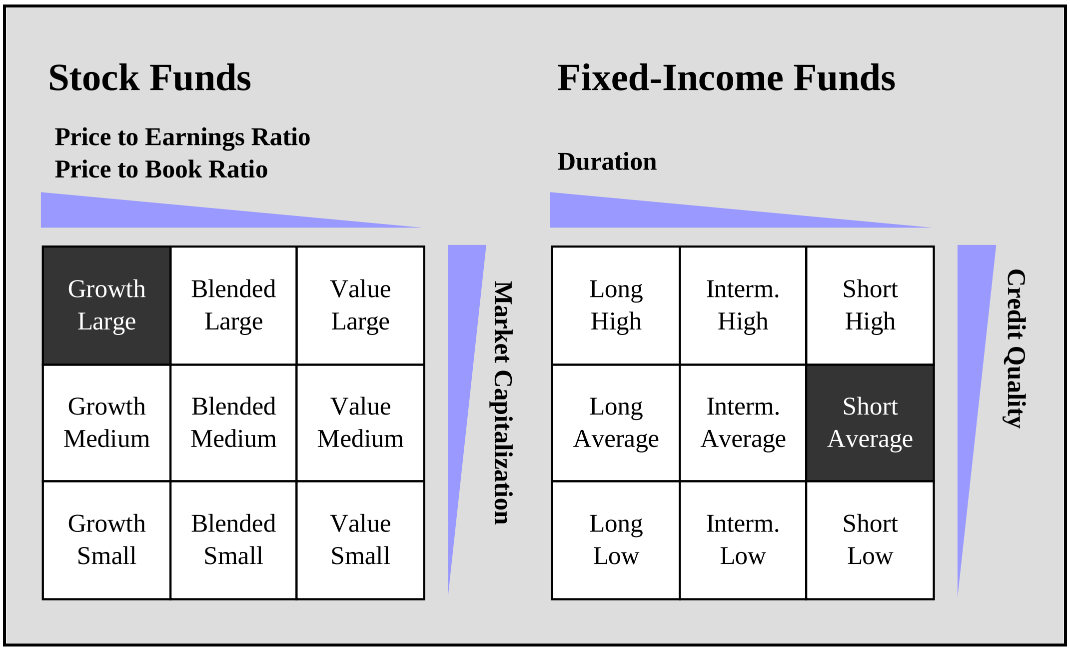
There are two main approaches to style analysis: on the one hand, the asset-based approach exists, which is often referred to as the holdings-based approach. On the opposite, there is the return-based approach. [16] These are explained in the following.

4.3.3.1 Asset Based Style Analysis

Asset based style analysis, in the following ABSA, is called a “bottom-up” approach, because it is based on the underlying assets among a certain portfolio. Therefore, ABSA requires two sets of data, which are expensive to obtain. First of all, one needs a security database that contains the characteristics of each security. Secondly, one needs a record of the security holdings. On the basis of these aggregated datasets of underlying securities, the ABSA identifies the characteristics of a certain portfolio. For this reason, ABSA is often referred to as "*fundamental*" or "*compositional*" analysis.

For example, the average market capitalization of a portfolio is equal to the sum of all value-weighted market capitalizations regarding each security within the portfolio. The same procedure is applied to other characteristics, such as price to earnings ratio, price to book ratio or return on equity. The investment style is given through the comparison between the parameter-values of the examined portfolio and a predefined benchmark index or market average value. This means, a certain style is always applied in relation to a benchmark, which can also be given through the market. [6]

Fig. 18: Morningstar - Style Box



Source: Sharpe; Alexander; Bailey; "Investments"; p. 720-725

Figure 18 represents a so called "*Style Box*". The style box was developed by the Morningstar Inc. The Morningstar Inc.[4], located in Chicago, is one of the most prominent organizations that deal with the identification of a funds' investment

[4] Morningstar Inc. is a leading provider of independent investment research in the United States and in major international markets. Our mission is to create great products that help investors reach their financial goals. We offer an extensive line of Internet, software, and print-based products for individual investors, financial advisors, and institutional clients. http://corporate.morningstar.com

style. Morningstar uses the S&P 500 as their benchmark index. The evaluation itself is based on asset based style analysis.

The box provides a good summary of how a funds' investment style can be estimated. If we look at the left table of the figure, the two extreme columns represent the investment styles of value (right column) and growth (left column). The three rows of the box are based on the size of the stocks within a fund. Morningstar indicates its classification of a fund by darkening one of the nine sections of the style box. Hence, the funds style represented by the darkened section means that the manager invests in growth stocks and stocks owning a large market capitalization. Here the author wants to point out that the denotation of the parameter growth and market capitalization are relatively measured to the overall market. In this special case, the style factors would represent the average price to earnings ratio, average price to book ratio and the average market capitalization of the fund's assets.

The right table of the figure examines the case of fixed-income funds. By now, the columns of the style box are based on the average duration of the securities. The rows are based on the average credit quality of the securities.

4.3.3.2 Return Based Style Analysis

Besides the qualitative description of the term "*investment style*" the author also presented an analytical definition in the previous sections. According to Sharpe, we defined:

> "*Investment style is a set of asset class exposures regarding a certain asset portfolio.*"

In practice, model builders face the problem how to estimate the "*correct*" asset class exposure. This problem has been disregarded to this moment. This section will close this gap. The economist William F. Sharpe [32], laid the foundations of return-based style analysis (RBSA). According to Sharpe (1988), RBSA is defined as follows:

> “*The use of quadratic programming for the purpose of determining a fund's exposures to changes in the returns of major asset classes is termed style analysis*”

RBSA is a mathematical optimization technique for the purpose of style analysis. The overall goal is to estimate a combination of predetermined benchmark-indices, which replicates the historical performance of the manager among a certain period of time at best. The resulting index combination is called style-benchmark. A certain style index characterizes a specific asset class. This means, RBSA is a technique that determines style by identifying, which combination of holdings across various asset classes, represented by a combination of indices, would have most closely replicated the actual performance of a portfolio. According to Sharpe [20] it is desirable that such style-indices (asset classes) have to satisfy the following characteristics:

- Mutually exclusive
- Being exhaustive
- Have returns that differ

This means, no security should be included in more than one style index; as many securities as possible should be included in the chosen style indices; the index returns should either have low correlations with one another or, in cases in which correlations are high, they should have different standard deviations.

Once these style indices are determined, the aim is to find the “*best*” set of asset class exposures. Hence, it has to be defined first, what is meant by the term “*best exposure*”.

Rearranging equation (5.2) results in:

$$R_t = \alpha + \sum_k \beta_k SF_{kt} + \varepsilon_{it} \quad , for\ i = 1,\ldots,N$$

$$\varepsilon_{it} = R_t - \alpha - \sum_k \beta_k SF_{kt} + \quad , for\ i = 1,\ldots,N \tag{5.3}$$

Writing equation (5.2) this way, the term on the left side can be interpreted as a difference between the return on the examined portfolio, R_t and the return on an imitation portfolio ($\alpha + \Sigma\, \beta_k\, SF_{kt}$) that is passively managed and applies the same strategy as the examined portfolio. The difference between the returns of the examined and imitation portfolio is termed the fund's "*tracking error*" and its variance ($Var(\varepsilon_{it})$) is denoted as the fund's "*tracking variance*". In this context, the set of “*best*” exposures (investment style) is the one for which the variance of ε_{it} is the least.

Note that the objective of such an analysis is not to minimize either the average value of this difference or the sum of the squared differences. Rather, the aim is to infer as much as possible about the fund's exposures to variations in the returns of the asset classes during the studied period. By applying equation (5.3), the exposures are estimated via multiple regressions regarding each period and predefined style factors.

4.4 Problems within the Application of traditional factor models

The fact that hedge fund managers generally diversify their funds performance across a variety of strategies complicates the task of building a model for hedge fund returns. The dynamic allocation of capital resources to a wide range of trading strategies dilutes the origin of a hedge funds' return. Therefore, the utilization of an analysis of a general hedge fund return sample is limited.

For this reason, it is useful to concentrate on a specific trading strategy that is identifiable with a large number of hedge funds (in chapter one the main hedge fund strategies were introduced). However, other problems still remain. In the previous section, the author presented the asset class factor model and explained its basic terms. Such a model provides the basis for many approaches to build factor models for hedge fund and also for fund of funds returns. But the amount of possibilities to establish such models on this basis is still large. As we have seen, an asset class factor model can be build using three different kinds of style factors: peer-group-based style factors, return-based style factors and asset-based style factors.

Therefore, this section will expose the problems related to the different points of departure to build these models. The problems involved among the use of these factors are presented next. In addition, one focus of this section is directed to problems, which are related to the nature of hedge fund data.

4.4.1 Problems within the Application of Peer-Group Style Factors

Although peer-group-based style factors are often used to describe the investment styles of managers, this method gives reason for criticism in many respects. According to FH [15] this method is not suitable to define hedge fund styles because of the following five main reasons:

- ***Search for performance similarity*** – there is no verification that similar sounding strategies do deliver similar performance characteristics

- ***Proliferation of styles*** **–** due to the lack of an analytical method to discern differences in return characteristics, there is a tendency to increase the number of PGS and style groups in order to compensate
- ***Lack of transparency*** **–** appears due to the lack of disclosure on how returns are generated; this is also very unsatisfactory to investors
- ***Measurement errors*** **–**it is not possible to relate the criteria used to form the groups of funds and the reported returns characteristics due to the lack of a definite analytical framework
- ***No support of style diversification and market dynamics*** **–** the risk of erroneously asserting that a fund has changed style with respect to broadly defined peer groups is very high, due to the inflexible aggregation among peers. But especially in the hedge fund industry dynamic strategies are applied, which leads to the fact that PGS are not suitable.

4.4.2 Problems within the Application of Return Style Factors

Due to the use of return–based style factors model builder can avoid the dependence on quality of the managers' disclosure. In addition, this approach provides an analytical tool, unlike the use of PGS.

The application of return-based style factors for fund returns was first proposed by Sharpe (1992). He was able to relate mutual fund strategies directly to asset classes by comparing historical returns to those of market indices (see section 4.2.1.2). Also FH (1997a) adopted this methodology to determine investment styles of hedge funds. However, the results of their work showed that also RBS lead to problems in modeling hedge fund returns:

- ***Database biases*** **–** databases do not exactly reproduce reality , so that these biases still remain when it comes to measuring average returns (see section 4.3.4)

- ***No further insight into the strategies*** **–** RBS do not give information about “how” returns are generated other than the fact that groups of funds statistically perform like each other
- ***Lack of stability over time*** **–** this means that the performance characteristics can change over time, so that the extracted factors of a certain time series capture a diluted picture of the actual situation
- ***Return-based style factors are mathematical constructs*** **–** this means, there is no unique qualitative interpretation of the factors, so that they are finally not worth to invest in

These are difficult problems to resolve. Consequently, FH have tried to find an alternative to the return-based style factors, which are less vulnerable to these problems. [11] From there point of view, asset-based style factors provide a very good possibility to describe the returns of hedge funds.

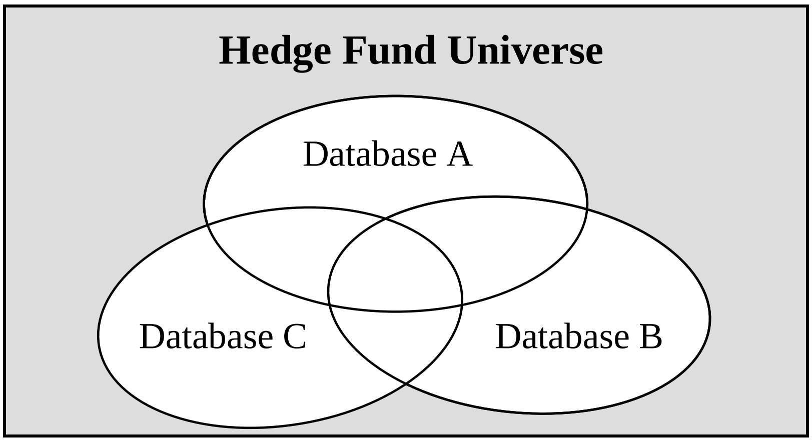
4.4.3 Measurement Biases in Hedge Fund Data

The hedge fund industry is still in its infancy compared to traditional investments. In addition, it has stayed pretty much unregulated to now, so that data and information are not easy to obtain. Consequently, researchers face a problem in the size of that portion of the industry, which they can not analyze by published data. The fundamental problem is that hedge fund data is subject to several measurement biases caused by the data collecting process and by the nature of the industry. FH (2000) provide an extensive analysis of these biases. They distinct between three different kinds of biases: selection bias, survivorship bias, and instant history bias. [11] These biases are commonly estimated as the difference between the average returns of funds, which caused the bias and the average returns of all funds that the database contains. [2] The different types of database biases are explained in the following:

4.4.3.1 Selection Bias

As a consequence of the unregulated industry, private database vendors are not able to capture all hedge funds existing at a certain point in time. On the one hand, managers can choose to which database vendor they report, if they report at all. On the data collecting side, different database vendors include hedge funds according to different criteria within their database. As selection bias one understands the difference between database and hedge fund universe. This means, the hedge funds of a database can not serve as representatives of the total population of hedge funds. In addition, the combination of different hedge fund data bases does not lead to a better reproduction of reality, due to the intersections between these. The following figure shows the problems described:

Fig. 19: Measurement Bias - Selection Bias



Source: Fung, William; Hsieh, David (2003) "Benchmarks for Alternative Investments"

4.4.3.2 Survivorship Bias

Next we come to survivorship bias. Jones established his fund in 1949. However, most database vendors started to collect hedge fund data in the early or mid-90s. Therefore, it is not surprising that there is only little information and data on hedge funds that ceased operating before then. These missing funds are the primary cause for survivorship bias.

The other reason for survivorship bias is that hedge fund managers do not have to report their data and information at all. Consequently, database vendors are not able to collect data about hedge funds that do not publish their results.

4.4.3.3 Instant History Bias

According to the extensive analysis of biases provided by Fung and Hsieh, database vendors generally do not differentiate between the performance during the initial trading period and the subsequent periods. But in fact, the performance of hedge fund managers tends to be better in the initial trading period than the later performances. FH attribute this performance characteristic to the manager’s engagement. Typically, when a fund gets started, the fund manager works much harder running a small business. However, when they grow bigger performance tends to decline. Hence, most funds enter the database with an existing track record. Their results are back filled over time since they can choose at which point in time they enter the database. The back-fill history can lead to an upward bias in results of the complete database. This difference is known as the “Instant History” bias, which affects estimates of historical mean returns.

4.4.4 Conclusion

Little can be done to eliminate the limitations of historical hedge fund data. Time remains the only solution for documenting hedge fund performance over a broader range of economic cycles. The stated caveat on the application of PGS and RBS speak against the use of these kinds of factors to model hedge fund returns. In order to overcome this problem, Fung and Hsieh have defined some kind of standards for style factors in order to make them suitable for modeling the returns of hedge funds. Therefore, style factors for hedge fund returns and for fund of funds returns should meet the following demands:

- *"First, there must be complete transparency in the way the factor returns are derived."*
- *"Second, there must be a sufficiently long performance history in order to generate reliable statistics."* [10]

These properties are neither present in peer group-based nor return-based hedge fund style factors. Besides other, Fung and Hsieh believe that asset-based style factors can satisfy both properties. Transparency is given through the link between strategy and observable assets. By just considering assets that provide sufficient performance history, one may avoid the problem of data biases.

In the end, the challenge is to define a set of style factors whose returns can be replicated by observable asset prices in accordance with the underlying hedge fund strategies. The following figure provides a summary of the work on asset-based style factors for hedge funds:

Fig. 20: Overview - Work on ABS for hedge funds

Merger Arbitrage		
Mitchell, Pulvino (2001) "Characteristics of risk and return in risk arbitrage"	They used a sample of 4,750 stock swap mergers, cash mergers, and cash tender offers during 1963 - 1998 to characterize the risk and return in risk arbitrage.	Fund returns are positively correlated with market returns in large down markets but uncorrelated with market returns during normal market conditions. Returns to risk arbitrage are similar to returns from selling uncovered index put options.
Equity Hedge Strategies		
Aggrawal, Naik (2001) "Characterizing the Risk and Return of Equity Hedge Funds,"	They used returns of the S&P 500 index options to capture option-like behavior in the returns of equity hedge funds.	They did not, explicitly model the option structure implicit in these trading strategies.
CTA - Trend Following		
Fung, Hsieh (2001) "Theory and Evidence From Trend Followers"	They used lookback straddels to model trend following strategies	They showed that lookback straddels can explain trend following funds returns better than standard asset indices
Fixed Income Arbitrage		
Fung, Hsieh (2002) "The Risk in Fixed-Income Hedge Fund Styles"	They analyzed the common risk of fixed-income hedge funds by extracting seven return-based style factors, which are then linked to ABS factors.	Fixed-income hedge funds have static exposure to fixed-income related spreads, such as convertible/treasury, high-yield/treasury, mortgage/treasury, and emerging market bond/treasury spread.
Convertible Arbitrage		
Agarwal, Fung, Loon, Naik (2004) "Risks in Hedge Fund Strategies: Case of Convertible Arbitrage"	Using data on Japanese convertible bonds and underlying stocks. By asset-based style analysis they extracted risk factors and related these to observable market prices.	They constructed three ABS. The results show that these can explain between 9% and 24% of the return variation of four popular convertible arbitrage indices.

Source: Self-made figure.

4.5 Summary

- Investment style is a combination of location and investment strategy, represented by a combination of exposures to predefined style factors
- Usually, the investment styles of mutual funds contain static investment strategies; this means their investment style is determined by location as the only variable. These strategies are referred to as buy-and-hold strategies
- Traditional asset class models, such as Sharpe’s model introduced in 1992, successfully describe static investment strategies or respectively the return characteristics of the mutual fund industry[5]
- On the contrary, investment styles of hedge funds apply a dynamic trading strategy, which means that both of the variables, location as well as strategy, determine their investment style.
- Although traditional asset class models serve as initial situation for modeling the returns of hedge funds, they are not able to capture the performance of dynamic trading strategies or respectively of hedge funds
- Neither peer group-based style factors nor return-based style factors are suitable to model the returns of hedge funds
- Asset-based style factors seem to be the solution in order to overcome the problems in hedge fund return modeling. They are the key input for modeling the returns of hedge funds successfully, due to their characteristics:

    1. ABS are transparent in the way the factor returns are derived
    2. They provide sufficiently long performance history in order to generate reliable statistics

[5] see performance analysis of hedge funds by Sharpe (1992) or Fung and Hsieh (1997a)

5 ASSET-BASED FACTOR MODEL FOR CTA'S

5.1 Introduction

Unlike mutual funds, it is not possible to develop one single model to describe the returns of all hedge funds. It is a well known fact that hedge funds show return characteristics, which are fundamentally different to those of traditional investment vehicles. Additionally, hedge funds that apply different styles own different return characteristics. For this reason, models should be developed that describe certain groups of hedge funds, which own "similar" return characteristics.

In this section the author introduces a methodology to model the returns of a certain hedge fund strategy, which is referred to as the *"trend following"* strategy. Trend following hedge funds belong to the class of the CTA's (see chapter one). The methodology was developed by FH and presented in their paper of 2001. [14] The basic idea is to construct asset-based style factors with the use of observable traded options. This idea is based on the results of the work of FH (1997). Within this work they proceeded on the assumptions:

- Linear factor models of investment styles, as in Sharpe (1992) are not suitable to capture hedge fund returns
- Hedge fund returns differ from those of mutual funds, because they apply dynamic trading strategies

In order to prove these assumptions, FH analyzed the trading strategies of hedge funds in general. The results of their analysis (1997), especially those of the examination of CTA's return data, served as initial situation for further developments. The work of FH (1997a) is summarized later in this section. In general, FH want to prove the assumption that hedge funds own returns that differ from those of traditional investment vehicles. Therefore, FH have proved their assumption that hedge funds do not show statistically significant results on Sharpe's style regression.

5.2 Initial Situation

On the one hand FH (1997a) examined the suitability of linear asset class models for the ability to capture the return behavior of hedge funds. Therefore, they applied "*Sharpe's style regression*" (5.1), $R_{it} = \alpha_i + \beta_{1i} SF_{1t} + \cdots + \beta_{ki} SF_{kt} + \varepsilon_{it}$, to both a mutual fund and a hedge fund database of monthly returns. On the other hand, FH applied factor analysis and a non-parametric regression to further determine dominant styles in hedge fund strategies.

5.2.1 Style Regression on Mutual Funds

In a first step, they applied "*Sharpe's style regression*" to a database of the Morningstar Inc., consisting of 3.327 U.S. mutual funds. The model used by FH differed from those in Sharpe (1992). The asset classes used within their model were represented by the following style factors:

Fig. 21: Fung & Hsieh - Style Factors

Equity		
	SF_1	MSCI U.S. equities
	SF_2	MSCI non - U.S. equities
	SF_3	IFC emerging market equities
Bonds		
	SF_4	JP Morgan U.S. government bonds
	SF_5	JP Morgan non - U.S. government bonds
Cash		
	SF_6	1-month eurodollar deposit
Commodities		
	SF_7	Price for gold
Currencies		
	SF_8	Federal Reserve's Trade Weighted Dollar Index

Source: Self-made figure.

The results of this style regression show the following:

- 47% of the mutual funds have R^2-value of regressions among the asset-based style factors above 75%

- 92% of the mutual funds have R^2-value of regressions among the asset-based style factors above 50 %

The results show that due to Sharpe's asset class model, managers were able to successfully replicate the performance of an extensive universe of U.S. mutual funds on the basis of a limited number of major asset classes. Evidence for this gives the high correlation of mutual fund returns to these asset-based style factors. Additionally, this implies that the location of investments is the key determinant of performance among mutual funds. This means, mutual fund managers basically apply "*buy-and-hold long-only*" strategies among various asset classes, as anticipated.

5.2.2 Style Regression on Hedge Funds

On the other hand, FH ran the style regression on a monthly return database consisting of 407 hedge funds. These funds met the requirements: three years of monthly returns with at least $5 million in assets under management. The statistical results are as follows:

- 48% of the examined hedge funds have R^2-values below 25%
- No single asset class showed a dominant behavior during the style regression
- Only 17% of hedge funds showed coefficients of the most significant asset class, which are statistically greater than zero, but still not statistically different from one

This evidence indicates that the returns of hedge funds are not likely to be correlated to the returns of the predefined asset classes. Hence, the returns of hedge funds are fundamentally different to those of mutual funds. For these reasons, traditional asset class factor models are not suitable to describe hedge fund returns.

5.2.3 Factor Analysis and non-parametric Regression

Since the traditional style regression on monthly hedge fund returns did not prove that the asset class model is able to successfully describe hedge fund returns, FH applied a factor analysis to further determine the dominant styles in hedge funds. For this reason, they analyzed these 409 single hedge funds as a whole.

Via factor analysis they were able to extract five mutually orthogonal principle components (PC). These five PC's are able to explain about 43% of the cross sectional variance among the underlying database of hedge funds. Later, FH constructed five return-based style factors by using hedge funds that were most highly correlated with these PC's. As already mentioned one of the problems within this methodology is to assign these PC's to a unique qualitative interpretation. Consequently, they associated the RBS with the most commonly used qualitative style categories, which are utilized by the hedge fund industry. In doing so they were able to provide an understandable interpretation of the strategies. These qualitative descriptions are:

- Opportunistic strategy
- Global / Macro strategy
- Value strategy
- Trend following strategy
- Distressed strategy

In order to find evidence for dynamic trading strategies in hedge funds, FH applied a non-parametric style regression. This means, if a fund manager applies a "buy-and-hold long-only" strategy, its returns should align with those of the predefined asset classes in any economic environment.[1] On the other hand, if a style uses a dynamic trading strategy in a certain asset class, its return should be large, when the underlying asset returns are at extremes, no matter if it is positive or negative. Consequently, FH divided the monthly returns of the hedge fund database into

[1] This means in severe declines / sharp rallies also the fund returns should be substantially high / low

states of different market environments. Finally, they defined five states, ranging from severs declines to sharp rallies and compared the behavior of hedge fund styles and predefined asset classes during these periods. Some part of the results is presented next:

Fig. 22: Fung & Hsieh – Return Characteristics (1997a)

State	U.S. Equity		Trend Following		non-U.S. Equity		Trend Following		U.S. Dollar		Trend Following	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
1	-2,82	0,29	1,45	1,26	-5,16	0,42	2,45	1,59	-3,33	0,27	5,58	1,28
2	-0,05	0,19	1,71	0,82	-1,77	0,22	-1,19	0,93	-1,53	0,1	-0,46	0,79
3	1,59	0,11	-0,77	0,51	0,81	0,15	0	0,7	-0,34	0,08	-0,75	0,44
4	3,04	0,12	1,91	1,7	3,35	0,19	-0,4	0,56	1,26	0,16	-1,04	0,49
5	5,13	0,59	0,5	1,55	6,99	0,5	3,82	1,58	4,48	0,58	1,47	1,73

Returns of trend following hedge fund style factor and U.S. equity, non-U.S. bonds, U.S. Dollar across different market environments: Jan 1991 - Dec 1995 (in percent per month)

State	U.S. Dollar		Global Macro		Gold		Global Macro		Emerging Markets		Global Macro	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
1	-3,33	0,27	0,81	0,5	-4,06	0,45	1,27	0,63	-4,8	0,71	0,38	0,82
2	-1,53	0,1	0,14	0,81	-1,2	0,11	1,4	0,22	-1,59	0,19	0,81	0,55
3	-0,34	0,08	0,95	0,4	0,03	0,08	1,2	0,41	0,56	0,14	1,17	0,42
4	1,26	0,16	2,24	0,59	1,33	0,2	0,37	0,88	2,76	0,22	1,47	0,41
5	4,48	0,58	2,29	0,43	4,27	0,38	2,15	0,62	8,52	1,33	2,56	0,59

Returns of trend global/macro hedge fund style factor and U.S. Dollar, gold, emerging markets across different market environments: Jan 1991 - Dec 1995 (in percent per month)

State	Gold		Oppor tunistic		U.S. Bonds		Oppor tunistic		non-U.S. Bonds		Oppor tunistic	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
1	-4,06	0,45	0,16	1,49	-0,95	0,18	0,07	0,96	-2,89	0,52	0,99	1,26
2	-1,2	0,11	0,38	1,56	0,21	0,07	0,03	1,04	-0,11	0,11	-1,09	0,81
3	0,03	0,08	0,09	1,08	0,79	0,05	2,07	1,19	1,05	0,07	0,84	1,34
4	1,33	0,2	1,23	1,16	1,36	0,05	0,21	1,37	2,12	0,11	1,96	1,13
5	4,27	0,38	3,58	1,04	2,25	0,16	3,72	1,61	4,52	0,49	3,39	1,61

Returns of opportunistic hedge fund style factor and gold, U.S. bonds, non-U.S. bonds across different market environments: Jan 1991 - Dec 1995 (in percent per month)

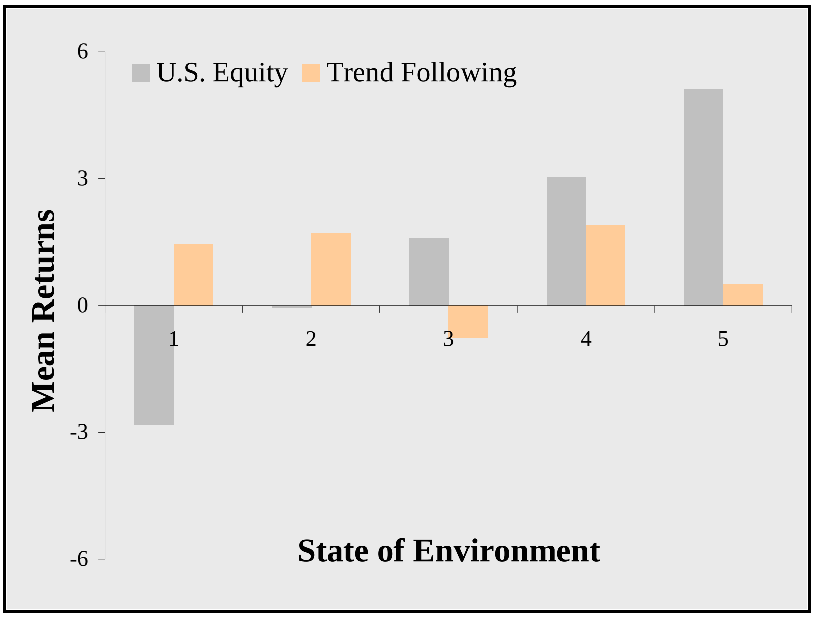
Source: Fung, William; Hsieh, David (1997a) "The Risk in Hedge Fund Strategies: Theory and Evidence From Trend Followers," Review of Financial Studies, 14, 313-341.

The part of FH's analysis represented by figure 22 shows that there exist nonlinear correlations between three style factors and some of the standard asset classes. This provides evidence for dynamic trading strategies. The information FH gained, can be summarized by the following statements:

- In the case of the trend following style, it is most profitable to invest in this strategy during rallies in: non-U.S. equities, non-U.S. bonds and during declines in the U.S. dollar
- The global/macro style is the most profitable during rallies in gold , the U.S. dollar and emerging markets
- Opportunistic strategies are most profitable during rallies in gold, U.S. bonds, non-U.S. bonds and during declines in the U.S. dollar

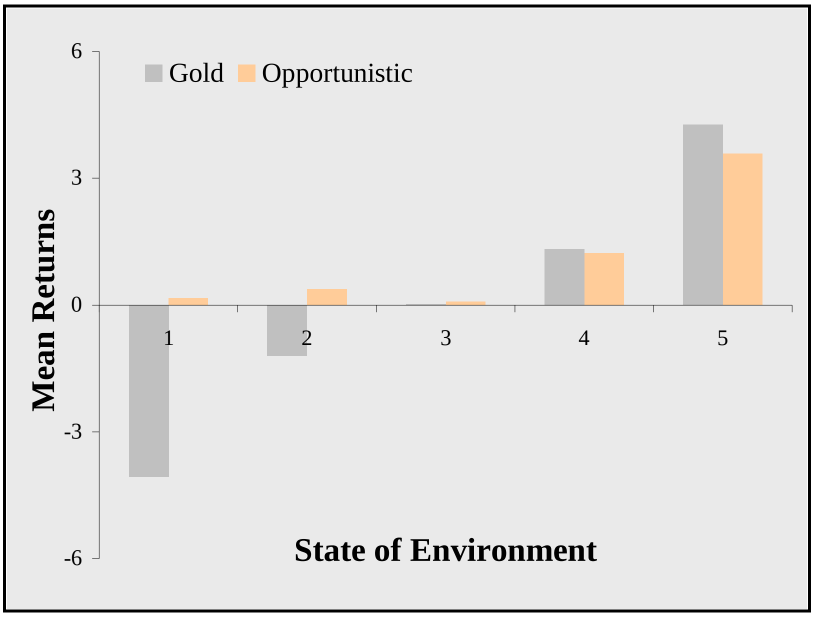
According to FH, these facts give rise to option-like payouts. This means hedge fund returns could be replicated by traded, observable options in the earlier identified locations (asset classes). The following figures illustrate the most dramatic examples of option-like payouts:

Fig. 23: Fung & Hsieh – Trend Following Style vs. U.S. Equity



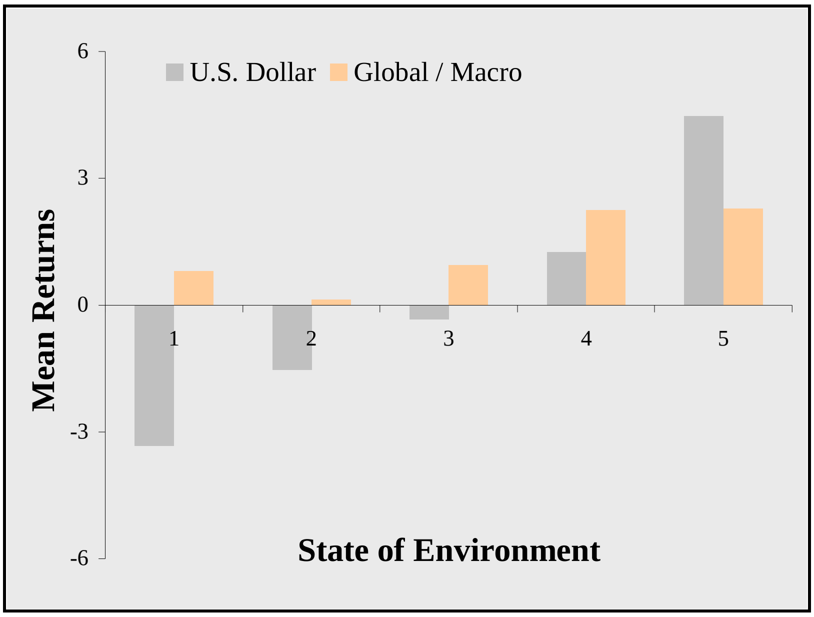
Source: Fung, William; Hsieh, David (1997a) "The Risk in Hedge Fund Strategies: Theory and Evidence From Trend Followers," Review of Financial Studies, 14, 313-341.

Fig. 24: Fung & Hsieh – Opportunistic Style vs. Gold



Source: Fung, William; Hsieh, David (1997a) "The Risk in Hedge Fund Strategies: Theory and Evidence From Trend Followers," Review of Financial Studies, 14, 313-341.

Fig. 25: Fung & Hsieh – Global/Macro Style vs. U.S. Dollar



Source: Fung, William; Hsieh, David (1997a) "The Risk in Hedge Fund Strategies: Theory and Evidence From Trend Followers," Review of Financial Studies, 14, 313-341.

Figure 23 reports that hedge funds using trend following strategies have performance characteristics that resemble straddles[2] on the equity market. Figure 24 shows that the Opportunistic style generates a return behavior, which is similar to a call option on gold. Figure 25 shows the Global/Macro style behaves like a straddle on the U.S. dollar. Overall the empirical results of FH (1997a) show:

- Linear-factor models, as in Sharpe (1992), are not able to capture the return features among hedge funds
- The extracted style factors from a broad sample of hedge fund returns show that there exist relationships between hedge funds and traditional asset classes, which own non linear characteristics
- The analyzed strategies feature:
    - Non-linear return characteristics
    - Much of option-like returns
- Hedge fund manager typically employ dynamic trading strategies

5.3 Look-back straddles to model trend following strategies

On the basis of these results, Fung and Hsieh focused their work of modeling the returns of hedge funds on a particular strategy. [14] In 2001 they introduced a methodology for modeling the returns of "*trend-following*" strategies. Due to the proved option-like return features, FH decided to use look-back straddles to model the specific return characteristics of trend-following hedge funds. This means trend-followers could be replicated by a combination of look-back straddles on traditional asset classes. Assuming that Black and Scholes (1973) holds, the prices of the utilized put and call options can be estimated. [4] Consequently, the price of a standard straddle is well known in this case and the prices of look-back options can be found in Goldman (1979). [12] Therefore, FH provide a link between the returns of trend-following funds and standard asset classes.

[2] The term straddle referrers to an options strategy with which the investor holds a position in both a call and put with the same strike price and expiration date.

The aim is to prove the hypothesis that the returns of "*primitive trend following strategies*" ,which are constructed by the combination of look-back straddles, show strong correlations with the returns of trend following funds. To explain this procedure the terms look-back straddle and "*primitive trend following strategy*" are explained below.

5.3.1 Look-back straddles

A look back straddle is a combination of look-back call options and look-back put options. The owner of a look-back call option or put option respectively has the right to buy/sell the underlying asset at the lowest/highest price during the maturity of the underlying option. Therefore, the payoff of a look-back straddle is not only determined by the settlement price but also by the maximum or minimum price of the underlying asset within the life of an option. Consequently, a look-back straddle delivers the ex-post maximum payout of a trend-following strategy.

In terms of trend-following strategies this means that look-back straddles deliver the payout of a manager that perfectly invests according to the trend. He sells securities when prices are high and purchases them if the prices are low. Hence, trend following strategies should theoretically deliver the returns of look-back straddles. Since the "perfect" trend-following fund manager does not exist in reality, FH defined the so-called primitive trend following strategy (PTFS). This PTFS is a theoretical construct, which represents a manager, who applies a perfect trend following strategy.

5.3.2 Primitive Trend following Strategy

Since trend followers can converge onto the same trend for different reasons, FH defined the term "*primitive trend-following strategy*", referred to as PTFS. PTFS should capture the general characteristics of trend-following strategies and therefore resemble the payout profile of look-back straddles. The strategy should not represent a particular trading strategy that benefits from trends among security price movements. The idea is to design a strategy, which is able to capture the performance profile of the trend-following strategy universe. Therefore, the model contributes to the explanation of the performance of CTA funds as well as other hedge funds, which use trend following as part of their strategy. In order to give a definition of the term PTFS, the term "*Trend*" should be defined first:

> "*A trend is a series of asset prices that move persistently in one direction over a given time interval, where price changes exhibit positive serial correlation.*"

According to this, the term "*PTFS*" can be defined as follows:

> "*A trend follower attempts to capture market trends by identifying developing price patterns with trend property and trade in the direction of the trend if and when this occurs.*" [14]

5.4 Constructing a Performance Database

Because look-back straddles are not exchange-traded options, their prices can not be observed directly. In order to analyze the correlation behavior between CTA's and primitive trend-following strategies FH had to construct a database of PTFS's returns. They generated the historical returns of the PTFS applied to the most active markets in the world:

Fig. 26: Fung & Hsieh – Active Markets

Stock Indices	
Futures Contracts on the:	S&P 500 (CME)
	Nikkei 255 (Osaka)
	FTSE 100 (LIFFE)
	DAX 30 (DTB)
	Australian All Ordinary Index (SFE)
Bonds	
Futures Contracts on the:	U.S. 30-year Treasury Bonds (CBOT)
	UK Gilts (LIFFE)
	German Bund (LIFFE)
	French 10-year Government Bond (MATIF)
	Australian 10-year Government Bond (SFE)

Currencies		
Futures Contracts on the:	British Pound	(CME)
	Deutsche Mark	(CME)
	Japanese Yen	(CME)
	Swiss Franc	(CME)
Three-months Interest Rates		
Futures Contracts on the:	3-month Eurodollar (CME)	
	Euro-Deutsche Mark (LIFFE)	
	Euro-Yen (TIFFE)	
	Paris Interbank Offer Rate (PIBOR, MATIF)	
	3-month Sterling (LIFFE)	
	Australian Bankers Acceptance Rate (SFE)	
Commodities		
Futures Contracts on the:	Soybean	(CBOT)
	Wheat	(CBOT)
	Corn	(CBOT)
	Silver	(NYMEX)
	Gold	(NYMEX)
	Crude Oil	(NYMEX)

Source: Fung, William and Hsieh, David (2001) "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers," Review of Financial Studies, 14, 313-341

5.4.1 Procedure

FH replicated the payout of a look-back straddle by "*rolling*" a pair of standard straddles on the predefine asset classes. Rolling is understood as the price adjustments of the applied options within the straddle, according to the actual price developments. FH adjusted the option prices and strikes at the end of each trading day by using the settlement prices of the option and the underlying asset.

One straddle was used to lock in the high price of the underlying asset. Whenever the price of the underlying asset moves above the current strike price they "*rolled*" this straddle to a higher strike price. This means, at expiration the straddle's strike must equal the highest price achieved since inception. On the opposite, FH used another straddle to lock in the low price of the underlying asset. Whenever the price of the underlying asset moves below the current strike price they "*rolled*" this straddle to a lower strike price. This means, at expiration the straddle's strike must equal the lowest price achieved since inception. Consequently, the combination of the two standard straddles must exactly obtain the payout of the look-back straddle.

5.4.2 Results

During 1989 and 1997 FH obtained the monthly returns of the PTFS for each of the 26 predefined markets and 5 asset classes. On this basis, they estimated five equally weighted PTFS portfolios of the single PTFS in the five groups of asset classes. The results of the analysis, according to these five PTFS portfolios and Trend-Following funds returns, are illustrated in figure 27.

Fig. 27: Monthly returns for trend followers and five PTFS portfolios

	Trend Following	**Stock PTFS**	**Bond PTFS**	**Interest Rate PTFS**	**Currency PTFS**	**Commodity PTFS**
Mean	0,0137[a]	-0,0193	0,0181	0,0195	0,0177	-0,0072
SD	0,0491	0,2094	0,1573	0,1867	0,2305	0,131
Maximum	0,1837	1,324	0,4739	0,8158	1,0006	0,6413
Minimum	-0,082	-0,5172	-0,2285	-0,2573	-0,3013	-0,2497
Skewness	0,79[a]	2,62[a]	1,07[a]	1,46[a]	1,68[a]	1,19[a]

[a] Statistically different from zero bat the 1% one-tailed test

Source: Fung, William and Hsieh, David (2001) "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers," Review of Financial Studies, 14, 313-341

The figure above shows that Trend-Followers as well as the five PTFS have strongly positively skewed returns. The PTFS portfolios and the funds, which apply a trend following strategy, differ in their mean-value characteristics. While the trend followers show a positive and statistically significant mean, this fact can not be observed among all of the PTFS-portfolios.

5.5 Evaluating the PMTS-Benchmark

In the following figure the regressions of trend-following fund returns against ten sets of risk factors are given.

Fig. 28: Regressions on ten Sets of Risk Factors

	Sets of Risk Factors	$\overline{R}^2$ of Regression (%) *
1.	**Eight major asset classes in Fund nad Hsieh (1997a)** (US and non-US equities, US and non-US Bonds, gold, US dollar index, emerging market equities, 1-month eurodollar)	**1,00**
2.	**Five major stock indices** (S&P 500, FTSE 100, DAX 30, Nikkei 225, Australian All Ordinary)	**-2,10**
3.	**Five government bond markets** (U.S. 30-year, UK Gilt, German Bund, Frensch 10.year, Australian 10-year)	**7,50**
4.	**Six three months interest rate markets** (Eurodollar, 3m Sterling, Euro-DM, Euro-Yen, Australian Bankers Acceptance, Paris Interbank Rate)	**1,50**
5.	**Four currency markets** (British pound, Deutsche Mark, Japanese Yen, Swiss Franc)	**-1,10**
6.	**Six Commodity markets** (corn, wheat, soybean, crude oil, gold, silver)	**-3,20**
7.	**Goldman Sachs Commodity Index**	**-0,70**
8.	**Commodity Research Bureau Index**	**-0,80**
9.	**Mount Lucas/BARRA Trend Following Index**	**7,50**
10.	**Five PTFS portfolios** (Stock PTFS, Bond PTFS, Currency PTFS, 3-month interest rate PTFS, Commodity PTFS)	**47,90**

* $\overline{R}^2$ refers to adjusted R^2 of the regression of trend-following funds' returns o ten different sets of risk factors

Source: Fung, William and Hsieh, David (2001) "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers," Review of Financial Studies, 14, 313-341

At first, the regression coefficient of FH asset class model (1997a) is presented. This regression is based on return-based style factors against the returns of funds applying trend-following strategies. An adjusted R^2-value of 1% and the fact that none of the variables is statistically significant different from zero is the result of this analysis. The following coefficients of the five sets of risk factors represent the result of the examination of the 26 different markets by groups. These groups are the five asset classes, which FH used to construct the five PTFS portfolios. But also this analysis surprisingly obtains low regression coefficients against trend-following returns. Also the regression analysis using other indices often associated with CTA's and Trend-Followers do not significantly show different results. So far, the results strengthen the statement that trend-following funds do not correlate with returns of traditional asset classes.

Now we take a closer look at the regression of trend-following funds' returns on the five PTFS portfolios. The result of this regression is a coefficient an adjusted R^2-value of 47.9%. Additionally, the F-test of the hypothesis:

H_o: PTFS-portfolios do not correlate with the returns of trend followers

is rejected at any conventional significance level. Unlike the earlier regression results, this indicates that trend followers do correlate with traditional asset class returns. The reason why earlier analysis did not deliver evidence for this is due to the fact that one did not consider the non-linear relationship between hedge funds and traditional investment vehicles. Through the use of look-back straddles FH did not only obtain an asset based methodology to model the returns of trend followers, they also proved that hedge fund returns actually do correlate with traditional asset classes in a non-linear way.

5.5.1 Summary

- The roots of FH's approach to model the returns of hedge funds can be found in the asset class factor model introduced by Sharpe
- In the approach of 1997, FH primarily applied the factor analysis to define return-based style factors:
    - RBS are not able to describe the returns of hedge funds successfully
    - Within their analysis FH found evidence for non-linear relationships between hedge fund strategies and traditional investment vehicles
- In 2001 FH focused on CTA's, using asset based style factors to model simple trend following strategies among predefined asset classes
    - A simple trend-following strategy can be replicated by using look-back straddles
    - A simple trend-following strategy obtains the performance of a perfect trend-follower
- Empirically FH showed that single PTFS are not able to describe the returns of hedge funds applying trend-following strategies ($\overline{R}^2$ between -3.2% and 7.5%)
- Only the portfolio consisting of the five PTFS was able to capture essential performance features of trend-following funds ($\overline{R}^2$ of 47.9 %)
    - Both PTFS and trend-following funds have strong positive skewness
    - Both feature non-linear relationships with traditional asset classes
    - PTFS can explain the returns of trend following hedge funds during extreme market situations

6 EMPIRICAL ANALYSIS

6.1 Introduction

The analysis procedure can be divided into two sections. The First section deals with the descriptive analysis of the return data. Here, special attention is directed to the performance measurement of the examined hedge fund indices and their relationship to alternative investment classes, such as the "*market*" and "*risk-free investments*". The second part contains the elaboration of a forecasting model for hedge fund returns. Both parts use the same hedge fund database, which is publicly provided by the VAN Company.

6.1.1 The underlying Database

Fig. 29: VAN Company – Hedge Fund Classification

VAN Global Market Neutral Group Index	
	Event-Driven Index
	Distressed Securities Index
	Special Situations Index
	Market Neutral Arbitrage Index
	Convertible Arbitrage Index
	Fixed Income Arbitrage Index
VAN Global Long/Short Equity Group Index	
	Aggressive Growth Index
	Market Neutral Securities Hedging Index
	Opportunistic Index
	Value Index
VAN Global Directional Trading Group Index	
	Macro Index
	Market Timing Index
	Futures Index
VAN Global Specialty Strategies Group Index	
	Emerging Markets Index
	Income Index
	Multi-Strategy Index
	Short Selling Index

Source: Self-made figure, based on the data provided by the VAN Company

The underlying database consists of monthly returns during the period 1995-2004. This return data is collected regarding predefined hedge fund indices. The funds included in this database are globally situated hedge funds. The classification of the database illustrates figure 29. All hedge funds recognized are grouped into one of four major categories. These categories are:

- Market Neutral
- Long Short Equity
- Directional Trading
- Specialty Strategies

These categories are again split into hedge fund sub indices, as it can be seen in figure 29. Finally, the single funds are assigned to a particular sub index. This assignment procedure is realized on the basis of the funds' self-made strategy disclosures. This means, the resulting indices base on performance information which is separately received from the U.S. as well as non-U.S. domiciled hedge funds. Later, all collected single funds, which are assigned to one certain sub index are combined in order to calculate the average monthly return of the particular Van Global Hedge Fund Index. The author accepts this kind of classification for the further analysis.

As a matter of policy, the VAN Company collects the data itself and does not rely on third party resources for the information. The Indices and their sub-indices are updated monthly and are produced as a service to institutions, plan sponsors, consulting firms, individual investors and the financial services industry. Finally, seventeen time series datasets regarding each predefined hedge fund index formed the dataset. Each hedge funds dataset includes 120 sets of monthly return data and served as input for the following empirical studies.

6.2 Descriptive Analysis

The attractiveness of an investment is generally determined by its performance characteristics, such as mean return and return volatility. After all, the selection of financial instruments depends on the investors return expectations in respect of a certain amount of risk he is willing to take. Consequently, a conservative manager will only purchase positions that own little return volatility.

In practice, it is not that easy to generate a portfolio, which satisfies the demands of an investor. For portfolio construction each single instrument has to be evaluated in the context of all other possible investment opportunities. In this regard, hedge funds represent investment vehicles that are particularly suitable for portfolio completion. Even though hedge funds seem to be similar to mutual funds from a superficial point of view, their performance characteristics vary extremely from those of traditional investments. The broad flexibility in the types of securities that hedge funds hold, the types of positions they take (long as well as short positions) and the possibility to invest in international as well as domestic equities, debt and the entire array of traded derivative securities leads to the unique performance characteristics of this asset class.

In addition to the eighteen VAN indices, the author included two more indices in the descriptive analysis. In order to get a better picture of the special performance characteristics of hedge funds the author completed the database by the following indices that represent certain classes of investment vehicles::

- The "*S&P 500*" index[1], provided by the BARRA Inc.[2] that serves as the representative of an investment in the overall market
- The "*90 Days Treasury Bills*" index, provided by the Federal Reserve[3], which serves as a benchmark of risk free investments

[1] Widely regarded as the best single gauge of the U.S. equities market, this world-renowned index includes a representative sample of 500 leading companies in leading industries of the U.S. economy. Although the S&P 500 focuses on the large-cap segment of the market, with over 80% coverage of U.S. equities, it is also an ideal proxy for the total market.
http://www2.standardandpoors.com (July 05)

[2] http://www.barra.com/Research/DownloadMonthlyReturns.aspx (July 05)

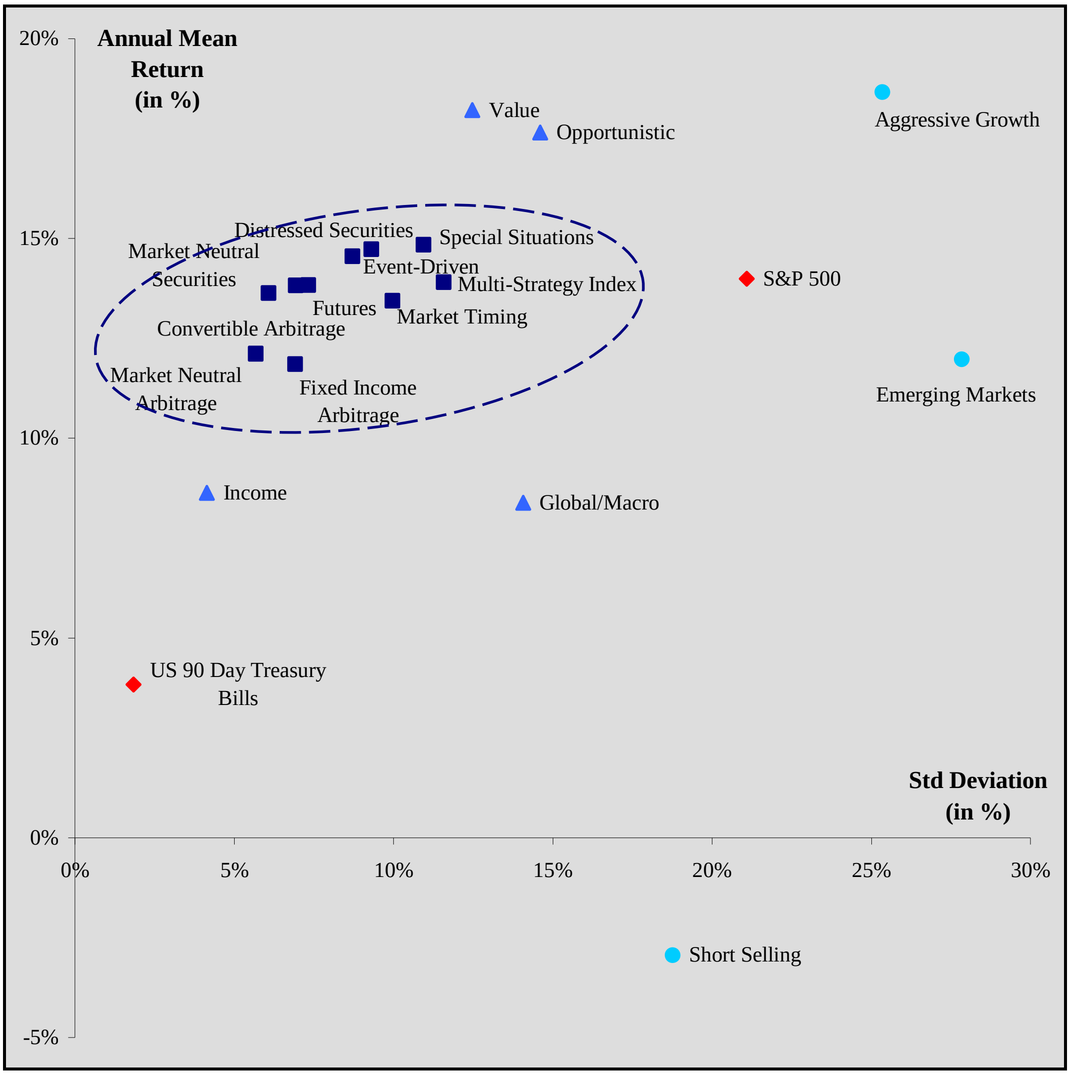
[3]http://www.federalreserve.gov/releases/H15/data.htm (July 05)

6.2.1 Performance Measurement

The general results of the descriptive analysis are summarized in figure 42 of the appendix. In this section and in the following sections of this part, the author shows some of the elaborated results in more detail.

Figure 30 shows the risk return relationship of each index. Within this figure the hedge fund asset class is marked by signs in a blue color scale and others are red colored.

Fig. 30: Descriptive Statistics – Risk-Return Diagram



Source: Self-made figure, based on the data provided by the VAN Company, BARRA Inc. and the Federal Reserve.

Although hedge funds are often characterized as investments that own "*very high*" risk exposures (high volatility), this analysis provides a more differentiating statement. One may clearly see that only two of the VAN-indices (the Aggressive Growth and Emerging Market index) have standard deviations that are higher than the σ^2-value of the S&P 500 index (21%). Consequently, most of the examined hedge funds are overall less risky (less volatile) than investments in ordinary shares of the S&P 500. On the opposite, no hedge fund index owns a standard deviation of its annual mean returns that is lower than the σ^2-value of the risk free rate, which is represented by the 90 days treasury bills index. In addition, most of the VAN indices show annual mean returns that are similar to the annual mean market returns, represented by the S&P 500 index.

The "*eye-catching fact*" of figure 30 is that there exists one main group of VAN hedge fund indices (marked by the blue dashed oval), which own similar performance characteristics. These particular characteristics are:

- The funds among this group own annual mean returns that vary between 12% and 15%, similar to the mean market performance
- The funds among this group own annual standard deviations that vary between 6% and 12%, far less then the volatility of the market

In the end, one may conclude that the examined fund indices feature mean returns, which are similar to the market and simultaneously show volatilities that are similar to the risk free rate.

Especially in this case, it makes sense to additionally compare the indices on the basis of their "*ex-post Sharpe Ratio value*"[4]. This ratio compares the historical mean return in relation to the taken risk of the asset during that time. The ex-post, also referred to as the historical S_h has been calculated according to the following equation (6.1):

[4] In 1966, Sharpe introduced a measure for the performance of mutual funds and proposed the term reward-to-variability ratio to describe it. This ratio is referred to as the SharpeRatio and also described in Sharpe (1975).

$$S_{hi} = \frac{\overline{R}_i}{R_{i\sigma}} \tag{6.1}$$

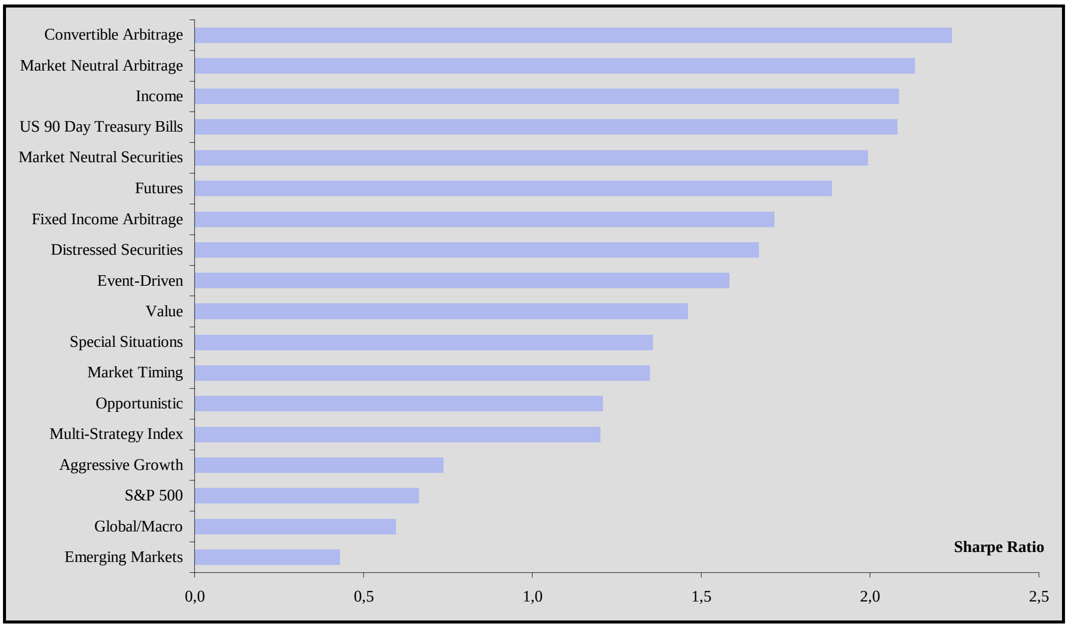
Where:

$\overline{R}_i$ $\quad \overline{R}_i = \frac{1}{T}\sum_{t=1}^{T} R_{it}$ Denotes the annual mean return of index i

$R_{i\sigma}$ $\quad R_{i\sigma} = \sqrt{\frac{\sum_{t=1}^{T}\left(R_{it} - \overline{R}_i\right)^2}{T-1}}$ Denotes the standard deviation of the return index i over the period t=1,…,T

R_{it} Denotes the annual return of index i in the period t=1,…,T

Fig. 31: Descriptive Statistics – Sharpe Ratio (estimated ex-post)



Source: Self-made figure, based on the data provided by the VAN Company, BARRA Inc. and the Federal Reserve.

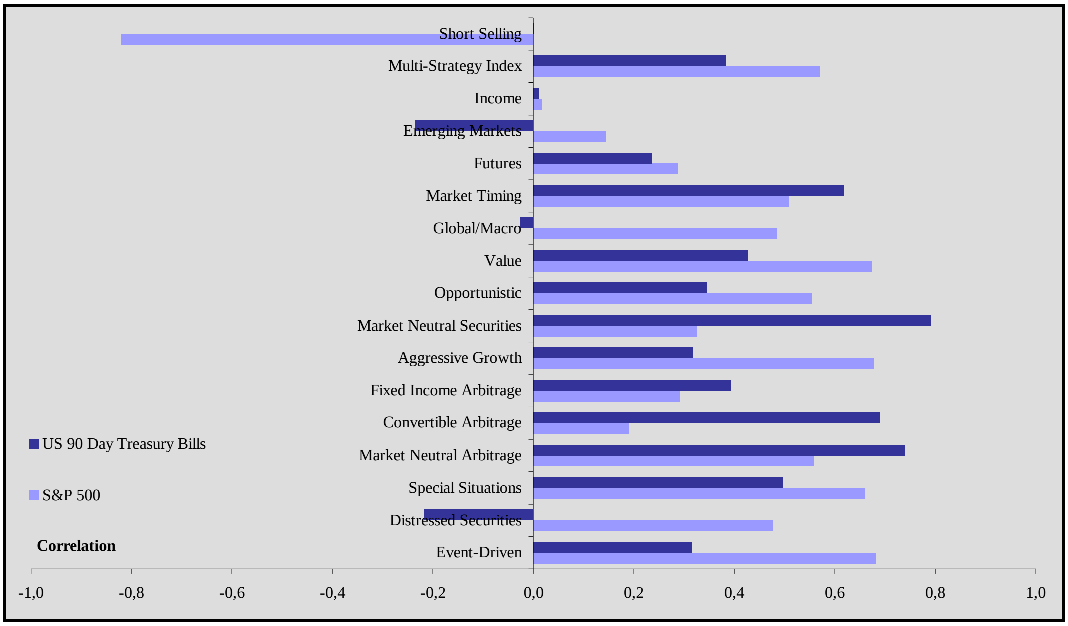
As one can see from figure 31, only the VAN indices Global/Macro, Emerging Markets and Short Selling show Sharpe Ratios, which are lower than the ratio of the market (S&P 500). This strengthens the facts, exposed by means of figure 30 before.

Also surprising is the result that the risk free rate has one of the highest ratios, although its mean return is by far the lowest (except of the short Selling index). Only three indices of the VAN hedge fund indices exhibit ratios that are higher than the ratio of the 90 days treasury bills index. Consequently, its very low volatility must account for the main part of the high Sharpe Ratio.

6.2.2 Correlation Behavior

When Alfred Winslow Jones established the first hedge fund, one of his aims was to create an investment vehicle, whose performance should be generated independently from overall market movements. This means, the market risk should be removed by a "*manager immanent*" risk. If the actual situation also reflects these original ambitions of the hedge fund industry can be proofed by the examination of the correlations between hedge fund strategies and traditional asset classes (market and risk free investments). For this reason, the following figure illustrates the correlations between each hedge fund strategy and the S&P 500 as well as the 90 Days Treasury Bills Index.

Fig. 32: Descriptive Statistics – Standard Asset Class Correlations



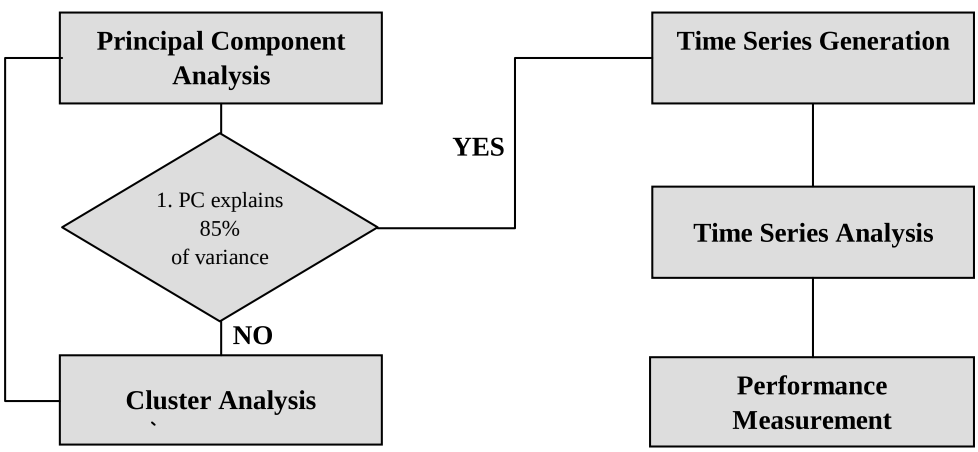
Source: Self-made figure, based on the data provided by the VAN Company, BARRA Inc. and the Federal Reserve.

6.3 Elaboration of a Forecasting Model

The second part of the empirical analysis contains the elaboration of a forecasting model for the returns of hedge funds, which are included in the VAN's database. The author utilized the principle component analysis as the basis of the model building process. Via PCA, the author wants to extract principle components, which contain information about the common performance characteristics of the different predefined hedge fund indices. The first extracted PC will be used to generate an "artificial" time series. The aim is to build a model, which is able to explain this time series. In doing so, the time series model should be able to reproduce the main return generating procedures of the examined hedge funds. Consequently, this model can be used for the prediction of hedge fund returns.

In order to maintain a reliable result of the time series analysis, the first PC should explain at least 85% of the total variance within the underlying database. If this level of significance is not reached in the analysis of the complete dataset, which includes all strategies, the author will utilize the cluster analysis to form a smaller group of hedge fund indices. This smaller group should own "similar" performance characteristics, so that the result of the PCA will be enhanced. Then, the PCA will be applied again to this smaller data set, in order to extract a first PC, which generates a more significant time series. The following figure illustrates the procedure:

Fig. 33: Model Building Procedure

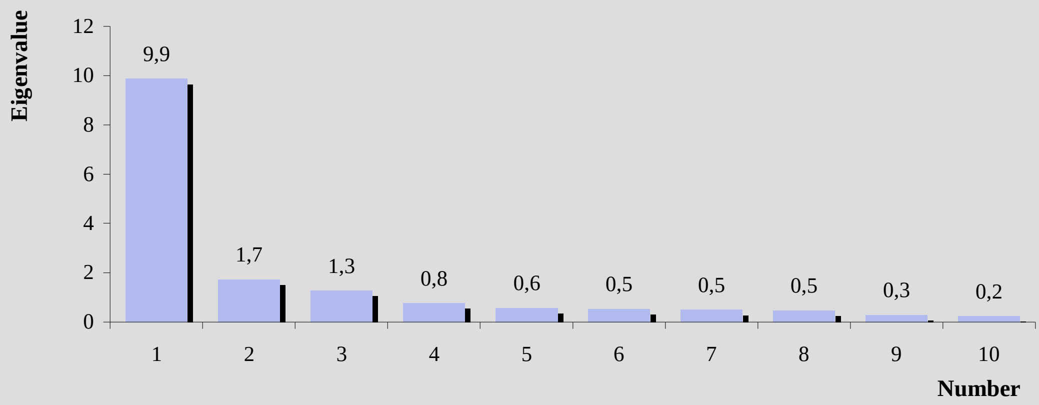


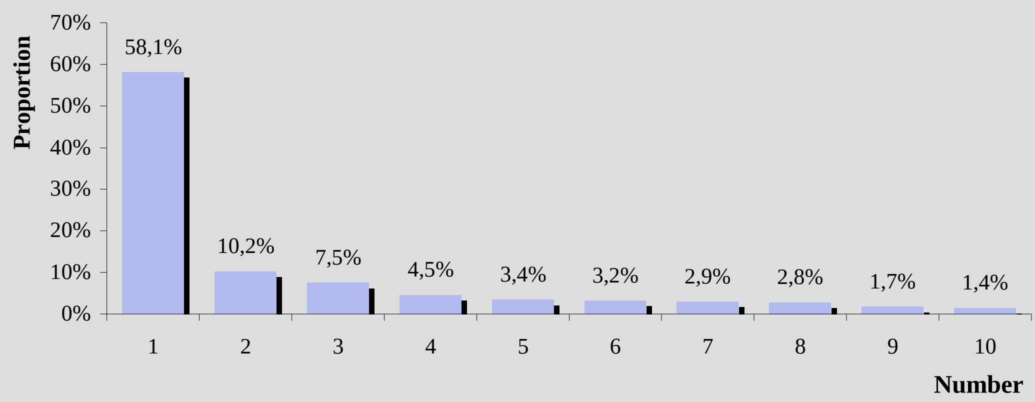
Source: Self made figure

6.3.1 Principal Component Analysis among all Strategies

Fig. 34: Results – Principal Component Analysis of all Strategies

	Eigenvalue	**Difference**	**Proportion in %**	**Cumulative in %**
1	9,871	8,144	58,1%	58,1%
2	1,727	0,452	10,2%	68,2%
3	1,274	0,508	7,5%	75,7%
4	0,767	0,192	4,5%	80,2%
5	0,574	0,038	3,4%	83,6%
6	0,537	0,045	3,2%	86,8%
7	0,492	0,021	2,9%	89,7%
8	0,471	0,187	2,8%	92,4%
9	0,283	0,048	1,7%	94,1%
10	0,235	0,028	1,4%	95,5%
11	0,207	0,019	1,2%	96,7%
12	0,188	0,032	1,1%	97,8%
13	0,156	0,063	0,9%	98,7%
14	0,093	0,017	0,5%	99,3%
15	0,076	0,027	0,4%	99,7%
16	0,049	0,048	0,3%	100,0%
17	0,001	0,001	0,0%	100,0%





Source: Self-made figure, based on the data provided by the VAN Company.

The principle component analysis of the 120 datasets among all hedge fund strategies obtains a component structure, which is dominated by the first three components. Within this structure the first principal component explains just about 60% of the total variance of the underlying database, having an eigenvalue of 9,871. The second and third component still has eigenvalues, which are greater than one (2nd:1,727, 3rd: 1,274). Hence, according to the MINEIGEN criteria, this PCA delivers three principal components.[5] In the end, these three components account for 75% of the total variance. The eigenvectors of these components and the related factor loadings (correlations of eigenvectors and strategies) are given in the following figure:

Fig. 35: PCA of all Strategies – Eigenvectors and Factor Loadings

		Eigenvectors			Factor Loadings		
		1st	2nd	3rd	1st	2nd	3rd
1	Event-Driven	0,296	0,018	-0,149	0,931	0,023	-0,169
2	Distressed Securities	0,235	0,154	-0,254	0,737	0,202	-0,286
3	Special Situations	0,293	-0,026	-0,111	0,928	-0,034	-0,126
4	Market Neutral Arbitrage	0,234	0,351	0,060	0,736	0,461	0,068
5	Convertible Arbitrage	0,181	0,431	-0,186	0,567	0,566	-0,210
6	Fixed Income Arbitrage	**0,099**	**0,563**	-0,108	**0,310**	**0,740**	-0,122
7	Aggressive Growth	0,286	-0,230	0,058	0,900	-0,302	0,066
8	Market Neutral Securities	0,223	0,090	0,226	0,701	0,118	0,256
9	Opportunistic	0,291	-0,117	0,105	0,913	-0,153	0,118
10	Value	0,294	-0,158	-0,072	0,922	-0,208	-0,081
11	Global/Macro	0,230	0,108	0,311	0,724	0,142	0,351
12	Market Timing	0,251	-0,204	0,297	0,788	-0,268	0,335
13	Futures	**-0,013**	0,204	**0,762**	**-0,042**	0,268	**0,860**
14	Emerging Markets	0,251	-0,033	0,022	0,788	-0,043	0,024
15	Income	0,208	0,172	-0,037	0,653	0,225	-0,041
16	Multi-Strategy Index	0,283	-0,126	-0,100	0,890	-0,166	-0,113
17	Short Selling	-0,261	0,330	0,058	-0,819	0,433	0,065

Source: Self-made figure, based on the data provided by the VAN Company.

A closer look at figure 35 and figure 43 (correlation matrix in the appendix) gives information about the disappointing result of the PCA. Figure 43 shows that most of the hedge fund strategies are highly correlated with each other. But in particular, the two strategies: "*Futures*" (13) as well as "*Fixed Income Arbitrage*" (6) form the exception. As one may see in the last row of figure 43, all the other

5 MINEIGEN criteria: the eigenvalue of the principal component has to be greater than 1.

strategies have average correlation intensities, which are higher than 0,4. On the opposite, the "*Fixed Income Arbitrage*" index only owns an average intensity of 0,23 and the "*Futures*" index even shows an average correlation intensity of 0,1. Consequently, these characteristics can probably not be captured by only one principal component. If one additionally considers figure 35, one may see that the 2nd component accounts on a massive scale for the "*Fixed Income Arbitrage*" index and the 3rd component for the "*Futures*" index. This leads to the conclusion that at least the strategies (6) and (13) should not be considered in further examinations. The cluster analysis will obtain deeper insights.

6.3.1.1 CLUSTERING

In order to enhance the explanatory power of the first principal component, the author decided to apply a cluster analysis to the underlying database. By grouping all the strategies together, which are highly correlated, the PCA of these groups should deliver more significant results. The correlations of the first five eigenvectors and the seventeen strategies (factor loadings) served as basis for the estimation of the original Euclid-distance matrix, D.

$$D = \begin{pmatrix} d_{11} & \cdots & d_{1i} \\ \vdots & \ddots & \vdots \\ d_{i1} & \cdots & d_{ii} \end{pmatrix} \quad i = 1,...,17$$

The distances between each strategy have been estimated according to the following equation:

$$d_{ij} = \sqrt{\sum_{n=1}^{5} \left(c_i - c_j\right)^2} \quad , for\, i \neq j \tag{6.1}$$

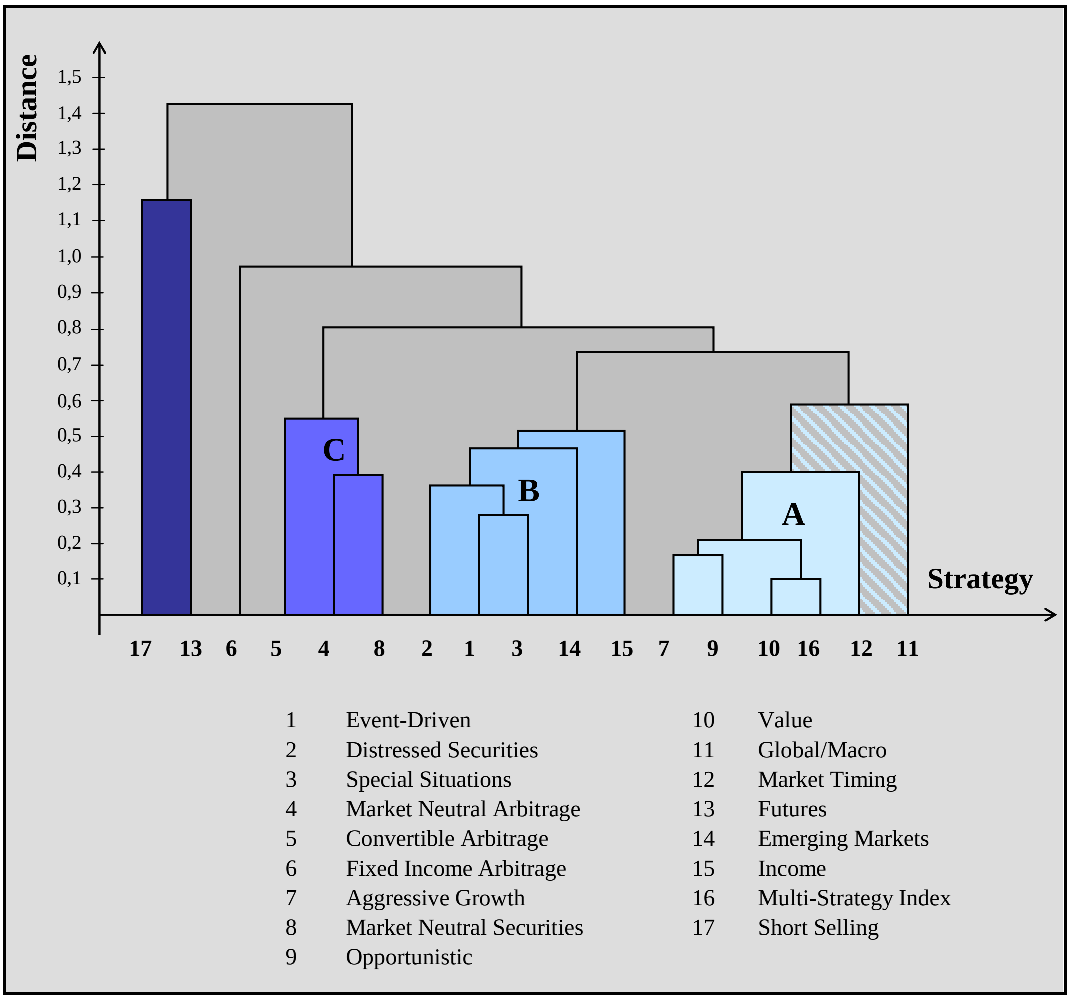
Where:

d_{ij}	Euclid-distance between strategy i and j (i,j=1,…,17 and i≠j)
c_i	The i^{th} *factor loading* (i=1,…,17) of the k^{th} eigenvector (k=1,…,5) represented by the correlation of eigenvector k and strategy i

The factor loadings matrix and the Euclid-distance matrix are presented in the appendix (figures 44 and 45). Strategies and already estimated clusters, which have the least Euclid-distance, are clustered together. The resulting new distance matrix within this procedure has been calculated according to the "*average linkage method*".

The results of the cluster analysis are illustrated in the figure 46 (Plot of 1st and 2nd main-plane in the appendix) and in the following figure:

Fig. 36: Custer Analysis – Dendrogramm



Source: Self-made figure, based on the data provided by the VAN Company.

One may see from the Dendrogramm (illustrated in figure 36), there exist four main clusters (A, B, C and A including strategy 11) of "*similar*" strategies. One can see that the strategies "*Fixed Income Arbitrage*", "*Futures*" and "*Short*

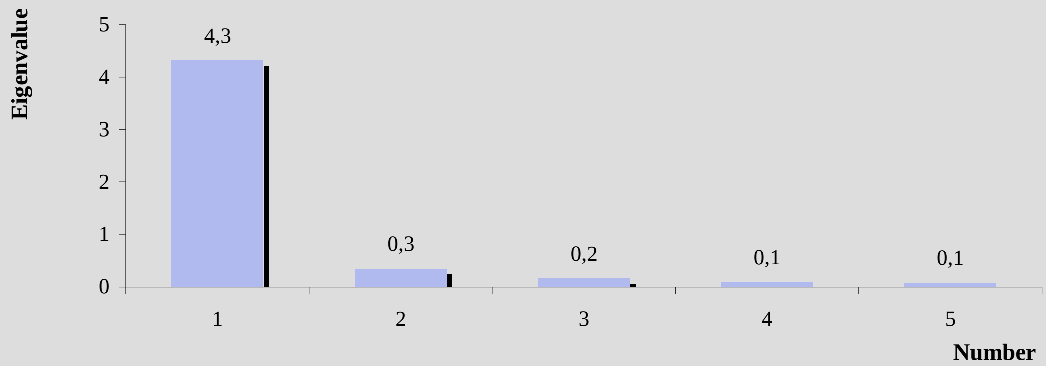
Selling" show the least similarity to other strategies. This strengthens the conclusion made at the end of section (6.3.1). Hence, these strategies will not be matter of further investigations.

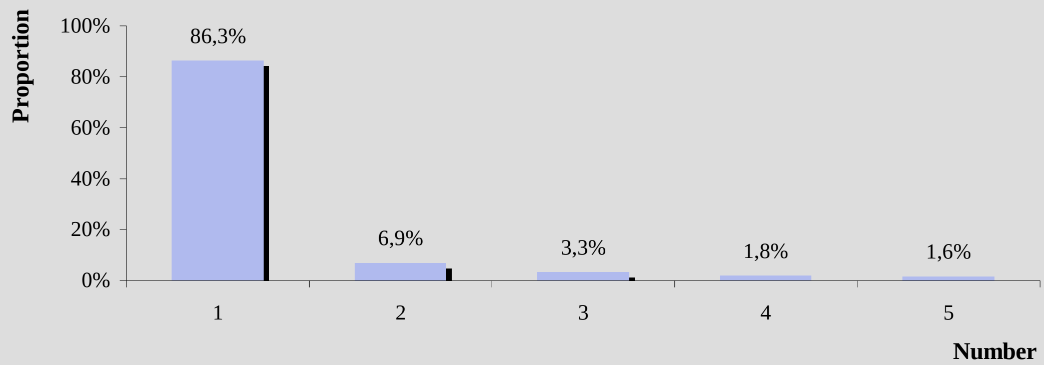
The principal component analysis of the clusters A, B and also C whereas, should lead to better results than the first PCA of all strategies. The repetition of the PCA to the clustered groups should result in the extraction of first principal components, which explain larger portions of the total variance among each dataset of strategies. Because the cluster A, consisting of the strategies "*Aggressive Growth*", "*Opportunistic*", "*Value*", "*Market Timing*" and "*Multi Strategy*" represents the group of "most similar" strategies, this cluster is subject to further factor analysis and time series analysis. The results of the factor analysis of the other clusters can be found in the appendix (47-48).

6.3.2 Principal Component Analysis of Cluster A

Fig. 37: Results – Principal Component Analysis of the clustered Strategies

	Eigenvalue	Difference	Proportion in %	Cumulative in %
1	4,315	3,969	86,30%	86,30%
2	0,346	0,180	6,92%	93,22%
3	0,165	0,074	3,31%	96,53%
4	0,091	0,009	1,83%	98,35%
5	0,082	0,082	1,65%	100,00%



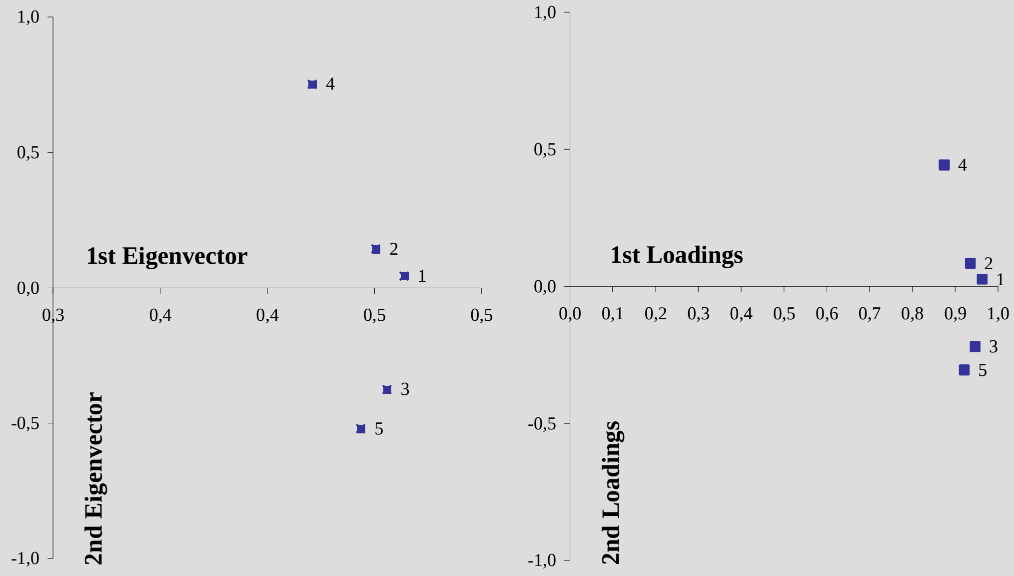


Source: Self-made figure, based on the data provided by the VAN Company.

The factor analysis of the datasets, which are grouped together in cluster A, obtains the desired explanatory power of the extracted first principle component. Already the first factor accounts for more than 85% of the total variance among the underlying dataset. The corresponding eigenvectors and their factor loadings are presented in figure 38:

Fig. 38: PCA of clustered Strategies – Eigenvectors and Factor Loadings

	Eigenvectors			Factor Loadings		
	1st	**2nd**	**3rd**	**1st**	**2nd**	**3rd**
1 Aggressive Growth	0,464	0,044	-0,111	0,963	0,026	-0,045
2 Opportunistic	0,451	0,143	-0,787	0,936	0,084	-0,320
3 Value	0,456	-0,375	0,093	0,947	-0,220	0,038
4 Market Timing	0,421	0,752	0,465	0,875	0,443	0,189
5 Multi-Strategy Index	0,444	-0,520	0,379	0,921	-0,306	0,154



Source: Self-made figure, based on the data provided by the VAN Company.

6.3.2.1 Stability Survey over Time

Besides the problem of the explanatory power of the first component, which the author had to face during the analysis of all hedge fund strategies, one has to cope with another problem within the underlying database. This additional problem is related to the stability of the performance characteristics among the clustered strategies during the time. Because the author wants to use the generated time series as a basis to build a time series model for the purpose of prediction, it has first to be proved, if the principal component shows the same characteristics over time. If this is not the case, the prediction would base on assumptions, which count for little in the future. Consequently, the prediction would not make sense.

For this reason, the author split the time series of the strategies within cluster A in two parts. On part contains the data of the period Jan.1995-Dec.1999 and the other part contains the data of the period Jan.2000-Dec.2004. If the factor analysis of these two datasets shows similar results, this points to stable connections within the complete underlying database. The analysis focused on the survey of the development of the eigenvalues, eigenvectors and their factor loadings. The results are presented and illustrated in the figures 49-51 in the appendix (stability survey). The main facts are summarized in the following:

- The development of the eigenvalues seems to be constant over time since the differences between each pair of eigenvalues does not exceed the margin of a tenth
- The portion of variance explained by each factor does not vary during the two periods (maximum deviation about 1%)
- By means of the linear regression of the first and second eigenvector in the periods 95-99 and 00-04, one can observe that the direction slightly changes (perfect fit is not reached by the runaway value of the market timing index)→ but it still indicates stable relationships over time
- Comparing the two regression lines of the factor loadings, strengthens the statement made on the basis of the regressions of eigenvectors, although the result is less significant

Over all, the results show that the main characteristics of the examined strategies seem to be stable over time. This means that the time series analysis of the clustered dataset makes sense for the purpose of prediction.

6.3.3 Time Series Analysis

The result of the factor analysis applied so far is an extracted factor, which explains as much as possible of the total variance among the group of examined strategies (86,3%). A time series, which is created by the factor loadings of this factor would consequently hold the main characteristic features of the examined strategies. Therefore, a model, which is able to explain and to reproduce this artificial time series can be used to predict the monthly returns of funds within this group of clustered hedge fund indices. Such a model can be estimated via time series analysis (in the following TSA). The focus of this section is:

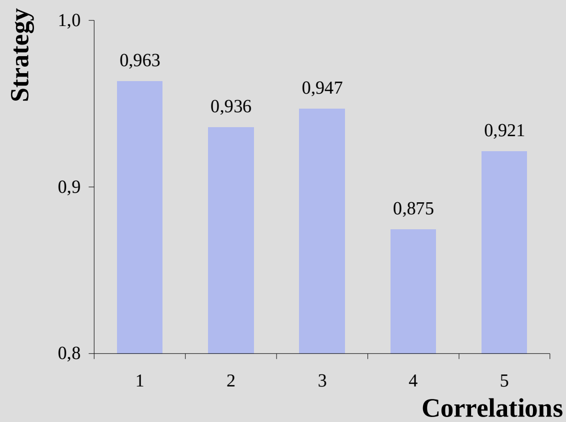
- Elaboration process of the time series model
- Evaluation of the estimated model.

At first the artificial dataset has to be generated in order to apply the time series analysis. The generation procedure is subject to the next paragraph 6.3.3.1.

6.3.3.1 Time Series Generation

Fig. 39: Time Series Generation – Factor Loadings of the first Eigenvector

	Factor Loadings 1st
1 Aggressive Growth	0,963
2 Opportunistic	0,936
3 Value	0,947
4 Market Timing	0,875
5 Multi-Strategy Index	0,921



The time series generation is based on the factor loadings of the first principle component. This means, the artificial dataset results from the correlation of each strategy and the first eigenvector. Consequently, the time series can be generated by the following general equation (6.2):

$$R_t = \frac{1}{k}\left(\beta_i f_{it} + \varepsilon_{it}\right) \quad i = 1,...,k \tag{6.2}$$

Where:

R_t	Monthly return on the generated time series (1,2,…,5) in time period t (t = Jan.1995,…,Dec.1999)
f_{it}	The i^{th} *factor realization* (i=1,…5) at time t, (t = Jan.1995,…,Dec.1999) represented by the realized return of the i^{th} strategy
β_i	The i^{th} *factor loading* represented by the factor correlation of strategy i (i=1,…,5)
ε_t	The *idiosyncratic error term* in time period t, (t = Jan.1995,…,Dec.1999)

In this special case, it follows that the time series will be generated according to equation (6.3), which is given next:

$$R_t = \frac{1}{5}\left(0{,}963 * r_{1t} + 0{,}936 * r_{2t} + 0{,}947 * r_{3t} + 0{,}875 * r_{4t} + 0{,}921 * r_{t5}\right) \tag{6.3}$$

The time series, which was generated by the application of equation (6.3) is illustrated in the figures 52 and 53 (in the appendix). Additionally, the realized monthly returns during this time period of the clustered hedge fund indices, which have been used to build equation (6.3) are presented.

6.3.3.2 Time Series Analysis

This section deals with the analysis of the time series, generated in part 6.3.3.1. A deeper look at the plot of the artificial time series, represented in the figures 52 and 53 of the appendix, gives first indications for the nature of the series.

1. One can see that the plot varies around a constant level. Consequently, neither a positive nor a negative trend is observable within the period of 01/95 to 12/04. This obvious fact leads to the conclusion of a

stationary series. Therefore, one possibly does not have to consider an integrated ARMA process (→ARIMA (p, 0, q)).

2. Additionally, the time series does not show any regularity in the variance during the examined time period. This excludes the possibility of a seasonal behavior among the hedge fund returns.

These two assumptions are strengthened by the results of the Dickey-Fuller single mean test for both, stationarity and seasonality within the time series. The results of the unit root test (0,001 at lag 1) as well as the result of the seasonal root test (0,001 at lag 1), lead to the conclusion that stationarity as well as stationary seasonality is likely at a significance level of 0,05. This already points to a time series, which is difficult to reproduce by the application of an ARMA-process. A closer look at the autocorrelations as well as the partial autocorrelations of the examined time series will give more information about the underlying characteristics of the series. These correlations are represented in the figures 54 and 55 of the appendix. The main facts of the examination of the autocorrelations and partial autocorrelations are presented next:

- The time series generally shows weak autocorrelations as well as weak partial autocorrelations
- Both, autocorrelation as well as partial autocorrelation show values, which are statistically different from zero at lag one → this points to an underlying ARMA(1,1) process
- The autocorrelations among the lags 2 to 24 do not exceed the amount of $\pm 0{,}16$
- The partial autocorrelations among the lags 2 to 24 do not exceed the amount of $\pm 0{,}2$
- The manner of autocorrelation as well as partial autocorrelation does not show any regularity in terms of intensity and direction (positive/negative) among the 24 examined lags

6.3.3.3 MODEL ESTIMATION

All the information collected so far, point to difficulties in modeling the underlying generated time series by ARIMA procedures. The following figure represents the results of the application of an ARMA(1,1)-process. The corresponding predictions, made by the application of the estimated model, are represented in the figures 56 and 57.

Fig. 40: Results – ARIMA Modeling

Parameter Estimates of an ARMA(1,1)-Process
(Evaluation Range: Jan. 1995 - Dec. 2004)

Model Parameter	Estimate	Std. Error	T	Prob > │T│ in %
Intercept	0,0117	0,0031	3,7188	0,03%
Moving Average (MA), Lag	0,1035	0,4787	0,2161	82,93%
Autoregressive (AR), Lag 1	0,2901	0,4605	0,6301	52,99%
Model Variance (σ2)	0,0007			

Statistics of an ARMA(1,1)-Process Fit
(Evaluation Range: Jan. 1995 - Dec. 2004)

Statistic of Fit	Value
Mean Square Error	0,0007
Root Mean Square Error	0,0271
Mean Absolut Error	0,0205
Mean Absolut Error (%)	1,4034
R-Square	0,0370

Source: Self-made figure, based on the data provided by the VAN Company.

The parameter estimates, presented in figure 40, show that the ARMA(1,1) model is not able to capture the performance characteristics of the analyzed time series properly. In particular, the standard errors of the MA and AR parameter emphasize this observation. Comparing the standard error with each estimated parameter makes clear that the error is greater than the estimated value itself.

What this means to the predictions of the model itself can be seen in the figures 56 and 57. One can clearly observe that the generated time series (red line) shows a sharp zigzag pattern, while the blue line (representing the ARMA-model predictions) runs at very flat level. This means, the model is not able to capture the high volatility of the generated time series. Consequently, forecasts made by this model would probably overestimate or underestimate the real value by far, so that the model finally is not suitable to anticipate the returns of hedge funds.

7 SUMMARY AND CONCLUSION

7.1 Conclusion and Insights of this Work

In the final chapter, the author would like to summarize the insights achieved by this thesis. These are differentiated into general perceptions and personal insights achieved by the author during this work.

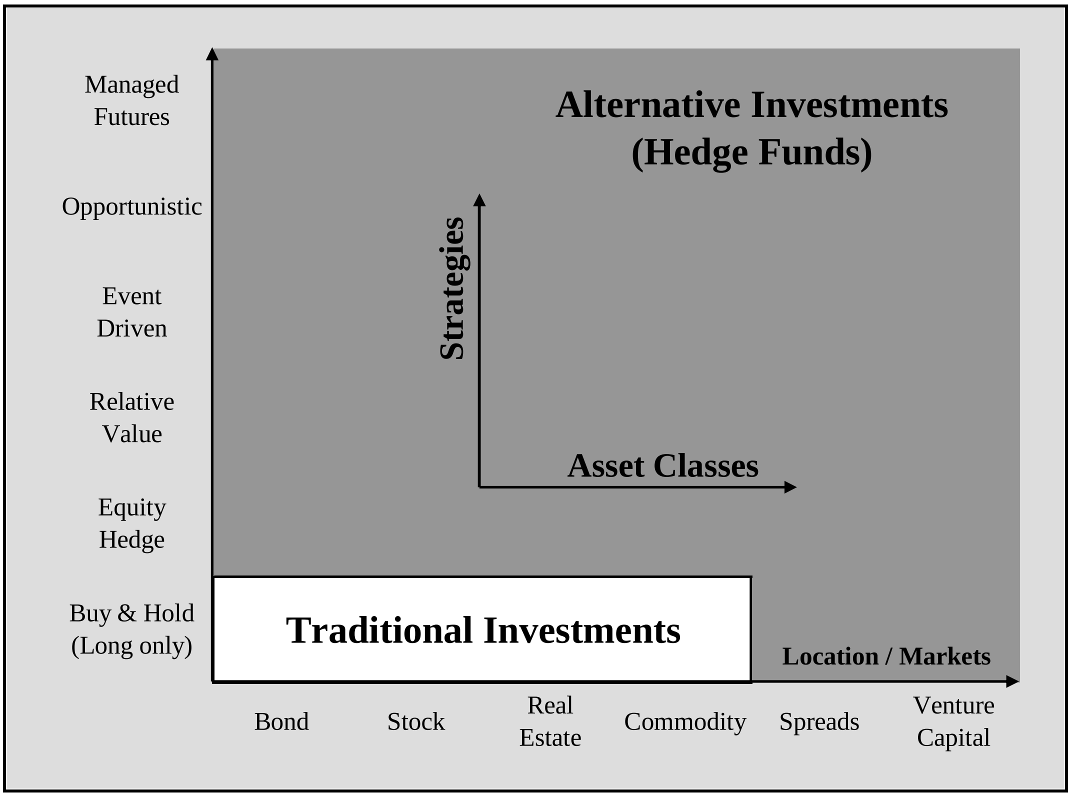
7.1.1 General Insights of the financial Product: "Hedge Fund"

The extraordinary performance of HF, which differs from the returns of traditional asset classes, forms the major reason why HF's became so popular at the beginning. Not least the political discussion in Germany about the so-called "Heuschrecken", which included also the managers of HF's has lead to the common use of the term "hedge fund" today. As the author has shown within the thesis, this term can be very misleading today. Therefore, it is not surprising that this kind of investment vehicle is often misunderstood and consequently wrongly judged.

For this reason, one objective of this diploma thesis was to explore the different areas of hedge fund research. In particular this includes the description and the explanation of their unusual return characteristics. Consequently, one important insight of this work is the definition of the term hedge fund itself. In the second chapter the author presented a clear definition for the term hedge fund. Through the thesis, hedge funds were defined as all forms of investment funds, companies and private partnerships that make use of derivates for directional investing, which are allowed to go short and additionally use a significant portion of leverage through borrowing.

Besides the definition of the term itself has emerged another problem. This kind of definition dilutes the differentiation of hedge funds from traditional investments. Additionally, the definition does not clearly explain the origin of the unique performance characteristics of hedge funds. For example, hedge funds act in similar markets as mutual funds and also take positions in traditional investment vehicles, but still they can not be differentiated just by the kind of positions a fund manager acquires. In order to find out, what forms the original difference of hedge funds, the author delivered the insight of the term investment style. By additionally considering this term, it is possible to explain on the hand the unique performance characteristics of this particular investment vehicle. On the other hand, it is possible to differentiate hedge funds from traditional investments through the use of the term investment style. Put differently, hedge fund returns differs from conventional assets not because they invest in different assets but because of the way the underlying investments are managed. This insight is illustrated in the following figure:

Fig. 41: Traditional Investments – Alternative Investments



Source: Joint Seminar "Asset Management and Benchmarks", March 5-7, 2003, Tokyo. The content of the presentation represents co-study by William Fung and David A. Hsieh. http://www.saa.or.jp/english/fung.pdf (06/2005)

7.1.2 General Insights of Equity Factor Models

On the basis of the gained perceptions into the matter of the hedge fund industry, the author set up priorities in the modeling of hedge fund returns. Hence, another objective of this thesis was to present a general overview of multi factor models, which are used to describe the extraordinary performance characteristics of HF's. Insights into this subject are provided in the chapter's three to five. The main facts of these parts are summarized in this paragraph.

The author showed that the application range of multifactor models is not limited to the area of equity factor models. But, starting from the "Capital Asset Pricing Model", multi factor models are indispensable in economic model building processes these days. The reasons, why factor models have found the way into the application to economic matters, are one important insight of this part of the thesis. During the third chapter, the author presented the great variety of multi factor models. This variety is determined by the multitude of different and applicable factors. Finally, this leads to a wide adaptability of this model class. On the other hand, the author showed the simplicity and parsimony of these models. For sure, this combination is the main reason, why these models are well received by model builders.

After explaining the organizational structure of equity factor models in general, the author directed attention to the modeling of the return generating process in the special case of HF's. The chapters four and five deal with this matter. Thereby, the perception gained from the fourth chapter is that traditional factor models, such as Sharpe's asset class model, are not able to capture the return behavior of HF's. The failure of traditional factor models is based on the fact that HF's differ from traditional investment vehicles due to their dynamic trading strategies. These dynamic trading strategies lead to a non-linear return behavior, which can not be reproduced by traditional (linear) factor models.

In order to cope with this problem, the economists William Fung and David A. Hsieh recommend the utilization of asset based style factors within multi factor models for hedge fund returns. They elaborated a particular methodology to capture the special return behavior of hedge funds by means of a certain hedge fund strategy, referred to as the trend following strategy. This methodology as well as the definition of the term “asset based style factor” itself were presented in chapter five. Due to the presentation and explanation of this methodology, this paragraph provided the perception that factor models are able to capture the performance characteristics of hedge funds, if the model uses asset based style factors. This fact was proved by FH during an empirical analysis, which was presented at the end of the fifth chapter.

7.1.3 Perceptions gained by the empirical Analysis and personal Insights

The last part included an empirical analysis, which is subdivided into two parts. One part consisted of a descriptive examination of the underlying hedge fund database and the second part dealt with the elaboration of a forecasting model. Due to the descriptive part, the author obtained some surprising insights into the performance characteristics of the examined hedge funds.

The access to hedge funds as well as the capacity of hedge fund managers to act is still limited in Germany today. Despite these restrictions hedge funds already developed into an essential enlargement of the traditional investment range. Due to their unique performance characteristics, shown in the descriptive analysis part, hedge funds provide the possibility to enhance the efficiency of portfolios of institutional investors. Although hedge funds are often publicly denounced as investments, which are exposed to high amounts of risks, the results of the descriptive analysis showed another picture of this investment vehicle. Most of the examined hedge fund indices owned higher Sharpe ratios than the market.[49] From the author’s point of view, the adjustment of the German environment for the establishment and utilization of hedge funds to international standards forms an essential move to reduce the regional disadvantage. In the end, institutional as well as private market participants should be able to take advantage of this particular investment vehicle.

[49] Here, the author wants to point out that these results are probably diluted by database biases. On the other hand, it is unlikely that the database shows an image, which is completely different from reality on basis of these clear results. Hence, conclusions can be drawn.

At the beginning of the second part of the empirical analysis, the author wanted elaborate a model, which should be able to forecast reliable hedge fund returns. But in the end, the achieved results were quite different from this ambitious aim.

The results of the factor analysis as well as the cluster analysis were very auspicious at first. Most of the examined hedge fund strategies could be assigned to a certain group of funds, which owns similar performance characteristics. Consequently, these results pointed to common risk factors within each clustered group of strategies. In turn, these risk factors should be captured by the application of time series analysis to form a particular multi factor model.

The fact that the first principle component, estimated via factor analysis of the hedge fund strategies “Aggressive Growth”, “Opportunistic”, “Value”, “Market Timing” and “Multi Strategy” is able explain more than 85% of the total variability of the examined group of funds, supported the expectation of promising results of the time series analysis. But finally, the results of the time series analysis have been very disappointing. The ARMA(1,1) model, presented in section 6.3.3.3 served as representative for the class of ARIMA models. The parameter estimates of the ARMA model showed that the class of ARIMA models is not able to capture the characteristics of the examined group of hedge fund strategies.

8 APPENDIX

Fig. 42: Descriptive Statistics – Summary

Index	Mean	Std Dev	Variance	Min Return	Max Return	Median	Range	Skewness	Kurtosis	Sharpe Ratio
Event-Driven	14,7%	9,3%	0,9%	-2,3%	24,2%	17,8%	26,5%	-0,81	-0,66	1,58
Distressed Securities	14,6%	8,7%	0,8%	1,8%	27,4%	17,6%	25,6%	-0,41	-1,04	1,67
Special Situations	14,8%	10,9%	1,2%	-5,4%	27,0%	18,9%	32,3%	-0,72	-0,70	1,36
Market Neutral Arbitrage	12,1%	5,7%	0,3%	3,6%	20,1%	10,3%	16,5%	0,12	-1,37	2,13
Convertible Arbitrage	13,6%	6,1%	0,4%	1,0%	21,6%	16,4%	20,6%	-0,96	0,74	2,24
Fixed Income Arbitrage	11,9%	6,9%	0,5%	-1,2%	20,4%	10,1%	21,6%	-0,42	-0,33	1,72
Aggressive Growth	18,7%	25,4%	6,4%	-12,0%	72,9%	17,5%	84,9%	0,89	1,21	0,74
Market Neutral Securities	13,8%	6,9%	0,5%	6,0%	25,3%	14,1%	19,2%	0,24	-1,50	1,99
Opportunistic	17,7%	14,6%	2,3%	-0,5%	50,5%	18,7%	51,0%	1,14	2,07	1,21
Value	18,2%	12,5%	1,6%	-4,7%	41,6%	19,1%	46,3%	0,05	1,02	1,46
Global/Macro	8,4%	14,1%	2,0%	-13,6%	36,5%	4,3%	50,1%	0,58	0,67	0,60
Market Timing	13,4%	10,0%	1,0%	0,9%	32,7%	13,5%	31,7%	0,54	0,05	1,35
Futures	13,8%	7,3%	0,5%	-0,2%	22,7%	15,8%	22,9%	-0,80	-0,29	1,89
Emerging Markets	12,0%	27,8%	7,8%	-28,0%	69,6%	7,3%	97,7%	0,88	0,99	0,43
Income	8,6%	4,1%	0,2%	-1,0%	15,8%	9,0%	16,8%	-1,02	4,01	2,08
Multi-Strategy Index	13,9%	11,6%	1,3%	-3,3%	39,5%	12,0%	42,8%	0,99	2,08	1,20
Short Selling	-2,9%	18,8%	3,5%	-24,4%	26,5%	-9,5%	51,0%	0,48	-1,56	-0,16
S&P 500	14,0%	21,1%	4,5%	-22,1%	37,6%	22,0%	59,7%	-0,73	-1,05	0,66
US 90 Day Treasury Bills	3,8%	1,8%	0,0%	1,0%	5,9%	4,7%	4,8%	-0,68	-1,41	2,08

Source: Self-made figure, based on the data provided by the VAN Company, BARRA Inc. and the Federal Reserve.

Fig. 43: Correlation Matrix – Principle Component Analysis 1995-2004

	Index	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1	Event-Driven	-	0,82	0,99	0,64	0,53	0,28	0,79	0,61	0,82	0,84	0,61	0,63	-0,12	0,68	0,63	0,80	-0,75
2	Distressed Securities	0,82	-	0,71	0,54	0,51	0,32	0,52	0,42	0,59	0,64	0,48	0,38	-0,10	0,58	0,55	0,59	-0,53
3	Special Situations	0,99	0,71	-	0,63	0,51	0,25	0,82	0,63	0,84	0,85	0,61	0,66	-0,12	0,67	0,61	0,81	-0,76
4	Market Neutral Arbitrage	0,64	0,54	0,63	-	0,72	0,47	0,56	0,57	0,58	0,57	0,60	0,53	0,09	0,53	0,49	0,57	-0,41
5	Convertible Arbitrage	0,53	0,51	0,51	0,72	-	0,46	0,35	0,39	0,41	0,44	0,36	0,29	-0,04	0,36	0,41	0,45	-0,26
6	Fixed Income Arbitrage	0,28	0,32	0,25	0,47	0,46	-	0,13	0,25	0,22	0,17	0,29	0,04	0,04	0,19	0,29	0,23	0,03
7	Aggressive Growth	0,79	0,52	0,82	0,56	0,35	0,13	-	0,61	0,89	0,89	0,62	0,83	-0,08	0,64	0,45	0,86	-0,89
8	Market Neutral Securities	0,61	0,42	0,63	0,57	0,39	0,25	0,61	-	0,69	0,55	0,55	0,58	0,09	0,47	0,44	0,52	-0,45
9	Opportunistic	0,82	0,59	0,84	0,58	0,41	0,22	0,89	0,69	-	0,85	0,67	0,80	-0,01	0,69	0,46	0,80	-0,78
10	Value	0,84	0,64	0,85	0,57	0,44	0,17	0,89	0,55	0,85	-	0,59	0,74	-0,13	0,74	0,54	0,91	-0,85
11	Global / Macro	0,61	0,48	0,61	0,60	0,36	0,29	0,62	0,55	0,67	0,59	-	0,58	0,20	0,63	0,40	0,56	-0,48
12	Market Timing	0,63	0,38	0,66	0,53	0,29	0,04	0,83	0,58	0,80	0,74	0,58	-	0,12	0,60	0,42	0,70	-0,72
13	Futures	-0,12	-0,10	-0,12	0,09	-0,04	0,04	-0,08	0,09	-0,01	-0,13	0,20	0,12	-	-0,03	0,07	-0,15	0,15
14	Emerging Markets	0,68	0,58	0,67	0,53	0,36	0,19	0,64	0,47	0,69	0,74	0,63	0,60	-0,03	-	0,59	0,71	-0,62
15	Income	0,63	0,55	0,61	0,49	0,41	0,29	0,45	0,44	0,46	0,54	0,40	0,42	0,07	0,59	-	0,51	-0,47
16	Multi-Strategy Index	0,80	0,59	0,81	0,57	0,45	0,23	0,86	0,52	0,80	0,91	0,56	0,70	-0,15	0,71	0,51	-	-0,80
17	Short Selling	-0,75	-0,53	-0,76	-0,41	-0,26	0,03	-0,89	-0,45	-0,78	-0,85	-0,48	-0,72	0,15	-0,62	-0,47	-0,80	-
	Average Intensity of |Corr.|	*0,66*	*0,52*	*0,65*	*0,53*	*0,41*	*0,23*	*0,62*	*0,49*	*0,63*	*0,64*	*0,51*	*0,54*	***0,10***	*0,54*	*0,46*	*0,62*	*0,56*

Source: Self-made figure, based on the data provided by the VAN Company.

Fig. 44: Cluster Analysis – Factor Loadings Matrix

	Index	1st Factor	2nd Factor	3rd Factor	4th Factor	5th Factor
1	Event-Driven	0,931	0,233	-0,169	0,112	-0,063
2	Distressed Securities	0,737	0,202	-0,286	0,298	-0,025
3	Special Situations	0,928	-0,034	-0,126	0,042	-0,065
4	Market Neutral Arbitrage	0,736	0,461	0,068	-0,200	-0,165
5	Convertible Arbitrage	0,567	0,566	-0,210	-0,200	-0,370
6	Fixed Income Arbitrage	0,310	0,740	-0,122	-0,163	0,437
7	Aggressive Growth	0,900	-0,302	0,066	-0,172	0,026
8	Market Neutral Securities	0,701	0,118	0,256	-0,205	-0,130
9	Opportunistic	0,913	-0,153	0,118	-0,135	0,061
10	Value	0,922	-0,208	-0,081	-0,009	0,030
11	Global / Macro	0,724	0,142	0,351	-0,038	0,307
12	Market Timing	0,788	-0,268	0,335	-0,146	-0,079
13	Futures	-0,042	0,268	0,860	0,248	-0,114
14	Emerging Markets	0,788	-0,043	0,024	0,259	0,237
15	Income	0,653	0,225	-0,041	0,557	-0,106
16	Multi-Strategy Index	0,890	-0,166	-0,113	-0,067	0,079
17	Short Selling	-0,819	0,433	0,065	-0,030	0,042

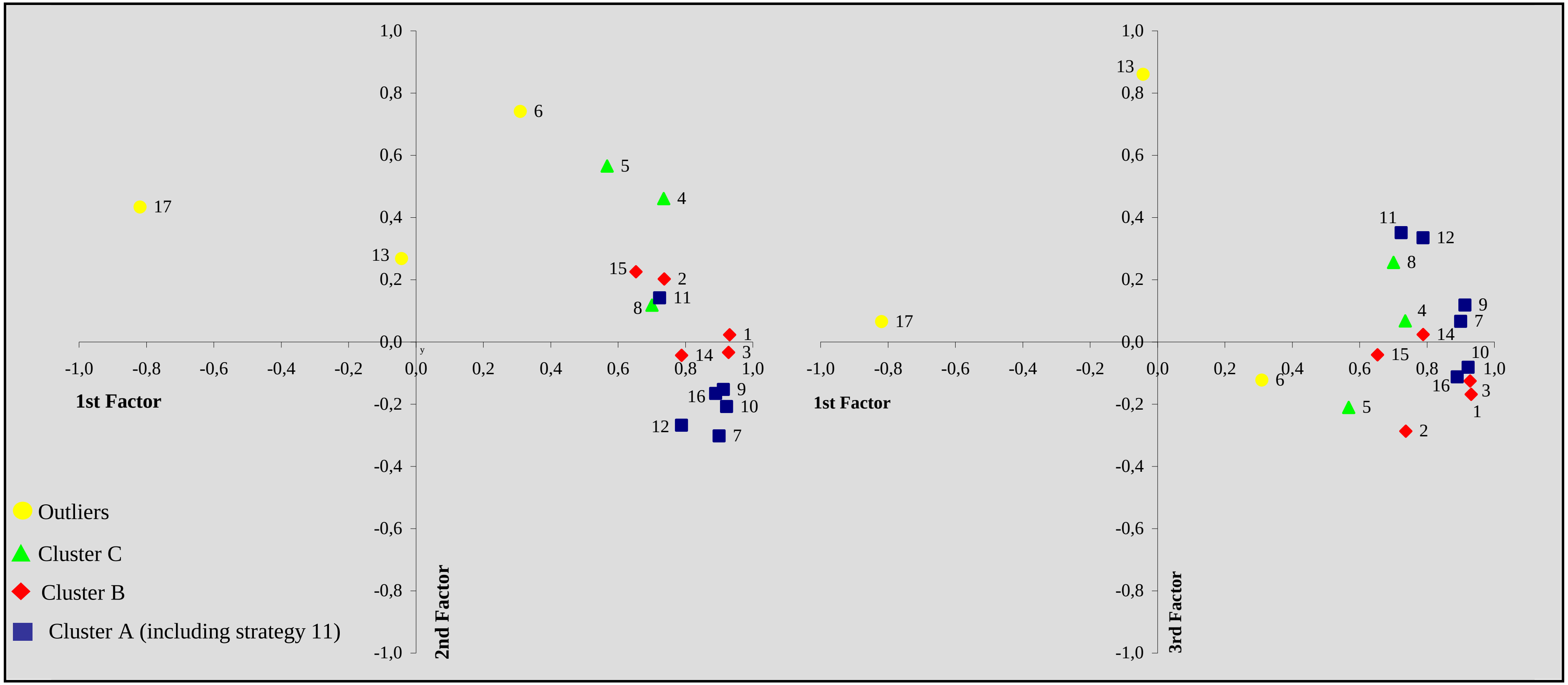
Source: Self-made figure, based on the data provided by the VAN Company.

Fig. 45: Cluster Analysis – Euclid-Distance Matrix

	Index	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Event-Driven	-	0,30	0,28	0,50	0,66	0,99	0,66	0,59	0,56	0,48	0,69	0,77	1,42	0,50	0,54	0,47	1,79
2	Distressed Securities	0,30	-	0,43	0,68	0,73	0,96	0,79	0,75	0,72	0,58	0,80	0,90	1,39	0,48	0,38	0,58	1,65
3	Special Situations	0,28	0,43	-	0,62	0,81	1,13	0,40	0,53	0,35	0,21	0,67	0,57	1,43	0,43	0,65	0,23	1,82
4	Market Neutral Arbitrage	0,50	0,68	0,62	-	0,40	0,81	0,80	0,39	0,68	0,76	0,66	0,78	1,21	0,79	0,81	0,73	1,58
5	Convertible Arbitrage	0,66	0,73	0,81	0,40	-	0,87	1,05	0,70	0,97	0,97	1,00	1,06	1,37	1,03	0,89	0,93	1,49
6	Fixed Income Arbitrage	0,99	0,96	1,13	0,81	0,87	-	1,28	1,00	1,17	1,21	0,89	1,31	1,34	1,04	1,10	1,14	1,26
7	Aggressive Growth	0,66	0,79	0,40	0,80	1,05	1,28	-	0,53	0,17	0,24	0,64	0,31	1,43	0,56	0,95	0,25	1,87
8	Market Neutral Securities	0,59	0,75	0,53	0,39	0,70	1,00	0,53	-	0,42	0,58	0,48	0,41	1,07	0,66	0,83	0,56	1,58
9	Opportunistic	0,56	0,72	0,35	0,68	0,97	1,17	0,17	0,42	-	0,24	0,50	0,31	1,35	0,47	0,86	0,24	1,83
10	Value	0,48	0,58	0,21	0,76	0,97	1,21	0,24	0,58	0,24	-	0,65	0,48	1,46	0,41	0,78	0,10	1,86
11	Global / Macro	0,69	0,80	0,67	0,66	1,00	0,89	0,64	0,48	0,50	0,65	-	0,58	1,06	0,49	0,83	0,62	1,62
12	Market Timing	0,77	0,90	0,57	0,78	1,06	1,31	0,31	0,41	0,31	0,48	0,58	-	1,19	0,64	0,95	0,50	1,78
13	Futures	1,42	1,39	1,43	1,21	1,37	1,34	1,43	1,07	1,35	1,46	1,06	1,19	-	1,27	1,18	1,46	1,17
14	Emerging Markets	0,50	0,48	0,43	0,79	1,03	1,04	0,56	0,66	0,47	0,41	0,49	0,64	1,27	-	0,55	0,42	1,71
15	Income	0,54	0,38	0,65	0,81	0,89	1,10	0,95	0,83	0,86	0,78	0,83	0,95	1,18	0,55	-	0,80	1,61
16	Multi-Strategy Index	0,47	0,58	0,23	0,73	0,93	1,14	0,25	0,56	0,24	0,10	0,62	0,50	1,46	0,42	0,80	-	1,82
17	Short Selling	1,79	1,65	1,82	1,58	1,49	1,26	1,87	1,58	1,83	1,86	1,62	1,78	1,17	1,71	1,61	1,82	-

Source: Self-made figure, based on the data provided by the VAN Company.

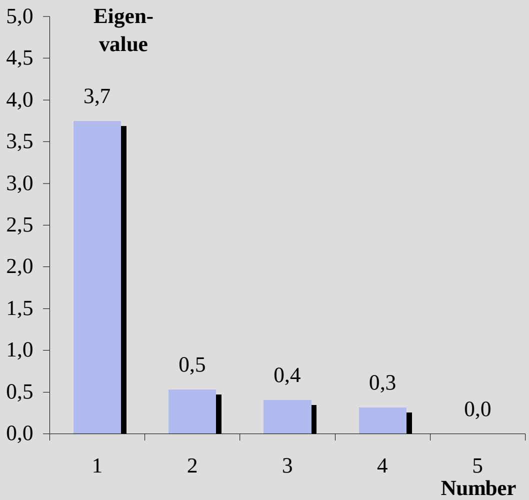
Fig. 46: Cluster Analysis – Plot of 1st and 2nd Main-Plane

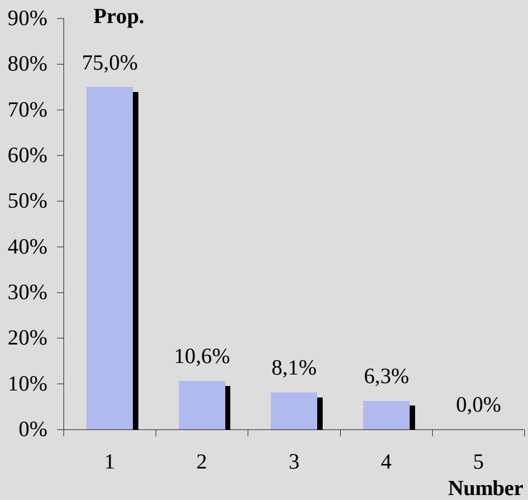


Source: Self-made figure, based on the data provided by the VAN Company.

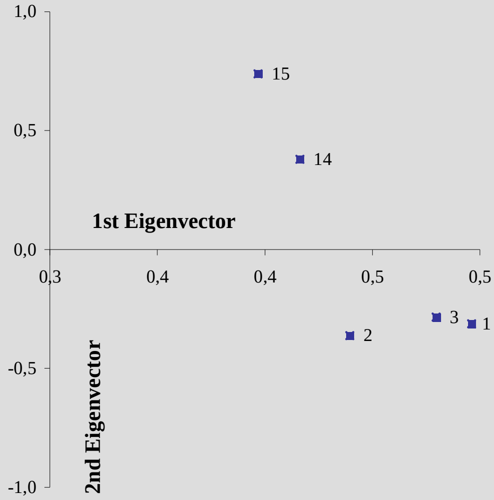
Fig. 47: Results – PCA of Cluster B

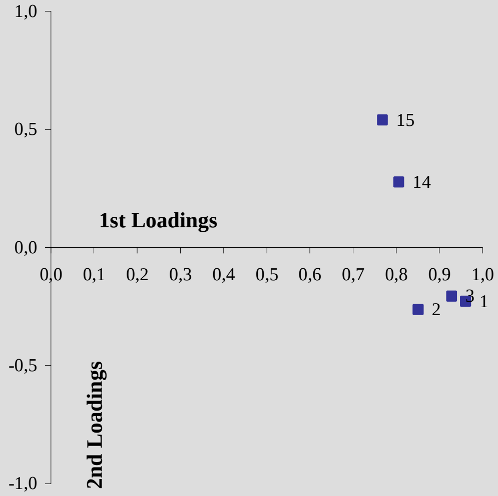
	Eigenvalue	Difference	Proportion in %	Cumulative in %
1	3,749	3,218	74,97%	74,97%
2	0,531	0,125	10,61%	85,58%
3	0,406	0,092	8,11%	93,70%
4	0,314	0,312	6,28%	99,97%
5	0,001		0,03%	100,00%





	Eigenvectors			Factor Loadings		
	1st	**2nd**	**3rd**	**1st**	**2nd**	**3rd**
1 Event Driven	0,496	-0,313	0,058	0,961	-0,228	0,037
2 Distressed Securities	0,439	-0,362	0,222	0,851	-0,264	0,141
3 Special Situations	0,480	-0,284	-0,012	0,929	-0,207	-0,008
14 Emerging Markets	0,416	0,379	-0,807	0,806	0,276	-0,514
15 Income	0,397	0,739	0,543	0,768	0,538	0,346

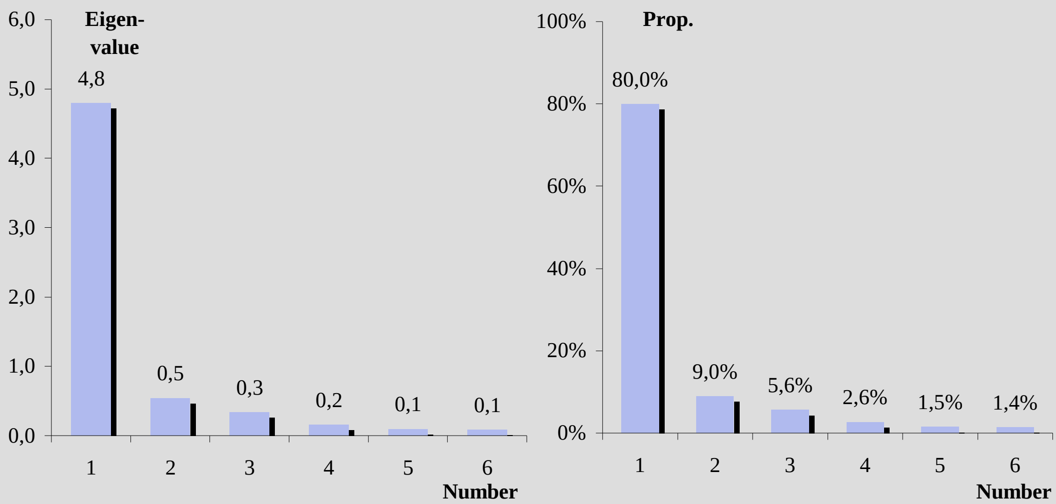




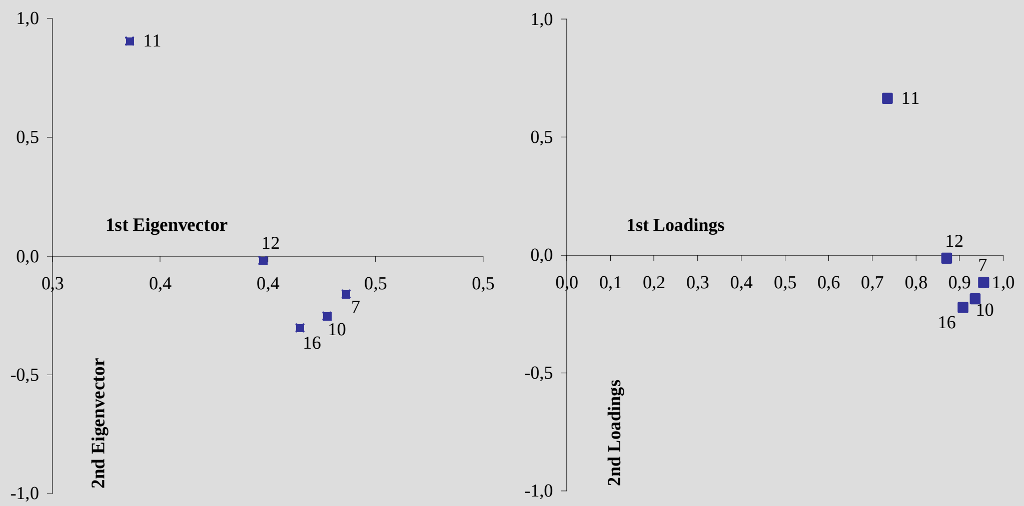
Source: Self-made figure, based on the data provided by the VAN Company.

Fig. 48: Results – PCA of Cluster A including strategy 11

	Eigenvalue	Difference	Proportion in %	Cumulative in %
1	4,797	4,259	79,95%	79,95%
2	0,538	0,203	8,97%	88,92%
3	0,335	0,178	5,58%	94,51%
4	0,157	0,067	2,62%	97,12%
5	0,090	0,008	1,51%	98,63%
6	0,082		1,37%	100,00%



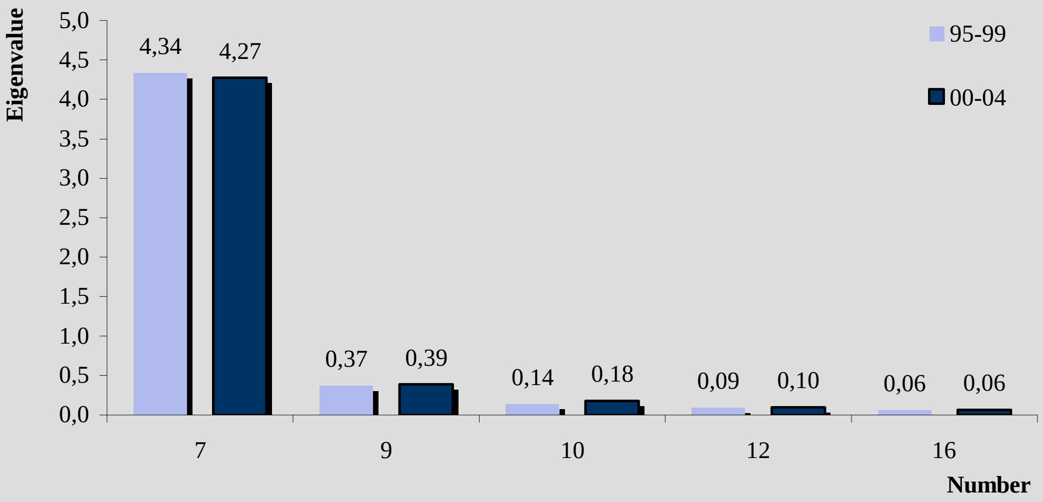
	Eigenvectors			Factor Loadings		
	1st	2nd	3rd	1st	2nd	3rd
7 Aggressive Growth	0,436	-0,159	-0,083	0,956	-0,117	-0,048
9 Opportunistic	0,429	0,013	-0,108	0,939	0,011	-0,062
10 Value	0,428	-0,253	0,323	0,936	-0,185	0,187
11 Global/Macro	0,336	0,905	0,213	0,735	0,664	0,123
12 Market Timing	0,398	-0,018	-0,792	0,871	-0,013	-0,458
16 Multi-Strategy Index	0,415	-0,302	0,453	0,909	-0,222	0,262

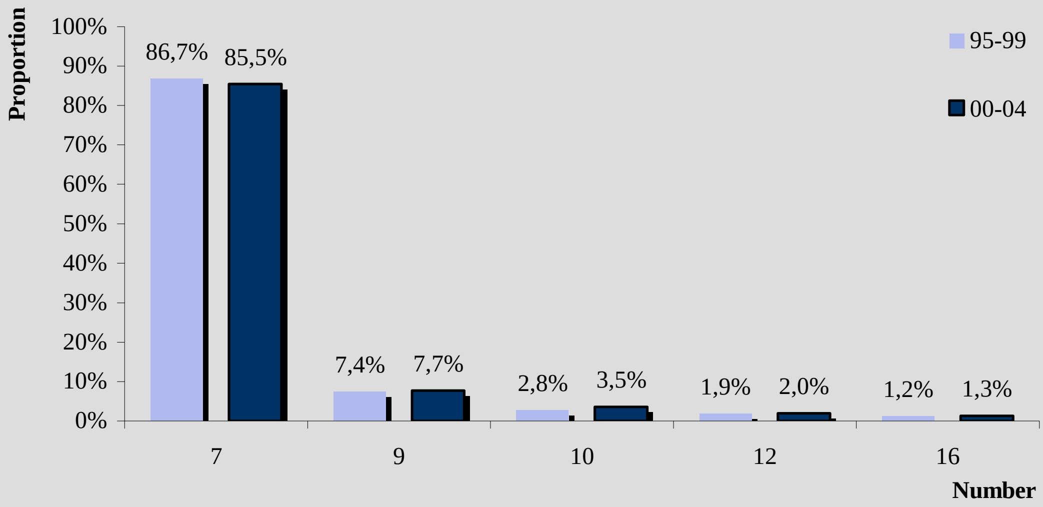


Source: Self-made figure, based on the data provided by the VAN Company.

Fig. 49: Stability Survey – Eigenvectors Development

	Eigenvalue		Difference		Proportion in %		Cumulative in %	
	95-99	**00-04**	**95-99**	**00-04**	**95-99**	**00-04**	**95-99**	**00-04**
7	4,34	4,27	3,97	3,89	86,73%	85,47%	86,73%	85,47%
9	0,37	0,39	0,23	0,21	7,37%	7,74%	94,10%	93,21%
10	0,14	0,18	0,04	0,08	2,79%	3,55%	96,88%	96,76%
12	0,09	0,10	0,03	0,04	1,90%	1,97%	98,78%	98,74%
16	0,06	0,06	0,06	0,06	1,22%	1,26%	100,00%	100,00%

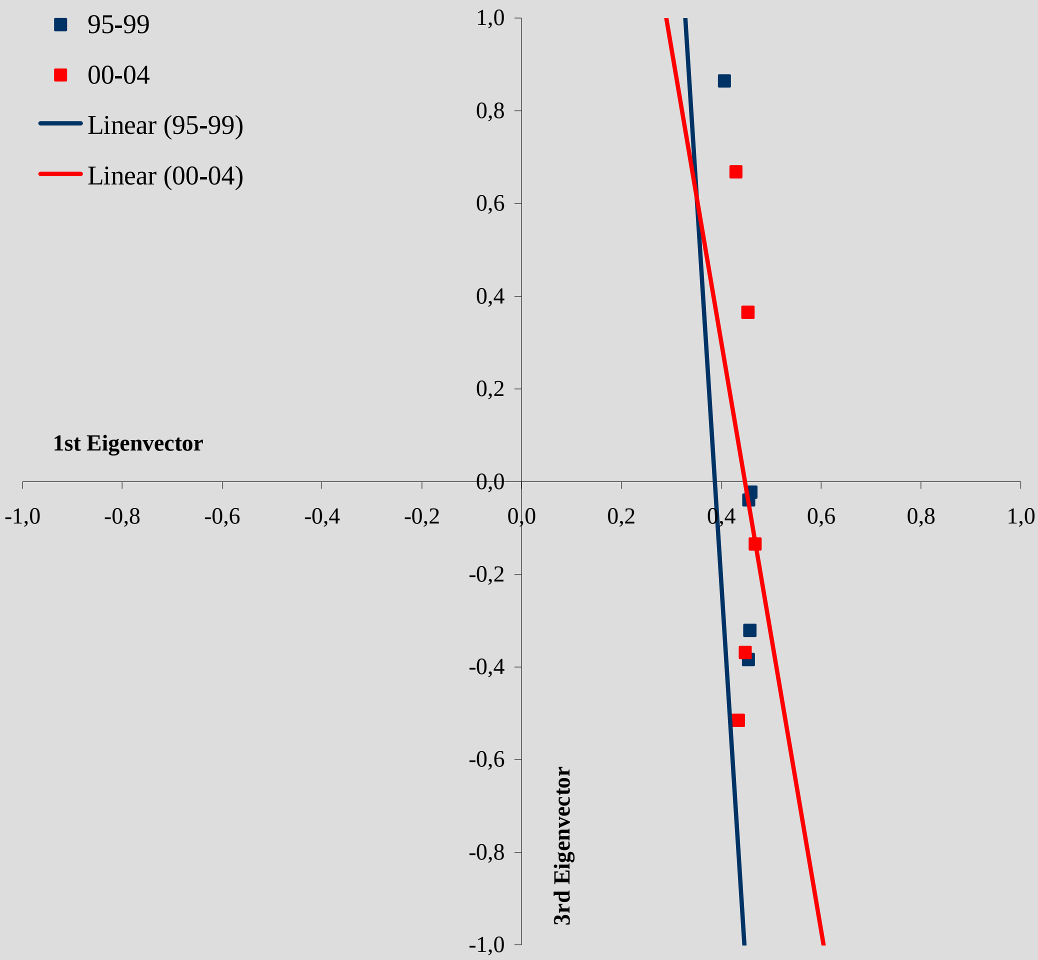




Source: Self-made figure, based on the data provided by the VAN Company.

Fig. 50: Stability Survey - Plot of Eigenvectors 1 and 2

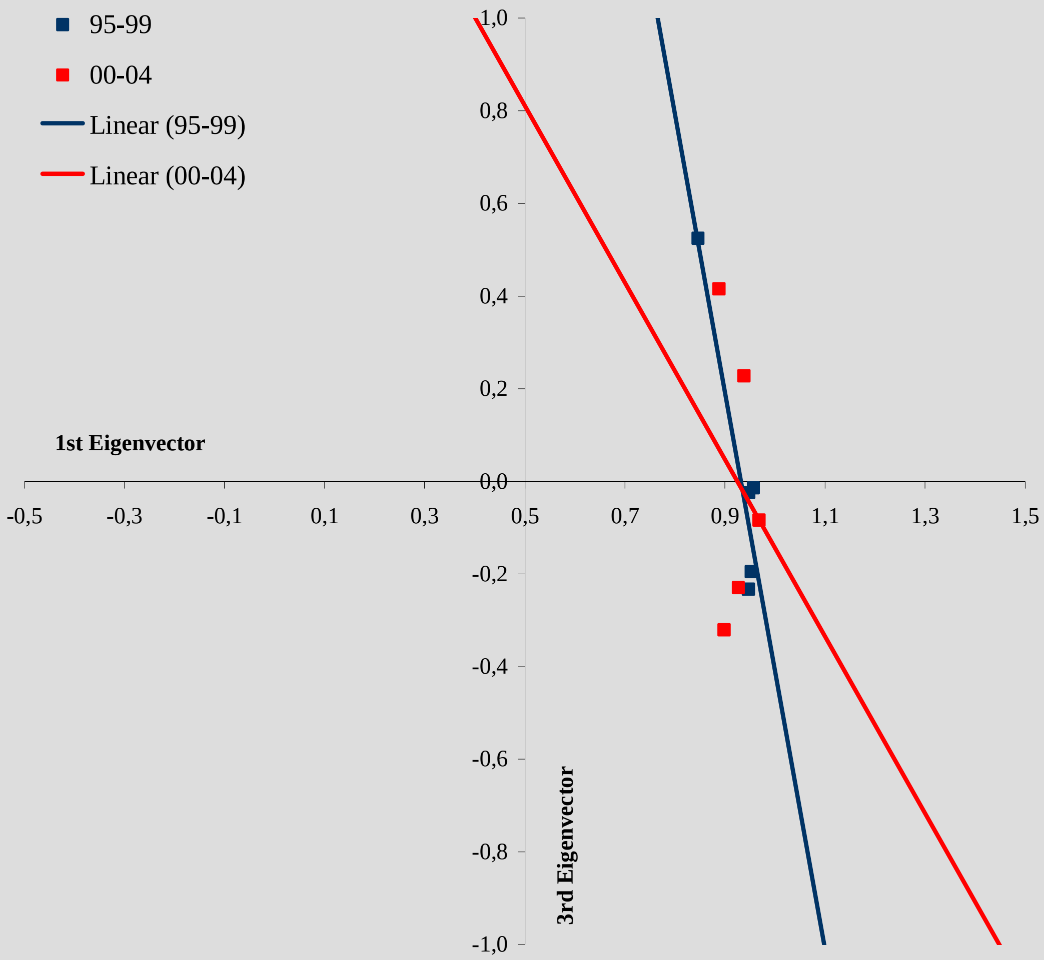
	Eigenvectors 95-99			Eigenvectors 00-04		
	1st	**2nd**	**3rd**	**1st**	**2nd**	**3rd**
7 Aggressive Growth	0,460	-0,023	-0,505	0,468	-0,135	-0,077
9 Opportunistic	0,455	-0,040	0,788	0,448	-0,369	-0,631
10 Value	0,458	-0,322	-0,333	0,454	0,365	-0,220
12 Market Timing	0,406	0,864	-0,054	0,435	-0,515	0,683
16 Multi-Strategy Index	0,455	-0,384	0,105	0,430	0,668	0,284



Source: Self-made figure, based on the data provided by the VAN Company

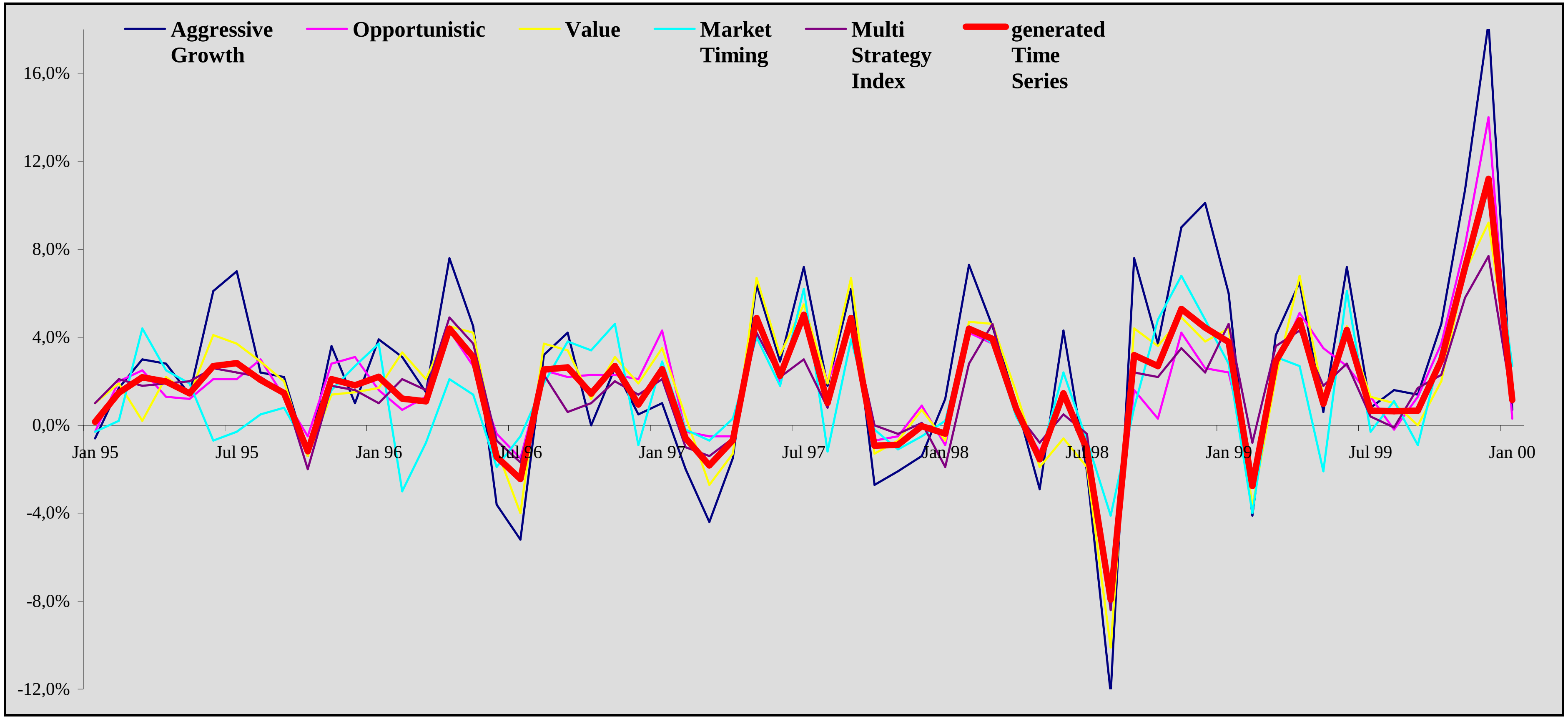
Fig. 51: Stability Survey - Plot of Factor Loadings

	Factor Loadings 95-99			Factor Loadings 00-04		
	1st	**2nd**	**3rd**	**1st**	**2nd**	**3rd**
7 Aggressive Growth	0,957	-0,014	-0,188	0,968	-0,084	-0,032
9 Opportunistic	0,948	-0,024	0,294	0,927	-0,230	-0,266
10 Value	0,953	-0,195	-0,124	0,938	0,227	-0,093
12 Market Timing	0,846	0,524	-0,020	0,899	-0,321	0,288
16 Multi-Strategy Index	0,948	-0,233	0,039	0,888	0,416	0,120



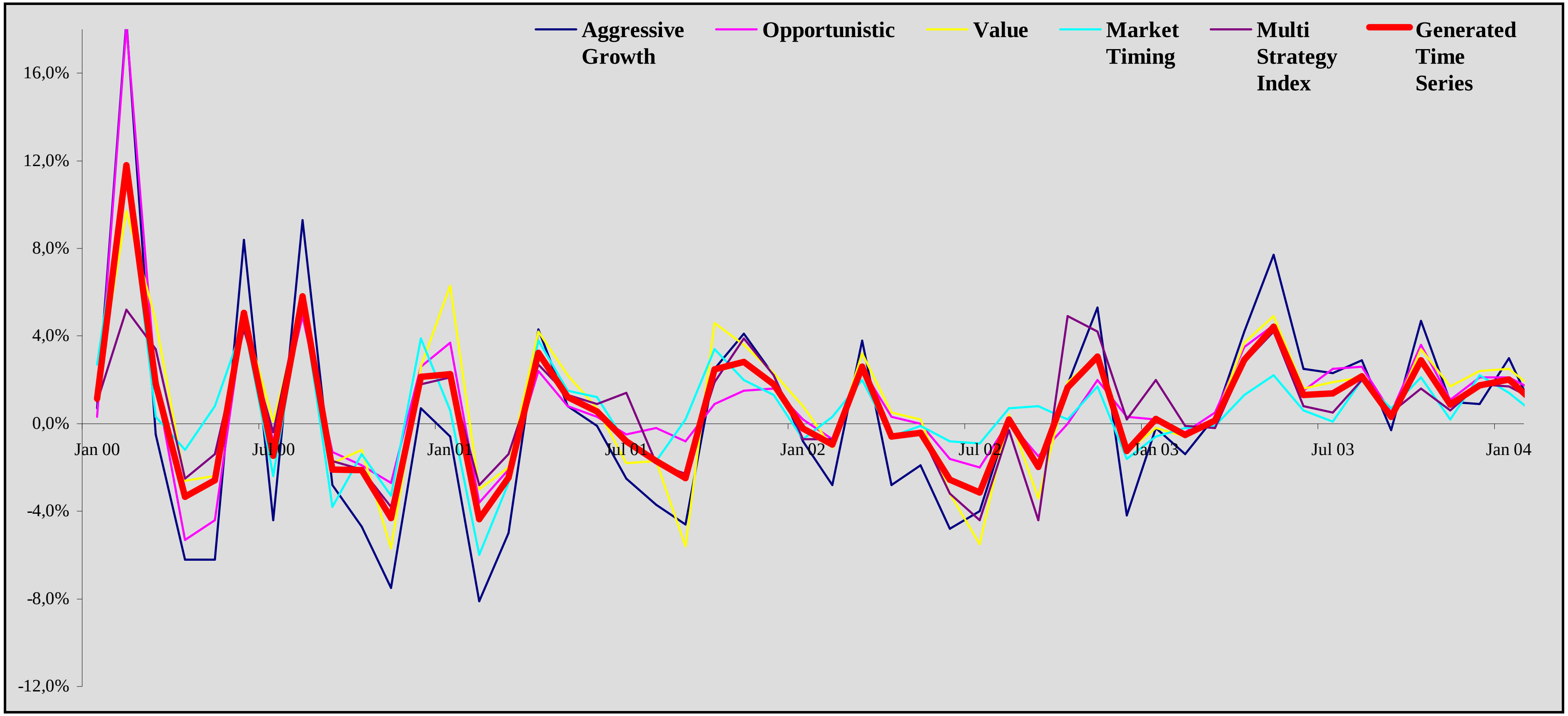
Source: Self-made figure, based on the data provided by the VAN Company.

Fig. 52: TSA – Generated Time Series during the Period 1995.1999



Source: Self-made figure, based on the data provided by the VAN Company.

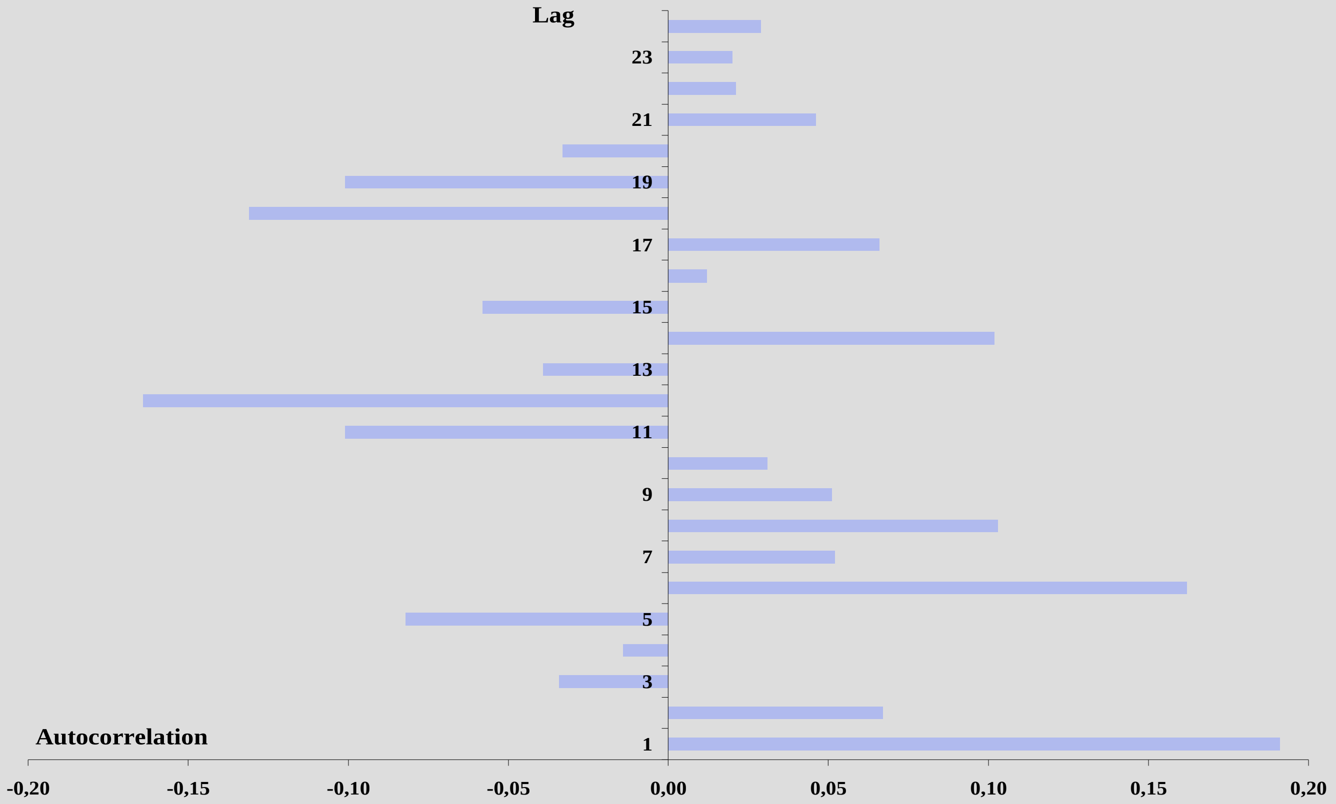
Fig. 53: TSA – Generated Time Series during the Period 2000-2004



Source: Self-made figure, based on the data provided by the VAN Company.

Fig. 54: TSA – Autocorrelations of the generated Time Series

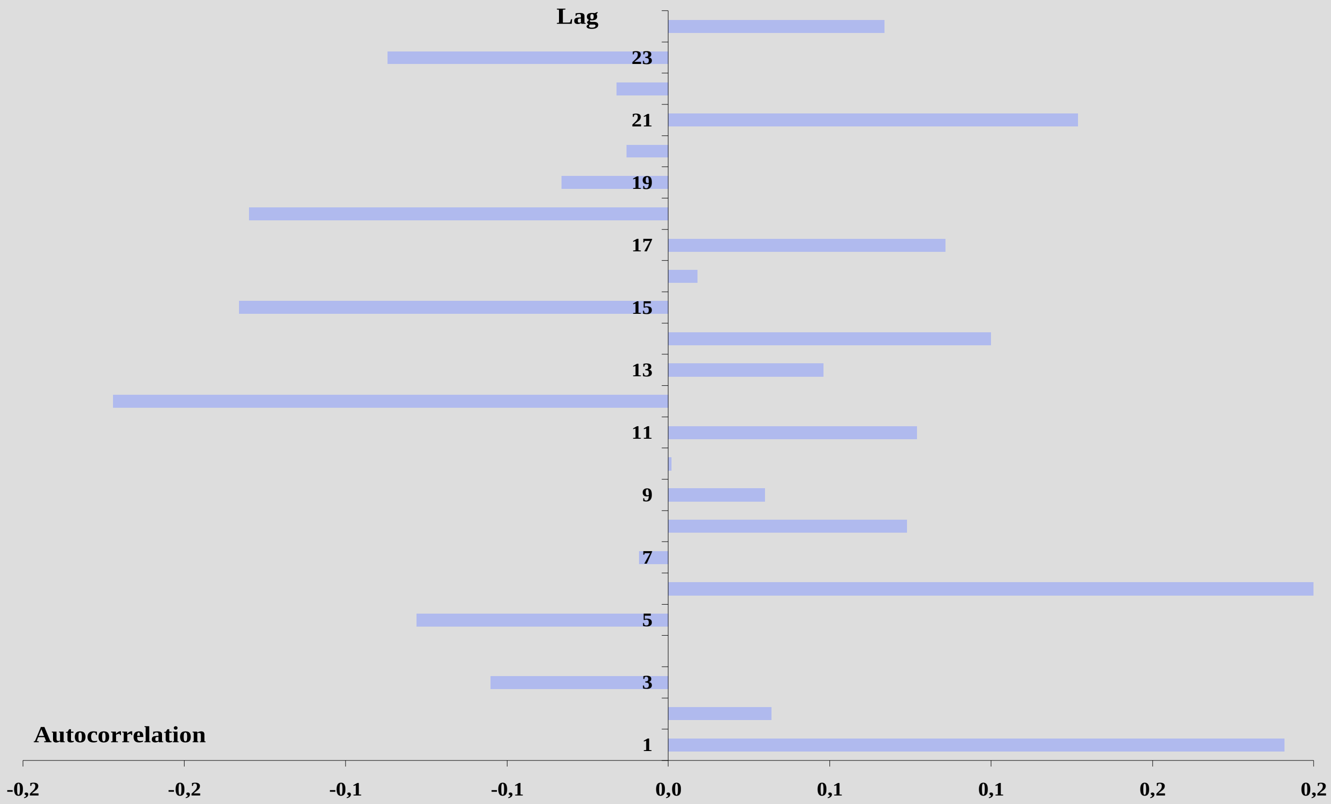
Lag	Autocorrelations
0	1,000
1	0,191
2	0,067
3	-0,034
4	-0,014
5	-0,082
6	0,162
7	0,052
8	0,103
9	0,051
10	0,031
11	-0,101
12	-0,164
13	-0,039
14	0,102
15	-0,058
16	0,012
17	0,066
18	-0,131
19	-0,101
20	-0,033
21	0,046
22	0,021
23	0,020
24	0,029



Source: Self-made figure, based on the data provided by the VAN Company.

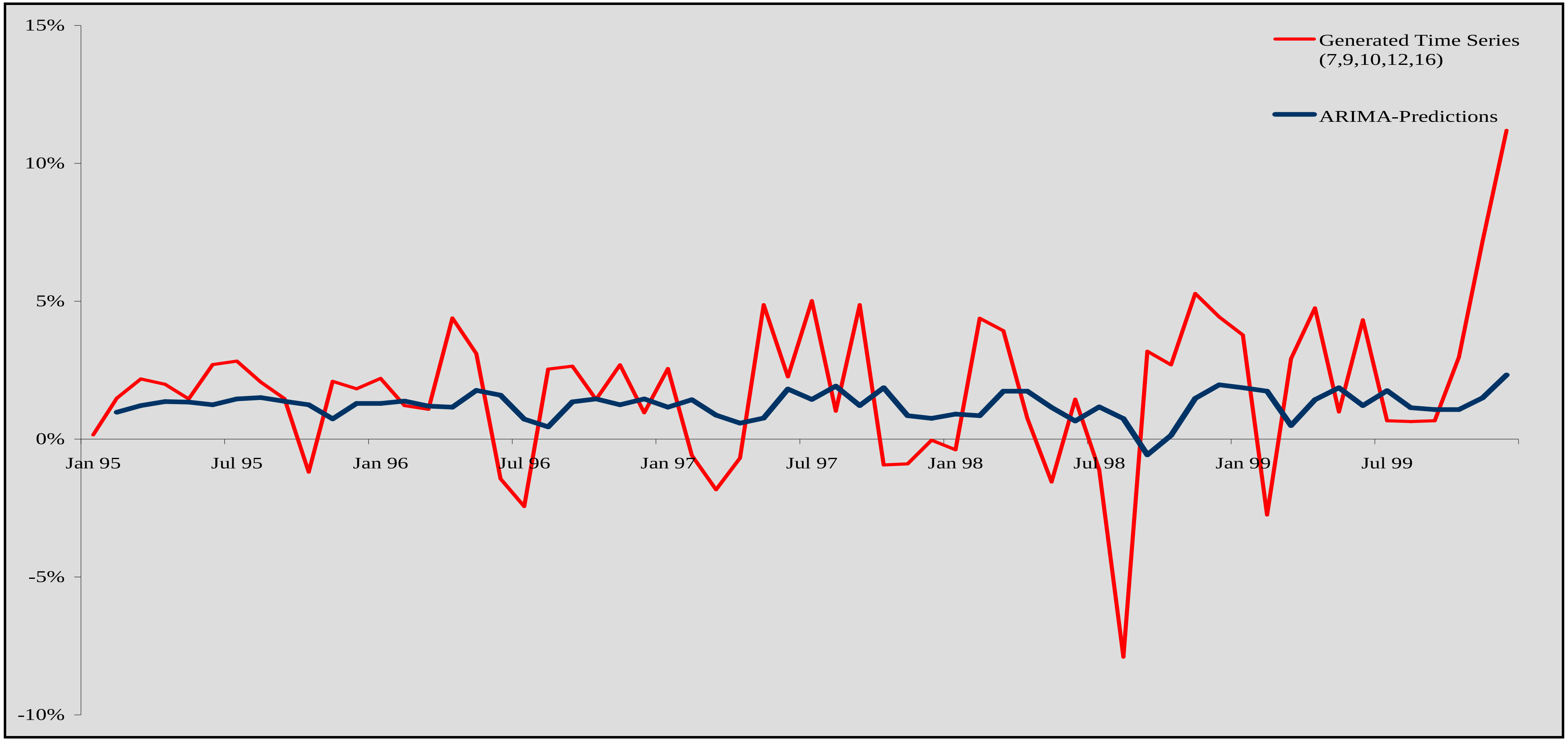
Fig. 55: TSA – partial Autocorrelations of the generated Time Series

Lag	Partial Autocorrelations
0	1,000
1	0,191
2	0,032
3	-0,055
4	0,000
5	-0,078
6	0,200
7	-0,009
8	0,074
9	0,030
10	0,001
11	0,077
12	-0,172
13	0,048
14	0,100
15	-0,133
16	0,009
17	0,086
18	-0,130
19	-0,033
20	-0,013
21	0,127
22	-0,016
23	-0,087
24	0,067



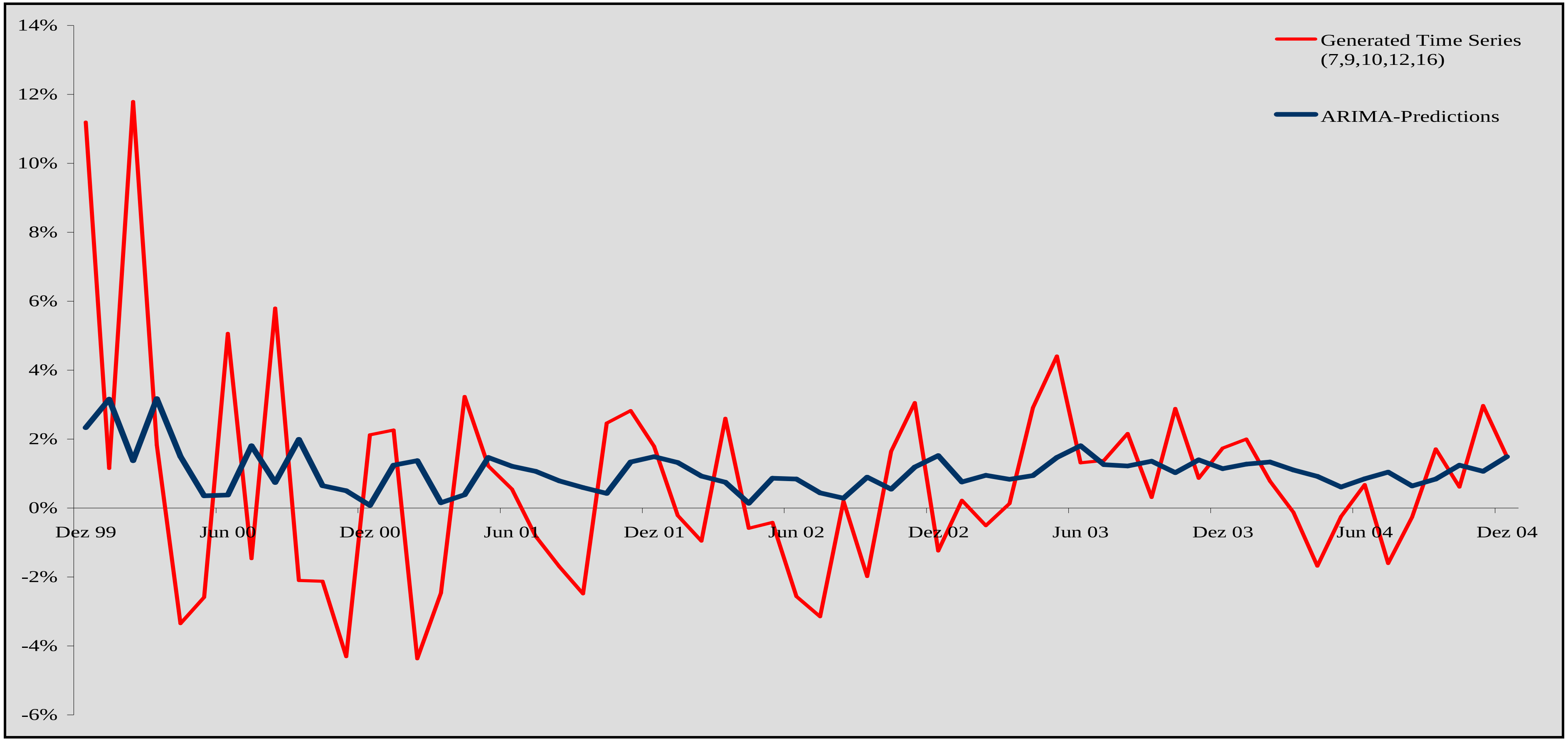
Source: Self-made figure, based on the data provided by the VAN Company.

Fig. 56: TSA – Model Predictions during the Period 1995-1999



Source: Self-made figure, based on the data provided by the VAN Company.

Fig. 57: TSA – Model Predictions during the Period 1995-1999



Source: Self-made figure, based on the data provided by the VAN Company.

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AFFIDAVIT

I declare that I wrote my diploma thesis independently and exclusively with the use of the cited sources.

Hamburg, 24 July 2005

Florian Hausen