Lappeenranta-Lahti University of Technology LUT
School of Business and Management
Master's Program in Strategic Finance and Analytics

The Performance of Commodity Trading Advisors' Investment Strategies

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ABSTRACT

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The purpose of this study was to examine the performance of Commodity trading advisors' investing strategies from January 1997 to December 2013. CTAs were divided into three groups according to their investment approach: technical CTAs, fundamental CTAs and those that combined the two strategies. The study employs several models to capture the performance of CTAs as well as to asses on which risk factors CTAs have exposure. The performance measurements included Sharpe ratio and extended Sharpe ratio to control for skewness and kurtosis. In addition, two multifactor models were applied: Fung and Hsieh 9-factor model and multi asset momentum model.

The fundamental strategy portfolio is the best performing portfolio during the full sample period when measuring with average returns, Sharpe ratio and SKASR. The significance of the differences in performance of the strategy portfolios are not statistically significant on any of the strategy pairs during the full sample period. The multifactor models implemented in the study have very limited ability to answer the question of whether the different strategies were able to create alpha. The explanatory power of the Fung and Hsieh 9-factor model is close to zero with fundamental and mixed strategies and only explains 28 % of the technical strategy's return variation. The multi-asset momentum factor model explains an even lower amount of variation for all three strategy portfolios during the full sample period. Also, the attempt to improve explanatory power by volatility adjusting the factors was not successful.

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1 Introduction

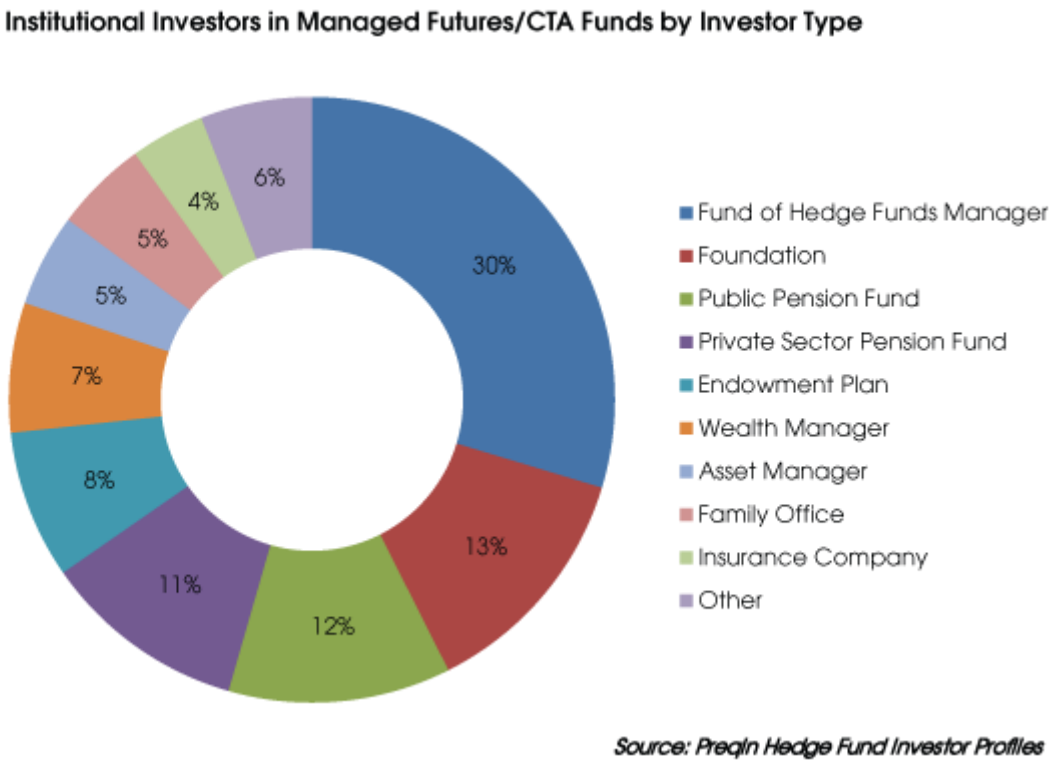
Managed futures investing has been increasing in its popularity as institutional investors look for more ways to make profit in an unpredictable and volatile investing environment with low interest rates. Managed futures involve usually a speculative investment in gold, oil and other commodities that change in value in accordance with price fluctuations and improves traditional portfolio performance or reduces risk because they typically have no correlation with traditional bond and equity markets. Managers of Managed futures accounts are known as Commodity Trading Advisors (CTA). (Gregoriou, et al. 2004; Mackey S. 2014; Do et al. 2015)

CTAs are professional fund managers that provide guidance and active financial services like derivatives trading or running managed futures account to and on behalf of their clients. The clients of CTAs are in general institutional investors such as pension funds and NGOs or high net-worth individuals and families. Typical characteristic of a client of a CTA is that they usually have large portfolios and are constantly seeking to diversify their risk exposures. CTAs are registered with and regulated and supervised by the U.S. Commodity Futures Trading Commission as well as the National Futures Association. (Kiymaz et al. 2018; National Futures Association 2019[1])

According to Garner (2012) commodity funds that are managed by CTAs count to the alternative investments sector of the investment world. They are publicly available investment instruments that invest in options, futures, forwards and other derivative contracts on a wide range of assets: physical commodities and financial instruments. Differing from the equity and bond markets that offer investors either partial ownership in a company and a relative share of its returns and losses or simply interest on its principal, an investment in a fund managed by a CTA yields profits or losses based entirely on the investment performance of this CTA. Additionally, while a CTAs investment process in general involves exchange-traded instruments in futures and options markets, the investment in the CTA's fund itself is not traded on exchange.

[1] Available https://www.nfa.futures.org/members/member-resources/files/regulatory-requirements-guide.pdf Read 16.10.2019

Another distinctive feature of CTAs' trading programs is that their funds are not pooled investment instruments like a mutual funds, which utilize capital from a large group of investors, even though mutual fund managers often involve investments in the futures and options markets for either speculative or hedging purposes. On the contrary, in order to increase liquidity, trustworthiness and openness, CTAs function under a separately managed account structure which means that portfolio of a client is always managed as a single account. (Kiymaz et al. 2018)



In their early years, trading of CTAs was indeed limited to just commodities – hence the name CTA – following the introduction of derivatives on a series of financial and other products, CTAs' investment space has widened significantly. Since 1980s, CTAs' trading programs are categorized by the investment strategy as well as the market segment in which they operate. It is worth noting that such funds often keep highly leveraged positions through borrowing or the use of economic leverage through derivative assets, thus generating non-linear returns and exceptional risk profiles. (Kiymaz et al. 2018)

CTAs are to a certain degree very similar to hedge funds as CTAs as well as hedge funds in general invest in similar assets and engage in similar investment strategies. The key difference with CTAs and hedge funds is, however, not in the investing strategies implemented, but a more structural one: while investors keeping managed accounts are

able to follow all the trading that takes place on their behalf on a regular basis, hedge funds still continue as an investment with very low visibility to the investor. (Edwards, 1999)

In academic literature CTAs' investment strategies are usually divided to either fundamental and technical approach, or further into discretionary, trend-following and systematic approaches. The fundamental or discretionary strategy means that the trading decisions are made by the discretion of the fund manager whereas technical approach lets a computer algorithm do the decision making. Trend-following and systematic approaches are sub-strategies of the technical approach. Many fund managers report to follow both of these sub-strategies so these strategies are not mutually exclusive. (Hedges, 2004) (Kazemi et al. 2009) Selection of the right CTA is very important decision for the investor as return differences between best and worst funds are relatively large compared to mutual funds (Brown and Meksi, 2013).

1.1 Objectives of the research

The purpose of this thesis is to study the two different investing strategies of CTAs and their performance. I will separate technical and fundamental investing strategies and try to find characteristics for their performance. I will explore their performance in bullish and bearish market conditions, risk factors and correlation with different asset classes.

I limit the research time period to cover the period from January 1997 to December 2013. During this period, the financial world faced the South Asian crisis, the IT-bubble, a bull market from 2003 to 2007 and The Great Financial Crisis 2007–2009 followed by the eurozone crisis and a subsequent bull market. As previous studies have shown (e.g. Fung & Hsieh, 2001), one important challenge in testing for the presence of market timing ability is that models employing traditional factors have low explanatory power on CTA returns (Kazemi et al. 2009)

My chosen research questions are the following:

1. *How do global market fluctuations affect the performance of different Commodity Trading Advisors' investing strategies?*
2. *To which risk factors Commodity Trading Advisors are exposed and do those change over time?*
3. *Can momentum factors explain the performance of Commodity Trading Advisors?*
4. *Can volatility adjusting increase the explanatory power of momentum factors?*

Many studies examining the performance of CTAs, the timing ability of CTAs' strategies and persistence of CTAs have been conducted. However, research on the performance differences of different CTA strategies and the sources of performance in different strategies remains uncharted territory. This study will bring valuable information for institutional investors contemplating on which CTA to invest in and to which risk factors to get exposure. It will create implications on how to diversify one's portfolio by including certain types of CTAs in it. While many previous studies have had more of a managerial perspective on CTAs, I will be observing the CTA industry from more of an investor's point of view.

One implication of the results could be that certain strategies could have a lower exposure to certain risk factors. This could offer institutional investors an opportunity to further diversify their portfolios by including a specific type of CTA in it. For example, if the results showed that technical investment approach CTAs with a focus on metal commodities have very low exposure to interest rate risk, then an investor with a large bond portfolio could lower its interest rate risk exposure by including those types of CTAs in his/hers portfolio.

1.2 Limitations

The sample period of this thesis is limited from January 1997 to December of 2013. This timeframe enables to examine the performance of CTAs during two major bear markets as well as three bullish periods. For the sake of simplicity, I will only consider the S&P 500 index as an indicator of market regimes.

The bull markets are defined as follows: the first bull market is considered to have started at the beginning of the study and to end at the burst of the IT-bubble in March 2000. This subperiod includes such major market events as the South Asia crisis and the collapse of Long-Term Capital Management hedge fund, but the index recovered within four months and the maximum drawdown was less than 20 %.

The first bear market starts where the bull market ends and continues until the S&P 500 reaches its local bottom at the end of 2002. The second bull market starts at the beginning of 2003 and ends in August 2007 when BNP Paribas freezes withdrawals from two of its hedge funds. The closing of these funds is often considered to be the starting point of The Great Financial Crisis, which is the second bearish period of this study. This subperiod ended when S&P 500 had lost half of its previous peak value (from summer of 2007) until March 2009. The last bull market, which turned out to be the longest in the history of S&P 500, is cut short in this study as the performance of CTAs is rather limited after December 2013.

Monthly data from a private database is used as the return data for CTAs. Monthly reporting is custom in hedge fund and alternative investments industry, thereby leaving much of valuable data out of researchers' reach. Monthly frequency causes a limitation for significance in analysing shorter performance periods of CTA. If the frequency was higher, one might be able to model the performance of these funds easier as the exposures to factors would become more apparent.

The technical strategy can be further divided into systematic and trend-following strategies. However, in this thesis they are pooled together. The reason is twofold. First, according to the data, the distinction between systematic and trend-following strategies is not necessarily clear even to fund managers themselves. Some funds have been classified in the dataset as trend followers, but the manager may have described the approach in general comments as systematic. Second, if we trust the classification in the dataset to be correct and we exclude those CTAs that would be classified in both strategies, the number of funds available for study would decrease dramatically, leading to unreliable results.

1.3 Structure of the thesis

The thesis is structured as follows. In the next two sections the background of the topic will be further discussed; section 2 presents the framework underlying the topic and section 3 will focus on previous relevant research on the topic. Section4 describes the data and section 5 the methodology used. In section 6 the results gained from the research are presented, which are then further discussed and based on which conclusions are made in section 7. The last section includes critique opposed to the study and the author's suggestions for further research around the topic as well.

2 Theoretical background

In this chapter I explore the characteristics of CTAs. First, I give an overview of the industry in which CTAs operate, how it has developed and what is the current state of the market. The industry itself is decades old and therefore we need to understand its development in order to analyze possible factors affecting its performance. Second, I break down CTAs' different investment strategies and their assumed decision-making processes. To understand the possible risk factors to which CTAs are exposed to, the full grasp of the investment approach is vital. I conclude the chapter with a look to previous studies: their implications, results and limitations.

2.1 CTA industry

CTAs have been available for institutional investors since late 1940s, when the first public commodity futures funds started trading. However, it was not until a couple decades later, in the late 1970s, for the industry to really start growing. (Kat, 2003)

According to Kat (2003) there are three different ways for an investor to invest in CTAs:

- An investor can buy shares of a public commodity fund in a similar fashion as they could purchase mutual stock or bond funds.
- An investor can place their capital privately with a commodity pool operator, who pools investors' capital and then employs one or more CTAs to make the pooled funds.
- Investors can have one or more CTAs directly to manage their money on an individual basis or one can hire a manager of managers to select CTAs for them.

Kat (2003) also states that initially the CTA industry's trading was limited to just commodity futures, but in the 1980s as more futures on different markets such as interest rates, bonds, currencies and equity indices were introduced, the CTAs trading spectrum widened markedly. Today CTAs trade both in commodities and financial futures as well as corresponding options. Some CTAs tend to focus on very niche part of futures markets, such as natural gas, precious metals or even carefully selected currency pairs, but most CTAs still diversify their trading portfolio over different kinds of markets.

The CTAs first started to make name for themselves during and after the burst of the IT-bubble in March 2000. As the IT-bubble sunk the equity markets into a deep turmoil, CTAs prevailed in comparison. As the equity markets declined over 5 trillion dollars in market capitalization, the CTA industry saw a large capital inflow from both institutional and high net-worth investors, who were at the time desperately looking for a diversification to their traditional bond and equity portfolios. (Matellini & Vaissie, 2003)

Nowadays CTAs seem rather inappropriately and misguidedly named as in reality, most of their trading is not in the commodity markets, but rather in the financial markets. In the alternative investment spectrum, CTAs like hedge funds and any other classes, have a wide range of investing and trading styles and substyles. (Darling, Mukherjee & Wilkens, 2003)

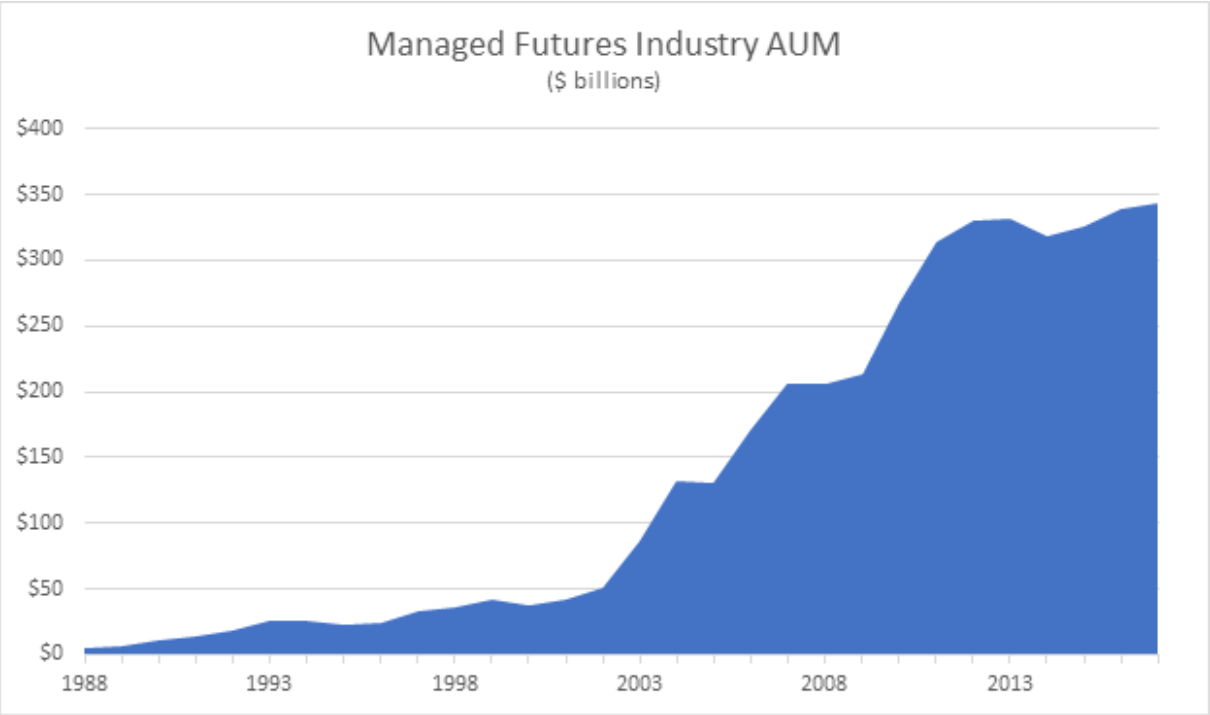


Figure 2. The development of assets under CTA management from 1988 to 2018. (BarclayHedge, 2019)

In early 2000s CTAs along with hedge funds draw a lot of concerned attention to themselves due to a general fear that those asset classes would exert a disproportionate and destabilizing influence on financial markets, which had led to increased volatility, and in worst cases, in financial crisis. The concerns about CTA and hedge fund trading

extended to the commodity markets as well. These concerns were expressed by US farmers to the Chicago Boards of Trade, that rogue traders might influence market direction without any regard to real world supply and demand or other economic factors. (Irwin & Holt, 2003)

There has been discussion on whether CTAs ought to be counted in the hedge fund asset class or whether they should be considered a class of their own. In the early 1990s hedge fund industry's predominant form were global macro hedge funds, which were in general managed by commodity trading advisors. This shared history creates the difficulty on separating CTAs and hedge funds from each other. By the end of the 1990s, however, several other hedge fund types surfaced as strategies such as event driven, M&A, and equity long/short emerged. After the late 90s CTAs became a much smaller part of the hedge fund world. (Anson & Ho, 2003)

CTAs typically have had a close to zero correlation to traditional equity and bond markets and from the investor's perspective the most important advantage of CTAs stems from this fact. Institutional investors tend to have strict rules in their mandates on how much risk they can have, and as the volatility is the most common risk measurement in the financial industry, alternative investments that have the ability to decrease the volatility of the mandate, become very tempting. The volatility of a CTAs portfolio itself may not be significantly lower, but as the correlation with other asset classes is very low, it has a lowering effect on volatility on a mandate level. According to Hedges (2003), positive attributes of CTAs include good negative correlation to equities during bear markets, diversified opportunities, low correlation to hedge funds, and transparency of positions. On the other hand, Hedges mentions that disadvantages of CTAs include, high fees and a high level of advisor attention is required to manage the portfolio.

The exchange-based nature of futures contracts plays a significant role in risks connected to CTAs. Positions can usually be opened and closed continuously, regardless of size. This becomes vital if a CTA believes that it must quickly liquidate a large position in order to cut losses. Good liquidity of futures markets allows CTAs to cut back or exit from large positions quickly during periods of market turmoil. Also, the limited counterparty risk associated with futures trading compared to other derivative markets, is valuable for

CTAs' risk management (Hedges, 2003)

2.2 Investment strategies

As CTAs employ different investment methods, potential investors must choose which CTA will provide the best addition to their existing investment portfolio based on the CTAs' performance and risk strategy. (Edwards, 1999) CTAs typically rely on either technical or fundamental analysis, or a combination of these two for their trading decisions. According to Kazemi et al. (2009) these two categories can be roughly identified by asking the question: "Who makes the trading decision?" If the trading decisions are made by a single person or a group of people, the strategy can be classified as discretionary strategy, but if the trading decisions are left to a computer, the strategy is categorized as technical.

Technical analysis, defined by Hedges (2004), asserts that future prices of commodities and financial instruments can be drawn from a historical analysis of the markets. The analysis can reveal valuable information of the markets, which than can be modelled to predict future market movements. Such applicable information includes, for example, daily, weekly, and monthly price fluctuations, volume variations and changes in open interest. Technical traders often apply charts to create patterns of the market movements and use sophisticated computer models in their analyses. Technical trading is generally rule based, i.e. it does not rely on context like news, fundamentals or trader speculation. When certain criteria are met by the applied data in a given market, the trade is made. Technical traders build and continuously test to improve their mechanical algorithm that is in the end monitored and managed by computers. The CTAs that are responsible for this trading algorithm are constantly testing and back testing the algorithm that is in place. The potential benefits of a technical trading system are that it is buying strictly based on data, which means that emotional fallacies of humans do not influence the trading strategy in a negative way. If the algorithm states that an increase in a price of a commodity over the course of 48 hours equals a buy, then the computer will buy that commodity. Even if that commodity is natural gas and the weather forecast for the winter show coldest winter in decades.

The positive consequences of the rule abased trading strategies create a clear edge in

certain circumstances over human trading. For instance, slight price distortions might create arbitrage opportunities to which a human being would not be nearly quick enough to react. If a technical trader would be capable of accurately creating something that could exploit such opportunities in different markets around the world, a profitable system might have little intervention necessary, or even possible. On the other hand, creating a trading system that is profitable over time takes a lot of time and dedication. (Garner, 2017)

Hedges (2004) points out that a fundamental trader in contrast, relies on the analysis of external factors that affect the supply and demand of a commodity or financial assets to predict their future market prices. Such factors can include the state of the economy, governmental policies, stage of the business cycle, domestic and foreign political risk, and in some cases even the weather. Fundamental analysis is predicated on the notion that over time, the actual value of a futures contract must reflect the value of the underlying commodity or financial asset and, further, that the value of the underlying commodity is based on these external values. In essence, the fundamental trader tries to profit from the convergence of market price and actual value.

The figure below illustrates the different strategies utilized by CTAs.

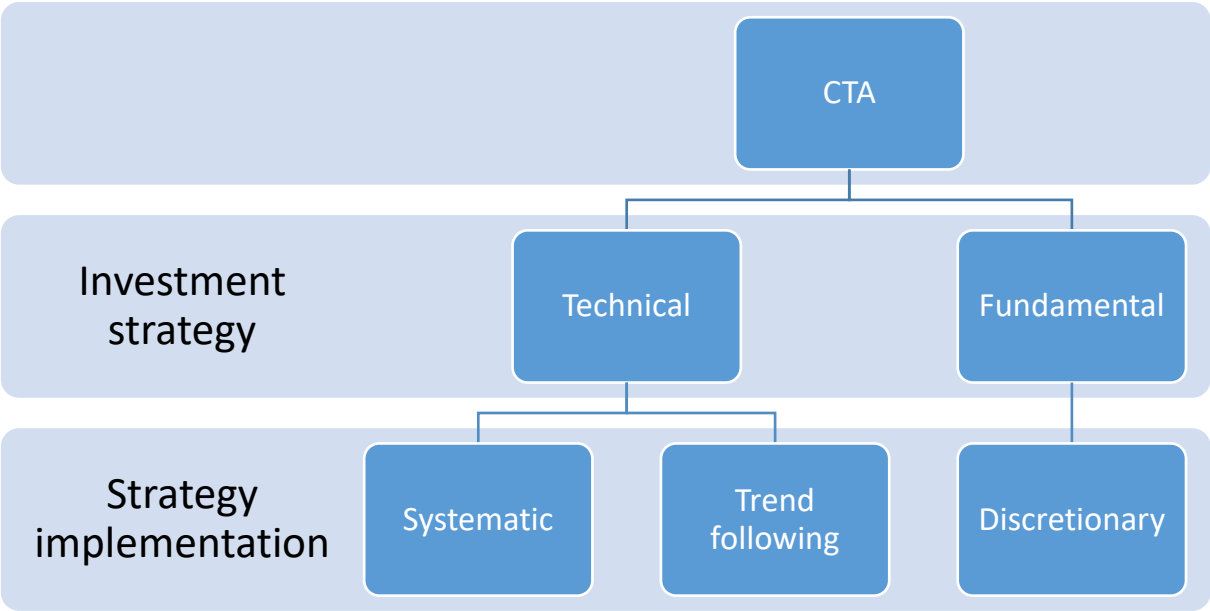


Figure 3. CTA strategy hierarchy

Investment strategies employed by CTAs fall into three categories: discretionary, trend-following and systematic. However, these categories tend to overlap, which creates challenges in evaluating the performance of each strategy.

According to Till et al. (2003) CTAs must address following steps in the process of constructing a futures trading program:

1. *Trade discovery*. The first step for a CTA is to discover in how many trades it is plausible for one to have an edge or advantage. Interestingly, even though several futures trading strategies are very well known and publicized on academic papers, CTAs have continued to apply them.
2. *Trade construction*. A CTA might have a correct view of the price movement, but the profitability of the trade can be largely affected by how the trade is constructed. Futures spreads are more analytically tractable than trading the asset outright. In general, some economic boundary constraint links related assets, which can limit risk in position construction. Also, a lot of first order risk can be hedged out by trading spreads. What affects the spread instead is second order risk factors such as timing differences in inventory changes among the two assets. It is often easier to analyse possible movements regarding second order risk factors than first order ones.
3. *Portfolio construction*. Ideally, the goal of portfolio construction is to manage portfolio level risk by combining strategies and trades that have low correlation with each other.
4. *Risk management*. The portfolio manager needs to ensure that during both normal and turbulent times, the trading program's losses do not exceed the client's comfort level. Tools for risk management usually include at least position sizing, limits to leverage and trade diversification.
5. *Leverage level*. Futures trading requires a relatively small amount of margin. Trade sizing is mainly a matter of how much risk one wants to assume. An investor is not very constrained by the amount of capital committed to trading. The chosen leverage level is more of a product design issue. The manager needs to determine how the program will be marketed and what the client's expectations will be.

6. *Unique contribution to the investor*. A final consideration in creating futures trading program is to understand how the program is going to fit into a potential investor's overall portfolio. For investors to be interested in a new investment, it must have a unique return stream: one that is not already obtained through their other investments. The new investment must be a diversifier, either during normal or turbulent times.

The strategies differ on the first and second step of the trading program. First, if the decision making is fully in the hands of a computer program, the number of plausible trades increases significantly. A human cannot analyse and execute hundreds of trades and keep track on how they are performing. It takes time to conduct a thorough fundamental analysis of the market at hand before trade can be executed.

Second, the construction of a trade gives a more different to the CTA that has not automized the trading process. A typical trend follower seeks trends from already tradeable instruments. If one wants to construct a more complex trade that includes multiple instruments, a contemporary trading program may not be able to initiate that trade. For example, if a CTA wanted to take a position that inflation in the U.S will increase while yield curve will steepen, one would need to take at least three positions to initiate this trade: first take long position on Treasury inflation-protected securities, second short long maturity bonds, and third take long position on short end of yield curve. It is rather unlikely that a trading program would put all these things together and benefit from this kind of market movement, while a CTA relying on his or her own analysis could quite easily organise this. (Garner, 2017)

2.2.1 Systematic CTAs

According to Hedges (2004), systematic CTAs typically use cutting edge computerized models, which are often described to as black boxes that usually include neural networks or complex computer algorithms determine trading activity. Systematic CTAs can differ with each other in the factors they choose to use as inputs into their models and how their models interpret different factors. Systematic CTAs design systems that analyze historical price relationships, probability measures and other statistical data to identify profitable trades.

Hedges (2004) states that for a signal to open a position, systematic CTAs rely on technical data including price patterns, price spreads, current price relative to historical price, price volatility, volume and open interest. Profitable positions may be closed out on one of these signals: if a trend reversal is recognized, the end of a trend is signaled based on an overbought or oversold situation, or another technical indicator. Some systemic CTAs use single system approach while others employ multiple systems that can operate either in tandem or in mutual exclusivity. An example of multisystem approach operating in tandem is when one system indicates a buy signal while other system indicates a flat or sell signal. The result is that the trade is not executed. The main advantage of a multisystem approach is the diversification of signals.

Contemporary trading systems do not have the same common sense as a human trader, which means that in the long run, trading systems do not have the capability to be profitable without some type of human involvement. This is because technical systems are driven by precise parameters that were established well before the trading takes place. As a result, mechanical trading systems often generate signals that might be considered low-probability trades by humans. For instance, a technically driven system might trigger a sell signal at or near the all-time low of a given tradable asset. Likewise, a system might look to buy a market at an exuberantly high price. (Garner, 2017)

Although systematic trading programs are meant to eliminate the emotions involved in deciding whether to open or close a position, there might be inadvertent psychological consequences. For example, enduring a trade that contradicts one's fundamental opinion of the market can be very challenging. This could mean that a system is going long a market in which one is very bearish or short an asset in which one's opinion is bullish. Either way, the turmoil that systematic trading programs are meant to avoid can easily re-emerge. Such emotions have been known to cause traders to interfere with the system and, often, greatly affect the performance in a negative way. (Garner, 2017)

2.2.2 Trend-following

Trend-following is a trading method that seeks to take positions on futures based on the

development of significant price trends in the underlying asset through an analysis of market price movement and other statistical analyzes. This method is consistent with the underlying concept of managed futures investing, which is based on the assumption that prices move from equilibrium to transitory stage and back to equilibrium. Trend-followers try to take advantage of this divergence of prices by capturing of various price signals. The implementation of a trend-following strategy on an instrument level includes two key elements: creation of price signal and position sizing. Although trend-followers can either employ systematic computerized trading programs or rely on human discretion to identify trends, they typically prefer the former. In general, the objective of trend-following CTAs is to identify medium to long-term trends in a systematic way (Sepp, 2019). This causes trend-followers sometimes to be classified in the general category of systematic CTAs (Hedges, 2004).

One common misunderstanding about trend followers is that their performance would be based on timing the market perfectly. On the contrary, trend followers are by definition reactionary, meaning that they do not attempt to predict a market top or bottom, but rather respond to an already existing trend. In general, trend followers seek to cut losses by quickly exiting losing positions and profit by holding and levering up profitable positions as long as the market trend is perceived to exist. Consequently, the number of losing trades may much surpass the number of profitable trades but the returns on the profitable trades are expected to more than offset the losses on losing contracts. (Hedges, 2004)

Sepp (2019) concurs that the trend-following program is not intended to capture the initial stages of a new trend, but the program will benefit from the further stages of the trend should it persist. A common question from the investment community is why trend-following programs can be too slow to benefit from quick and steep reversals in broad markets. This, however, is not the purpose of a trend-following CTAs to begin with. Sepp finds that trend-followers are more likely to deliver alpha during market turmoil that lasts over extended periods as most of trend-following CTAs apply medium- to long-time time horizons for signal generation. Therefore, trend-followers could serve as robust diversifiers of equity portfolio during corrections that last over longer periods of time.

2.2.3 Discretionary

In their purest form, discretionary CTAs rely on fundamental research and analytics to determine when and where to carry out trades. For example, a discretionary fund manager may analyze that severe weather conditions have reduced the estimate for the supply of wheat and corn this season. Applying basic rules of supply and demand asserts that the price of wheat should rise in these circumstances. Discretionary trading can therefore be identified as decision-based trading. The discretionary traders continuously analyze fundamental factors that may affect the price of a commodity or financial asset, which is used to formulate the decision in which to trade. Discretionary CTAs make decisions based on the contexts of the market, current events, historical fundamentals, expected demand and other related factors. However, discretionary CTAs naturally have a disadvantage of being susceptible to human error. Whereas the systematic trader would wait until these fundamental data are reflected in the futures prices before trading, the pure discretionary advisory immediately trades based on this information. (Hedges, 2004)

The success of any of these trading philosophies depends largely on the unique systematic program, experience, or discretion of each CTA. Hence there is a place for a study that focuses on the performance of the very strategies implemented. In previous studies, the vast variety of CTAs have been pooled together even though the very foundation of the trading process can be completely different.

3 Literature review

In this section I will examine the previously conducted studies that are most relevant to the issue at hand. The performance persistence and drivers of CTAs' have been widely studied in academic literature since the late 1990s. I have summarized four previous studies from last few years that are closely related to my thesis and give some valuable input. These studies have utilized at least partially similar data, methodology as well as timeframe as my thesis. Hence, these studies give a clear view of the CTA landscape.

3.1 An analysis of CTAs' risk and return

In their study Foran, Hutchinson, Mcarthy and O'Brien (2017) analyzed the risk and return associated with CTAs. Their study was twofold; first they studied whether CTAs follow a homogenous, easily modeled strategy and second, whether CTAs' returns could be modeled using alternative risk premiums. They initially created alternative risk premiums at the asset class level, where each asset is equal dollar-weighted, before combining asset-class alternative risk premiums into a final alternative risk premium. Then the risk premiums of the asset classes were aggregated by using an equal volatility weighting.

Their first finding was that CTAs represent more than one single homogeneous style. They used statistical clustering techniques to identify different types of CTAs and classify them into eight substrategies. They found that these different substrategies generally had low correlation between clusters and the source of their returns differed significantly. For a full sample of CTAs, they found evidence to suggest that the likelihood of these expectations being met is not high, which is primarily caused by the heterogeneity in the sample. They further summarize that there are significant differences in the return characteristics of these funds.

The second key finding of their study was that it is difficult to model returns using alternative risk premiums that are derived from the academic literature. The alternative risk premiums do not explain a large share of CTA returns, as the share of CTA portfolio returns explained by the premiums ranges between 14% and 44%. When Foran et al. divided CTA returns into alternative risk premium exposure and alpha, they found that

only three out of eight CTA clusters were able to create alpha. Hence, developing products based on those types of clusters with low tracking error to CTAs, can be difficult. By looking at the portion of returns unexplained by the alternative risk premiums, they concluded that, on average, CTAs have been historically able to create alpha, even if at low significance levels. When Foran et al. repeated the analysis by focusing on within-strategy self-classifications, they found that systematic-diversified CTAs have historically offered the highest returns and performance. For portfolios of CTAs formed by using statistical clustering, the results demonstrate that there is a lack of homogeneity among CTAs and reinforce the earlier finding that the category of funds with a high trend exposure has historically generated the highest performance.

3.2 Factors affecting the birth and fund flows of CTAs

The latest study of the factors affecting the birth and fund flows of CTAs is by Do, Faff, Veeraraghavan and Tupitsyn from 2015. This study was threefold, focusing on the births of new CTAs, their fund flows and performance and the institutional investors' effect within CTAs.

First, Do et al. found that the number of new CTAs and their fund flows is driven by the performance of CTAs and performance of other markets such as equity and commodity markets. Following Kaplan and Schoar (2005), they tested the relation between the number of new CTAs and market performance using simple linear regressions. Do et al. found that performance of existing CTAs had a different effect on the number and fund flows of new CTAs in the short and long-term; in the short-term, the industry's aggregate performance had a negative impact on new funds. They also noted that it became more difficult for new CTAs to raise capital because they do not have a strong track record compared to their competitors. As a result, strong CTA performance will influence investors to allocate their capital into senior CTAs with strong track record. However, in the long run, CTAs' aggregate performance creates a positive investor sentiment towards the whole industry and helps to attract more capital to both existing and new funds. In other words, Do et al. conclude that long-term and short-term effects can be explained by style chasing investor behavior and intra-style competition.

Second, Do et al. investigated the relationship between fund flows into CTAs and past

performance on top of other characteristics of individual CTAs. They measured the performance by using the Sharpe ratio. They discovered that there were noticeable differences in the relationship between individual CTA performance and fund flows for different types of CTAs; systematic CTAs had a linear, positive flow-performance relationship, while the relationship is concave shaped with CTAs that are classified as discretionary. In their opinion, one explanation for this could be that within discretionary CTAs, there could be higher capacity constraints or more share constraints. Do et al. also found that the financial crisis has influenced investors' preferences for CTAs. Before the crisis, individual CTAs' absolute and relative performances were the main drivers of fund flows for both systematic and discretionary CTAs.

Third, Do et al. examined whether investors are successful in selecting the better performing CTAs. They conducted both short-term and long-term analysis of the 'smart money' effect by using the Fama and MacBeth (1973) method. Two main performance measures used in the short-term analysis were absolute and relative raw performance. They found no evidence at short or long-term horizons of investors' ability to select better performing systematic CTAs. They concluded that the 'smart money' effect among discretionary CTA investors is very limited at quarterly horizon and absent at longer than one-year horizon. To summarize, the results of Do et al. confirm that chasing past performance does not work for CTA investing.

3.3 The performance and persistence of CTAs

Bhardwaj, Gorton and Rouwenhorst (2014) studied the performance and persistence of CTAs over the period of 1994 to 2012. The key question in their study is simply to find out whether CTAs are worthwhile investments for investors. To answer the question, Bhardwaj et al. study whether CTAs have earned above average risk-adjusted returns and which benchmarks should be then used for the risk adjustment of CTAs' returns. As they analyze CTAs specifically from the investors point of view, Bhardwaj et al. specifically analyze the returns which investors would reach after the management fees are discounted and how an investor can decide on whether to invest in CTAs. Bhardwaj et al. examine separately on whether CTAs are able to generate alpha and whether CTAs' investors receive positive risk-adjusted returns by looking at both estimated gross returns

and returns net of management fees. Furthermore, if the CTAs would show ability to generate alpha, Bhardwaj et al. examine how the value added is then divided between CTAs and their investors. Also, a central point Bhardwaj et al. make in their study is that biased data and a lack of benchmarks are problems faced by both investors and researchers alike.

As CTAs are not publicly traded, there are no price data available, only the past performance data. In the case of CTAs, the available vendor data on their performance is biased, and there are only limited number of realistic benchmarks for performance analysis. Bhardwaj et al. assert that due to limitations on performance data, it is very difficult to measure the performance of CTAs. These issues raise problems for investors as well as researchers as to how to conclude on whether hedge funds and CTAs are attractive asset classes to invest in. Bhardwaj et al. point out that these issues potentially raise questions for public policy, to the extent that the hedge fund industry is sufficiently large to cause systemic risks. Bhardwaj et al. illustrate these issues by narrowing the universe of hedge funds to CTAs, because CTAs are in their opinion more homogeneous, CTAs' strategies are better known, and the strategy space is smaller.

Bhardwaj et al. show that survivorship and backfill bias overstate the reported average return of CTAs by roughly 8 % per annum during the full sample period. Bias-corrected annualized average returns to investors were 4,8 %, which is merely 1,81 % over the return of Treasury bills during this period. However, Bhardwaj et al. estimate that gross average CTA returns before fees significantly exceed Treasury bill returns, which implies that CTAs keep the gains of most of their alpha creation to themselves by charging high fees. Bhardwaj et al. propose simple dynamic futures-based trading strategies for performance evaluation. Because these trading strategies are generally known, they should provide a natural hurdle that CTAs ought to overcome.

Bhardwaj et al. conclude that poor CTA performance has persisted for at least twenty years and that CTAs can be considered a kind of market failure. In their view, asymmetric information would normally be viewed as leading to an absence of a market, but in the case of CTAs, it may be that precisely the absence of information has led to the persistence of the market.

3.4 Market timing of CTAs

Kazemi and Li (2009) studied the market and volatility timing ability of CTAs and further studied whether discretionary and systematic CTAs display significantly different market timing skills. They assert that trend-following CTAs could possess timing ability of the markets, because of empirical similarities between market timers and trend-followers as well as indication by anecdotal evidence. The goal of their study was to formally test this hypothesis and to determine whether CTAs display market timing ability in those markets that are the focus of their trading strategy.

Kazemi and Li found that CTAs indeed exhibit market return timing and volatility timing ability. More importantly, they found that CTAs were generally able to time the futures markets in which they claim to be specialized. For example, the currency CTA index is found to display market timing skill in Euro–Yen futures market. Similarly, the financial CTA index displays the same skill in currency and fixed income markets, whereas the diversified CTA index displays market timing skill in multiple markets. On the other hand, the equity indices display negative timing ability in some equity markets. The estimated coefficients of return timing are economically significant as well. For example, the systematic currency CTAs on average can generate 11.44% excess return when the returns from the Euro futures contracts increase by 1%.

Kazemi and Li found that discretionary and systematic CTAs behave quite differently from each other. The model used in the study has higher explanatory power for returns on systematic CTAs. In equity markets, CTAs were estimated to have negative returns on their market timing ability, whereas in other asset classes the returns were positive. The model's explanatory power is lower when applied to discretionary CTA indices, and the model shows weaker timing ability for this class of CTAs.

3.5 Summary of literature

In many respects, the previous academic literature discusses the topics similar to my thesis, while still leaving research gaps to fill. The data limitations for example, are something that basically all studies must face and accept. The same biases and

assumptions of unreliability will apply. Many studies apply the Fung and Hsieh model in some form. For example, Bhardwaj et al. (2014) used the primitive trend-following strategy factors from Fung and Hsieh model while leaving other factors out of their study.

	Study focus	**Method**	**Data**	**Conclusions**
Foran, Hutchinson, Mcarthy & O'Brien	Do CTAs follow a homogenous, easily modeled strategy and are their returns possible to model with alternative risk premiums.	Different alternative risk premium models, such as value, momentum and options strategy (Fung and Hsieh-model).	BarclayHedge CTA database from 1987 to 2015.	There are significant differences in the return characteristics of CTAs and CTA classes have varying exposure to alternative risk factors.
Do, Faff, Veeraraghavan & Tupitsyn	The timing of the inception of commodity trading advisors and the relationship between their fund flows and performance.	They use Kaplan and Schoar (2005) method to test the relation between the number of new CTAs and market performance.	A dataset of 587 active and 1823 liquidated CTAs sourced from TASS 'Live' and 'Graveyard' databases that span the period January 1994 to September 2010.	CTAs performance has, over the long-run (short-run), a positive (negative) effect on new commodity trading advisors.
Bhardwaj, Gorton & Rouwenhorst	Performance and persistence of CTAs. How the return is divided between the funds and their investors.	Fung and Hsieh (2004) trend-following factors. Rules based active strategies using primitive assets that include currency futures, commodity futures, and country equity indices.	Lipper-TASS database consisting 1127 CTAs during the time period of January 1994 to July 2012.	They show that CTA excess returns to investors were insignificantly different from zero while gross excess returns were 6.1%, which implies that managers captured the performance in fees.
Kazemi & Li	Market timing ability of Systematic and Discretionary CTAs	Market timing models from Treynor & Mazuy (1966) and Henriksson and Merton (1981) as well as Fung and Hsieh (2001) factors.	CISDM database, with monthly, net-of-fees returns, AUM, and information on other fund characteristics, such as fund inception date, self-declared strategy of the fund, as well as the name of the management company.	They find that systematic CTAs are generally more skilled at market timing than discretionary CTAs, with the latter having slightly better overall risk-adjusted performance during the study period 1994-2004.

Table 1. Summary of literature

The conclusions regarding the performance of CTAs are similar; the performance has been rather good in 90s and early 2000s but has diminished after the Great Financial Crisis as stated by the latest studies. To the extent that studies compared different strategies implemented by CTAs, they found significant differences between those strategies, and in addition, that it is difficult to model all of them.

4 Data

4.1 CTA Return data

For this thesis I will use the Lipper-TASS hedge fund data base. The data base has data of 2237 CTA funds from 1970 until early 2014. The time period in my study is from January 1997 to December 2013 and the database has performance data of 1027 CTA funds from this time period.

The data available of CTAs is time series data of each fund's monthly net returns. The database allows the user to filter CTAs for example according to their investment approach, geographical investing target, industry, currency etc. The database also includes time series data for many indices that can be used in this study such as equity and bond indices as well as commodity baskets. To control for survivorship bias, both alive and defunct funds in the database are included in this study.

As the purpose of this study is to evaluate the performance of strategies, I will use the funds with different strategies that have no overlap. This means that in the technical category there are only those funds that have reported trend-following or systematic investment approach and stated that they have no discretionary approach. When using time series data of those CTAs that do not report any overlap in strategies, the performance of the strategies can be accessed in its purest form. Mixed strategy includes only those funds that have reported to use both strategies. Hence, a fund can be included in only one category. The number of funds that have no overlap with other strategies is following:

- Technical: 613
- Fundamental: 161
- Mixed: 253

The division to these three categories can be done by using information on the database itself. The funds have reported their investment approach as well as the focus on certain instruments or asset classes. However, it should be acknowledged that this leaves us

trusting that the CTA managers themselves have reported their investment style accordingly. There is no apparent reason why the manager would be dishonest in reporting the investment approach. However, there might be some that do not report the right approach as they might think that they do not fit in categories given or that they simply leave the approach field empty.

4.2 Other variables

The Fung and Hsieh 9-factor model factors consist of monthly time series data. The data has been previously used in William Fung and David A. Hsieh's studies, "Hedge Fund Benchmarks: A Risk-Based Approach" and "Hedge Funds: An Industry in Its Adolescence" to capture the risk of well-diversified hedge fund portfolios. The data consists of five primitive trend-following strategies, two equity-oriented risk factors and two bond-oriented risk factors.

The factors are as follows:

- PTFSBD: Return of PTFS Bond lookback straddle
- PTFSFX: Return of PTFS Currency Lookback Straddle
- PTFSCOM: Return of PTFS Commodity Lookback Straddle
- PTFSIR: Return of PTFS Short Term Interest Rate Lookback Straddle
- PTFSSTK: Return of PTFS Stock Index Lookback Straddle
- Equity Market Factor: The Standard & Poors 500 index monthly total return
- The Size Spread Factor: Russell 2000 index return - Standard & Poors 500 return
- The Bond Market Factor: The monthly change in the 10-year treasury constant maturity yield
- The Credit Spread Factor: The monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield.

Momentum factors in this study are constructed by using 51 different futures contracts in commodities, stocks, currencies and fixed income. The data is end of the month time series data of the prices of futures contracts. The futures contracts are always front month contracts i.e. they are the closest contract to maturity. Hence, the futures contracts are rolled forward four times a year at the expiry.

Commodity futures are divided into four groups: metals, energy, livestock and agriculture. Equities, fixed income and currencies are each considered to form one group. All futures contracts that are used to create these momentum variables are listed in the appendices.

4.3 Descriptive stats

4.3.1 CTA time series

Table 2 below summarizes descriptive stats for monthly CTA returns for the full sample period from January 1997 to December 2013. The table presents stats for all strategy portfolios as well as a pooled CTA portfolio which includes all funds from all three strategies. It is worth noticing that during the observation period all CTA strategies show positive average monthly returns. Fundamental strategy shows the highest monthly mean return (+0,62 %), while technical strategy has the lowest (+0,39 %).

Variable	CTA funds	Technical	Fundamental	Mixed
Mean	0,52 %	0,39 %	0,62 %	0,47 %
Std.Dev	2,18 %	2,58 %	1,80 %	2,08 %
Kurtosis	1,57	0,86	3,80	1,22
Skewness	0,11	0,49	-0,59	-0,11
t-statistic	3,46	2,37	4,95	3,43
Min	-7,62 %	-6,46 %	-7,62 %	-7,08 %
Max	9,56 %	9,56 %	5,75 %	6,50 %

Table 2. Descriptive statistics of monthly returns of Commodity trading advisors in January 1997- December 2013. Table presents descriptive statistics for all CTAs pooled together and strategy portfolios. Mean and standard deviations are monthly figures. Kurtosis reports the excess kurtosis of a given time series. T-statistic reports the result of a one sample t-test for the time series data.

While fundamental strategy shows highest average monthly returns it also has the lowest monthly standard deviation (1,80 %) of the three CTA strategies. This would imply that the risk associated with this strategy is lower than others. However, the kurtosis and skewness statistics suggest that the return distribution is negatively skewed. Fundamental strategy has negative skewness (-0,59), while technical strategy has clearly positive (+0,49) and mixed has one only a little below zero. A higher kurtosis suggests a

higher chance of outliers, which in the case of fundamental strategy could mean that there are big negative outliers as the skewness is negative.

Minimum and maximum values are best with the technical strategy. Its minimum monthly return is least negative (-6,46 %), while its highest single month return is over three percentage points higher than the second-best maximum of mixed strategy (+9,56 % versus +6,50 %).

4.3.2 The Fung and Hsieh factors

Table 3 presents the descriptive stats for the Fung and Hsieh 9-factor (FH9) model for the full sample period from 1997 to 2013. It is interesting to notice at first glance that all the primitive trend-following factors post a negative average monthly return. The static factors in the model (i.e. other than primitive trend-following strategy factors) show both positive and negative monthly average returns.

Standard deviations are higher with the PTFS-factors than for static factors or CTA strategies. There seems to be a lot of variation within these factors in terms of monthly returns. As we can see, the highest monthly return is enormous +221,92 % in the case of the PTFS-interest rate factor and that factor also has the greatest negative return (-34,64 %).

Variable	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	S&P 500	Size spread	10-year treasury	Credit Spread
Mean	-1,96 %	-0,24 %	-0,22 %	-0,07 %	-5,06 %	0,54 %	0,22 %	0,03 %	-0,08 %
Std.Dev	15,19 %	18,14 %	14,14 %	27,71 %	14,12 %	4,59 %	3,42 %	7,78 %	6,32 %
Kurtosis	2,94	1,56	2,11	26,21	3,41	0,86	5,34	2,25	2,40
Skewness	1,44	1,16	1,17	4,29	1,39	-0,64	0,23	0,34	-0,25
t-statistic	-1,85	-0,19	-0,22	-0,04	-5,13	1,70	0,92	-0,06	-0,19
Min	-26,63 %	-30,00 %	-24,65 %	-34,64 %	-30,19 %	-16,94 %	-16,36 %	-26,93 %	-25,33 %
Max	68,86 %	69,22 %	64,75 %	221,92 %	60,48 %	10,77 %	18,43 %	27,56 %	21,59 %

Table 3. Descriptive statistics of monthly returns of Fung and Hsieh factors in January 1997– December 2013

4.3.3 Momentum factors

Table 4 below presents the descriptive stats for Momentum factors model for the full sample period from 1997 to 2013 and their magnitude is much closer to that of CTA strategies than were PTFS-factors. The highest average monthly return is 0,70 % for the

6-month equity momentum factor (+0,68 %) whereas the lowest is generated by the 6-month livestock commodity factor (-1,16 %).

Variable	MEM3	ENM3	LIM3	AGM3	EQM3	BOM3	FXM3
Mean	0,46 %	0,68 %	-0,06 %	-0,12 %	0,60 %	0,08 %	0,26 %
Std.Dev	4,79 %	5,99 %	5,83 %	3,41 %	3,00 %	0,72 %	1,62 %
Kurtosis	2,00	0,83	1,01	3,19	4,80	5,92	8,44
Skewness	0,64	0,29	0,28	0,92	0,93	1,02	1,46
t-statistic	1,37	1,62	-0,15	-0,51	2,85	1,69	2,27
Min	-13,5 %	-15,1 %	-17,0 %	-8,5 %	-9,0 %	-2,2 %	-3,9 %
Max	19,0 %	20,7 %	20,9 %	15,9 %	16,6 %	4,3 %	10,7 %

Variable	MEM6	ENM6	LIM6	AGM6	EQM6	BOM6	FXM6
Mean	0,61 %	0,44 %	-1,16 %	-0,11 %	0,70 %	0,00 %	0,15 %
Std.Dev	4,86 %	6,27 %	5,68 %	3,47 %	3,10 %	0,71 %	1,60 %
Kurtosis	1,81	1,11	1,40	3,07	4,13	6,65	3,84
Skewness	0,68	0,21	0,07	0,53	0,50	0,98	0,70
t-statistic	1,80	1,00	-2,94	-0,47	3,25	-0,05	1,35
Min	-13,5 %	-18,8 %	-20,3 %	-10,9 %	-9,0 %	-2,2 %	-4,8 %
Max	19,0 %	22,0 %	20,4 %	15,9 %	16,6 %	4,3 %	8,4 %

Variable	MEM12	ENM12	LIM12	AGM12	EQM12	BOM12	FXM12
Mean	0,59 %	0,38 %	-0,33 %	-0,03 %	0,63 %	0,07 %	0,13 %
Std.Dev	5,03 %	6,69 %	5,85 %	3,82 %	3,36 %	0,75 %	1,67 %
Kurtosis	3,28	0,96	0,92	2,24	3,16	7,43	2,78
Skewness	0,07	-0,19	-0,03	0,25	0,22	1,44	-0,36
t-statistic	1,69	0,82	-0,81	-0,12	2,68	1,40	1,13
Min	-20,21 %	-20,67 %	-20,27 %	-12,10 %	-9,38 %	-2,18 %	-7,46 %
Max	23,29 %	21,97 %	20,40 %	15,93 %	16,57 %	4,44 %	5,39 %

Table 4. Descriptive statistics of monthly returns of trend-following momentum factors in January 1997–December 2013

The average monthly averages of the momentum factors have the same signs over each selection period, i.e. those factors with negative 3-month mean returns, have negative returns for 6- and 12-month periods as well. This similarity between the factors constructed based on different selection period lengths might imply that the length of the selection period does not necessarily play a significant role in explaining the returns of the momentum factors and the ability of these factors to explain the variation of CTA returns.

Variable	3MCBR	6MCBR	12MCBR
Mean	0,41 %	0,53 %	0,18 %
Std.Dev	4,32 %	4,30 %	4,33 %
Kurtosis	3,28	3,39	3,72
Skewness	0,93	0,57	-0,86
t-statistic	1,34	1,76	0,59
Min	-10 %	-14 %	-22 %
Max	22 %	22 %	12 %

Table 5. Descriptive statistics of monthly returns of the momentum factor based on The Thomson Reuters/CoreCommodity CRB Index in January 1997– December 2013

The momentum factors based on CBR index all show positive average monthly returns, of which the highest is reported for the 6-month selection period (+0,53 %). All factors have similar standard deviations of a little over 4 %, as well as similar kurtosis that are a little above 3. Also, the 12-month selection period factor has interestingly a negative skewness (-0,86) while for the other two it is positive.

4.4 Biases

CTAs are essentially prohibited from advertising. Individual CTAs can release their own performance data, but not comparative data for advertising purposes. This will create a certain bias in the reported data as the performance data is basically the only "advertising method" for CTAs. There are at least four sources of bias in the CTA database that is employed in this study: selection bias, survivorship bias, look-back bias, and backfill bias. These biases will most likely skew the average returns of CTAs upwards. (Bhardwaj et al, 2014)

4.4.1 Survivorship bias

Survivorship bias arises when a sample of CTAs includes only those CTAs that are operating at the end of the sample period and excludes CTAs that have ceased their operations during the sample period. According to Bhardwaj et al. (2014), in most cases, CTAs that have stopped operating, have done so because of their weak performance. Therefore, the historical return performance of the sample is biased upward, and the historical risk is biased downward relative to the universe of all CTAs. This bias is a natural consequence of the way the hedge fund industry evolved in the past. Therefore,

survivorship bias cannot be completely controlled in the framework of analyzing hedge fund or CTA data.

Basically, non-operational CTAs in a database are not necessarily dead funds in the universe of hedge funds. Defunct funds may include dead funds, delisted funds (that may or may not be dead), and operating funds that reached their capacity constraints or otherwise chose to stop reporting returns. Given a set of CTAs for a sample period, the observable portfolio consists of an equally weighted investment in all CTAs in the portfolio rolling forward from the beginning of the period.

Using data provided by the same database as in this study, Fung and Hsieh (1997) examined surviving and defunct funds operated by CTAs from 1989 to 1995. They found that a commodity funds' attrition rate per year is 19%, which is high compared to the 5% attrition rate in mutual funds. The survivorship bias, which can be calculated by subtracting the return of the surviving portfolio from the observable portfolio, was averaged 3,4% per year. In contrast, the survivorship bias in mutual funds was estimated to be in the range from 0,5% to 1,5% per year.

4.4.2 Backfill bias

A backfill bias occurs if database vendors backfill the performance of a CTA while adding new CTAs into their database. Park (1995) finds that funds come into a database with "instant histories", which happens because it is naturally much easier for CTAs to market their funds if they have great past performance. Fung et al. (1997) state that new CTAs in general go through a so called "incubation" period, during which they trade on their friends' and relatives' money. After recording good enough performance over time, these CTAs then market themselves to database vendors and hedge fund consultants. When vendors put funds of these CTAs into their databases, they "backfill" the earlier returns during the incubation period.

To control for backfill bias in this study, a 12-month selection period is required to include a CTA in a portfolio. This, of course, is not bullet proof as the backfill might occur for a longer period than 12 months, but it does give more accurate results for the CTA strategy portfolios.

4.4.3 Selection bias

Selection bias arises from the fact that a managed futures consultant needs the permission from a fund manager before information about the performance can be released to a data vendor. It is often assumed that only those CTAs with good past performance want to be included in a database, which then leads to an outcome that the returns of CTAs in the database are higher than the returns of all existing funds in the CTA universe. This means that a vendor's database may not give a realistic view of the performance of all CTAs' funds that are available for investors.

However, while there are no estimates of the magnitude of the selection bias in hedge funds and CTAs, Fung and Hsieh (1997) found anecdotal evidence suggesting that the selection bias could be more constrained than expected. They found that managers with excellent performance did not necessarily participate in vendors' databases, particularly when the managers were not interested in gathering more capital. For example, George Soros' Quantum Fund has been closed to new investments since 1992 even though Quantum has a legendary performance record. Furthermore, Quantum has regularly returned capital to investors to keep the fund's assets under management around $5 billion. Anecdotal evidence indicates that there are offsetting factors at work regarding selection bias. While some hedge fund managers and CTAs are eager to include their good performance in vendors' databases, other managers have intentionally kept their performance away from them, which limiting effect on the magnitude of the selection bias.

4.4.4 Look-back bias

Look-back bias refers to ex-post data withholding by a CTA after observing performance. For example, if a fund that is liquidated due to poor performance is unlikely to report the return prior to liquidation. In other words, it is probable that CTAs delay reporting poor returns of their funds. If performance improves subsequently, CTAs may report the delayed returns, or alternatively they may leave the fund's returns out of the database if returns remain poor. According to Bhardwaj et al. it is plausible that unsuccessful CTAs have higher incentive to remove their performance data ex-post, which would lead to an upward bias in the performance of the funds that remain in the database.

5 Methodology

5.1 CTA returns

The annual returns of different CTA strategies are calculated by using cumulative returns on all funds that follow the strategy in question. It is assumed that in the beginning of a holding period equal amount of capital is incepted to each fund in the portfolio. At the end of the holding period I calculate the average return that portfolio was able to produce. The strategy portfolio is rebalanced after each holding period i.e. the capital invested is again redistributed to the funds equally. This means that equal weight CTA strategy indices are created for each holding period.

To reduce the exposure on backfill bias, a fund is required to have at least twelve months of returns before the holding period in question in order to be included in the strategy portfolio. Fund cannot be included in the strategy portfolio midst of the holding period; the portfolio consists only of those funds that were eligible in the beginning of the holding period.

If a CTA stops reporting during the holding period, it is removed from the strategy portfolio. Then the strategy portfolio is rebalanced according to remaining CTAs. This means that the "capital" left over from the exiting CTA is equally divided with remaining funds. Therefore, this rebalancing takes into account remaining CTAs' performance during the holding period. One scenario for a fund to stop its performance reporting to the database is that it has either dismal returns that its manager does not want to be acknowledged or it has failed and thus stopped trading. If we assume that this would be the case, then the returns would be skewed upwards by only rebalancing of the portfolio upon CTA stopping the reporting. One way to work around this could be to give a CTA -100 % return when its time series stops. However, as discussed earlier, there are famous examples where a very successful fund simply does not want to be included in databases and have its performance assessed. Hence, it is very difficult to determine whether the effect of a CTA to stop reporting has a positive or negative impact on portfolio returns as a whole.

When testing the effect on returns simply rebalancing the portfolios compared to assumption that every CTA that stops reporting has a return of -100 % in the last month of its time series. The former way of calculating the returns showed results that were much closer to the ones found in previous literature. Therefore, I simply rebalance the portfolio upon a CTA leaving the database.

5.2 Sharpe ratio

The reward-to-volatility measure (Sharpe ratio) which was first proposed by William Sharpe (1966) and therefore named after him, is widely used to evaluate the performance of portfolio managers. Sharpe ratio is a measure of risk–adjusted performance that indicates the level of excess return per unit of risk. Sharpe ratio divides average portfolio excess return over the sample period by the standard deviation of excess returns over that period. It measures the reward to volatility trade-off. The greater the Sharpe ratio, the greater the risk–adjusted return. Therefore, we would like to see this number as high as possible. One thing to consider closely is the risk-free rate used in the calculation which can greatly affect the final number. (Bodie et al, 2017)

The traditional Sharpe ratio is employed as follows:

$$Sharpe\ ratio = \frac{R_{CTAi} - R_f}{\sigma_{CTA}}$$

where R_{CTA} is the return of CTA strategy i, Rf is the risk free rate and σ_{CTA} is the standard deviation of the CTA strategy's excess return.

Pätäri and Tolvanen (2009) compared the prediction power of a standard frequentist style-adjusted 9-factor alpha, a corresponding Bayesian alpha and the Sharpe ratio to determine whether the performance persistence of hedge funds and CTAs is dependent on the performance metrics employed. When they used past Sharpe ratios as predicators for the next period Sharpe ratios, they found strongest evidence of performance persistence within every hedge fund style studied. Their results were highly significant for convertible arbitrage, event driven, global macro and equity market neutral style at the 1 % level hedge fund styles, but for CTAs the results were significant only at the 10 % level.

Their results showed that both the degree and existence of performance persistence vary among hedge fund styles and depend on both methodology and performance metric employed. In comparison to the performance metrics that are based on factor models, model-free performance metrics such as the Sharpe ratio turned out to be more sensitive in detecting performance persistence within the sample they employed.

5.3 Skewness and Kurtosis adjusted Sharpe ratio (SKASR)

Even though the use of the Sharpe ratio is a popular approach for performance measurement in empirical finance studies, it has been frequently criticized for some of its shortcomings. Mainly due to the risk calculation used in the method, i.e. standard deviation of returns, the Sharpe ratio does not make a distinction between upside and downside volatility which are considered equally bad. Yet, from the investor's perspective, a sharp volatility to the upside and left skewed return distribution is not explicitly a bad thing even though it is penalized in the Sharpe formula. Hence, for portfolios which do not follow a normal distribution curve of returns, the Sharpe ratio alone or used as a leading performance metric is not automatically the best measure of performance. Because of these weaknesses, I employ an additional adjusted Sharpe ratio to control for skewness and kurtosis characteristics of portfolio return distributions. (Pätäri, 2011)

Skewness and Kurtosis adjusted Sharpe ratio (SKASR), introduced by Pätäri (2011) is an extension to the traditional Sharpe ratio that accounts for skewness and kurtosis in returns distributions. SKASR has the benefit of considering all distributional asymmetries of returns that are revealed by skewness and kurtosis. In the calculation of SKASR, the adjusted Z-value (i.e. Z_{CF}) is determined first and this is done by applying the so called fourth order Cornish-Fisher (1937) expansion as described in the below equation.

$$Z_{CF} = Z_c + \frac{1}{6}(Z_C^2 - 1)S + \frac{1}{24}(Z_C^3 - 3Z_C)K - \frac{1}{36}(2Z_C^3 - 5Z_C)S^2$$

Where Z_C is the critical value for the probability based on normal distribution, S is skewness of the return distribution and K is kurtosis of the return distribution. Formulas for sample skewness and kurtosis are presented in equations below.

$$S = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{r_{it}-r_i}{\sigma}\right)^3$$

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{r_{it}-r_i}{\sigma}\right)^4 - 3$$

Where N denotes number of outcomes and ri is the average return. Next in the calculation of the adjusted Sharpe ratio, the skewness and kurtosis adjusted deviation (SKAD) is determined by multiplying the standard deviation by the ratio Z_{CF}/Z_c . Finally, the SKASR is obtained by substituting SKAD for standard deviation and the resulting formula manages to capture the problem with traditional Sharpe ratio stemming from periods of negative excess returns and initially addressed by Israelsen (2005).

$$SKASR = \frac{r_p - r_f}{SKAD_p^{(ER/|ER|)}}$$

Where $SKADp$ is skewness and kurtosis adjusted deviation of the monthly excess returns of a portfolio p and ER is average excess returns of a portfolio p.

5.4 Fung and Hsieh 9-factor model

Comparing CTAs to conventional bond and equity benchmarks would be flawed as the CTAs can be considered as an alternative asset class with very different characteristics in risk and returns compared to mutual funds (Gregoriou, Sedzro and Zhu, 2005). In order to properly evaluate and benchmark the non-linear performance associated with CTAs, benchmarks that imitate their dynamic trading strategies are necessary (Sepp, 2019).

I employ the Fung-Hsieh 9 –factor model in this thesis. Several models have been suggested to evaluate the performance of hedge funds. Multifactor models that are designed to capture the typical risk factors of diversified portfolios of hedge funds are often used for this purpose. The most commonly used model of this type is the Fung-Hsieh 9-factor model (Pätäri & Tolvanen, 2008). Fung and Hsieh (1997, 2001) recognized that the explanatory power of traditional asset index factors is particularly low for CTAs and

have shown that the returns of the CTAs show option-like return distributions relative to the return of the underlying assets. This finding drove them to model CTAs' returns in relation to a dynamically traded look-back straddle portfolio. They discovered that these factors together with certain fixed income and equity market factors could explain a large share of CTAs' returns. In result, their model is nowadays widely used in performance evaluation in the hedge fund and CTA literature.

The 9-factor model includes the following factors: S&P 500 return in excess of the risk-free rate, Wilshire small cap minus large cap return, month-end to month-end change in the US Federal reserve 10-year constant maturity yield, corresponding change in the difference between Moody's Baa yield and the Fed's 10-year constant maturity yield, bond PTFS, currency PTFS, commodity PTFS, short maturity interest rate PTFS and stock market PTFS where PTFS denotes primitive trend-following strategy. (Fung & Hsieh, 2004)

$$r_t = \alpha_0 + \beta_1 PTFSBD_t + \beta_2 PTFSFX_t + \beta_3 PTFSCOM_t + \beta_4 PTFSIR_t + \beta_5 PTFSSTK_t + \beta_6 EQ_t + \beta_7 ES_t + \beta_8 BM_t + \beta_9 BS_t + \epsilon_t$$

where, PTFS are the trend-following factors for bonds, currencies, commodities, short term interest and stock market, EQ is the equity factor, ES is the equity size factor, BM is the bond market, and BS is the credit spread factor.

The PTFS has the same pay-out as a structured option position known as the lookback straddle. The owner of the lookback call options has the option to buy the underlying asset at the lowest price over the life of the call option. Conversely, the owner of the lookback put option has the right to sell the underlying asset at the highest realized price over the option's lifespan. The combination of these two lookback options is the "lookback straddle", which delivers the ex post maximum pay-out of any trend-following strategy. The lookback straddle is designed to capture the general characteristics of the entire family of trend-following strategies. The strategy yields the return pattern that of a perfect market timer who can take either long or short positions.

Fung and Hsieh (2004) acknowledged that there are a few technical complications that

occur when constructing the PTFS returns. First, the lookback options are not exchange traded so they do not have market prices that could be used. Instead of market prices, they replicated the pay-out of a lookback straddle by using method created by Goldman et al. (1979). Second, the strategy of rolling standard straddles does not replicate all the cash flows of the lookback straddle, as the lookback straddle has only two cash flows: the premium and a pay-out equal to the maximum range of price of the underlying. While replicating this, the straddle rolls could create extra cash flows when straddles are rolled from one strike price to another. They included these cash flows in calculating the returns of the straddle-rolling strategy.

Third complication stems from the fact that the straddle rolling strategy does not consider that numerous exchange traded options are in fact American options instead of Europeans. Due to the possibility to exercise the option at any point during its life span, American options in general have higher prices than Europeans, which creates a bias of downward returns of the PTFS. Fourth, the strategy would require using at-the-money option, but Fung and Hsieh (2004) assert that they in many occasions do not observe at-the-money options. Instead they use approximations of the at-the-money by using closest to-the-money options. They state that the error that arises from this is likely to be small or insignificant.

Fifth complication is that the lookback straddle's returns are affected by the decision over its time horizon. Fung and Hsieh chose options with quarterly expirations due to their liquidity, larger volume and longer history. Lastly, the straddle-rolling strategy would require it to be continuously implemented by using high frequency data, which means that implementing the strategy would be rather unfeasible and time-consuming procedure. In practice, Fung and Hsieh rolled the straddles only at the end of each trading day using the settlement prices of the options and corresponding underlying assets. Then they aggregated the daily returns up to monthly returns which is the standard reporting frequency for hedge funds.

Despite these obstacles Fung and Hsieh were able to show that these factors can explain a substantial part of the variation of the hedge fund and CTA returns. Their benchmark model is now the standard pillar of the hedge fund performance evaluation studies.

5.5 Momentum factors

In addition to the Fung and Hsieh model, I will also employ multifactor momentum model to test whether it explains the variability of CTA returns better and if the 9-factor model's explanatory power could be improved. Bhardwaj et al. (2014) found higher explanatory power when introducing momentum benchmarks to the model.

As a dynamical style benchmark, Bhardwaj et al. (2014) applied the Mount Lucas Index, which is an index that weights equally twenty-five different futures contracts that cover foreign exchange, energy, financials, metal, and agricultural futures. It works as a momentum index for this basket of commodity futures and it is calculated monthly as follows: if the 200-day moving average is greater than the closing price of the future then it takes a short position; otherwise it takes a long position. This index was able to explain over 40 % of the return variation in the sample period from 2003-2012, a highest explanatory power of the models Bhardwaj et al. applied for this period. Therefore, there is a possibility for a multi-asset momentum model to explain variation of CTA returns. The momentum model applied in this study further breaks down the index to different variables according to their asset class.

I will create seven different momentum factors based on similar method as implemented by Moskowitz et al. (2012). As CTAs still have more bias in leaning towards commodity markets, I have separated commodities in four different sectors: metals, energy, livestock and agriculture. In addition to these four commodity categories, I have equity, fixed income and currency momentum factors as well. This differs from the momentum factors created by Bhardwaj et al (2014) as well as from Mount Lucas Index as they had all the commodities pooled into one momentum factor. The futures contracts included in these factors are listed in the appendices.

I will calculate the returns of the futures contracts by using rolling 3-, 6- and 12-month selection periods. This means that for each futures contract three momentum time series are created. If the selection period shows a positive return, we assume a long position is taken and if the return is negative, we take a short position. Those positions are then

pooled together to create the corresponding momentum factor. The return calculation of the futures is done at the end of each month and hence the momentum factor is rebalanced at the end of each month.

This differs from the momentum factor of Bhardwaj et al (2014) in that their momentum factor was relative whereas the factor used here is absolute. Bhardwaj et al (2014) ranked the securities inside the factors and assumed that long or short positions are taken based on the ranking instead of the actual return. They took the past best securities and assumed that a long position is taken with those and worst performing and those were shorted. This could result in a problem if there are selection periods where even the best performing securities might have negative returns. It is rather peculiar to assume that a trend-follower would take a long position if the underlying asset has had downward returns for a past six months.

The construction of the time series momentum factors follows the Moskowitz (2012) method. It focuses on 3-, 6- and 12-month momentum strategy with 1-month holding period. I start by looking each commodity and financial asset separately and then pool the assets together according to their category. The momentum factor regression is as follows:

$$r_{CTAi} = \alpha + \beta MME_t + \beta MEN_t + \beta MAG_t + \beta MLI_t + \beta MEQ_t + \beta MFI_t + \beta MCU_t + \epsilon_i$$

where, MME stands for momentum metal factor, MEN momentum energy, MAG momentum agriculture, MLI momentum livestock, MEQ momentum equity, MFI momentum fixed income, MCU momentum currency.

The position is sized so that it has an ex ante annualized volatility of 40 %. That is if the size of the position is chosen to be 40%/volt-1, where volt-1 is the estimate of the ex-ante volatility of the instrument. Moskowitz et al. (2012) acknowledges that the choice of 40 % annual volatility is not necessarily vital, but it makes it easier to intuitively compare portfolios to others. They state that the 40% volatility is simply chosen as it is comparable to the risk of an average individual stock, and when the average return is calculated on equal weighted basis across all securities to form the portfolios of securities which represent the momentum factors the volatility is similar to factors presented by Fung and

Hsieh (2004) and Asness et al. (2012). Another benefit from scaling the returns according to volatility arises from the fact that the leverage for each position a CTA would take is not likely to be the same. For example, in foreign exchange markets the movements of major currencies against each other is usually rather small compared to equity market movements and therefore in order to generate significant profits a fund manager must use larger leverage in currency positions. (Moskowitz and Pedersen 2012) The momentum factor's return for any commodity or financial instrument *s* at time of *t* is thus:

$$r_{t,t+1}^{TSMOM,s} = sign(r_{t-12,t}^{s}) \frac{40\%}{\sigma_t^s} r_{t,t+1}^{s}.$$

where, sign is the either +1 or -1 depending whether the position is long or short according the selection period, σ_t^s is the instrument's volatility and $r^s_{t,t+1}$ is the return of the futures contract at time t+1. For each month from January 1997 to December 2013 a return for each security is calculated using the formula above.

In addition to above momentum factors I will also apply a momentum factor based on The Thomson Reuters/CoreCommodity CRB Index which is based on Exchange Traded Futures. The Index represents 19 commodities, grouped by liquidity into 4 groups. Petroleum products capped at 33%, other 3 groups equal weighted. Thomson Reuters Commodity Indices also offers Non-Agri, Non-Energy and 3-month Forward versions.

The components of the index are following: Aluminium, Cocoa, Coffee, Copper, Corn, Cotton, Crude Oil, Gold, Heating Oil, Lean Hogs, Live Cattle, Natural Gas, Nickel, Orange Juice, RBOB Gasoline, Silver, Soybeans, Sugar and Wheat.

The weighting of the futures in the index is done as follows. Commodities are organized into 4 groups based on liquidity:
Group 1: Petroleum products – capped at 33%.
Group 2: Seven highly liquid commodities (equal weighted at 6%) – capped at 42%,
Group 3: Four liquid commodities (equal weighted at 5%) – capped at 20%.
Group 4: Five commodities (equal weighted at 1%) – capped at 5%.

$$CPS_{t,i} = CPS_{t-1,i} \times \left(\frac{W^F_{t-1,i} \times P^F_{t,i} + W^B_{t-1,i} \times P^B_{t,i}}{W^F_{t-1,i} \times P^F_{t-1,i} + W^B_{t-1,i} \times P^B_{t-1,i}} \right) \quad , \ t > 0$$

for i = 1 to 19

where:

CPS = Commodity Performance Series for i^{th} commodity at time t.

$W^F_{t,i}$ = Weight in the Front Month for commodity i at time t.

$W^B_{t,i}$ = Weight in the Back Month for commodity i at time t.

$P^F_{t,i}$ = Price of the Front Month Futures Contract for Commodity i at time t.

$P^B_{t,i}$ = Price of the Back Month Futures Contract for Commodity i at time t.

The CPS are then used to construct the Percent Return Series (PR) for each commodity. The Thomson Reuters CoreCommodity CRBt, is the Thomson Reuters/CoreCommodity CRB Index at time t, which is simply the sum of all the PR:

$$CRB_t = \sum_{i=1}^{19} PR_{t,i}$$

The momentum factor based on this index is rebalanced monthly as follows: if the moving average is greater than the closing price of the future then it takes a short position, otherwise it takes a long position. I will construct three different time series based on 3-, 6- and 12-month moving averages.

In order to be certain that there is no presence multicollinearity due to the independent variables of the model, the variance inflation factor (VIF) is applied for all variables. VIF indicates how much of the variation of one explanatory variable is affected by other explanatory variables. VIF is calculated as follows:

$$VIF_i = \frac{1}{1 - R_i^2}$$

where R-squared is the coefficient of determination of the regression equation, with X_i on the left-hand side of the equation, and other explanatory variables on the right-hand side of the equation.

	R-squared	VIF		R-squared	VIF		R-squared	VIF
MEM3	*0,20*	*1,24*	*MEM6*	*0,23*	*1,29*	*MEM12*	*0,25*	*1,34*
ENM3	*0,14*	*1,16*	*ENM6*	*0,27*	*1,37*	*ENM12*	*0,35*	*1,54*
LIM3	*0,03*	*1,03*	*LIM6*	*0,03*	*1,03*	*LIM12*	*0,01*	*1,01*
AGM3	*0,18*	*1,21*	*AGM6*	*0,18*	*1,22*	*AGM12*	*0,20*	*1,26*
EQM3	*0,18*	*1,22*	*EQM6*	*0,19*	*1,24*	*EQM12*	*0,13*	*1,15*
BOM3	*0,01*	*1,01*	*BOM6*	*0,04*	*1,04*	*BOM12*	*0,02*	*1,02*
MFX3	*0,26*	*1,36*	*FXM6*	*0,21*	*1,27*	*FXM12*	*0,20*	*1,25*
3MCBR	*0,34*	*1,51*	*6MCBR*	*0,43*	*1,75*	*12MCBR*	*0,48*	*1,93*

Table 6. Variance inflation factor test for multicollinearity

A VIF of 5 or 10 and above would indicate a multicollinearity problem with the model (O'Brien, 2007). However, the table 6 shows that there is no multicollinearity among momentum factors used in the study as the highest VIF-value is 1,93.

5.6 Autocorrelation and heteroscedasticity

Ordinary Least Square Estimates is a classic linear regression model which contains an assumption of homoscedasticity. If the variance of the error terms is not constant the assumption does not hold, and error terms are said to be heteroscedastic. If heteroscedasticity is ignored, then according to Brooks (2008) the OLS estimators will still give unbiased coefficient estimates, but they are no longer BLUE (Best Linear Unbiased Estimator), hence they do not have the minimum variance among the class of unbiased estimators. If the error terms are heteroscedastic, the formula for the coefficient standard errors does not hold. In other words, if the error terms are in fact heteroscedastic the standard errors could be wrong, which affects the determination of statistical significance and the interpretation of the model could be wrong.

According to Brooks (2008,) if autocorrelation is present and it is ignored the effects are quite like those in the presence of heteroscedasticity. The coefficients are not efficient; hence the standard error estimates could be wrong which leads to wrong interpretations of statistical significances.

The presence of autocorrelation and/or heteroscedasticity affects the conventional t-statistics and therefore the t-statistics need to be calculated in a different way. Following

the previous studies of Pätäri and Tolvanen (2009) and Kosowski et al. (2007), Newey West (1987) standard errors are used in statistical tests to avoid econometric problems stemming from autocorrelation and heteroskedasticity.

5.7 Hypotheses

The performance of the strategies is measured by their ability to create alpha. Therefore, the interpretation whether one investment strategy is better than the others will be determined by the size of the intercept of the models. Hence, the null hypothesis is that the intercept is equal to or less than zero:

$$H_0: \quad \alpha \leq 0$$
$$H_1: \quad \alpha > 0$$

To test significance of the performance differences between strategy portfolios, I apply the Z-test developed by Jobson and Korkie (1981), and later modified by Memmel (2003) to the following form:

$$z = \frac{\hat{S}h_i - \hat{S}h_n}{\sqrt{\hat{V}}} = z_{JK}$$

$$NV = 2 - 2\rho_{in} + \frac{1}{2}(Sh_i^2 + Sh_n^2 - 2Sh_i Sh_n \rho_{in}^2)$$

where,

Sh = Sharpe ratio of the portfolio, which is here replaced by SKASR-values.

V = the asymptotic variance of the SKASR-value differences.

ρ = correlation of portfolio returns

N = number of observations

The significance of risk factors affecting the returns of CTA strategies is measured by the p-value. If a risk factor has a statistically significant effect on the variation of a CTA portfolio's returns, the p-value is less than 0,05. Hence the null hypothesis is that p-value

is larger than 0,05:

$$H_0: \quad p > 0{,}05$$
$$H_1: \quad p \leq 0{,}05$$

The purpose of assessing the risk factors is to discover whether the sources of returns of different strategy portfolios change over different market conditions or do CTAs have rather static exposures. This is done by comparing significant risks factors of the strategy portfolios in different time periods.

The explanatory power of volatility adjusting with regards to momentum factors is measured or defined by comparing R-squared values of momentum factor-models with volatility adjusting and without it. The null hypothesis is therefore that there is no difference in R-squared of these two models:

$$H_0: \quad R^2_{VOL} = R^2_{NORM.}$$

$$H_1: \quad R^2_{VOL} \neq R^2_{NORM.}$$

6. Results

In this section I will present the CTA returns of different strategies and results from regressions with analysis of their significance. First, I will go through the CTA returns from the whole period of interest and from all subperiods. Second, I will analyse the results from Sharpe ratio and rank the strategy portfolios accordingly. Third, I will analyse the results from regressions to determine possible alpha of strategies and significant risk factors.

6.1 Full sample period

Fundamental strategy shows the best average monthly return over the whole period from 1997 to 2013. Fundamental strategy's mean is clearly higher than technical strategy's average return as well as that of the mixed strategy. The annualized difference between fundamental and technical strategies is 2,70 percentage points. Technical strategy shows the worst return of the three strategies, but its average return is still positive. Compared to the stock market index S&P 500 both fundamental and mixed strategies have had higher returns while technical strategy has underperformed against the S&P 500 index.

Fundamental strategy also outperforms other two strategies when comparing top performing funds. All three strategies' top quartiles posted annualized returns that are exceptionally high and clearly outperform the stock market. Interestingly, the worst performing funds using the fundamental strategy have been on average worse than funds using either technical or mixed strategies. Fundamental strategy seems to have much larger outliers on monthly returns than technical strategy as also indicated by larger kurtosis (3,81) than that of technical strategy (0,86). Thus, judging by descriptive stats, they show higher uncertainty in their performance than other strategies.

	Technical	*Fundamental*	*Mixed*	*S&P 500*
Annualised return	*4,84 %*	*7,54 %*	*5,85 %*	*5,53 %*
Top quartile	*15,25 %*	*12,62 %*	*13,83 %*	
Bottom quartile	*-1,57 %*	*-2,90 %*	*-2,47 %*	
Skewness	*0,49*	*-0,59*	*-0,11*	*-0,66*
Kurtosis	*0,86*	*3,81*	*1,22*	*1,00*
Volatility	8,94 %	*6,22 %*	*7,16 %*	*15,87 %*

Table 7. CTA strategy portfolio returns January 1997-December 2013. Reported annualized return is the return for strategy portfolio. Bottom and top quartile returns are returns for CTAs on a quartile limit, i.e. for technical CTAs, 25 % of funds had a return of +15,25 % or higher per annum.

As Bhardwaj & al. (2014) showed, CTAs have an option like characteristic on their returns. This would imply that CTAs should show positive skewness on their monthly returns. However, only technical strategy shows positive skewness (0,49) during the study's full sample period. Fundamental strategy has clearly negative (-0,59) skewness, which suggests that if there are large outliers, they are most likely negative. Therefore, the fundamental strategy portfolio is having largely positive returns during most months, while the average return pulled down by negative outliers. Nonetheless, all CTA strategies have better skewness and lower annualized volatility compared to the stock market, thus indicating them to be a safer bet for the investor.

Looking at the yearly returns in the Figure 4 below, it becomes clear why CTAs caught the interest of academia and the financial world after the great financial crisis. The strategy portfolio returns are in many years after 2001 well into double figures, while negative returns are only slightly below zero. The only odd observation before 2011 was the year 1999, when both technical and fundamental strategies posted returns well into negative territory. The largest negative returns in fundamental and technical strategy portfolios seem to occur when equity markets are experiencing bullish periods as in 1999 and from 2011 onwards. Mixed strategy has negative returns in both bullish and bearish periods.

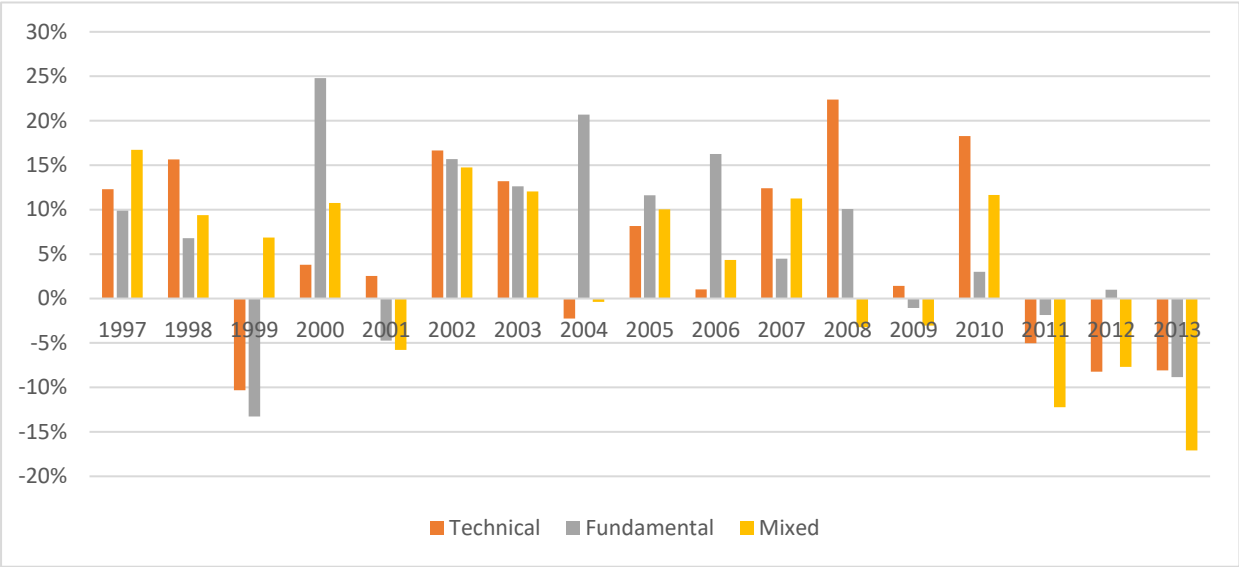


Figure 4. Yearly returns of CTA strategy portfolios

The last three years of the timeframe tell a similar story as other studies have discovered. The good performance of CTAs vanished after the financial crisis as the markets in the US started to recover and Europe was struggling with its own crisis. The fall in returns occurs at the same time as the falling inflation and commodity prices. One explanation could be the increase in the volatility of the commodity market prices, as many commodity types experienced increased volatility after 2008 (IMF 2012[2]). This would suggest that CTAs have a higher tendency to take long positions in commodity markets than short positions.

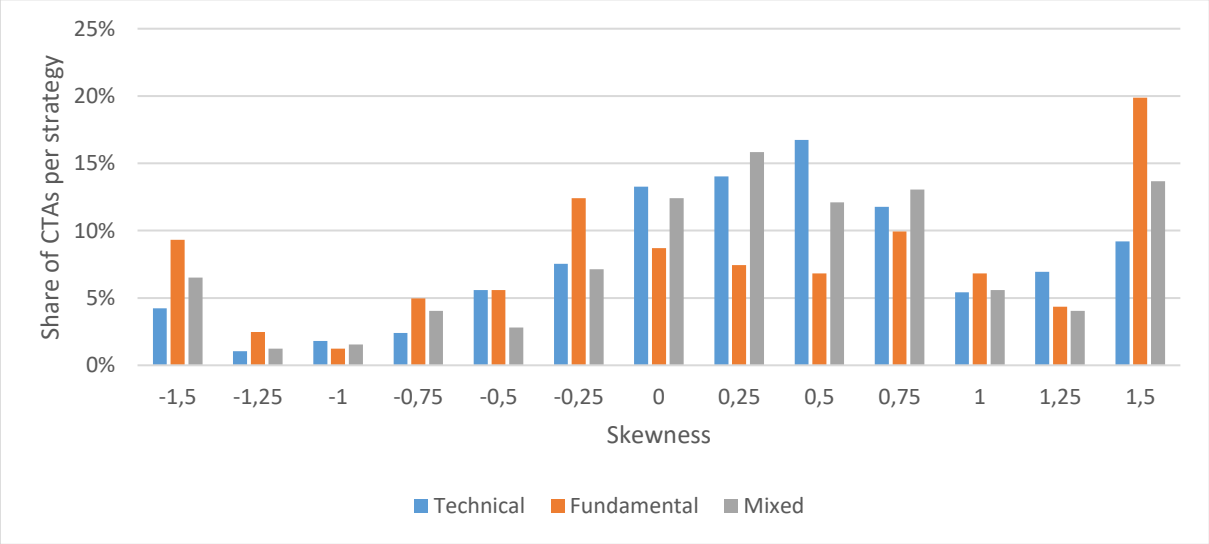


Figure 5. Skewness distribution of individual CTAs

[2] Available in https://www.imf.org/external/pubs/ft/fandd/2012/06/helbling.htm Read 16.10.2019

The skewness distribution shows the wide difference in individual CTAs and their abilities to perform in a monthly frequency. The fundamental strategy, interestingly, has the largest share of CTAs both at the low and high end of the distribution. This would further indicate that CTAs that follow the fundamental strategy have more wide-ranging returns for better or worse, than those that follow technical or mixed strategies. Technical and mixed strategies seem to have the largest share of CTAs at zero skewness or a little above. From investor's perspective, the decision to pick just one CTA from one strategy seems riskier with fundamental strategy as the returns could be either very much negatively or positively skewed.

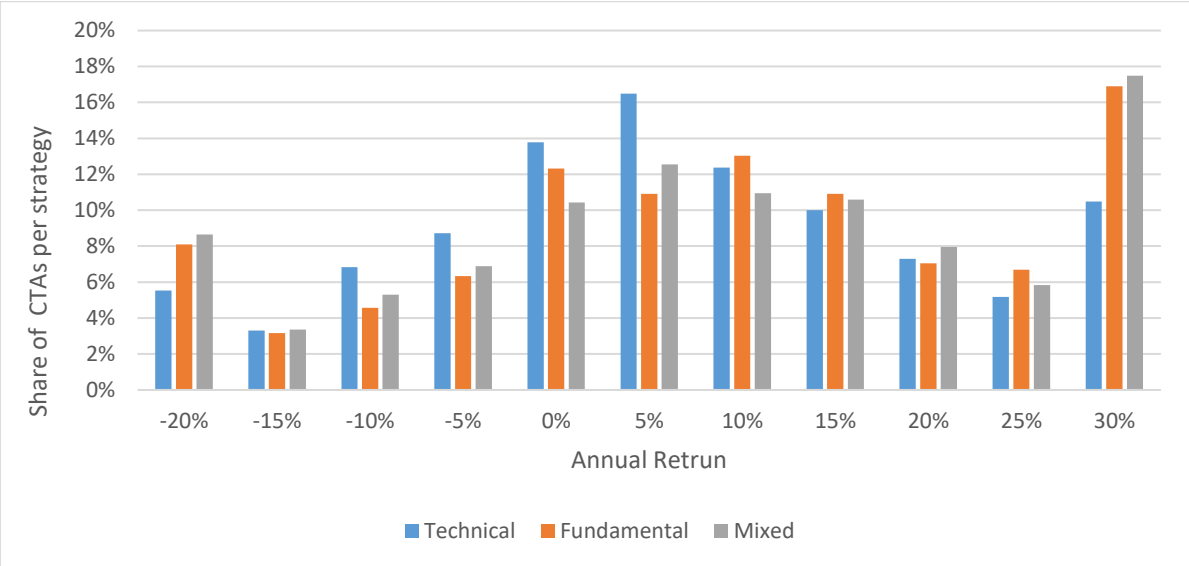


Figure 6. Return distribution of individual CTAs

The return distribution displays that for mixed strategy CTAs the share of managers achieving the upside is largest of the three strategies, but similarily, the share of poorly performing managers is the largest as well. The technical strategy has the largest share of CTAs in the middle of the distribution, but it has fat tails as well. The annualised return distribution of individual CTAs tells a similar story as the skewness distribution about fundamental CTAs: the strategy has fat tails and flat distribution. The variety of different return patterns is very large and would impose great challenges for investor for the selection process of CTA.

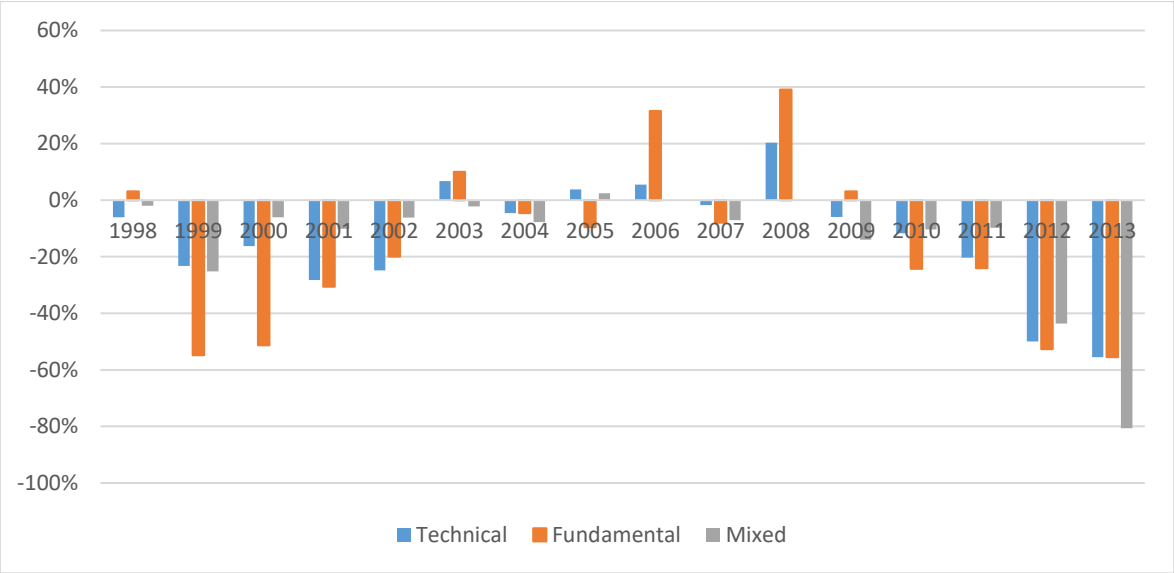


Figure 7. Change in number of reporting CTAs (y/y)

The number of reporting CTAs decreased drastically during two periods: from 1999 to 2002 and from 2010 to 2013. The latter period is easily explained by poor performance through all three strategies, but during the first decline period the returns were mixed. The fundamental strategy has the sharpest relative decline of reporting CTAs during the first few years, which in part is explained by the lower number of CTAs to begin with. Also, the fundamental strategy had the lowest returns on average in 1999. During the period from 2003 to 2009 there are no dramatical changes year over year in number of CTAs as during this period the strategy portfolio returns were almost entirely positive. Only fundamental strategy has two large increases on reporting CTAs, one in 2006 and second in 2008.

The fundamental strategy reports the best Sharpe ratio from the full sample period (0,520). The fundamental strategy portfolio's better Sharpe ratio is explained by its much larger excess return (+4,95 %) than other strategy portfolios, as well as its lower excess volatility (9,53 %). All three strategy portfolios have been able to create positive excess returns during the full sample period. All three strategy portfolios rank in the same order according to desirability of both excess returns and excess volatility: Technical strategy has lowest returns and highest volatility, mixed strategy is in the middle and fundamental is the best.

1997-2013	*Technical*	*Fundamental*	*Mixed*
Sharpe ratio	*0,232*	*0,520*	*0,341*
Excess return	*2,42 %*	*4,95 %*	*3,34 %*
Excess volatility	*10,44 %*	*9,53 %*	*9,78 %*

Table 8. Sharpe ratio January 1997–December 2013.

The SKASR results in the table 9 below also ranks strategy portfolios in same order as Sharpe ratio for the full sample period; for fundamental strategy the SKASR is the highest (0,499), mixed portfolio has the second best (0,327) while technical reports the lowest ratio (0,243). However, the differences between the portfolios' performance are not statistically significant at any confidence level on any strategy pair when measuring with SKASR.

1997-2013	Technical	Fundamental vs Technical	Mixed vs Technical	Fundamental vs Mixed
SKASR	0,243	0,499	0,327	0,499
signif.		0,252	0,766	0,456

Table 9. SKASR January 1997–December 2013. SKASR-row displays the SKASR for the former strategy, i.e. the SAKSR-ratio in the Fundamental vs Mixed-column is for the Fundamental strategy. The signf. reports the significance of the difference between strategies' SKASR.

The SKASR for fundamental and mixed portfolios is slightly higher than the corresponding Sharpe ratios, which indicates that these portfolios impose more risk that could be interpreted from volatility. The technical portfolio has a little higher SKASR than Sharpe ratio (0,243 v 0,232), which indicates that its volatility is more on the upside compared to fundamental and mixed portfolios. For fundamental and mixed strategy portfolios the Sharpe ratios are a little higher than SKASR values, which indicates the opposite. However, the differences are rather small for all three strategy portfolios, which would suggest that effect of skewness and kurtosis to the Sharpe ratios interpretations is not very significant during the full sample period.

Fung and Hsieh 9-factor model explains only a limited amount of the variation in returns of the three different CTA strategy portfolios. The technical strategy portfolio has the highest explanatory value, as the model explains 31 % of the monthly variation for the

entire period of interest 1997–2013. The model explains only about 6 % of the monthly variation in the fundamental and mixed strategy portfolios.

Alphas (intercepts) of all the three strategy portfolios are positive. The fundamental portfolio has the highest alpha of 0,7 % monthly, which translates to roughly 8,7 % annually. Technical portfolio is the second best with an annual alpha of 7,4 % (0,6 % monthly) and the mixed portfolio is the lowest with 6,2 % (0,5 % monthly). These results are in line with Bhardwaj et al. (2014) who found in their study that CTAs as a whole were able to generate an alpha of 6,1 % annually before fees. Other studies such as Foran et al. (2017) and Kazemi et al. (2009), have found alphas which are lower than the ones in this study, as annualized alphas in those studies were roughly 5 %.

	Technical			*Fundamental*			*Mixed*		
	Coeff.	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*
Intercept	*0,006*	*3,21*	*****	*0,007*	*4,06*	*****	*0,005*	*2,95*	****
PTFSBD	*0,018*	*1,37*	***	*0,005*	*0,45*		*-0,019*	*-1,83*	***
PTFSFX	*0,041*	*3,65*	*****	*0,016*	*2,03*	***	*0,006*	*0,62*	
PTFSCOM	*0,033*	*2,65*	****	*0,006*	*0,49*		*-0,018*	*-1,77*	***
PTFSIR	*-0,003*	*-0,39*		*-0,003*	*-0,63*		*0,012*	*2,17*	***
PTFSSTK	*0,032*	*2,39*		*0,009*	*0,79*		*0,004*	*0,32*	
S&P 500	*-0,004*	*-0,09*		*0,003*	*0,11*		*-0,041*	*-1,20*	
Size spread	*0,055*	*1,15*		*0,040*	*1,27*		*-0,026*	*-0,75*	
10-year treasury	*0,110*	*2,29*	****	*0,043*	*-1,32*		*0,046*	*-1,16*	
Credit Spread	*-0,080*	*-1,37*		*-0,032*	*-0,89*		*-0,041*	*-0,79*	
R-squared	*0,31*			*0,06*			*0,06*		
Adj. R-squared	*0,28*			*0,02*			*0,01*		
Standard Error	*0,02*			*0,02*			*0,02*		
N	*204*			*204*			*204*		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Table 10. Fung and Hsieh 9-factor model January 1997–December 2013. The table shows multivariate OLS-regression results for strategy portfolios with Newey-West based t-stats. Signf. columns indicate the statistical significance of a regression parameter.

Alphas of technical and fundamental strategy portfolios are statistically significant with 99 % confidence level and 95 % confidence level for mixed portfolio. All other variables for fundamental and mixed portfolios are not significant at the 95 % confidence level. Only weak significance can be discovered in PTFS-factors and none in other factors. Thus, the

slope being not significant, the intercept in these two cases merely tells us the mean of the raw return data. Indeed, the annualized return for fundamental strategy was 7,81 % and for mixed 6,83 %. Hence the goodness of fit of the model does not let us reject the null hypothesis in these cases.

For technical strategy portfolio the FH9-model shows in addition to the intercept, that also the primitive trend-following strategies in currency and commodity markets are significant at 95 % confidence level as well as 10-year treasury factor. Also, trend-following bond market factor expresses weak significance. The explanatory power with regards to technical portfolio is close to the results of previous studies, such as Foran et al. (2017), where the FH9-model explains around 30 % of the monthly changes.

The momentum model results in table 11 below are similar with FH9 in that they explain more of the return variations for technical strategy portfolio than for the other two. The model explains between 17 % and 24 % of returns of technical portfolio depending on selection period length, but less than 10 % for other two strategy portfolios. The 6-month selection period has the highest explanatory power on technical portfolio (24 %), whereas highest adjusted R-squared for fundamental is with the 3-month model (4 %). For mixed portfolio the explained variation is very close to zero on all different selection periods. The explanatory powers are similar to previous studies and we face the same problems with interpretations. The performance cannot be credibly ranked as the model explains so little of the return variations.

	Technical			Fundamental			Mixed		
	Coeff.	*t-stat*	*Signf.*	*Coeff.*	*t-stat*	*Signf.*	*Coeff.*	*t-stat*	*Signf.*
Intercept	*0,002*	*1,19*		*0,01*	*4,02*	*****	*0,005*	*3,11*	*****
MEM3	*0,080*	*2,59*	****	*0,07*	*2,77*	****	*0,045*	*1,53*	
ENM3	*0,044*	*1,58*		*0,03*	*1,61*	***	*0,008*	*0,34*	
LIM3	*0,024*	*0,94*		*-0,03*	*-1,27*		*0,001*	*0,04*	
AGM3	*0,097*	*2,40*	****	*0,02*	*0,66*		*0,028*	*0,59*	
EQM3	*0,012*	*0,23*		*-0,05*	*-1,10*		*0,049*	*0,93*	
BOM3	*0,521*	*1,57*		*0,15*	*0,82*		*-0,086*	*-0,95*	
MFX3	*0,312*	*2,67*	****	*-0,07*	*-0,73*		*-0,061*	*-0,53*	
3MCBR	*0,059*	*1,62*	***	*0,02*	*0,64*		*-0,024*	*-0,70*	
R-squared	*0,26*			*0,08*			*0,02*		
Adj. R-squared	*0,23*			*0,04*			*-0,02*		
Standard Error	*0,02*			*0,02*			*0,02*		
N	*204*			*204*			*204*		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Table 11. 3-month selection period momentum factors January 1997– December 2013. The table shows multivariate OLS-regression results for strategy portfolios with Newey-West based t-stats. Signf. columns indicate the statistical significance of a regression parameter.

The significant risk factors for technical strategy portfolio are metals and currencies for all three different selection periods. For fundamental strategy portfolio only metal momentum factor of 3- and 12-month selection periods are significant along with 6-month bond factor. The metal momentum factor is the only momentum factor to which both technical and fundamental strategy portfolios have exposure to on at least two selection periods at 95 % confidence level. Interestingly, there are no risk factors that are statistically significant at the 95 % level for mixed strategy portfolio. Its performance has been between the other strategy portfolios in different performance measurements, so one might assume that it would have at least some shared factors to which it has exposure. As this is not the case, the performance could be driven by completely different kind of investment approach, rather than just a combination of technical and fundamental.

	Technical			Fundamental			Mixed		
	Coeff.	*t-stat*	*Signf.*	*Coeff.*	*t-stat*	*Signf.*	*Coeff.*	*t-stat*	*Signf.*
Intercept	0,003	1,77	*	0,006	4,09	***	0,005	3,00	***
MEM6	0,095	2,91	**	0,036	1,26		0,009	0,29	
ENM6	0,035	1,24		0,021	0,92		0,014	0,51	
LIM6	-0,015	-0,57		-0,022	-0,89		0,008	0,33	
AGM6	0,096	2,41	*	0,069	1,99	*	0,006	0,13	
EQM6	-0,070	-1,25		-0,038	-0,87		0,104	1,92	*
BOM6	0,904	3,12	***	0,363	2,51	**	0,082	0,47	
FXM6	0,349	2,50	**	0,007	0,08		-0,065	-0,72	
6MCBR	0,061	1,49		-0,029	-0,82		-0,065	-1,61	
R-squared	0,27			0,06			0,03		
Adj. R-squared	0,24			0,02			-0,01		
Standard Error	0,02			0,02			0,02		
N	204			204			204		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Table 12. 6-month selection period momentum factors January 1997–December 2013. The table shows multivariate OLS-regression results for strategy portfolios with Newey-West based t-stats. Signf. columns indicate the statistical significance of a regression parameter.

	Technical			Fundamental			Mixed		
	Coeff.	*t-stat*	*Signf.*	*Coeff.*	*t-stat*	*Signf.*	*Coeff.*	*t-stat*	*Signf.*
Intercept	0,002	1,39		0,006	4,26	***	0,005	3,17	***
MEM12	0,099	2,74	**	0,063	2,85	**	0,021	0,76	
ENM12	0,053	1,59	*	0,012	0,69		0,025	0,87	
LIM12	-0,011	-0,39		-0,006	-0,28		0,027	1,09	
AGM12	0,076	1,63		0,030	0,98		0,013	0,34	
EQM12	0,033	0,63		-0,040	-1,18		0,013	0,27	
BOM12	0,663	2,34	**	0,167	1,03		-0,034	-0,23	
FXM12	0,305	1,99	***	-0,052	-0,65		0,023	0,27	
12MCBR	-0,055	-1,02		-0,026	-0,82		-0,021	-0,51	
R-squared	0,2			0,04			0,02		
Adj. R-squared	0,17			0,00			-0,02		
Standard Error	0,02			0,02			0,02		
N	204			204			204		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Table 13. 12-month selection period momentum factors January 1997– December 2013. The table shows multivariate OLS-regression results for strategy portfolios with Newey-West based t-stats. Signf. columns indicate the statistical significance of a regression parameter.

The volatility adjusting does not seem to have an improving impact on the momentum factor model with technical and fundamental strategy portfolios. Instead, the volatility adjusted model seems to have close to zero explanatory power with these portfolios.

However, with the mixed strategy portfolio there is a slight improvement. The volatility adjusted model explains about 18 % of the variation in monthly returns of the mixed strategy portfolio, whereas the not adjusted model had below zero explanatory power. Therefore, the null hypothesis that R-squared of the not adjusted model is higher than the adjusted can be rejected with the case of mixed strategy portfolio. However, the explanatory power is still very low which means volatility adjusted model is not necessarily very applicable. Further research in this matter is needed.

	Technical			*Fundamental*			*Mixed*		
	Coeff.	*t-stat*	*p-value*	*Coeff.*	*t-stat*	*p-value*	*Coeff.*	*t-stat*	*p-value*
Intercept	*0,005*	*2,44*	*****	*0,006*	*4,26*	*****	*0,004*	*2,89*	*****
MEM3	*-0,007*	*-0,12*		*-0,083*	*-1,46*	***	*0,147*	*2,69*	*****
ENM3	*-0,035*	*-0,47*		*0,003*	*0,05*		*0,089*	*1,63*	
LIM3	*-0,005*	*-0,08*		*0,008*	*0,18*		*-0,056*	*-1,29*	
AGM3	*0,012*	*0,15*		*0,024*	*0,51*		*0,120*	*2,62*	*****
EQM3	*-0,028*	*-0,38*		*0,065*	*1,46*		*-0,079*	*-1,74*	***
BOM3	*0,133*	*1,97*	***	*-0,011*	*-0,26*		*0,113*	*2,50*	*****
MFX3	*-0,097*	*-1,37*		*-0,062*	*-1,43*		*0,071*	*1,08*	
3MCBR	*0,060*	*0,78*		*-0,040*	*-0,84*		*-0,007*	*-0,11*	
R-squared	*0,03*			*0,05*			*0,21*		
Adj. R-squared	*-0,01*			*0,01*			*0,18*		
Standard Error	*0,03*			*0,02*			*0,02*		
N	*204*			*204*			*204*		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Table 14. Volatility adjusted 3-month momentum-model

6.2 Bullish periods

The fundamental strategy portfolio has the best annualized returns on all three bullish periods and is also the least volatile of the three in the first two periods. The technical strategy portfolio underperforms the other two portfolios during first two periods, and it is only slightly less negative than mixed strategy portfolio in third bullish period. The technical strategy portfolio, however, is the only one with positive skewness during all bullish periods. All three strategy portfolios have negative returns from the last period.

		01/1997 - 03/2000	01/2003 - 06/2007	04/2009 - 12/2013
Average	Technical	6,43 %	5,33 %	-2,82 %
	Fundamental	8,23 %	15,97 %	-0,39 %
	Mixed	7,40 %	9,72 %	-2,91 %
Volatility	Technical	9,85 %	8,04 %	6,30 %
	Fundamental	6,81 %	5,26 %	6,84 %
	Mixed	6,99 %	6,61 %	7,28 %
Kurtosis	Technical	1,914	-0,251	-0,550
	Fundamental	-0,557	0,659	6,199
	Mixed	-0,054	-0,400	2,195
Skeweness	Technical	0,782	0,122	0,094
	Fundamental	0,040	0,626	-1,612
	Mixed	-0,080	0,144	-0,805

Table 15. CTA returns in bullish periods

Also, the fundamental strategy portfolio performs better than the other portfolios during all three bullish periods, when Sharpe ratio is used as a measurement as presented in table 16. Its excess volatility is a little higher in first bullish period than that of mixed portfolio, but higher excess returns explains its higher Sharpe ratio. The technical strategy portfolio shows weakest performance as it has the lowest Sharpe ratio on first two bullish periods and is tied with worst Sharpe on third period. Its excess returns are lower than other portfolios' on first two periods and only slightly better than mixed strategy portfolio's on third bullish period.

		Technical	Fundamental	Mixed
01/1997 - 03/2000	Sharpe ratio	0,397	0,650	0,604
	Excess return	4,39 %	6,08 %	5,33 %
	Excess volatility	11,07 %	9,36 %	8,84 %
		Technical	Fundamental	Mixed
1/2003 - 06/2007	Sharpe ratio	0,765	2,186	1,333
	Excess return	7,42 %	18,20 %	11,86 %
	Excess volatility	9,70 %	8,32 %	8,89 %
		Technical	Fundamental	Mixed
04/2009 - 12/2013	Sharpe ratio	-0,003	-0,001	-0,003
	Excess return	-3,19 %	-0,79 %	-3,29 %
	Excess volatility	9,27 %	9,99 %	10,13 %

Table 16. Sharpe ratios in bullish periods. Sharpe ratios used are modified Sharpe ratios, which means that negative Sharpe ratios are calculated by multiplying excess return with volatility.

The performance differences in SKASR for strategy portfolios in three bullish periods is statistically significant only during the second bullish period with fundamental strategy portfolio outperforming both technical and mixed strategy portfolios. During this subperiod, all three strategy portfolios show a better SKASR-value than the Sharpe ratio, which as previously discussed, means that the volatility experienced by portfolios is more on the upside rather than downside. Fundamental strategy portfolio is also the best performing portfolio on all three periods. All three strategy portfolios report negative SKASR for the last bullish period as their excess returns are negative. Due to low excess returns, technical strategy performs worse than others on all bullish periods.

	Technical	*Fundamental vs Technical*	*Mixed vs Technical*	*Fundamental vs Mixed*
01/1997 - 03/2000				
SKASR	*0,424*	*0,728*	*0,615*	*0,728*
signif.		*0,545*	*0,800*	*0,864*
1/2003 - 06/2007				
SKASR	*0,778*	*2,931*	*1,443*	*2,931*
signif.		*0,01<*	*0,256*	*0,01<*
04/2009 - 12/2013				
SKASR	*-0,372*	*-0,084*	*-0,332*	*-0,084*
signif.		*1,000*	*1,000*	*1,000*

Table 17. SKASR results for strategy portfolios in bullish periods. SKASR-row displays the SKASR for the former strategy, i.e. the SKASR-ratio in the Fundamental vs Mixed-column is for the Fundamental strategy. Signf. tells the significance of the difference between strategies' SKASR.

The Fung and Hsieh 9-factor regressions explain very little of the return variations for fundamental and mixed strategy portfolios. For the mixed strategy, the model shows an adjusted R-squared close to zero or even slightly negative, while for fundamental strategy, the highest value is 0,14. For technical strategy the adjusted R-squared is between 0,30 and 0,43 on different bullish periods. The technical strategy has its lowest adjusted R-squared (0,30) on the second bullish period, while the fundamental strategy has its highest (0,14) on the same period.

None of the factors is statistically significant on all bullish periods for any of the strategy portfolios. The trend-following bond-variables are significant for technical strategy during first and second bullish periods, as the variable is statistically significant at 99 % confidence level during first and at 95 % level during the second bullish period.

	Technical			Fundamental			Mixed		
	Coeff.	*t-stat*	*p-value*	*Coeff.*	*t-stat*	*p-value*	*Coeff.*	*t-stat*	*p-value*
Intercept	0,003	0,76		0,005	1,82		0,012	2,90	**
PTFSBD	0,088	3,29	***	0,043	1,54		-0,041	-1,39	
PTFSFX	0,033	1,42		-0,004	0,00		0,012	0,14	
PTFSCOM	0,038	1,04		0,021	1,10		-0,038	-1,59	
PTFSIR	-0,01	-0,69		-0,007	-0,71		-0,011	-1,13	
PTFSSTK	0,018	0,68		0,02	0,94		0,025	0,93	
S&P 500	0,026	0,23		0,018	0,19		-0,182	-2,80	**
Size spread	0,035	0,59		0,018	0,38		-0,085	-1,61	
10-year treasury	0,355	-1,85		-0,062	0,45		0,161	-1,15	
Credit Spread	-0,465	-1,91	*	0,113	0,60		-0,202	-1,12	
R-squared	0,56			0,23			0,2		
Adj. R-squared	0,43			0,00			-0,04		
Standard Error	0,02			0,02			0,02		
N	39			39			39		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Table 18. Fung and Hsieh 9-factor model January 1997–March 2000. The table shows multivariate OLS-regression results for strategy portfolios with Newey-West based t-stats. Signf. columns indicate the statistical significance of a regression parameter.

	Technical			Fundamental			Mixed		
	Coeff.	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*
Intercept	0,006	1,39		0,01	3,94	***	0,005	1,27	
PTFSBD	0,041	2,24	**	-0,015	-0,95		-0,009	-0,58	
PTFSFX	0,035	1,49		0,018	2,29	**	0,017	0,75	
PTFSCOM	0,023	1,08		0,006	0,40		-0,029	-1,26	
PTFSIR	0,008	0,58		-0,018	-1,28		-0,002	-0,13	
PTFSSTK	0,03	1,61		-0,023	-1,23		-0,006	-0,02	
S&P 500	0,256	2,17	**	-0,03	-0,44		0,117	1,60	
Size spread	0,21	1,71	*	0,216	1,95	**	-0,006	-0,53	
10-year treasury	0,087	-0,37		0,006	0,02		0,186	-1,15	
Credit Spread	0,028	0,14		0,071	0,65		-0,292	-1,12	
R-squared	0,41			0,28			0,145		
Adj. R-squared	0,30			0,14			-0,02		
Standard Error	0,02			0,01			0,02		
N	54			54			54		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Table 19. Fung and Hsieh 9-factor model January 2003– June 2007. The table shows multivariate OLS-regression results for strategy portfolios with Newey-West based t-stats. Signf. columns indicate the statistical significance of a regression parameter.

During the third bullish period, the technical strategy portfolio has its second highest adjusted R-squared of the three periods (0,33). The equity market factors show high statistical significance as the S&P 500-variable has a p-value of less than 0,01 and equity market size spread factor has a p-value less than 0,05. Interestingly, the coefficient of the S&P 500 variable is positive during the strong bull market, while the returns of the technical strategy during this period have been clearly negative. This would indicate that while the equity market has moved upwards most of the time, it has had movements to the downside as well. Hence, the equity market's downside movements have affected technical strategy CTAs, but they have not benefited from the upside movements.

	Technical			*Fundamental*			*Mixed*		
	Coeff.	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*
Intercept	*-0,004*	*-2,25*	*	*0,003*	*1,10*		*-0,001*	*-0,24*	
PTFSBD	*0,018*	*1,04*		*-0,001*	*-0,02*		*0,005*	*0,24*	
PTFSFX	*0,029*	*2,30*	*	*0,016*	*0,81*		*-0,024*	*-1,59*	
PTFSCOM	*0,018*	*1,11*		*0,001*	*0,04*		*0,014*	*0,81*	
PTFSIR	*-0,003*	*-0,19*		*0,033*	*1,36*		*0,035*	*2,06*	*
PTFSSTK	*-0,011*	*-0,66*		*-0,001*	*-0,03*		*-0,025*	*-0,89*	
S&P 500	*0,300*	*4,33*	***	*0,014*	*0,20*		*-0,082*	*-0,96*	
Size spread	*-0,171*	*-2,37*	**	*0,106*	*1,22*		*0,282*	*1,62*	
10-year treasury	*0,068*	*-1,16*		*0,007*	*-0,11*		*-0,045*	*0,68*	
Credit Spread	*0,008*	*0,13*		*0,009*	*0,15*		*0,073*	*0,93*	
R-squared	*0,43*			*0,11*			*0,16*		
Adj. R-squared	*0,33*			*-0,07*			*0,00*		
Standard Error	*0,02*			*0,02*			*0,02*		
N	*57*			*57*			*57*		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Table 20 Fung and Hsieh 9-factor model April 2009–December 2013 The table shows multivariate OLS-regression results for strategy portfolios with Newey-West based t-stats. Signf. columns indicate the statistical significance of a regression parameter.

The fundamental and mixed strategies do not have any variables that show p-values less than 0,05 and for the fundamental strategy the adjusted R-squared even goes to the negative territory (-0,07), which means that the model fits very poorly to the data. The ability to generate alpha is difficult to determine for either fundamental or mixed portfolios as the model explains a very small part or none of the returns. Hence the intercept in these cases is very close to the monthly returns of the strategy portfolios. The intercept of the technical portfolio during the second bullish period is 0,7 % which is 7,4 % annualized and hence higher than its average returns during this period (5,33 %).

6.3 Bearish periods

From investor's perspective the performance of CTAs during bearish periods is very important as they are often used to diversify portfolios where equities play a large role. They become useful tools for investors if they can provide hedge against diminishing stock market returns during bearish periods. This means that CTAs would have to perform much better during bearish than during bullish periods. The average returns for technical and mixed strategy portfolios on both bearish periods is clearly positive and higher than on any of the bullish periods. The technical strategy appears to thrive during bearish periods as on the worst bearish period the return was 11,08 % annualized, whereas the best bullish period was only 6,43 % annualized.

		04/2000 - 12/2002	*07/2007 - 03/2009*
Average	*Technical*	*11,08 %*	*13,01 %*
	Fundamental	*7,82 %*	*7,31 %*
	Mixed	*10,88 %*	*10,41 %*
Volatility	*Technical*	*12,19 %*	*8,06 %*
	Fundamental	*5,91 %*	*3,42 %*
	Mixed	*7,26 %*	*6,59 %*
Kurtosis	*Technical*	*-0,270*	*-0,138*
	Fundamental	*1,468*	*0,440*
	Mixed	*0,867*	*-0,028*
Skeweness	*Technical*	*0,154*	*0,509*
	Fundamental	*0,209*	*0,633*
	Mixed	*0,757*	*0,505*

Table 21. CTA returns in bearish periods.

All strategy portfolios create positive excess returns and perform well by measuring with Sharpe ratio, but now the technical strategy is the worst of the three during the first bearish period. It has a Sharpe of 0,788 while the mixed portfolio has 1,108 and fundamental 0,920. The technical portfolio clearly has a higher volatility on its excess returns compared to the other portfolios and its excess returns are below the mixed portfolio's.

		Technical	Fundamental	Mixed
04/2000 - 12/2002	*Sharpe ratio*	*0,32*	*0,00*	*0,40*
	Excess return	*3,64 %*	*0,34 %*	*3,29 %*
	Excess volatility	*11,49 %*	*8,03 %*	*8,18 %*

		Technical	Fundamental	Mixed
07/2007 - 03/2009	*Sharpe ratio*	*0,46*	*-0,01*	*-0,00*
	Excess return	*0,05 %*	*-5,2 %*	*-2,6 %*
	Excess volatility	*11,63 %*	*10,9 %*	*13,1 %*

Table 22. Sharpe ratios in bearish periods.

During the second bearish period, however, the technical strategy portfolio is the best performing portfolio. Technical strategy portfolio demonstrates positive excess return as the only one of the three portfolios. This would indicate that the returns during bearish periods are heavily influenced by interest rate changes as the raw returns were all clearly positive. As the interest rates decline (10-year treasury returns increase), all strategy portfolios have generated good returns. But excess returns then indicate that the upward movement is not as beneficial as in treasury bonds for the mixed and fundamental strategy portfolios.

The SKASR results in bearish periods for all strategy portfolios are clearly higher than for bullish periods. The worst SKASR for any of the portfolios is for the technical strategy on the first bearish period (0,742) while the highest SKASR in any bullish period is for the fundamental strategy in the first bullish period (0,465). The highest reported SKASR is for mixed strategy portfolio (1,038) in the first bearish period. However, the differences in portfolio performance are not statistically significant at any confidence level for any of the portfolio pairs.

	Technical	Fundamental vs Technical	Mixed vs Technical	Fundamental vs Mixed
04/2000 - 12/2002				
SKASR	*0,443*	*0,044*	*0,502*	*0,044*
signif.		*0,526*	*0,941*	*0,397*
07/2007 - 03/2009				
SKASR	*0,004*	*-0,373*	*-0,173*	*-0,373*
signif.		*0,993*	*0,995*	*0,999*

Table 23. SKASR results for strategy portfolios in bearish periods. SKASR-row displays the SKASR for the former strategy, i.e. the SKASR-ratio in the Fundamental vs Mixed-column is for the Fundamental strategy. Signf. tells the significance of the difference between strategies' SKASR-values.

	Technical			Fundamental			Mixed		
	Coeff.	*t-stat*	*p-value*	*Coeff.*	*t-stat*	*p-value*	*Coeff.*	*t-stat*	*p-value*
Intercept	*0,004*	*1,05*		*0,006*	*1,47*		*0,007*	*2,12*	**
PTFSBD	*0,039*	*1,93*	*	*0,01*	*0,50*		*-0,033*	*-1,34*	
PTFSFX	*0,089*	*6,67*	***	*0,029*	*1,34*		*0,042*	*2,69*	***
PTFSCOM	*0,006*	*0,13*		*-0,008*	*-0,23*		*-0,006*	*-0,16*	
PTFSIR	*0,033*	*1,72*		*0,006*	*0,41*		*-0,001*	*-0,44*	
PTFSSTK	*-0,001*	*0,14*		*0,012*	*0,49*		*-0,011*	*-0,16*	
S&P 500	*-0,058*	*-0,06*		*0,05*	*0,41*		*-0,224*	*-1,81*	*
Size spread	*0,129*	*0,55*		*0,033*	*0,33*		*-0,215*	*-2,68*	***
10-year treasury	*0,151*	*-0,96*		*0,034*	*-0,33*		*0,29*	*-2,37*	***
Credit Spread	*0,105*	*0,70*		*0,071*	*0,42*		*-0,551*	*-2,40*	***
R-squared	*0,71*			*0,238*			*0,443*		
Adj. R-squared	*0,6*			*-0,048*			*0,234*		
Standard Error	*0,02*			*0,018*			*0,019*		
N	*33*			*33*			*33*		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Table 24. Fung and Hsieh 9-factor model April 2000– December 2002. The table shows multivariate OLS-regression results for strategy portfolios with Newey-West based t-stats. Signf. columns indicate the statistical significance of a regression parameter.

For the FH9-model no factors are significant over the different bear markets for any of the strategy portfolios except for one occasion. The technical strategy portfolio has significant risk factor or factors on all five periods, but only on the first bear market and the second bull market share one significant risk factor: the PTFSFX. On all other periods the technical strategy portfolio has one or two different risk factors.

It is noteworthy, that technical strategy is the only one with significant risk factors on all periods. Fundamental strategy has only one significant risk factor at 95 % confidence level and that is the stock market size spread factor on the second bull market.

The mixed strategy portfolio has three significant risk factors on the first bear market: size spread, S&P 500 and Credit spread. This would implicate that the technical strategy is latent when it comes to the returns of the mixed strategy portfolio as no PTFS-factors have statistically significant effect on its returns on any of the periods. Instead, the only significant factors are the ones that have traditionally explained returns of actively managed funds by the discretion of the manager.

	Technical			Fundamental			Mixed		
	Coeff.	*t-stat*	*p-value*	*Coeff.*	*t-stat*	*p-value*	*Coeff.*	*t-stat*	*p-value*

Intercept	*0,007*	*1,47*		*0,003*	*0,61*		*0,01*	*1,12*	
PTFSBD	*0,027*	*0,72*		*-0,039*	*-1,62*		*0,062*	*1,20*	
PTFSFX	*-0,05*	*-2,78*	***	*-0,026*	*-2,05*	*	*-0,037*	*-2,48*	**
PTFSCOM	*0,141*	*5,26*	***	*0,03*	*1,26*		*0,004*	*0,19*	
PTFSIR	*-0,02*	*-3,90*	***	*-0,003*	*-1,31*		*0,019*	*4,97*	***
PTFSSTK	*-0,009*	*-0,35*		*-0,057*	*-2,48*	**	*0,011*	*0,12*	
S&P 500	*-0,086*	*-2,03*	*	*0,003*	*0,05*		*0,15*	*1,75*	
Size spread	*-0,164*	*-0,84*		*-0,129*	*-1,27*		*-0,107*	*-0,79*	
10-year treasury	*0,157*	*1,56*		*0,112*	*2,11*	*	*0,088*	*0,54*	
Credit Spread	*0,204*	*1,95*	*	*0,2*	*2,91*	***	*0,039*	*0,17*	
R-squared	*0,76*			*0,57*			*0,53*		
Adj. R-squared	*0,57*			*0,21*			*0,15*		
Standard Error	*0,02*			*0,01*			*0,02*		
N	*21*			*21*			*21*		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Table 25 Fung and Hsieh 9-factor model July 2007– March 2009. The table shows multivariate OLS-regression results for strategy portfolios with Newey-West based t-stats. Signf. columns indicate the statistical significance of a regression parameter.

7. Conclusions

Commodity trading advisors have been a widely studied niche in the hedge fund world since the early 2000s. The purpose of this study was to examine the performance of Commodity trading advisors' investing strategies from January 1997 to December 2013. This timeframe included three bullish and two bearish periods, which made it possible to interpret the effect of global market fluctuations on the performance of different CTAs' investing strategies. CTAs were divided into three groups according to their investment approach: technical CTAs, fundamental CTAs and those that combined the two strategies. The study employs several models to capture the performance of CTAs as well as to asses on which risk factors CTAs have exposure. The performance measurements included Sharpe ratio and extended Sharpe ratio to control for skewness and kurtosis. In addition, two multifactor models were applied: Fung and Hsieh 9-factor model and multi asset momentum model.

According to the results of this study, the fundamental strategy portfolio is the best performing portfolio during the full sample period when measuring with average returns, Sharpe ratio and SKASR. However, the significance of the differences in performance of the strategy portfolios are not statistically significant on any of the strategy pairs during the full sample period. It is, however, interesting to notice, that fundamental strategy shows lowest top quartile limit returns as well as lowest bottom quartile returns of the three strategy portfolios. The technical strategy portfolio is the only one with average returns below the equity benchmark S&P 500-index, but it also has the higher top and bottom quartile limit returns than the other two strategies. Hence, the return distribution of the technical strategy resembles the one of a desirable call option return distribution. The bottom quartile limit is important from investors' perspective as it might indicate that the selection of a CTA with a certain strategy affects the probability of downside risk. As the bottom quartile returns are higher, the chance of losing invested capital could be lower. At the same time the top quartile limit is higher as well, which indicates more upside potential from historical perspective. However, the significance of the historical returns

can be put to question as the latest subperiod shows that on average CTAs have destroyed capital rather than added value.

The multifactor models implemented in the study have very limited ability to answer the question of whether the different strategies were able to create alpha. The explanatory power of the Fung and Hsieh 9-factor model is close to zero with fundamental and mixed strategies and only explains 28 % of the technical strategy's return variation. The multi-asset momentum factor model explains an even lower amount of variation for all three strategy portfolios during the full sample period. Also, the attempt to improve explanatory power by volatility adjusting the factors proved wanting. Therefore, the intercept or alpha shown in the results is not a measurement of CTAs' skill or ability to create added value to the investor, but instead only the average return of the given strategy portfolio.

All CTA strategy portfolios have positive returns in both bearish periods as well as in the first two bullish periods and the only period with negative returns is the last and longest bullish period. Especially the technical and mixed strategies seemed to thrive during bearish periods. Both strategy portfolios' average return during the bearish periods is higher than the average return during the bullish periods. On the opposite side, fundamental strategy has better average returns during bullish periods. The Sharpe and SKASR tell a different story; on average the both ratios on bullish periods are higher than during bearish periods. This would indicate that the performance of CTAs is at least partly driven by the changes in monthly returns of the 10-year treasury bond which is used as a risk-free rate. This means that the returns of technical and mixed strategies increase as the 10-year treasury bond's returns increase (the interest rates decline), but not at the rate as the treasury bond's. Their performance is hence heavily linked to the interest rates during bearish periods. During the first two bullish periods both technical and mixed strategies were able to create excess returns which could mean that they dynamically change the exposure to interest rates depending on the market fluctuations. However, the FH9-factor model shows that the 10-year treasury factor is only strongly statistically significant for mixed strategy during the first bearish period and shows weak significance with technical strategy during the second bearish period. The interest rate straddle,

however, is strongly significant for both technical and mixed strategies during the second bearish period. Also, the momentum bond factors are statistically significant during the first bearish period for the technical strategy portfolio.

The market fluctuations might have an impact on CTA performance, but the number of observed periods is rather low to make strong conclusions. The poor performance of the last period in the study could be an anomaly to an otherwise well performing asset class or it could be a regime change to a constant underperformance. The studies that have been conducted lately, as the one of Foran et al. (2017), does not support the former as the poor performance has continued with the still ongoing bullish period.

The classification of strategies may not be flawless as the CTAs themselves are categorising their investing approach as to whether trend-following, technical or discretionary/fundamental. The definitions of these investment approaches are not set in stone and different fund managers may view the different styles in their own way. Even though two CTAs might follow a very similar approach to building trades one might categorise themselves as trend follower and the other as discretionary trader. In academic literature in general it is assumed that the trend-following strategy is categorized under the technical approach, but there are numerous trend-following CTAs that also claim to take a discretionary approach in the investing process. However, in this study it is assumed that the investing approaches that fall under the technical strategy the decision making is done by computer. This implies that there are different conceptions among CTAs on how the trend-following, systematic and discretionary approaches are defined. One explanation to the low explanatory power of the models could be that the strategy portfolios themselves contain CTAs with vastly different investing strategies and exposures to different markets. The FH9-model and multi-asset momentum models are designed to capture performance of certain exposures and trading strategies. These might be diluted in a strategy portfolio that consists of CTAs that implement very different strategies as the returns of individual CTAs do not have strong correlation.

The data of CTAs' performance is a time series with monthly datapoints, which presents limitations to the models and interpretations of the results as the number of observations in the smallest subperiods can be quite low. The period of the Great Financial Crisis from July 2007 to March 2009 consists of 21 data points of CTA performance. The explanatory power of models and significance of variables can be affected by a small number of observations, and at the very least, the comparison of results between subperiods is challenging due to differences in period length. There is not really a way to work around this if the reporting of CTAs is done on a monthly basis. A daily or even weekly return series would allow for a more robust interpretation of models and results.

The multifactor models applied in the study have very low explanatory power during the full sample period and explanatory power varies between subperiods. There are no well-known or easily mimicked investing strategies that would apply to a whole CTA strategy. The Fung and Hsieh 9-factor model applies straddle-based trend-following strategies that should dynamically track the performance of hedge funds, but they do not seem to be as efficient with tracking the performance of CTAs. Further research on CTAs' strategies and their performance characteristics is needed in order to create a dynamical performance measurement model to capture the CTAs ability to create alpha and benchmark the performance.

One reason for CTAs' popularity as a portfolio diversification tool for institutional investors', could precisely be the fact that their performance is so difficult to track and benchmark. The mystery of their performance characteristics combined with a promise of a call option like return distribution is naturally tempting to investors. If one could create a model with similar returns as CTAs that would be applicable in real world, there would be no performance-based reason for an investor to allocate capital to CTAs. The investor could simply construct a trading program with the same rules as in the model and it would perform similarly to a CTA portfolio. As this is not the case, it implies that CTAs keep changing the investing strategies and exposures to risk factors. Therefore, a more dynamic model than the ones implemented in this study should be created in order to capture the skill of CTAs.

The examined sample period of CTA performance ranges from 1997 to 2013 which is a period that contains a tremendous amount of technical development and increase in computation power. This must be considered when interpreting the results, as a systematic or trend-following strategy in the late 90s is bound to be different to their counterparts in the early 2010s. Also, in fundamental strategy, one conducts research and tests trading ideas using computer programs. These programs have seen some dramatical development during the full sample period, which cannot be unaffecting the trade construction and decision making of CTAs, regardless of the strategy they follow.

Another development that stems from technical development is the accessibility to markets and implementation of trading strategies. As the computational power of computers and programs increases, it becomes relatively more affordable for individuals who trade on their own account. Hence, the number of potential market participants should increase. The CTAs employed by institutional investors do not achieve as significant technical edge compared to individual traders as in the 1990s, as the playfield is more even. Futures markets are by definition a zero-sum game, which means that an increase in market participants should decrease CTAs' returns, if the new entrants are capable of using the same strategies and thus competing with CTAs. If the new entrants are mostly individual traders or family offices without any clients, they have no incentive to report their returns to any data bases. Thus, the reporting CTAs are the part of the speculative futures market that experienced edge in 1990s and early 2000s but sees diminishing returns as the old strategies and trades are becoming overcrowded.

The limitations of this study leave room for further research. An interesting idea one could attempt is to create criteria selection to construct a CTA portfolio that would outperform consistently in different market regimes. The private database used in this study allows to categorize reporting funds in many different categories including investment approach and market or asset class focus. This can be used to classify CTAs in different ways and to create portfolios of many different criteria to examine if there is a possibility of alpha discovery by criteria selection. If one could show that there are ways to classify CTAs to

create an outperforming portfolio, this would have great implications on portfolio diversification and return enhancing for institutional investors.

Also, another extension to this study could be a study of the performance persistence of CTAs' investing strategies. Pätäri and Tolvanen (2009) found that there is weak significance on performance persistence within CTAs if they are considered as one group. The performance persistence of different strategies, however, is yet to be examined. This examination would bring valuable information on whether previous returns have any implication on future returns depending on investing strategy.

The differences in the performance of CTAs' different investing strategies are not significant and therefore from the investor's perspective the strategy should not necessarily play an important role in managers' selection process. However, the differences in returns between individual CTAs, if not strategies, are clearly quite dramatic. There are evidently return enhancing strategies to be discovered among CTAs, which means that the world of CTAs still has potential to bring value to investors if the selection process of individual CTAs can be made considerable, comprehensive and consistent.

References

Literature

Anson M. & Ho H., (2004) Measuring the Long Volatility Strategies of Managed Futures, in Gregoriou, Greg N., Karavas, Vassilios N., Lhabitant, Francois-Serge, Rouah, Fabrice (ed.), Commodity Trading Advisors: Risk, Performance Analysis and Selection, John Wiley & Sons Inc., Hoboken, New Jersey.

Baker, H. K., Filbeck, G. & Harris, J. H. (2008) *Commodity Trading Advisors and Managed Futures*, Oxford Scholarship Online.

Bodie, Z., Kane, A. & Marcus, A. (2017) Investments. 11th edition. McGraw-Hill Higher Education. New York.

Bhardwaj, G., Gorton, G. B. & Rouwnhorst, K. G. (2014) Fooling Some of the People All of the Time: The Inefficient Performance and Persistence of Commodity Trading Advisors. *The Review of Financial Studies*, Volume 27, Issue 11, 3099–3132

Brooks Chris, 2008 "Inroductory Econometrics for Finance", 2nd Edition, Campridge University Press, UK.

Brown. J. & Meksi. L. (2013) An Overview of Managed Futures: Evolving attitudes towards hedge funds*. The Hedge Fund Journal,* 86.

Do, V., Faff, R., Lajbcygier, P., Veeraraghavan, M. & Tupitsyn, T. (2015) Factors affecting the birth and fund flows of CTAs *Australian Journal of Management.* 41, 2, 324–352.

Edwards, F. R. & Liew, J. (1999) Hedge funds versus managed futures as asset classes. *Journal of Derivatives*, 6, 45–64.

Elaut, G., Frömmel, M. & Mende, A. (2017) Duration Dependence, Behavioral Restrictions, and the Market Timing Ability of Commodity Trading Advisors. *International Review of Finance*, 17, 3, 427–450.

Foran, J. & Hutchinson, M. C., McCarthy, D. F. & O'Brien, J. (2017) Just a one-trick pony? An analysis of CTA risk and return. *Journal of Alternative Investments,* 20, 2, 8–26.

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

Fung, W. & Hsieh, D. (2001) The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers," *Review of Financial Studies*, 14, 313–341.

Fung, W. & Hsieh. D. (1997) Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds. *Review of Financial Studies*, 10, 275–302.

Fung, W. & Hsieh, D. (1997) Investment Style and Survivorship Bias in the Returns of CTAs: The Information Content of Track Records. *Journal of Portfolio Management*, 24, 30–41.

Fung, W. & Hsieh, D. (2000) Performance Characteristics of Hedge Funds and Commodity Funds: Natural vs. Spurious Biases. *Journal of Financial and Quantitative Analysis*, 35, 3, 291–307.

Garner, C. (2017) *A Trader's First Book on Commodities: Everything you need to know about futures and options trading before placing a trade*. DeCarley Trading, LLC. Kindle Edition.

Goldman, M., Sosin, H. & Gatto, M. (1979) Path Dependent Options: 'Buy at the Low, Sell at the High'. *Journal of Finance*, 34, 1112–1127.

Gregoriou, G. N., Karavas, V. N., Lhabitant, F. S., Rouah, F. (2004), *Commodity Trading Advisors: Risk, Performance Analysis and Selection*, John Wiley & Sons Inc., Hoboken, New Jersey.

Gregoriou, G. N. (2008) Encyclopedia of Alternative Investments pp.93, Taylor & Francis Group, LLC, New York.

Gregoriou, G. N., Hübner, G., Papageorgiou, N. & Rouah, F. (2005) Survival of the commodity trading advisors: 1990–2003. *The Journal of Futures Markets*, 25, 8, 795–815.

Hedges, J. (2004) Commodity Trading Advisors: Risk, Performance Analysis and Selection, in Gregoriou, G. N., Karavas, V. N., Lhabitant, F. S., Rouah, F. (ed.), Commodity Trading Advisors: Risk, Performance Analysis and Selection, John Wiley & Sons Inc., Hoboken, New Jersey.

Hedges J. (2004) Managed Futures Investing, in Gregoriou, G. N., Karavas, V. N., Lhabitant, F. S., Rouah, F. (ed.), Commodity Trading Advisors: Risk, Performance Analysis and Selection, John Wiley & Sons Inc., Hoboken, New Jersey.

Irwin H. S. & Holt B. R. (2004) The Effect of large Hedge Fund and CTA Trading on Futures Market Volatility in Gregoriou, G. N., Karavas, V. N., Lhabitant, F. S., Rouah, F. (ed.), Commodity Trading Advisors: Risk, Performance Analysis and Selection, John Wiley & Sons Inc., Hoboken, New Jersey.

Jobson, J.D. & Korkie, B. 1981. Performance Hypothesis Testing with the Sharpe and Treynor Measures. Journal of Finance, 36, 889-908.

Kaplan S.N. & Schoar A. (2005) Private equity performance: Returns, persistence, and capital flows. *Journal of Finance,* 60, 1791–1823.

Kat M. (2004) Managed Futures and Hedge Funds: a Match Made in Heaven, in Gregoriou, G. N., Karavas, V. N., Lhabitant, F. S., Rouah, F. (ed.), Commodity

Trading Advisors: Risk, Performance Analysis and Selection, John Wiley & Sons Inc., Hoboken, New Jersey.

Kazemi, H. & Li, Y. (2009) Market Timing of CTAs: an Examination of Systematic CTAs vs. Discretionary CTAs. *The Journal of Futures Markets*, 29, 11, 1067–1099.

Kiymaz, H. & Simsek, K. D. (2008) Commodities: Markets, Performance, and Strategies, in Baker, H. K., Filbeck, G. & Harris, J. H. Commodity Trading Advisors and Managed Futures, Oxford Scholarship Online.

Kosowski, R., Naik, N.Y. & Teo, M. (2007) ”Do hedge funds deliver alpha? A Bayesian and Bootstrap analysis”, Journal of Financial Economics, Vol. 84, no. 1, 229-264.

Mackey, S. (2014) Commodity trading advisor indexes and alpha generation relationships. *Journal of Applied Business Research,* 30, pp. 1821-1836.

Memmel, C. 2003. Performance Hypothesis Testing with the Sharpe Ratio. Finance Letters, 1, 2003.

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

Newey, Whitney K., and Kenneth D. West. "A Simple, Positive SemiDefinite, Heteroskedasticity and Autocorrelation Consistent." Econometrica, 55, 1987: 703-708.

O’Brien, R. M. (2007). "A Caution Regarding Rules of Thumb for Variance Inflation Factors". Quality & Quantity. 41 (5): 673–690.

Park, J. (1995) *Managed Futures as an Investment Set*. Doctoral dissertation, Columbia University.

Pätäri. E. & Tolvanen, J. (2009) Chasing performance persistence of hedge funds – Comparative analysis of evaluation technique. *Journal of Derivatives & Hedge Funds,* 15, 3, 223–240.

Sepp. A. (2019) Trend-Following CTAs vs Alternative Risk-Premia: Crisis beta vs risk-premia alpha. *The Hedge Fund Journal*, 138.

IMF. 2012 available in:

https://www.imf.org/external/pubs/ft/fandd/2012/06/helbling.htm

Databases

Fung & Hsieh 9-factor model data, available in, http://faculty.fuqua.duke.edu/Bdah7/DataLibrary/TF-Fac.xls (The same PTFS index data are also employed by Fung and Hsieh (2004) and Bhardwaj et al, (2014) for example).

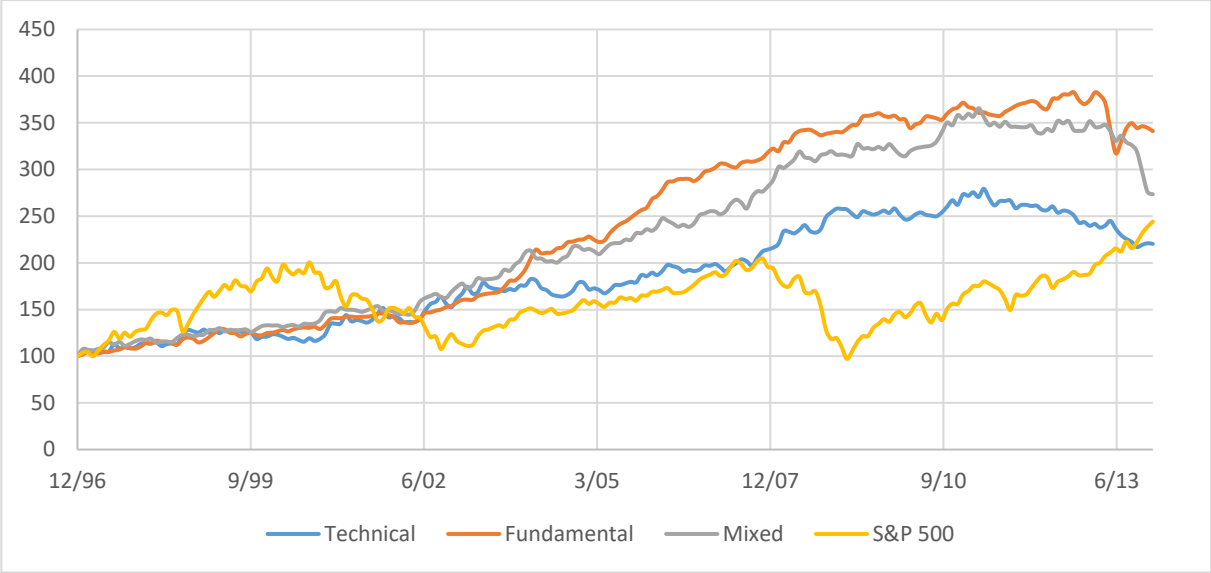
Thomson Reuters, Core Commodity CRB Excess & Total Return Index. Methodology description, available in
https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/cc-crb--index-methodology.pdf

Quandl, The futures data, available in
https://www.quandl.com

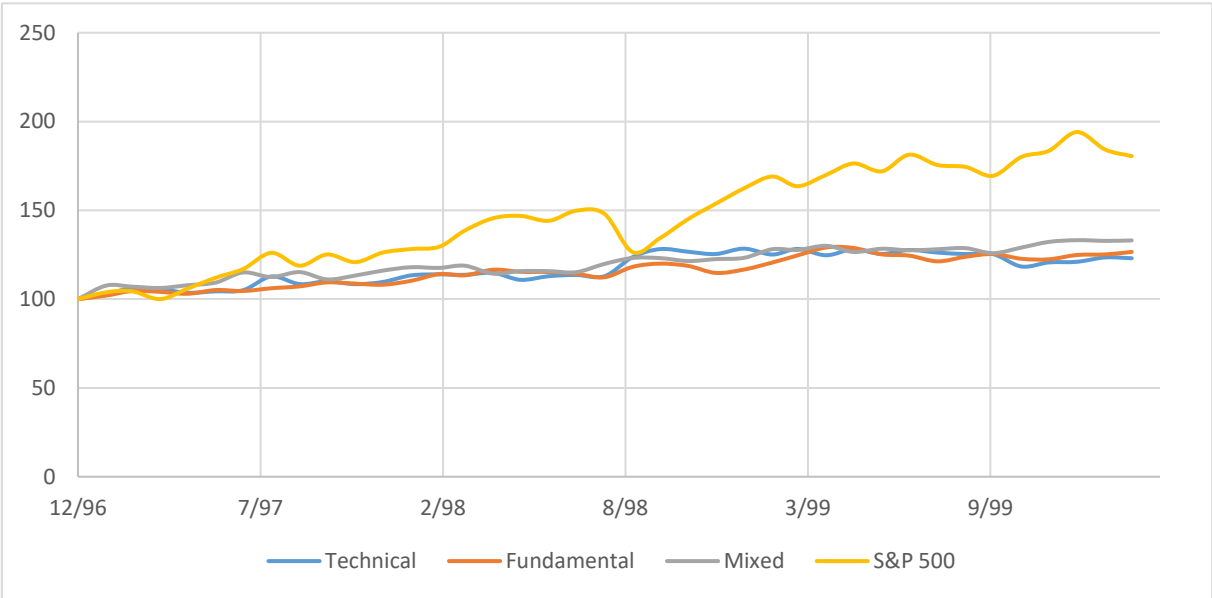
Figures and tables

Figure 2. aiSource, available in
https://www.managedfuturesinvesting.com/size-and-access-matter-when-it-comes-to-managed-futures/managed-futures-aum-1988-2018/

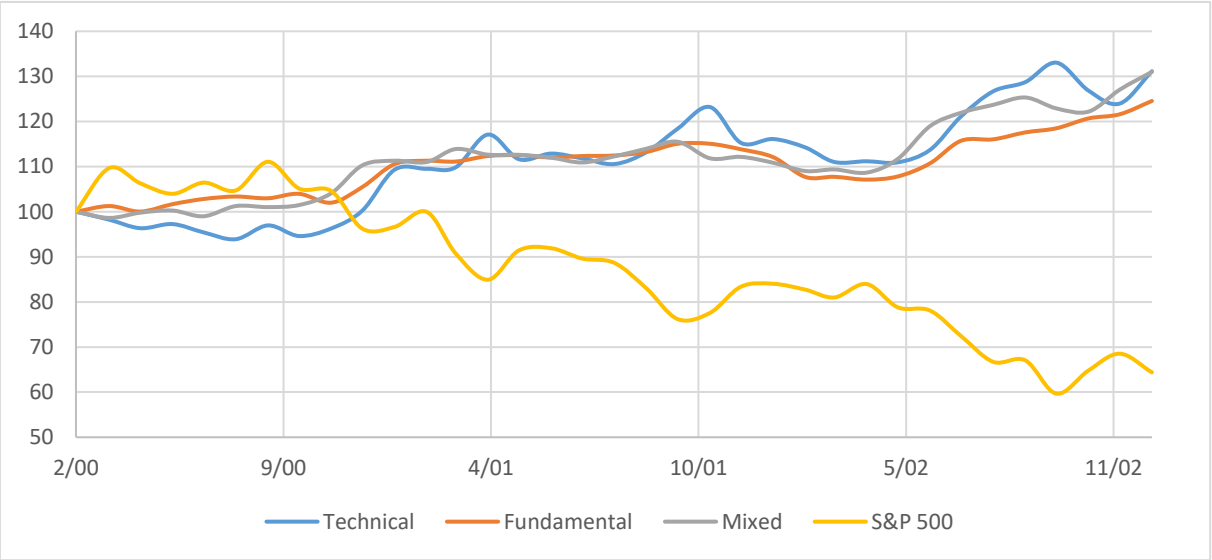
Appendices



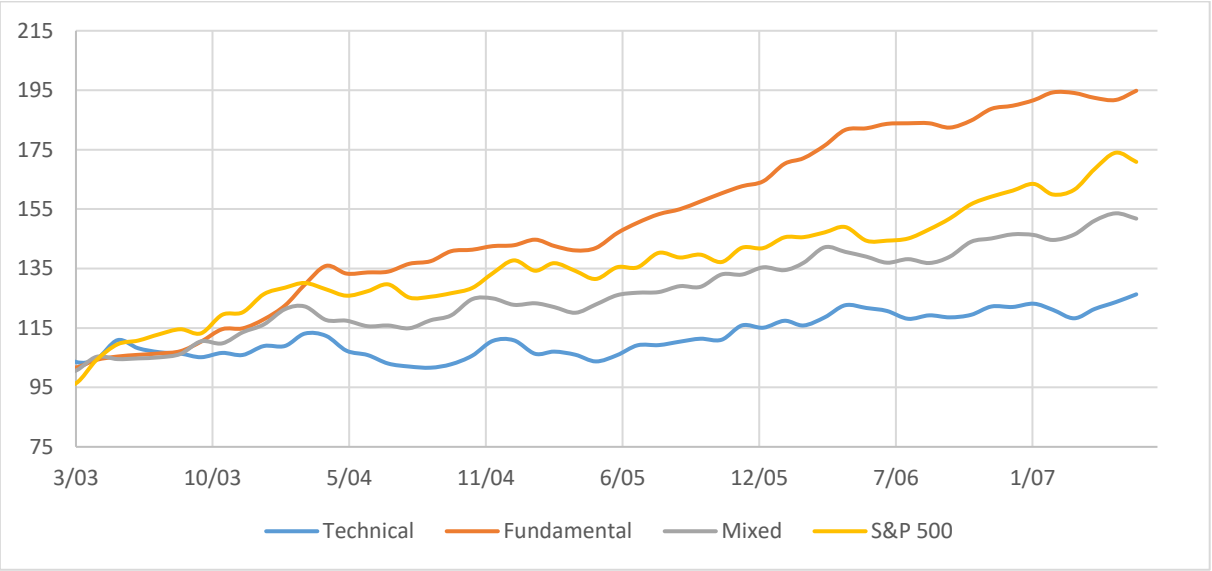
Appendix 1. cumulative CTA portfolio returns 1997-2013



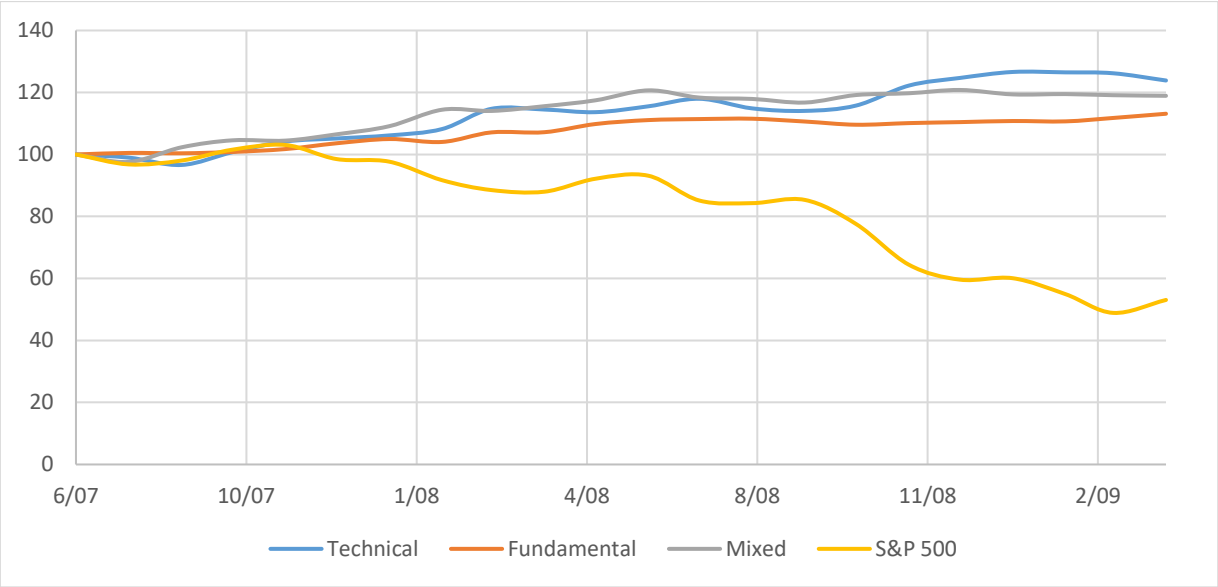
Appendix 2. cumulative CTA portfolio returns 1997-2000



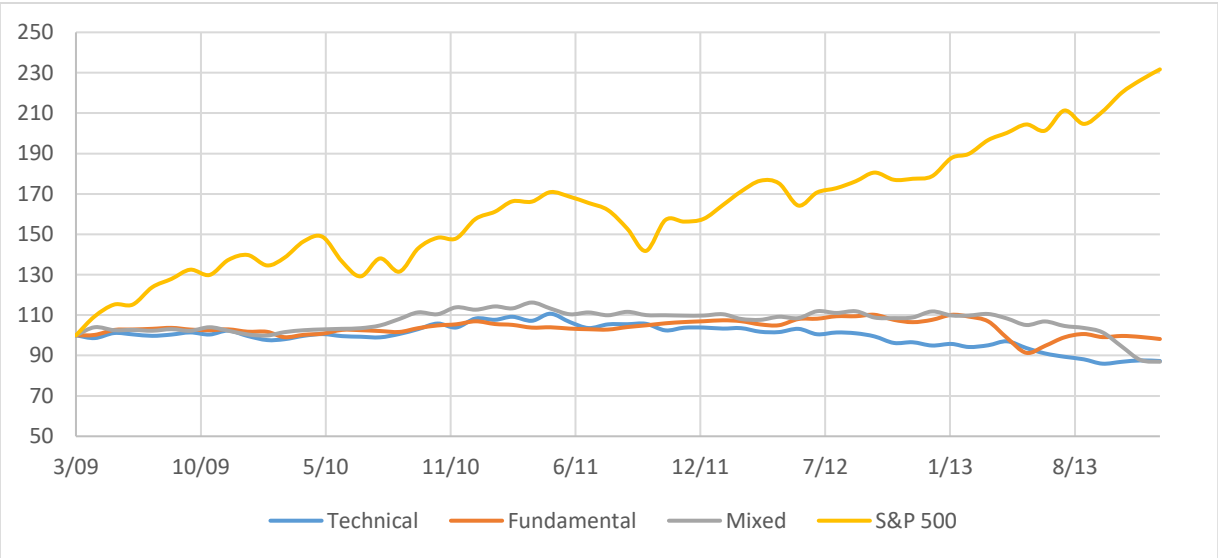
Appendix 3. cumulative CTA portfolio returns 2000-2002



Appendix 4. cumulative CTA portfolio returns 2003-2007



Appendix 5. cumulative CTA portfolio returns 2007-2009



Appendix 6. cumulative CTA portfolio returns 2009-2013

	Technical			Fundamental			Mixed		
	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value
Intercept	0,004	2,24	0,026	0,004	4,26	0,000	0,005	3,48	0,001
Metals	0,059	1,65	0,0996	0,059	2,93	0,004	-0,018	-0,58	0,566
Energy	0,064	2,33	0,0211	0,064	2,27	0,024	-0,011	-0,47	0,640
Agriculture	-0,001	-0,02	0,9804	-0,001	-0,16	0,875	0,019	0,53	0,599
Livestock	-0,011	-0,39	0,7003	-0,011	0,35	0,728	-0,029	-1,17	0,245
Equity	-0,155	-3,28	0,0012	-0,155	-0,66	0,51	0,026	0,63	0,531
Fixed income	0,444	3,00	0,0031	0,444	2,00	0,047	0,103	0,81	0,420
FX	0,063	0,46	0,649	0,063	-0,85	0,398	-0,018	-0,15	0,878
R-squared	0,14			0,11			0,02		
Adj. R-squared	0,11			0,08			-0,02		
Standard Error	0,02			0,02			0,02		
N	205			205			205		

Appendix 7. Regression results of long-only futures 1997-2013

	Technical			Fundamental			Mixed		
	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value	Coeff.	t-stat	p-value
Intercept	0,004	2,36	0,0194	0,006394	4,82	0,000	0,004603	3,20	0,002
MEM6	-0,008	-0,10	0,917	-0,08319	-1,62	0,107	0,147627	2,65	0,009
ENM6	-0,034	-0,44	0,6588	0,003539	0,07	0,947	0,08689	1,52	0,131
LIM6	-0,008	-0,11	0,909	0,006311	0,14	0,891	-0,05189	-1,04	0,298
AGM6	0,012	0,17	0,864	0,023854	0,48	0,633	0,120183	2,22	0,027
EQM6	-0,027	-0,38	0,7075	0,065812	1,31	0,192	-0,08141	-1,49	0,137
BOM6	0,132	1,98	0,0487	-0,01191	-0,26	0,796	0,114982	2,30	0,023
FXM6	-0,099	-1,36	0,1767	-0,0641	-1,26	0,209	0,075166	1,36	0,175
6MCBR	0,060	0,70	0,4856	-0,04043	-0,68	0,498	-0,00636	-0,10	0,922
R-squared	0,03			0,04			0,15		
Adj. R-squared	-0,01			0,00			0,12		
Standard Error	0,03			0,02			0,02		
N	205			205			205		

Appendix 8. Regression results of volatility adjusted 6-month momentum factors 1997-2013

	Technical			*Fundamental*			*Mixed*		
	Coeff.	*t-stat*	*p-value*	*Coeff.*	*t-stat*	*p-value*	*Coeff.*	*t-stat*	*p-value*
Intercept	*0,004*	*2,24*	*0,0261*	*0,006326*	*4,89*	*0,000*	*0,004182*	*2,90*	*0,004*
MEM12	*0,031*	*0,41*	*0,6801*	*-0,04508*	*-0,86*	*0,39*	*0,1764*	*3,03*	*0,003*
ENM12	*-0,109*	*-1,39*	*0,1663*	*-0,04238*	*-0,78*	*0,438*	*0,09474*	*1,56*	*0,121*
LIM12	*-0,003*	*-0,04*	*0,9682*	*-0,04993*	*-1,10*	*0,272*	*-0,01734*	*-0,34*	*0,732*
AGM12	*0,041*	*0,57*	*0,5721*	*0,030583*	*0,61*	*0,545*	*0,070401*	*1,25*	*0,212*
EQM12	*-0,034*	*-0,50*	*0,6205*	*0,029207*	*0,60*	*0,546*	*-0,00183*	*-0,03*	*0,973*
BOM12	*0,142*	*2,16*	*0,0316*	*0,00038*	*0,01*	*0,993*	*0,049166*	*0,97*	*0,335*
FXM12	*-0,066*	*-0,92*	*0,3601*	*-0,0933*	*-1,85*	*0,066*	*0,052227*	*0,93*	*0,354*
12MCBR	*0,078*	*0,89*	*0,3769*	*0,048624*	*0,79*	*0,431*	*-0,06342*	*-0,92*	*0,357*
R-squared	*0,04*			*0,04*			*0,11*		
Adj. R-squared	*0,00*			*0,00*			*0,07*		
Standard Error	*0,03*			*0,02*			*0,02*		
N	*205*			*205*			*205*		

Appendix 9. Regression results of volatility adjusted 12-month momentum factors 1997-2013

	MEM3	**ENM3**	**LIM3**	**AGM3**	**EQM3**	**BOM3**	**MFX3**
1997-2013	**4,24 %**	**6,19 %**	**-2,73 %**	**-2,13 %**	**6,84 %**	**1,48 %**	**2,97 %**
1997-2000	-2,18 %	11,53 %	-5,55 %	-5,47 %	3,05 %	3,63 %	3,27 %
2000-2002	3,29 %	7,99 %	11,52 %	-4,59 %	1,03 %	1,46 %	4,11 %
2003-2007	8,91 %	2,50 %	-12,37 %	2,39 %	9,75 %	-0,54 %	0,12 %
2007-2009	15,03 %	43,35 %	4,97 %	11,51 %	15,19 %	-0,40 %	12,31 %
2009-2013	1,42 %	-6,88 %	-2,55 %	-5,87 %	9,21 %	2,79 %	2,11 %

	MEM6	**ENM6**	**LIM6**	**AGM6**	**EQM6**	**BOM6**	**FXM6**
1997-2013	**4,24 %**	**6,19 %**	**-2,73 %**	**-2,13 %**	**6,84 %**	**1,48 %**	**2,97 %**
1997-2000	-2,18 %	11,53 %	-5,55 %	-5,47 %	3,05 %	3,63 %	3,27 %
2000-2002	3,29 %	7,99 %	11,52 %	-4,59 %	1,03 %	1,46 %	4,11 %
2003-2007	8,91 %	2,50 %	-12,37 %	2,39 %	9,75 %	-0,54 %	0,12 %
2007-2009	15,03 %	43,35 %	4,97 %	11,51 %	15,19 %	-0,40 %	12,31 %
2009-2013	1,42 %	-6,88 %	-2,55 %	-5,87 %	9,21 %	2,79 %	2,11 %

	MEM12	**ENM12**	**LIM12**	**AGM12**	**EQM12**	**BOM12**	**FXM12**
1997-2013	**5,75 %**	**1,91 %**	**-5,85 %**	**-1,26 %**	**7,06 %**	**0,85 %**	**1,41 %**
1997-2000	2,62 %	6,14 %	-3,83 %	-0,83 %	6,48 %	1,67 %	1,52 %
2000-2002	9,87 %	4,01 %	-13,55 %	4,31 %	10,64 %	0,86 %	6,36 %
2003-2007	13,34 %	5,56 %	-9,49 %	-0,84 %	11,19 %	-0,60 %	2,98 %
2007-2009	-6,65 %	2,98 %	-16,11 %	14,12 %	23,82 %	3,70 %	3,29 %
2009-2013	3,80 %	-4,48 %	2,42 %	-9,17 %	-1,63 %	1,11 %	-3,47 %

Appendix 10. Annualized returns of momentum factors

	CBR	Metals	Energy	Agriculture	Livestock	Equity	Fixed income	FX
1997-2013	**0,83 %**	**8,48 %**	**9,10 %**	**5,96 %**	**4,18 %**	**7,22 %**	**0,29 %**	**1,47 %**
1997-2000	-4,26 %	2,56 %	16,54 %	-8,62 %	-1,34 %	23,36 %	-0,65 %	-0,41 %
2000-2002	3,32 %	-2,94 %	15,24 %	7,36 %	-0,51 %	-18,14 %	3,04 %	2,04 %
2003-2007	5,58 %	21,45 %	15,82 %	10,66 %	5,80 %	21,68 %	-0,36 %	1,87 %
2007-2009	-20,63 %	-8,67 %	-19,64 %	2,96 %	-7,64 %	-28,68 %	5,15 %	-1,47 %
2009-2013	5,07 %	13,75 %	5,94 %	9,00 %	10,30 %	15,74 %	-1,74 %	2,68 %

Appendix 11. Returns of futures categories used for momentum factors

Fixed Income	Equity	Currency (vs USD)
Eurodollar	S&P 500	Yen
5 Yr U.S. Note Futures,	E-mini S&P MidCap 400 Futures	CAD
10 Yr U.S.Note Futures,	Nikkei/USD Futures	CHF
U.S. Treasury Bond Futures	DAX Futures	GBP
Bund 10y	CAC 40 CR USD	AUD
Bund 2y	FTSE 100 TR USD	MEX
Japan 10y	MSCI EAFE TR USD	SEK
Japan 2y	MSCI Far East TR USD	EUR
FTSE A British Govt 5 to 15 yTR	Russell 3000 TR	BRL
		NZD
		ZAR

Agriculture	Energy	Livestock	Metals
Corn	Crude Oil	Live Cattle	Gold
Rice	Natural Gas	Lean Hog	Silver
Soybean	Heating Oil	Feeder Cattle	Copper
Wheat			Palladium
Coffee			Platinium
Cocoa			
Orange juice			
Random Length Lumber			
Oats			
Canola			
Sugar			

Appendix 12. List of futures contracts used in momentum variables

	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,002	0,37		0,005	1,33		0,007	1,89	*
MEM3	-0,010	-0,11		0,046	0,49		0,107	1,34	
ENM3	0,030	0,34		0,129	2,46	**	-0,031	-0,50	
LIM3	0,034	0,57		-0,017	-0,30		-0,039	-0,72	
AGM3	0,112	0,89		0,070	0,53		0,097	0,68	
EQM3	-0,028	-0,17		-0,100	-0,76		0,119	0,77	
BOM3	0,875	1,02		0,455	1,33		-0,091	-0,42	
MFX3	0,554	1,25		0,197	0,63		0,077	0,44	
3MCBR	0,174	1,15		-0,046	-0,42		-0,056	-0,38	
R-squared	0,21			0,23			0,07		
Adj. R-squared	-0,01			0,03			-0,17		
Standard Error	0,03			0,02			0,02		
N	39			39			39		

	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,007	1,51		0,007	1,76		0,007	1,42	
MEM6	-0,146	-1,62		-0,061	-0,66		-0,059	1,02	
ENM6	0,170	2,97	**	-0,080	-1,08		-0,074	-0,81	
LIM6	0,021	0,27		0,034	0,52		0,03	0,23	
AGM6	0,291	1,50		0,204	1,11		0,211	1,13	
EQM6	-0,443	-2,39	**	-0,012	-0,11		-0,013	0,46	
BOM6	0,124	0,29		0,360	1,28		0,366	0,71	
FXM6	0,606	1,83	*	0,150	0,46		0,155	-0,16	
6MCBR	-0,142	-1,02		-0,035	-0,18		-0,046	0,26	
R-squared	0,31			0,12			0,12		
Adj. R-squared	0,13			-0,12			-0,12		
Standard Error	0,03			0,02			0,02		
N	39			39			39		

	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,006	1,266		0,007	2,058	**	0,006	1,96	*
MEM12	-0,204	-1,831	*	0,047	0,420		0,056	1,18	
ENM12	0,102	1,375		0,007	-0,140		-0,135	-1,84	*
LIM12	0,004	-0,079		-0,063	-1,014		0,069	0,93	
AGM12	0,226	0,969		-0,035	-0,215		0,107	0,83	
EQM12	-0,328	-1,312		-0,255	-1,299		-0,019	-0,28	
BOM12	0,525	1,048		0,346	0,988		0,211	1,24	
FXM12	0,685	2,177	**	0,244	0,963		0,03	0,31	
12MCBR	-0,055	-0,603		-0,142	-1,197		0,191	0,74	
R-squared	0,28			0,19			0,26		
Adj. R-squared	0,08			-0,03			0,06		
Standard Error	0,03			0,02			0,02		
N	39			39			39		

*p-value <0,1; ** p-valule < 0,05; *** p-value <0,01

Appendix 13. Momentum factor regression January 1997- March 2000

	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,002	0,31		0,005	1,43		0,006	2,02	*
MEM3	0,090	0,58		0,166	1,98	*	0,163	1,80	
ENM3	0,058	0,90		0,006	0,21		0,073	1,43	
LIM3	-0,015	-0,19		-0,030	-0,94		0,080	2,04	*
AGM3	-0,098	-0,53		-0,225	-2,84	**	-0,163	-1,39	
EQM3	0,118	0,67		0,051	0,51		0,252	3,15	***
BOM3	2,036	3,03	***	0,182	0,57		-0,829	-1,82	
MFX3	0,321	0,66		-0,313	-1,10		0,052	0,20	
3MCBR	0,565	3,16	***	0,312	4,07	***	0,053	0,37	
R-squared	0,46			0,41			0,32		
Adj. R-squared	0,30			0,23			0,11		
Standard Error	0,03			0,02			0,02		
N	33			33			33		
	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,003	0,42		0,002	0,77		0,005	1,42	
MEM6	-0,049	-0,41		0,038	0,57		0,081	0,69	
ENM6	-0,066	-0,78		-0,037	-0,87		0,021	0,26	
LIM6	-0,081	-1,26		0,003	0,09		0,012	0,25	
AGM6	-0,059	-0,31		-0,271	-2,05	*	-0,156	-0,64	
EQM6	0,088	0,49		0,012	0,17		0,255	2,49	**
BOM6	2,541	2,75	**	0,494	1,03		-0,022	-0,03	
FXM6	-0,268	-0,53		-0,174	-0,67		0,201	0,92	
6MCBR	0,439	1,76		0,230	3,45	***	-0,112	-0,99	
R-squared	0,45			0,29			0,24		
Adj. R-squared	0,29			0,07			0,01		
Standard Error	0,03			0,02			0,02		
N	33			33			33		
	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,007	0,72		0,007	1,95	*	0,007	2,26	*
MEM12	-0,025	-0,15		0,072	0,69		0,124	1,27	
ENM12	0,039	0,31		0,050	1,38		0,107	2,23	*
LIM12	-0,051	-0,93		0,024	0,90		0,097	1,85	
AGM12	-0,087	-0,39		-0,078	-0,71		-0,066	-0,66	
EQM12	0,149	0,71		0,112	0,65		0,243	2,47	**
BOM12	1,850	2,34	*	0,303	0,50		-0,263	-0,44	
FXM12	-0,001	0,00		-0,335	-1,12		-0,116	-0,51	
12MCBR	-0,057	-0,15		-0,067	-0,42		-0,212	-1,24	
R-squared	0,22			0,22			0,32		
Adj. R-squared	-0,02			-0,02			0,11		
Standard Error	0,04			0,02			0,02		
N	33			33			33		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Appendix 14. Momentum factor regression April 2000- December 2002

	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,000	0,18		0,010	4,85	0,000	0,006	2,22	*
MEM3	0,126	2,80	***	0,135	3,55	0,001	-0,005	-0,08	
ENM3	0,064	1,90	*	0,029	1,36		-0,020	-0,37	
LIM3	0,032	0,67		-0,049	-1,39		-0,066	-1,02	
AGM3	0,040	0,74		0,154	2,02	*	0,005	0,05	
EQM3	0,375	2,99	***	0,069	0,70		0,194	1,45	
BOM3	1,173	2,49	**	0,701	2,54	**	-0,219	-0,50	
MFX3	0,830	2,98	***	-0,197	-1,17		0,093	0,37	
3MCBR	-0,076	-1,29		0,001	0,02		-0,016	-0,17	
R-squared	0,604			0,416			0,089		
Adj. R-squared	0,534			0,312			-0,073		
Standard Error	0,016			0,013			0,02		
N	54			54			54		
	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,003	0,84		0,010	4,12	***	0,004	1,15	
MEM6	0,090	1,43		0,157	4,59	***	-0,034	-0,56	
ENM6	-0,002	-0,04		0,009	0,39		-0,024	-0,56	
LIM6	-0,077	-1,68		0,042	1,27		0,041	0,66	
AGM6	0,057	0,68		0,161	1,99	*	0,018	0,22	
EQM6	0,096	0,59		0,117	0,93		0,397	3,02	***
BOM6	1,828	3,49	***	0,402	1,29		-0,486	-0,96	
FXM6	0,425	1,73		-0,102	-0,79		0,048	0,26	
6MCBR	0,133	1,56		0,014	0,23		-0,063	-0,95	
R-squared	0,47			0,465			0,234		
Adj. R-squared	0,375			0,37			0,098		
Standard Error	0,019			0,012			0,018		
N	54			54			54		
	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,001	0,48		0,011	4,97	***	0,005	1,68	
MEM12	0,178	4,23	***	0,159	4,89	***	-0,009	-0,16	
ENM12	0,015	0,33		0,017	0,66		0,004	0,08	
LIM12	0,000	0,01		0,000	0,00		-0,055	-1,07	
AGM12	0,124	1,64		0,148	2,96	***	0,116	1,05	
EQM12	0,007	0,06		-0,071	-0,83		0,173	0,93	
BOM12	1,625	2,41	**	0,171	0,72		-0,310	-0,80	
FXM12	0,402	2,01	*	0,019	0,13		0,212	0,99	
12MCBR	0,085	1,01		0,020	0,26		-0,022	-0,27	
R-squared	0,497			0,297			0,142		
Adj. R-squared	0,408			0,173			-0,01		
Standard Error	0,018			0,014			0,019		
N	54			54			54		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Appendix 14. Momentum factor regression January 2003- June 2007

	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,006	1,22		0,007	3,63	***	0,008	1,77	*
MEM3	-0,002	-0,02		-0,007	-0,24		0,017	0,15	
ENM3	0,047	0,56		-0,024	-1,09		0,046	0,54	
LIM3	0,003	0,02		-0,016	-0,43		0,034	0,20	
AGM3	0,228	1,87	*	0,062	1,33		0,133	1,06	
EQM3	-0,026	-0,35		-0,114	-3,08	***	0,030	0,23	
BOM3	1,187	2,15	*	-0,134	-0,46		0,131	0,17	
MFX3	0,238	0,89		-0,093	-1,02		-0,106	-0,26	
3MCBR	-0,024	-0,17		0,074	1,75	*	-0,098	-0,57	
R-squared	0,65			0,62			0,15		
Adj. R-squared	0,42			0,37			-0,42		
Standard Error	0,02			0,01			0,02		
N	21			21			21		
	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,010	1,96	*	0,008	4,28	***	0,010	1,59	
MEM6	0,216	2,32	**	0,043	1,17		0,075	0,52	
ENM6	0,097	1,80	*	0,012	0,37		-0,026	-0,23	
LIM6	0,133	1,45		0,030	0,66		-0,114	-0,91	
AGM6	0,023	0,32		0,041	0,91		0,023	0,12	
EQM6	-0,154	-1,83	*	-0,175	-4,22	***	-0,002	-0,01	
BOM6	-0,033	-0,08		-0,199	-0,64		0,445	0,42	
FXM6	0,258	2,13	*	-0,013	-0,13		0,221	0,84	
6MCBR	0,002	0,03		0,031	1,04		-0,164	-1,23	
R-squared	0,78			0,59			0,19		
Adj. R-squared	0,63			0,32			-0,35		
Standard Error	0,01			0,01			0,02		
N	21			21			21		
	Technical			Fundamental			Mixed		
	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.	Coeff.	t-stat	signf.
Intercept	0,006	1,32		0,009	6,27	***	0,006	1,28	
MEM12	0,158	5,35	***	0,056	2,65	**	-0,039	-0,41	
ENM12	0,125	1,69		0,032	1,18		0,054	0,67	
LIM12	-0,036	-0,61		-0,021	-0,59		-0,138	-1,15	
AGM12	0,070	1,15		-0,017	-0,53		0,026	0,18	
EQM12	0,058	1,71		-0,090	-3,20	***	-0,080	-0,75	
BOM12	0,334	1,20		-0,290	-1,41		0,262	0,53	
FXM12	0,332	3,78	***	-0,020	-0,24		0,255	1,00	
12MCBR	-0,153	-1,46		-0,009	-0,35		-0,059	-0,81	
R-squared	0,8			0,57			0,14		
Adj. R-squared	0,67			0,29			-0,43		
Standard Error	0,01			0,01			0,02		
N	21			21			21		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Appendix 15. Momentum factor regression July 2007- March 2009

	Technical			Fundamental			Mixed		
	Coeff.	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*
Intercept	-0,003	-1,56		-0,001	-0,19		-0,002	-0,62	
MEM3	0,088	1,96	*	-0,008	-0,17		0,037	0,53	
ENM3	-0,022	-0,46		-0,052	-1,05		0,043	0,41	
LIM3	-0,005	-0,12		-0,014	-0,25		0,009	0,13	
AGM3	0,113	2,13	**	-0,027	-0,56		0,074	0,91	
EQM3	0,071	0,78		-0,047	-0,43		0,007	0,05	
BOM3	0,117	0,94		0,138	0,59		0,106	0,67	
MFX3	0,269	1,64		-0,011	-0,05		-0,444	-2,47	**
3MCBR	0,071	1,47		0,123	1,91	*	0,054	0,67	
R-squared	0,43			0,07			0,09		
Adj. R-squared	0,33			-0,08			-0,06		
Standard Error	0,01			0,02			0,02		
N	57			57			57		
	Technical			*Fundamental*			*Mixed*		
	Coeff.	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*
Intercept	-0,003	-1,37		0,001	0,21		-0,002	-0,61	
MEM6	0,166	3,47	***	0,025	0,54		0,081	1,38	
ENM6	-0,028	-0,62		0,017	0,20		0,124	1,60	
LIM6	-0,017	-0,47		-0,085	-1,53		0,037	0,71	
AGM6	0,085	1,23		0,115	2,08	**	0,053	0,68	
EQM6	-0,104	-1,71	*	-0,099	-1,08		-0,077	-0,61	
BOM6	0,451	1,08		0,905	1,84	*	0,784	1,86	
FXM6	0,339	2,58	**	0,064	0,51		-0,492	-2,72	***
6MCBR	-0,002	-0,05		-0,105	-1,05		-0,114	-1,50	
R-squared	0,44			0,14			0,23		
Adj. R-squared	0,35			0			0,1		
Standard Error	0,01			0,02			0,02		
N	57			57			57		
	Technical			*Fundamental*			*Mixed*		
	Coeff.	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*	*Coeff.*	*t-stat*	*signf.*
Intercept	-0,004	-1,86	*	-0,001	-0,17		-0,003	-1,03	
MEM12	0,185	3,10	***	0,018	0,31		0,041	0,61	
ENM12	0,008	0,11		-0,019	-0,30		0,181	1,93	*
LIM12	0,096	2,24	**	0,042	0,69		0,004	0,07	
AGM12	0,100	1,26		0,056	0,82		-0,036	-0,65	
EQM12	-0,041	-0,75		-0,091	-1,10		-0,067	-0,75	
BOM12	0,656	1,75	*	0,459	0,66		-0,268	-0,43	
FXM12	-0,142	-0,57		0,004	0,02		-0,309	-1,37	
12MCBR	-0,072	-1,06		-0,059	-0,63		-0,002	-0,03	
R-squared	0,28			0,06			0,16		
Adj. R-squared	0,16			-0,09			0,02		
Standard Error	0,02			0,02			0,02		
N	57			57			57		

**p-value <0,1; ** p-valule < 0,05; *** p-value <0,01*

Appendix 17. Momentum factor regression April 2009- December 2013