Position sizing methods for a trend following CTA

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Positionsskalningsmetoder för en trendföljande CTA

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av

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Godkänt	Examinator	Handledare
2014-06-04	Hans Lööf	Tomas Sörensson
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Sammanfattning

Denna studie undersöker huruvida en trendföljande managed futures-fond kan förbättra sina resultat genom att ändra positionsskalningsmetod. Handel med en enkel trendföljande strategi simulerades på 47 futureskontrakt åren 1990-2012, för olika metoder att för bestämma positionsstorlek. Elva positionsskalningmetoder undersöktes, exemplevis *Target Volatility, Omega Optimization* och metoder baserade i korrelationsrankning. Både tidigare beskrivna metoder och nya tillvägagångssätt testades, och jämfördes med den grundläggande strategin med avseende på risk och avkastning. Denna studies resultat visar att framförallt *Target Volatility*, och i viss uträckning *Max Drawdown Minimize* and *Dynamic Stop Lock-In* förbättrade nyckeltalen för den handlade strategin. Den slutgiltiga rekommendationen för en trendföljande managed futures-fond är att använda *Target Volatility* som positionsskalningsmetod, möjligtvis tillsammans med *Max Drawdown Minimize*.

Nyckelord

CTA, managed futures, trend following, positionsskalningmetoder, target volatility, omega optimization.

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Abstract

This study examines whether a trend following managed futures fund can improve its performance by changing its position sizing method. Trades for a simple trend following strategy was simulated on 47 futures contracts over the period 1990-2012, using varying methods for determining position size. Eleven different position sizing methods where investigated, among them *Target Volatility, Omega Optimization* and correlation ranking methods. Both methods previously detailed in academic papers as well as novel approaches was implemented, and compared to the baseline performance of the strategy. The results from this study show that the *Target Volatility* method, and to some degree *Max Drawdown Minimize* and *Dynamic Stop Lock-In,* improved the performance of strategy. The final recommendation for a trend following managed futures fund is to use *Target Volatility* as position sizing method, possibly in conjunction with *Max Drawdown Minimize*.

Key-words

CTA, managed futures, trend following, position sizing, target volatility, omega optimization.

Acknowledgments

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Henrik Sandberg & Rasmus Öhman

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1. Introduction

1.1 Background

There is a problem common for mutual funds, stock portfolios, and traditional investments of any kind. Equity markets are characterized by high volatility across long time periods, paired with high internal correlation. That is, no matter how asset managers try to diversify their assets, investors all too often see ten-twenty year of returns wiped out by a single market crash. Any investment that remains untouched by such disastrous events, even prospers from market distress, is of great and obvious benefit to investors. This is the appeal of *managed futures*, since this type of investment is less exposed to crashes and market cycles.

The case for investing in managed futures is a compelling one. Barclays TOP50, tracking the top 50 CTAs, has had 8.2% annualized return since its inception 1987 (BarclayHedge, 2014). And, perhaps more importantly, the index has low correlation with equity markets— its monthly returns had a slight negative correlation of -7.5 % with S&P 500 for this time period. Several authors have showed how an investor's portfolio might be significantly improved by the addition of managed futures hedge funds (Darius, Ilhan, Mulvey, Sircar, & Simsek, 2002; Lamm, 2003; Kaminski, 2011). The hedging properties of CTA funds are intuitively visible in Figure 1.1.

Behavioral finance may offer an explanation to the effectiveness of CTAs: During periods of equity market distress, large groups of investors are driven into action and flock to other asset classes to find liquidity and safety. This behavior creates predictable trends in auxiliary markets, across a wide range of asset classes, including futures markets. (Clare, Seaton, Smith & Thomas, 2012)

By now, the foundations of trend following strategies are well documented, and several books have been written on how to capture market trends using relatively simple trading rules (Covel, 2009; Clenow, 2013). These simple rules are concerned with the timing of buying and selling, position sizing is done using a relatively naïve approach: Equal risk in every position. Is there a better way to manage position sizing for trend following funds? In collaboration with Swedish CTA fund Spektrum, the aim of this thesis is to investigate this issue.

***CTA* (*Commodity Trading Advisor*):** Also referred to as *managed futures*, this is a type of hedge fund investing in futures, generally using a *systematic* (rule based), *momentum-type* (based on price movements) strategy.

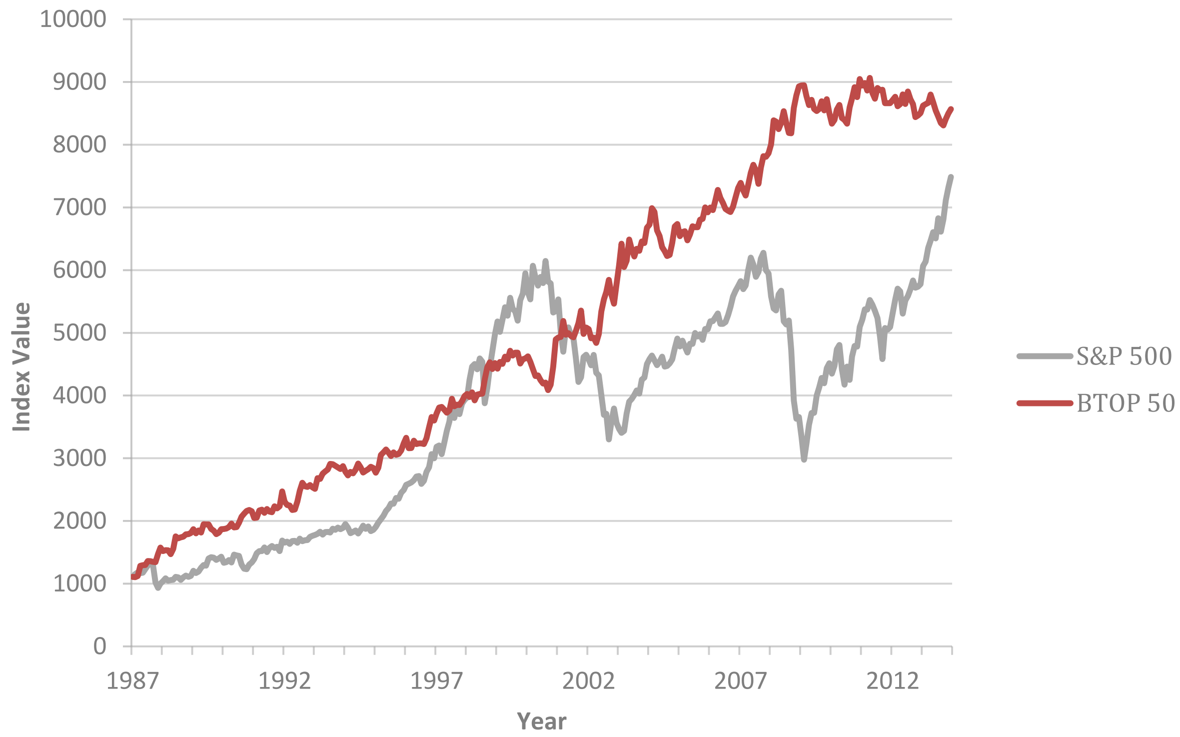

Figure 1.1: The Barclays BTOP50 managed futures index, compared to the S&P 500 during the period 1987-2012. (The S&P series is normalized in order to be equal to BTOP50 at its inception) Source: Yahoo Finance, barclayhedge.com

Note: Portfolio allocation methods and position sizing methods both adequately describe the focus of our effort, and the terms will be used interchangeably throughout the text.

1.2 Research issue

When it comes to the management of mutual funds, the literature is most often concerned about the portfolio – how different assets might be weighted according to e.g. mean-variance optimization and Sharpe ratio. A lot have thus been written about portfolio allocation of mutual funds, but these conclusions does not necessarily translate to investors with wildly different philosophies, behaviors and objectives - for instance, a trend following hedge fund. Mutual funds tend to invest in equities, and keep investments over long time periods. A trend following CTA deals in futures, which due to their very nature cannot be held for extended periods of time. Mutual funds usually have strict risk management principles, need to keep a percentage of capital in risk-free assets, are not allowed to short or use leverage. CTAs have much laxer constraints. A mutual funds main objective is to give high returns with limited risk. Trend following CTAs serve as a complement to regular investments, and needs to have limited correlation to the rest of the investment universe, especially in times of crisis. (Billingsley & Chance, 1996; Kat, 2004; Liang, 2004)

In the last couple of years, alternative methods of portfolio construction have gained attention both in the academic community and among practitioners, for example target volatility (Bruder & Roncalli, 2012), conditional drawdown (Harris & Mazibas, 2013) or omega optimization (Kane, Bartholomew-Biggs, Cross & Dewar, 2009). Is it possible to use these novel methods to further improve the portfolio allocation of a trend following CTA? Similar, earlier research has shown alternative types of portfolio optimization can reap large benefits when constructing portfolios comprised of several hedge funds (Harris & Mazibas, 2013).

1.3 Purpose

The purpose of this study is to determine whether a trend following hedge fund can improve its performance by changing its position sizing method. As a proxy for the trend following hedge fund, trades for a simple trend following strategy (referred to as the *Core strategy*) will be simulated over a period of 20 years. The performance of the position sizing methods will be compared to a benchmark. This benchmark consists of *Fixed Fraction*— position sizing by equal volatility contribution. The aim is thusly is to investigate whether the result of the *Core strategy* can be improved upon by letting different portfolio allocation methods change the position sizes given by the *Fixed Fraction* method.

An investment universe made up by 47 futures contracts, distributed between five sectors, will be used and traded on in this study. Clenow (2003) demonstrates a simple trend following strategy which can be used to replicate a CTA fund. The same strategy will be used in this study to trade on the portfolio. This will be done by using a sample size of data stretching from 1990-2012 with historical daily data for the 47 futures contracts, covering both historical periods of distress and prosperity.

The position sizing methods will be evaluated based on measures of risk and return, and a comparison of these to the performance measures of *Fixed Fraction*. In order to be said to improve performance, a portfolio allocation method should increase return and reduce risk, at least improve one measure while not worsening any other. Changing position sizing method means rules for entering and exiting positions will be held constant, varying only how the size of the position is determined. Several position sizing methods will be evaluated, both methods previously detailed in academic sources as well as novel approaches.

1.4 Research questions

In order to determine whether a managed future fund can improve its performance by refining their position sizing method, there is a three-step evaluation process. First, each of the position sizing methods needs to be evaluated for returns and risk. A managed future fund can increase return and risk at the same time by just increasing leverage, so risk and return will need to be considered in relation to each other. Second, the main selling point of CTAs is not the highest absolute returns, but moderately high and uncorrelated returns. It will be determined how each of the sizing methods correlates with traditional investments, to make certain they retain this coveted property. Finally, working methods needs to be checked for ease of implementation— if a method leads to higher performance, but also an unreasonable amount of rebalancing, it might not be viable to use in real world trading. The research questions this study will aim to answer are thus:

1. Which, if any, of the investigated position sizing methods give better returns in relation to risk, compared to *Fixed Fraction*?
2. Do the investigated position sizing methods still have the low correlation with equity markets traditionally associated with managed futures?
3. Are these position methods feasible to implement?

1.5 Delimitations

There will be no optimizing of method parameters. Instead, when a method uses one or several parameter as input (e.g. what the target volatility should be), the method will run a few times, alternating between a few reasonable values for each parameter. This is equally delimitation as well as a measure of caution against over-fitting. Intraday trading is beyond the scope of this study, decisions to buy, sell or change position size will be made on close, and carried out the following day at open. Lastly, when in reality a CTA is likely to run several strategies at once, a single trading strategy will be in use when simulating trades. Commissions for transactions are set at zero.

1.6 Target audience

This study will be of interest for a number of stakeholders. Firstly, it will be of interest for practitioners in the hedge fund industry, and for CTA-managers in particular, by presenting the effects of using different portfolio allocation methods and how the use of them may improve the performance of a trend following strategy. The study will also be of interest to investors and academia, highlighting an additional aspect of how asset managers might differ between each other. It will be of interest to those who study portfolio optimization and asset allocation. For instance, how target volatility and omega optimization perform outside the buy-and-hold equity-universe, and how they perform compared to more novel allocation approaches. Finally, this study will be of interest to the research community concerned with momentum and trend following trading strategies.

2. Theoretical framework

This chapter will cover the theoretical framework of this study. It will act as a guide to readers not familiar with financial derivatives, the nature of CTAs, trend following, target volatility, or Omega Optimization. It will also define terms used for the remainder of the text. This is a chapter covering a broad spectrum of topics, the reader may be aware of futures and the nature of CTAs, but perhaps not of Omega Optimization, which is a crucial part of one of the methods for portfolio sizing and risk allocation.

2.1 Futures

A futures contract is a standardized agreement between two parties, either to buy or sell an asset for a predefined price at a certain time in the future. The current futures price is simply the price for one futures contract today with delivery of the underlying asset at the predefined delivery period (Kaminski, 2011). Future contracts are similar to forward contracts in many ways, but futures are normally traded on an exchange rather than over-the-counter (OTC). The exchange also provides the two parties a mechanism that gives them the guarantee that the contract they have entered into will be honored; as the two parties most likely do not know each other. When constructing a contract between the two parties, the agreement between them must be specified in exact detail: The underlying asset to be delivered, the size of the contract, where and when the delivery will occur. There is also room for alternatives to be specified, for some commodities the grade of the asset is also important to specify in the contract, the quality of the commodity may vary according to where it is produced and therefore needs to be specified. (Hull, 2011)

The value of a futures contract, for a simple asset with no dividends, is equivalent to the value of investing the present value of the underlying asset in a risk-free investment until the futures contracts time to maturity. The valuation formula can become more complex if the underlying asset is in short supply or does not exist, causing above mentioned rational pricing formula not be appropriate. But the valuation of a futures contracts price is not related to the research issue connected to this study.

There exists a very wide range of possible futures contracts to enter into. On exchanges throughout the world there are contracts on a vast amount of different commodities and financial assets as the underlying asset in the futures contract. Contrast with commodities like sugar, live cattle or gold as the underlying asset. One important thing to take note of is the fact that the vast majority of futures contracts do not lead to a delivery of the underlying asset. This is because most traders use these contracts not for the delivery of the asset but as a hedging instrument or for speculation about price movements. To close out a position in a contract prior to the delivery period, the trader enters into the opposite and equal trade to the original one taken, thereby offsetting the original position in the contract. Delivery is so unusual that when it happens, traders have been known to sometime forget how this delivery process works. For some futures contracts with financial assets as the underlying asset for the contract, delivery is impossible and they are thereby settled in cash between the parties. A futures contract on the S&P 500 would otherwise result in the party with the short position would have to deliver a vast portfolio perfectly replicating S&P 500. (Hull, 2011)

The futures markets are heavily regulated, in the USA for instance by the Commodity Futures Trading Commission. They license futures exchanges and contracts, and approves changes to these contracts. This means that the contracts must serve some useful economic purpose in order to be approved, e.g. not only for pure speculation by traders but also as an instrument for hedging.

Two parties can of course agree to trade an asset by themselves in the future for a specified price settled in advanced, but this is highly risky due to counter-party credit risk - partners not having the financial capacity to honor their agreement. As mentioned previously in this section, the exchanger is responsible for organizing trading and to prevent contract default due to lack of financial resources from one of the parties. They do so by using a margin account for the parties in the contract. When an investor wishes to enter into a position in a contract, a margin account is opened for this position. The investor needs to deposit an initial amount per contract to this account; this is known as the initial margin. The amount per contract varies greatly depending on the underlying asset and market, and is usually about 10% of the initial value of the contract, but it varies depending on the volatility of the underlying asset, but is usually between 5-15% (Clenow, 2013). As it is just a fraction of the underlying amount, an investor can trade on the margin and achieve a higher leverage. This is of course risky if not properly diversified. Then at the end of each trading day, this account is adjusted after gains and losses. If the account drops below the initial margin amount, the investor needs to refill the account to a required level; otherwise the investor will be forced to unwind the position. The investor is allowed to withdraw an amount from the margin account as long as the account exceeds the initial margin. (Hull, 2011)

The contract size is the amount of the underlying asset that is to be delivered by the investor holding the short position in one contract. If this size represents too large an amount of the underlying asset, investors wanting to hedge a small portfolio will be unable to do so, and speculators may be forced to take a larger exposure than desired, or may be unable to enter into the desired position. If the contract size is very small, that will lead to higher prices due to high costs for multiple trades. An example of a contract size is the size for a future contract on Corn that represents 5000 bushels of corn. Point value is the lowest amount with which the price can change. (Clenow, 2013)

The code for a contract is defined by the exchanger and consists of three parts: the tick, the month, and the year. The tick for the underlying asset varies depending on the data vendor which may be confusing when using multiple data vendors. An example for the tick of a futures contract is GC, this is a future on Comex Gold. The month for which delivery of the asset is to occur is denoted by one letter following the following schematic: From January to December – F, G, H, J, K, M, N, Q, U, V, X, Z. The year is then denoted by the last digit of the year. Thusly the code for a futures contract on Comex Gold with Mars as delivery month in 2014 is GCH4.

When the futures contract is approaching the delivery period, the price of the futures contract will begin to converge towards the current spot price of the underlying asset, and finally be equal to, or according to Hull (2011), very close to it when the delivery period is reached. Why this is, is easily illustrated with that otherwise there would be an arbitrage opportunity. If the futures price is higher than the spot price at the delivery period, an investor would simply short the futures contract and buy the asset and deliver it. This leads to certain, and risk free, profit for the investor. A profit equaling the amount by which the futures price exceeded the spot price, and vice versa for when the futures price is below the spot price. This leads to the fact that the futures price will converge towards the spot price when the contract approaches the delivery period, as seen in Figure 2.1.

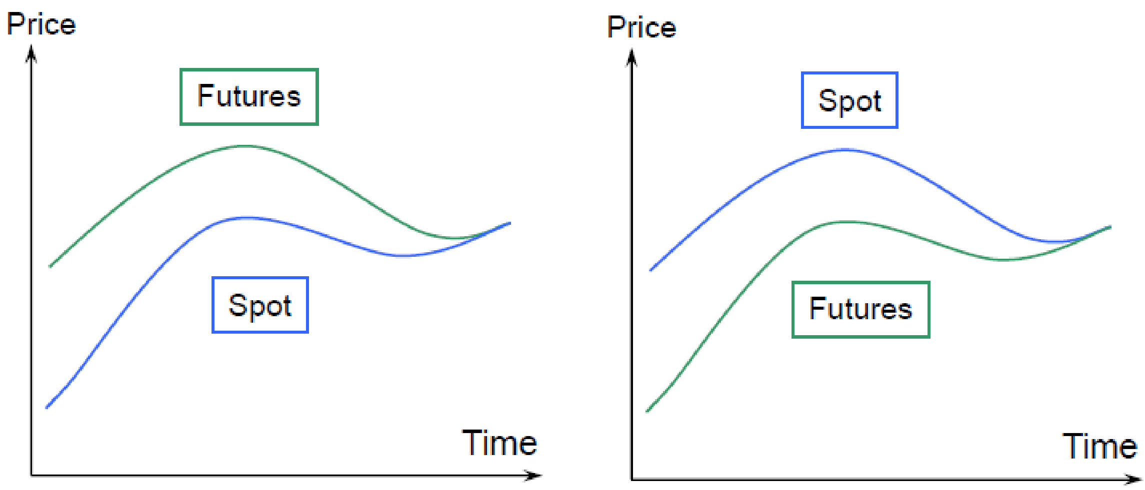

Figure 2.1: The convergence of futures prices towards spot price. Source: Hull (2011) page 27.

When the futures price also is higher than the expected spot price at delivery for the underlying asset, it is said to be in Contango and the contract will decrease in value until the delivery period where it will be, as mentioned above, equal to or a little more, than the spot price at delivery. The reverse situation is known as a contract being in Backwardation, i.e. the value of the contract is lower than the expected spot price at delivery; in which case the value of the contract will increase until it reaches the delivery period.

2.2 Commodity Trading Advisors (CTAs) and how they operate

Managed futures traders are commonly referred to as Commodity Trading Advisories (CTA) and are a special kind of hedge fund that has its origin in the trading of commodities futures contracts (Dori, 2013). The acronym has its origin in the 1970s when the Commodity Futures Trading Commission was founded in the USA the general term "Commodity" was at that time broadly understood to cover all forms of futures contracts (Dori, 2013). A CTA can be described as an organization that provides futures contracts, commodity options and swaps for a client (Lemke, Lins, Hoenig & Rube, 2012). They generally act as asset managers using different strategies for trading with futures contracts or options on futures and are currently the largest sub-section of what is known as alternative investments— traditional investments being equities, bonds, money market and real estate (Gregoriou, 2012). There are many types of managed futures strategies that CTAs use, but the most common one to use, according to Kaminski (2011), is a systematic trend following strategy, where different methods are used to identify a trend and momentum in the market, regardless of its direction, and profit from said price trend in the market. Two other common strategies applied by CTAs are fundamental trading and short term trading.

Trend following CTAs have done well in both bull- and bear-markets, but particularly in periods of market distress due to the negative correlation to the equity market. CTAs are also highly restricted and sensitive when it comes to what they actually do and how they do it, not wanting to release any unnecessary information to outsiders. (Clenow, 2013)

These CTAs primarily take positions and trade in futures markets, using futures contracts and sometimes options on futures (Kaminski, 2011). The portfolio will usually be exposed to numerous markets and asset classes; fixed income, energy, agriculture and currencies to mention a few. One of the main reasons for using futures in the portfolio is that the belief that it will decrease overall risk due to the history of negative correlation between asset groups (Kolanovic, Silvestrini, Lee, & Naito, 2011). This negative correlation is also the reason why managed futures are used by, for instance pension funds, as a tool to diversify their portfolio and reduce the risk of the portfolio and capitalize on its historical track record of CTAs during times of distress for traditional investments as seen during the 2008 credit crisis. By investing in a CTA they will have an exposure to assets that move in different ways from the traditional investments like stocks and bonds (Fletcher & Wilkes, 2012). Since CTAs are just slightly negatively correlated to the S&P 500 they are therefore not a perfect hedging instrument for the stock market, but an investment in a CTA can be considered as a diversifier for stock market risk and should therefore make up a minor part of a typical financial portfolio according to Czkwianianc & Koulajian (2010).

Most of a CTAs *assets under management* will be in the form of cash, a smaller but highly volatile part will be in the form of unrealized profit on active positions in futures contract. The cash held can be used to buy new futures contract or resize already active positions in futures contracts. It is also possible to trade on the margin and achieve a higher leverage. An illustration of the distribution between the cash held and the unrealized profit on active positions in futures contracts for a hypothetical CTA can be seen in Figure 2.2.

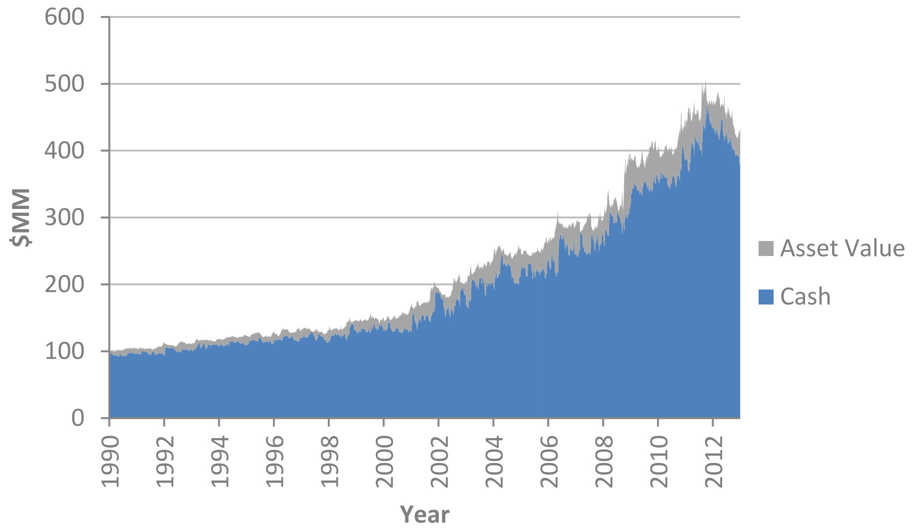

Figure 2.2: Equity curve for a simulated trend following strategy (*Core strategy* with *Fixed Fraction* as position sizing method) divided into cash held and current value of outstanding investments in futures contract.

In the US, a CTA is authorized and regulated by the Commodity Futures Trading Commission (CTFC). It is the CTAs responsibility to register with the CTFC, and follow the regulations put forward by the CTFC, and to provide records and reports. (Lemke et al., 2012)

2.3 Trend following - capitalizing on systematic price movements

This section of the theoretical framework will be devoted to trend following and the most common strategies and indicators used for constructing a trend following strategy. Trend following differs from other algorithm-based trading systems by the algorithms used and what aspects of financial markets it tries to capitalize on. High-frequency traders, for instance, work at lightning speed in order to profit from market inefficiencies existing for fractions of a second. Trend following investors seek to capitalize on prices systematically rising or falling over days, months or even years (Fletcher & Wilkes, 2012). And for trend following strategies that use a diversified portfolio of futures contract; it is common that up to 70% of all trades will be losses. That might seem like a high number, but the illustrious track record of trend following CTAs is not due to the number of successful trades they make, but the size of the very successful ones. Due to the nature of the strategy, a typical trend following investor has a large number of small losses and a small number of huge profits (Covel, 2009; Clenow, 2013).

2.3.1 Trend following

The main aim for a trend following strategy is to follow an already occurring trend in the price time series, and follow it as long as the price does not make a significant move against that trend. This means that the strategy of trend following is deliberately targeting not the lowest point but rather more the middle of an already occurring trend and trying to capitalize on the trend to continue for a long period of time. For the most part, such a strategy will enter into a lot of potential trends that will not continue, the investor will close these positions rather quickly and make a loss. A single futures symbol can remain for a long time without a long-lasting trend to follow and it results in many, but in comparison small losses. The financial instrument may in fact never enter into a long lasting trend. But for a trend-follower with a well-diversified portfolio this is not a problem though, because long lasting trends will likely occur in other instruments. And the profits made on these other instruments will more than make up for the poor results during non-trending periods, when considering historical data and performance of CTAs. (Czkwianianc & Koulajian, 2010; Clenow, 2013)

The essence of following a trend on futures contracts, and the underlying economic justification for it, is based on time series analysis and behavioral finance. Time series analysis can be used to predict or determine whether the time series of the financial instrument is trending, and theories from behavioral finance can be used to explain why and justify the phenomenon from an economic standpoint (Clare et al., 2012). Trend following is a widely used strategy in futures markets and has been so for decades. If one just looks at the vast amount of successful CTAs using trend following strategies on managed futures one will see that they have been active since the 1970s, using trend following strategies (Czkwianianc & Koulajian, 2010; Clenow, 2013).

The core concept of trend following is, as mentioned above, systematic movements in the price time series of a financial instrument. The core concept is not to identify and buy at the price series very lowest value and sell at its highest, it is to capitalize on long-term price movements. All trend following strategies are based on this conception that financial markets tends to move in trends for an extended period of time. They can trend up, or down, or the financial markets could move sideways, which is the phase where trend following strategies make most of their losses. It may be the case that a financial price series' most of the time is not moving in a general direction for a long period of time, but the assumption is that there will always be periods where it is moving in a general direction for a long enough time to capitalize on it.

Trend following strategies tend to make almost all of their money during limited time periods, and from a small number of very successful trades. Trend following strategies are different in distribution to simple buy-and-hold equity strategies. The returns of trend following managed futures strategies are typically non-correlated or slightly negatively correlated with the equity market and are positive in expectation with a large amount of small losses and are also positively skewed with a fat right tail as managers tend to allow winning trades to run and quickly cut losses as momentum or general trend movements in the markets fade (Rzepczynski, 1999; Czkwianianc & Koulajian, 2010).

For a trend-follower it is all about waiting for the market to make a significant movement and hold the position if that trend continues. Trading signals are used in order to determine when to enter a position and they can be generated by various methods. The two most popular and highlighted in the literature about trend following are two classical but still widely used methods called *Breakout* and *Moving Average*. They are used to determine the presence of a trend in the price series and they will be further discussed in 2.3.2 and 2.3.4. A long position is taken if the method of choice is giving a signal for an upward trend and a short position for a signal of a downward trend in the price series. (Clare et al., 2012)

2.3.2 Channel Breakout as a trend following strategy

The purpose for all methods used for identifying a trend is to see past the underlying noise that exists in a time series. The method described here is classical and rather simple but an effective one and it is called the n-period channel breakout, or just breakout. The *n* refers to the number of points in the time series that make up the look-back period. The price series for financial instruments are usually made up by trading days and *n* would thusly refer to the number of previous trading days, including the current trading day, and the data points under consideration in the time series are the closing prices for said instrument. This method can be used for both determining a positive trend as well as a negative trend in the price series. If the closing price for the present trading day is the highest closing price the last n-trading days, including the present day, a positive trend is signaled for and a long position should be taken. And conversely, if the closing price is its *n*-day lowest, a negative trend is signaled for and a short position in the financial instrument should be taken. (Aronson, 2007)

If $P_t = \max(P_t, P_{t-1}, P_{t-2}, \ldots, P_{t-(n-1)})$ an upward trend is signaled, and if $P_t = \min(P_t, P_{t-1}, P_{t-2}, \ldots, P_{t-(n-1)})$ a downward trend is signaled. Where P_t is the closing price for trading day t.

Figure 2.3: Breakout with 50 trading day's look-back period signaling an upward trend due to the closing price on January 11 2001 being the highest in 50 days, resulting in a long position the next trading day. The solid line represents the current 50-day lookback maximum, and when the price reaches above this line the strategy gives a signal to open a long position.

Figure 2.4: Breakout with 50 trading day's look-back period signaling a downward trend due to the closing price on January 7 1992 being the lowest in 50 days, resulting in a short position the next trading day.

Figure 2.3 and 2.4 are examples of a 50-day breakout signaling an upward trend respectively a downward trend, used to illustrate the simplicity of the method. A shorter breakout period could later be used as a method to indicate a stop and closing of the position. For instance when using a 50-trading-day breakout signaling an upward trend, a 25-trading-day breakout could be used to signal the covering of a position if the closing price then is the lowest in 25 trading days. Consequently, if the 50-trading-day method signals for a downward trend and a short position, the financial instrument should later be covered if the closing price then is the highest in 25 days.

But despite the simplicity of the method, it has proven to be as effective as even more complex trend following methods (Kaufman, 2005), and can be improved upon by changing the number of trading days used for the look-back period, the choice of stop signal and the use of a trend filter, see 2.3.5 for more about trend filters. The value of *n* is as mentioned the parameter that determines the length of the look-back period and the value of it heavily impacts the result of this method. A larger *n* will result in a larger look-back period and make this trend indicator method less sensitive to rapid changes in the time series (Aronson, 2007). Thus making it better for identifying larger and longer trends, but a too big *n* would result in very few signals and trading opportunities.

2.3.3 Simple moving average

Before discussing the second classical method for trend determination, we first need to describe what moving average (MA) means, and particularly what simple moving average (SMA) is. Moving average is one of the most widely used operators for statistical analysis of a time series, and it is a series created from the average for a rolling subset of length *n* on the full time series. It filters out high frequency fluctuations in the time series, while passing through low frequency components of the time series, i.e. it fillers out short term fluctuation and keeps the long term movement of the time series. In other words, it illustrated the underlying trend in the time series.

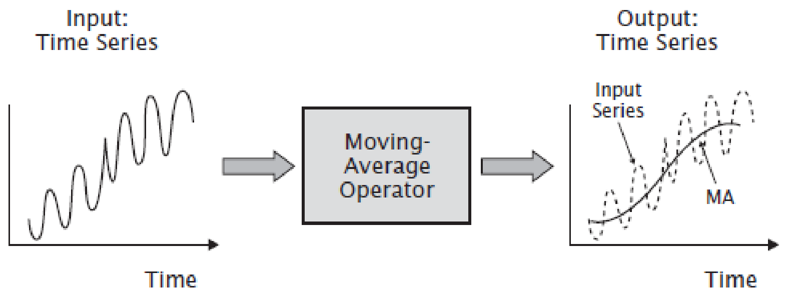

Figure 2.5: Illustration of moving average filtering out high frequency fluctuations and showing the underlying trend of an arbitrary time series. Source: Aronson (2007) page 398.

This smoothening effect on the time series is due to taking the average of a subset of the time series, a look-back period of the last *n* data points, which reduces the fluctuation that has occurred during the look-back period. A 10 day moving average will for instance reduce the less than 10 day fluctuation in the data series and completely eliminate the 10 day fluctuation. But it is important to note that the smoothing of the time series will lead to an inherent delay in the smoothed time series, moving average series. This is referred to as lag, and it means that changes in the full data series will not show up and fully impact the moving average until some data points later, i.e. it reacts slowly to a new trend. This delay is increased when using a longer time span for the look-back period. (Aronson, 2007)

There are many types of moving average, ranging from the most basic called simple moving average to more sophisticated smoothing methods that use more complex functions for weighing the data points in the look-back period. The simple moving average on the other hand is simply just the equally-weighted arithmetical mean of the last *n* data points in of the time series, i.e. all data points are weighted equally and have an equal impact on the current SMA value regardless of where in the look-back period that data point is.

$$\mathrm{SMA_t} = \frac{\mathrm{P_t} + \mathrm{P_{t-1}} + \mathrm{P_{t-2}} \dots + \mathrm{P_{t-n+1}}}{\mathrm{n}} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{P_{t-i+1}}}{\mathrm{n}} \tag{2.1}$$

$\mathrm{SMA_t}$ is the simple moving average at time t. $\mathrm{P_t}$ is the closing price at time t and n is the length of the look-back period for the SMA.

The lag introduced by the SMA is easy to calculate and is equal to half of the look-back period, minus one data point (Aronson, 2007). Thusly the 15 day SMA has a lag of (15-1)/2 which equals 7 data points. This means that a long term trend reversal in the time series will not show up in the 15 day SMA until 7 data points later. SMA is widely used for financial applications for determining a trend in the closing prices of a financial instrument.

2.3.4 Moving average as a trend following strategy

Another classic trend following method that is still popular among investors is based on simple moving average, a long term SMA is used here as an indicator of trend direction (Annaert, Van Osselaer, & Verstraete, 2009). This look-back period can range from a few months to over a year depending on the preferences of the investor, but the most common choice for trend-followers is to use a 200 trading day look-back period for the simple moving average. When the instruments closing price moves above the simple moving average, an upward trend is signaled and the investor should cover his short position in the instrument and immediately take a long position. When the closing price moves under the simple moving average, the method signals for a change in direction of the trend towards a downward trend and the investor should sell the instrument and take a short position instead. So by using this method the trader will always be in the market, as opposed to those using breakout as their trend following indicator.

The intuition behind using this trend following method as an indicator is that the long term SMA does not take any particular data point into consideration, but rather shows the general direction the time series is moving. Though it is certain that the most recent data points are relevant, it is less relevant what data points these should be compared with in order to determine the direction of the trend. The SMA will reduce the high frequency fluctuations and smoothen the time series so that a general trend direction can be seen. The appropriate choice of the look-back period for the SMA on the particulate time series is harder to determine. Previous research, including Annaert et al (2009) and Clare et al (2012), recommend using a range of look-back periods ranging from 6 to 12 months and to use the one with the best historical performance for the portfolio of futures on commodities. The research of Anneart et al (2009), which is based on an equity portfolio, suggests that the one year look-back period is the best choice.

2.3.5 Trend filter

A trend filter can be used in order to make sure the trend following methods only signals for a long or short position when there is a clear trend in the market, thus better avoiding the periods where the market moves sideways or even in the opposite direction. The biggest problem with using simple moving average as an indicator is that a pure moving average strategy will always be in the market – even if there is no clear trend. This may be the most common case, because the time series may just be mean-reverting for a long period of time. When the market is moving sideways the moving average strategy will be entering and closing position on a short term basis, losing on most of these trades. A trend filter will stop it from entering into trades when there is no significant trend to profit from. The simple moving average is in itself a trend filter, just not a very good one on its own. By adding a second trend indicator as a trend filter the performance may be improved by the elimination of short term trades. (Czkwianianc & Koulajian, 2010; Clenow, 2013).

The breakout strategy would also benefit greatly from a simple trend filter. It does not have the same problem as the simple moving average as it is not always in the market, just after a price breakout. But because it enters into a position when the time series has its lowest or highest value in the past n data points, it sometimes has the tendency to do so when the main market trend is moving in the opposite direction because of a pullback in the market. A pullback is fairly common after a strong market trend and it is usually not a good time to enter into a position. So the time series may have its lowest or highest value in the past n trading days but at the same time the main trend is moving in the opposite direction of the breakout signal. For example; the strategy will signal for a long position during a strong bear market resulting in over-trading and taking long- and short-positions back and forth with overall losses.

The remedy for this is to use a second trend indicator as a trend filter. The easiest one to use is a combination of two simple moving averages as the trend filter, one with a short look-back period and the other with a much longer one. A breakout is now only allowed if its signaled trend is moving in the dominant market trend direction. The two mixed SMAs are not used as a trend signal, but rather as a filter for when the markets general direction does not coincide with the breakout signal. When the faster changing short term SMA, faster due to lower lag, crosses over and as long as it is above the slowly changing long term SMA it is an indication for that the price series of the instrument is changing upwards due to resent event. This is because the short term SMA is better at catching recent changes in the time series than the long term one because of the smaller lag. Consequently, when the faster changing SMA is below the slower changing SMA it is an indication for that the price series of the instrument is changing downwards due to resent event. (Clenow, 2013)

2.3.6 Autocorrelation

In statistics, the autocorrelation is the correlation of the time series with itself at different points of time, i.e. it is not the correlation of two different variables, but the correlation of the same variable but at a different time points, where time is measured in lags starting at 0. Autocorrelation describes the similarity of the observations at different time lags between them; it is a useful tool to find repeating patterns in a time series (Box & Jenkins, 1976). If a market exhibit positive autocorrelation, then previous price movements on the market can be seen as an indicator for the direction the market is moving, because of the positive correlation with previous observations of the time series. Since trend following strategies depend on predictions of market movements, they perform well in markets that exhibit positive autocorrelation.

The autocorrelation for lag k for process X with N number of observations and mean $\bar{X}$ is defined as:

$$r_k = \frac{\sum_{t=1}^{N-k} (X_t - \bar{X})(X_{t+k} - \bar{X})}{\sum_{t=1}^{N} (X_t - \bar{X})^2} \tag{2.2}$$

2.4 Methods for volatility calculation

Both standard deviation and average true range are tools used to measure the historical volatility for a stock or an index over a fixed period of time. They are sometimes used interchangeably but they are two different tools and average true range is by some considered the better choice. Mostly because it encompasses more information and better reflect the historical price movements, due to the fact that it apart from closing prices also take highest and lowest prices into consideration. (Fontanills & Gentile, 2003)

2.4.1 Standard Deviation

Standard deviation is according to Berk and DeMarzo (2011) a measure of the dispersion of the returns and has the same unit as the returns and it is an established measure for the risk of an asset. The standard deviation is simply equal to the root of the historical variance.

$$\mathrm{SD_n} = \sqrt{\frac{1}{\mathrm{n}} * \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{x_i} - \bar{\mathrm{x}})^2} \tag{2.3}$$

Where n is the size of the sample used to calculate the standard deviation, and $\{\mathrm{x_1}, \mathrm{x_2}, \mathrm{x_3}, \dots, \mathrm{x_n}\}$ are the observed values for the sample and $\bar{x}$ is the arithmetical mean of the observations in the sample. Standard deviation for financial assets are calculated using the assets returns as observations and is usually calculated on a yearly basis, corresponding to n = 252 which is the approximate number of trading days in a year. In this case, the above expression for the standard deviation needs to be adjusted to:

$$SD_{252} = SD * \sqrt{252} \tag{2.4}$$

2.4.2 Average True Range

Average true range was introduced by Wilder (1978) and has since then been widely used in trading systems as an alternative to standard deviation to measure the historical volatility of a financial asset (Clenow, 2013). The argument goes that volatility is directly proportional to range, and that range is equal to the distance the price moves per increment of time, i.e. the difference between the highest and the lowest price for a specific timeframe (Wilder, 1978). But more than one day's range must be considered for any given trading day due to the fact that price series are not continues and price levels are limited by the closing and opening price. The range takes intraday volatility into consideration without having exact data for intraday volatility, since this is generally not available for historical simulation. Therefore the *true range* is defined as the greatest value of the following three distances:

1) The distance between today's high and low.
2) The distance between yesterday's closing price and today's high.
3) The distance between yesterday's closing price and today's low.

And this can be formulated as:

$$\mathrm{TR_t} = \max(\mathrm{H_t}, \mathrm{C_{t-1}}) - \min(\mathrm{L_t}, \mathrm{C_{t-1}}) \tag{2.5}$$

Where $\mathrm{TR_t}$ is the true range for the day at time t. H_t and L_t are that day's high respectively low and C_{t-1} is the previous day's closing price.

But in order for this to be a meaningful measure for historical volatility, more than one day's true range must be considered (Wilder, 1978). The solution is to calculate the true range for a number of previous days and take the average of that, and this is the average true range. So average true range is an estimate of the price movement a financial asset may make in a typical trading day, based on previous historical movements.

2.5 Methods for portfolio allocation

The purpose of this study is to determine whether a trend following hedge fund can improve its performance by changing its position sizing method. The different approaches for position sizing under consideration in this study are:

- Equity curve-based
- Target Volatility
- Correlation
- Omega
- Max Drawdown
- Dynamic Stops

2.5.1 Equity curve-based

Equity based is a novel approach of position sizing that emerged from discussions with the collaborating CTA fund for this study. The idea is to analyze the equity curve, i.e. the change in value over time for an account or asset, for one future or a group of futures. If the equity curve is increasing, the positions taken in these futures increases. In the implementation of this method, trend following filters, such as SMA-crossover or Clenows *Core strategy* (2013) can be used to determine whether the equity curve of a specific future have moved up or down.

2.5.2 Target Volatility

Target Volatility originated as an improvement of the traditional 60/40-rule used by many mutual funds – 60% of managed capital in risky assets, 40% in fixed income (Morningstar, 2012). The problem with this traditional approach to asset management is when a market crash occurs. When the price of equities falls, the percentage of capital in equity decreases, causing fund managers to sell bonds in order to buy equity, essentially creating riskier portfolios in times of crisis. *Target volatility* instead works by targeting a certain volatility level, say 10%, and leveraging and deleveraging the portfolio each time step in accordance with the relation between realized and target volatility:

$$\mathrm{w_{t+1}} = \mathrm{w_t} * \min(\max \text{exposure}, \frac{SD_{252_t}}{SD_{252_{target}}}) \qquad (2.6)$$

Where w_t is the weight placed in the risky asset at time t, and SD_{252_t} and $SD_{252_{target}}$ is the realized and target volatilities respectively, SD_{252_t} measure the annualized intraday volatility of logarithmic returns.

Bruder & Roncalli (2012) shows how this might be implemented as a portfolio allocation method. *Target volatility* is a powerful tool. Cooper (2010) show how one can find an optimal volatility level, balancing higher volatility and higher long term returns. He shows how a dynamic portfolio of exchange traded funds, replicating the same index at different leverage levels, can produce excess risk-adjusted returns.

2.5.3 Correlation

Sizing positions using correlation might be used to decrease risk of the strategy, by increasing diversification effects. Faith (2005) describes how followers of his trading strategy are limited in the number of positions they might take at the same time, and a lower limit if the futures in question happen to be highly correlated with each other. It is a simple idea: Trend following strategies such as the one used in this study rely on the assumption that futures are independent and interchangeable, and that the only relevant variables for determining position size is volatility and contract size. This is of course a simplification. If our fund has one position in gasoil, crude oil and gasoline and one in USD/YEN, the total portfolio is presumably more exposed to changes in oil price than the dollar-yen exchange rate. It stands to reason that by increasing the position in that by taking correlation into account, such over-exposures could be decreased.

Tomasini & Jaekle (2009) suggests analysis pairwise correlations between each of the futures traded. For each instrument, count the number of futures with which it has a correlation below a previously determined threshold. This number is then used as a proxy for how correlated the instrument is with the other ones. The instruments with the highest number of low correlations take larger positions, while the instruments with a lower number take smaller positions. (Tomasini & Jaekle, 2009)

2.5.4 Omega Optimization

The performance measures of financial assets can broadly speaking divided into two groups of measures. One group of measures that assume normally distributed returns, which includes Sharpe ratio for instance, and another group that do not make that assumption. An example from the latter group is *Omega,* which takes into account moments higher than five.

The Omega measure was originally proposed by Keating & Shadwick (2002a). The authors argued for the necessity of a new measure in order to better compare the performance of financial assets. Their paper especially addresses the impact that skewness, kurtosis and higher moments have on the performance of financial assets. This is because more classical performance measures over-simplify by letting the mean and variance fully describes the distribution of returns, and sometimes makes the assumption that the returns are normally distributed. But it is generally accepted that returns from investments are not normally distributed. This is especially the case for hedge fund returns that historically have been non-normally distributed as well as having a negative skew and a high kurtosis, which advocates the use of a measure that takes these statistical aspects into consideration (Harris & Mazibas, 2013). The measure incorporates all the distributional characteristics, moments, of a returns series. It is a function that simply depends on a return level, or threshold value, and one strength of the measure is that it does not require any parametrical assumptions of the returns distribution.

Even if the returns would be normally distributed, the Omega measure will provide additional information because of the threshold value for the Omega function which represents the investors risk aversion or desired rate of return. And since it also measures the total impact of the moments of the distribution, instead of the impact the different moments have individually, it can reduce the estimation error (Keating & Shadwick, 2002a). In their original paper, Keating & Shadwick referred to this new measure as Gamma but in a later paper they renamed the measure to Omega (Keating & Shadwick, 2002b). In this paper they further develop the concept of the measure, discussing the properties of the Omega function, and supplying a thorough mathematical derivation.

Let F be the univariate cumulative distribution function on the interval *(a, b)* for the returns of a financial asset, where a can be $-\infty$ and b may be $+\infty$. If F satisfies a simple growth condition then there exists a unique monotone function from (a, b) to $(0, \infty)$. This is the Omega function, denoted $\Omega_F(r)$. This function depends on a return level r, or loss threshold. Returns below this threshold are regarded as losses and above it as gains. The mean, known as the first moment, for a distribution is for example the unique value for r which the Omega function is equal to 1. High moments are also encoded in the shape of the Omega function and therefore make the measurement particularly well suited for financial time series where non-normality is crucial but hard to estimate through the use of higher moments because of noise in the time series or scarcity of data. (Keating & Shadwick, 2012b)

The Omega function can now be defined, and it is the following simple fraction of probability density functions on the interval [a, b] for the univariate cumulative distribution function F for the financial assets returns with the loss threshold *r*:

$$\Omega_F(r) = \frac{I_2(r)}{I_1(r)} \tag{2.7}$$

Where

$$I_1 = \int_a^r F(x)dx \tag{2.8}$$

And

$$I_2 = \int_r^b 1 - F(x)dx \tag{2.9}$$

Let r_{min} be the worst return and r_{max} be the highest return for a financial asset. The cumulative distribution of the returns for this financial asset will be a monotonically non-decreasing curve on the interval $[r_{min}, r_{max}]$. The choice of a loss threshold r will, as mentioned previously, determine the value of the Omega function and the performance of the financial asset. A high value of the Omega function is always preferred over a lower value. (Kane et al., 2009)

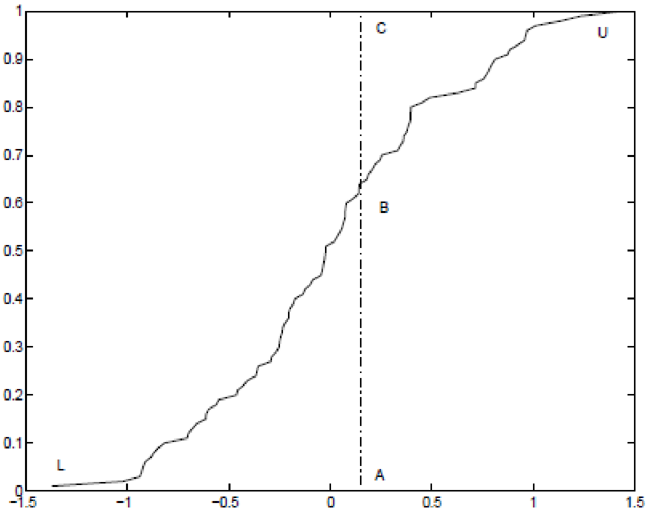

Figure 2.6: Cumulative distribution of asset returns with loss threshold at point A. Source: Kane et al (2009) page 2.

A typical cumulative distribution for returns of a financial asset can be seen in the Figure 2.6. In the figure there is also a dotted line going through a points A, B and C. This line corresponds to a loss threshold of 0.1, i.e. returns below 10% are considered as losses and above 10% as gains. Now by using this line as an illustrative example, the Omega value for this financial asset can now be interpreted as the fraction of area [BCU] divided by area [LAB]. The Omega function can now, in this case, be expressed as:

$$\Omega_F(r) = \frac{\int_r^{r_{max}} 1 - F(x)dx}{\int_{r_{min}}^{r} F(x)dx} = \frac{\text{Area [BCU]}}{\text{Area [LAB]}} \qquad (2.10)$$

If the loss threshold value would be smaller, than area Area [BCU] would increase and Area [LAB] would decrease and the Omega value would be larger. This means that $\Omega \rightarrow 0$ as $r \rightarrow r_{max}$. And if one would consider the loss threshold as a desired rate of return, Omega would be a measure to the extent to which the historical performance of the financial asset has exceeded this desired rate of return. Thusly, an asset with a higher Omega would be considered a better investment given the desired rate of return. For another loss threshold value, another asset may give a higher Omega as seen in Figure 2.7.

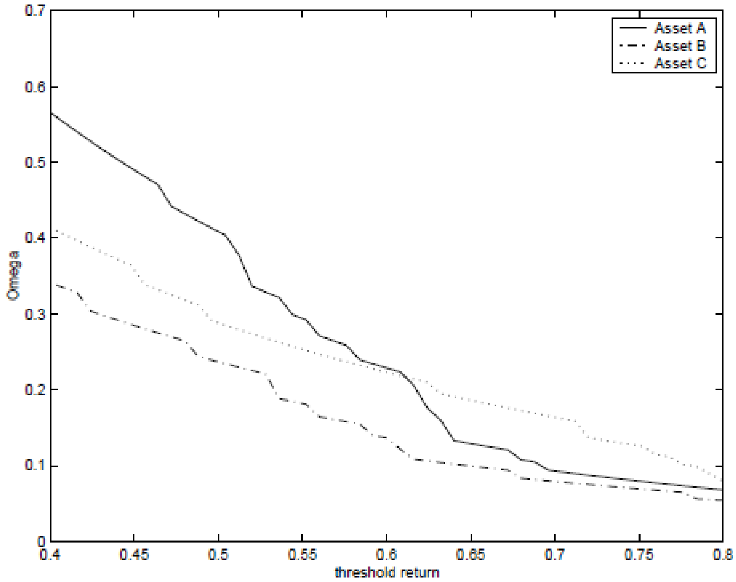

Figure 2.7: Value of omega function depending on loss threshold value for three financial assets. Source: Kane et al (2009) page 4.

2.5.5 Max Drawdown

Max drawdown is the largest percentual loss from a peak in equity price or portfolio value to following trough. The current drawdown of a portfolio $DD(T)$ at time T is defined as the decline from the historical maximum:

$$DD(T) = \max\left\{0, \max_{t\in(0,T)} X(t) - X(T)\right\} \tag{2.11}$$

And the maximum drawdown $MDD(T)$ is the highest drawdown to date:

$$MDD(T) = \max_{\tau\in(0,T)} [DD(\tau)] \tag{2.12}$$

Max Drawdown is a measure of realized risk, used by several authors in the context of the alternative investment universe (Clenow, 2013; Czkwianianc, P. & Koulajian, 2010; Darius et al., 2002). The *Max Drawdown*, considered in relation to returns, is interesting both for the desirability of the strategy as well as feasibility of implementation. Harris & Mazibas (2013) uses *Conditional Drawdown* (*CdaR*) optimization to construct a portfolio of hedge funds, substantially improving performance over a parametric mean-variance model. This method is based on calculating *Max Drawdown* for different scenarios, minimizing the expected drawdown in an adverse scenario.

2.5.6 Dynamic Stops

The trading strategy used in this study makes use of trailing stops, where the exit condition is related to the highest observed closing price since the position is entered. Instead of changing position size, the idea of dynamic stops is to change this exit condition based on the fraction of the portfolio currently invested.

3. Literature Review

The history of technical analysis begins with Dow Theory, as formulated by Reah (1932). His work in turn was based on a series of editorials written by Charles Dow at the turn of the 20th century. Reah formulates the breakout strategy (or “support-and-resistance” in the Dow terminology), that is to buy when a price exceeds its short term high, albeit as a qualitative method rather than a quantitative one. Schulmeister (1988) uses the breakout method as a quantitative strategy, and reports it to be widely used within the industry, as does Pring (1998).

Asness, Moskowitz & Pedersen (2013) showed how there is high returns for momentum across a wide variety of asset classes and time periods. There may be behavioristic explanations to why trend following works. Hurst, Ooi & Pedersen (2013) argues that a combination of investor herding and the disposition effect gives rise to autocorrelation observed within markets, enabling trend following strategies. Griffoen (2003) does a comprehensive review of the technical versus fundamental analysis antagonism of asset prices, and points out that “Chartism” (an older term for technical analysis) has been treated with skepticism by the academic establishment. Griffoen also goes on to do a high number of backward testing for thousands of variations of trend-capturing strategies (Griffoen, 2003).

There is further complication by results like that of Gorton & Rouwenhorst (2005), showing commodity futures to be a highly profitable investment vehicle for the 50 years preceding the study, solely as a buy and hold strategy. This may imply that the high performance and low correlation with the equity markets managed futures funds may have been mostly by virtue of the investment universe in which they have been active. The debate over the efficiency of markets and the profitability of momentum trading is far from over. And with the recent underperformance of the CTA industry (see 1.1.), the debate may have rekindled. This question is, however, beyond the scope of this study.

In 1984, Dennis conducted an experiment in which he taught 23 amateur traders simple rules meant to capture trends, based on a breakout strategy. These traders were all given 1M$ to manage, and where allowed to keep 15% of all profits. After a trial months, some traders were shut out due to not being able to follow the rules. The experiment ran for five years, after which the remaining traders had, according to Dennis, produced $175 million in returns. (Covel, 2009)

Clenow (2013) show how a modification of the rules written by Dennis has produced excess returns for the last 20 years, and how this strategy closely replicates the behavior of major CTA funds. Czkwianianc & Koulajian (2010) show how a moving-average crossover strategy can produce similar results.

There is another approach to hedge fund replication, championed by, among others, Takahashi & Yamamoto (2010) and Kat & Palaro (2005) using an method based on copulas and stochastic calculus in order to replicate the risk profile of the fund.

In all of these rules, risk allocation is made by the naïve approach: Each position is sought to have equal risk. There are arguments against this approach. First of all, correlation within assets complicate this picture. Holding equal parts crude oil, petrol, heating oil and natural gas is a riskier position than holding the same volatility-adjusted positions in crude, Nikkei, lean hogs and gold – the former position is riskier than the latter. The trading rules constructed by Dennis accounted for this, by letting the limit the number of open positions vary –more positions could be opened if correlations were low. (Curtis, 2005)

Secondly, and perhaps most importantly, there is both theoretical arguments as well as empirical evidence that market autocorrelation and return predictability, that is the market inefficiencies that trend following trading builds upon, varies with time. Andrew Lo (2004) puts forward a theory called the Adaptive Market Hypothesis (AMH), which is an attempt to modify the Efficient Market Hypothesis in order to account for finding from behavioral finance. One of the predictions of the AMH is that autocorrelation within markets will vary over time. There is some empirical support for this (Urquhart & Hudson, 2013; Kim, Shamsuddin & Lim, 2011).

Portfolio allocation, in the context of managed futures, is inseparable from risk allocation. As Clenow (2013) points out, it is easy to increase the position sizes in order to increase returns (at the same time, of course, increasing the magnitude of drawdowns and the risk of going bust). This means that we also must look to risk management. Lo (2001) gives an overview of the specific challenges of risk management within the hedge fund world, listing survivorship bias, non-linearity and liquidity as factors especially important to consider.

Portfolio aspects of hedge fund research has largely been concerned with fund-of-funds – that is, how to best invest in hedge funds, according to risk profile and other assets in the portfolio. Lamm makes such an analysis, using a mathematical approach, testing his findings on a few indices (Lamm 2003). Giamourdis & Vrontos (2007) construct similar hedge fund portfolios that are then tested against indices. Popova, Morton, Popova, & Yau (2006) looks to simulate hedge funds by replicating their risk profile. Darius et al. (2002) shows how a portfolio made up of traditional investments can be greatly improved by ways of including a hedge fund, using a straddle option as a proxy. Harris & Mazibas (2013) suggests optimizing portfolios of hedge funds based on conditional drawdown or Omega instead of classical mean-variance, in order to preserve the risk-return profile unique to hedge funds. Finally and perhaps most relevant to this study, Tomasini & Jaekle (2009) suggests improving trend following strategies by adjusting positions according to pairwise correlations between individual traded symbols.

To summaries, we have identified two major lines of research of relevance to this study: The first one is concerned with the nature of managed futures, and trend following strategies. This area can be subdivided further, into those who aim to simulate the return of CTAs using mathematical constructions such as Kat & Palaro (2005), and those who aim to investigate the managed futures phenomenon using simulated trading with simple trend following rules. The latter group is where the works of Covel (2007), Czkwianianc & Koulajian (2010) and Clenow (2013) are found.

The second line of research aims to find novel approaches to portfolio optimization, moving beyond mean-variance analysis. *Omega Optimization* as described by Cascon, Keating & Shadwick (2002) and *Target Volatility* as implemented by Bruder & Roncalli (2012) is two of the more prominent products of this area of study, but Tomasini & Jaekles (2009) correlation method and Harris & Mazibas (2013) use of *Conditional Drawdown* can also be said to belong to this second category.

These two areas of research are largely uninformed of each other. Granted, there is some overlap; Tomasini & Jaekles (2009) suggests using his correlation method over a trend following strategy, and in Harris & Mazibas (2013) study of optimizing a portfolio of funds-of-funds, novel approaches of portfolio optimization are utilized, albeit not for position sizing of individual traded symbols but on a higher level of abstraction. However, the main finding of the literature review is that trend following strategy research has yet to utilize recent advances in alternative portfolio optimization, and that there is great academic interest and potential real-world benefits in bringing together these two developed, but largely separated areas of research. This study aims to bridge this gap, by investigating how trend following strategies might benefit from alternative portfolio optimization.

4. Methodology

In order to investigate the research questions, stated earlier in this thesis, the methods and data sample that will be used in order to answer them needs to be defined. By trying to answering them, we will acquire the knowledge needed to achieve our purpose with this study. In this section we will present the research strategy to be conducted and the choice of methods to be used. The approach will be of a deductive nature, drawing theories and concepts from the prevailing literature, and testing the chosen methods on empirical data in order to later draw conclusions from the empiric research. (Collins & Hussey, 2009)

This is done in order to investigate whether or not the allocation of capital can be improved, in the sense of risk reduction, performance during periods of distress and return of the portfolio, by using different methods to determine the position sizes of the underlying assets. Ranging from the static equally weighted portfolio risk contribution method, Fixed Fraction, to the dynamic stop changing method.

4.1 Data collection and sample

The underlying data used in this study are 47 futures contracts spread across five different sectors; agricultural, metal and energy, currencies, equity, and rates[1]. The metal and energy sector will also be referred to as the non-agricultural sector, and the equity class contains futures contracts on stock market indexes.. The different futures contracts used can be seen in Table 4.1.

In this study, the focus will be on the historical closing prices of the futures contracts that makeup the investment portfolio. Spanning from 1990 to 2012, thereby covering different periods of the futures market, both periods of distress as well as periods of high equity returns. This will increase the validity in the findings by both giving a good amount of data points for statistically significant conclusions as well as covering periods of different performance of the market as a whole, so the results will not be one sided as they take both periods of distress and prosperous periods into consideration. It will also shine light onto how the different methods of portfolio allocation have performed during different periods.

[1] Data were collected from the Tickdata (2013) database.

Agriculture	Metal and Energy	Currency	Stock indices	Rates
Cocoa	Crude Oil	AUD/USD	DAX	Australian 90-Day Bank Bill
Corn	Gasoil	GBP/USD	FTSE 100	Euro-Bund 10-Year
Cotton	Heating Oil	CAD/USD	Hang Seng	Euro-Schatz 2-Year
Lumber	Natural Gas	EUR/USD	Nikkei 225	US 10-Year T-Note
Live Cattle	Gasoline	JPY/USD	NASDAQ 100	US 2-Year T-Note
Lean Hogs	Gold	NZD/USD	Russell 2000	Long Gilt
Oats	Copper	CHF/USD	S&P 500	Eurodollar CME
Sugar	Silver		EURO STOXX 50	Euribor 3-Month
Soybeans	Palladium		CAC 40	Sterling 3-Month
Wheat	Platinum		MSCI Taiwan	US 30-Year T-Bond

Table 4.1: Future contracts, ordered by sector.

These 47 future contracts were chosen in order to replicate the portfolio used by Clenow (2013). They were chosen because they were either in the portfolio presented in the book, or were of a similar in nature. But the structure of the portfolio was mainly chosen because it is appropriate for this study; it has a high level of diversification across different sectors that have their own uniquely different behaviors. This results in a well-diversified portfolio that allows the possibility to draw valid results and conclusions from the empirical data. The choice of this investment universe and a simple trend following strategy, see 2.3, also allowed Clenow to nearly replicate the performance of the major CTAs during the last decades (2013).

All data are of a secondary nature (Collins & Hussey, 2009), and the historical data for most of these futures contracts were collected from the TickData (2013) database, and sent to us by the CTA we collaborated with as they had access to this database. The data for some future contracts start a little bit after 1990 but they are of interest and are used and traded in the models as the data for them becomes available.

But in order to analyze this vast amount of historical data and portfolio allocation methods, described later in this chapter, a good and reliable software platform was essential. The choice fell on RightEdge, after a comparison to WealthLab. RightEdge seemed more suitable for this study when it came to modeling position sizes and portfolio allocation. Access to RightEdge was given by aforementioned CTA. RightEdge is a trading platform where trading strategies can be constructed using programing in C#. Using this software, a simple trend following strategy called "*Core strategy*", the rules for it are described in 4.2., will be constructed and used on all the futures contracts, and then later the different portfolio allocation methods will be used on top of this trend following *Core strategy*.

4.2 Choice of underlying trend following strategy

The underlying trend following strategy used for this study for both *Fixed Fraction* and all the alternative position sizing methods is referred to as the *Core Strategy,* and was developed by Clenow (2013). Using this strategy in conjunction with *Fixed Fraction* position sizing, he was able to replicate the performance of the major CTAs during the last decades by using a simple breakout strategy together with a trend filter. So by using this strategy, our study and the findings in it can be deemed to be highly generalizable and transferable to practitioners as well as researchers, as the findings of the behavior of different portfolio allocation methods are not fictional but related to what one could expect to be the case of a CTA if they employed the same portfolio allocation method. This strategy will be denoted *Core strategy* as it is not a general breakout strategy due to the extra trend filter.

The construct of the trend following strategy used in this study is fairly simple and straightforward. A more complex version could be constructed but that is outside the scope of this study, as the focus in this study is on the portfolio allocation methods, and the *Core strategy* has proven to be reliable when it comes to replicating the past performance of CTAs. The theory behind the underlying parts of the *Core strategy*, breakout and trend filter is highlighted in the theoretical framework chapter under the trend following section 2.3. But the fundamental concept of the *Core strategy* is to first identify a possible trend, upward or downward trending, and hold the position as long as the trend is not wearing of. The idea is not to hit the absolute high and low of the time series, but rather capitalize on the overall trend movement. This strategy will signal for entering and closing a position in an instrument and the strategy is as follows:

- Long entries are only allowed when the 50-day SMA is above the slower changing 100-day SMA (this is the first part of the trend filter).
- Short entries are only allowed when the 50-day SMA is below the slower changing 100-day SMA (this is the second part of the trend filter).
- If there is no position already in the instrument and a long position is allowed by the trend filter, a 50-day breakout of the closing prices will signal for either buying or selling the instrument. I.e. if the present closing price is the highest in 50 trading days a certain number of contracts in that instrument, corresponding to the position size determined by the portfolio allocation method, are bought on the next day's opening price. Consequently, if the closing price is the lowest in 50 trading days, that amount of contracts are sold.
- A long position is closed when the closing price for the instrument is three ATR-units below the highest closing price the instrument has had since the position was taken.
- A short position is closed when the closing price for the instrument is three ATR-units above the lowest closing price the instrument has had since the position was taken.

Both long and short positions are allowed, but not at the same time on the same futures contract, and a position is only allowed to be taken or closed when the *Core strategy* signals for it and no other position is taken on the instrument.

Fixed Fraction

This method will be used to determine the position sizes for the positions signaled by the trend following strategy, and the results from this basic position sizing method will be compared against the results from using the other position sizing methods.

The general idea behind this method of position sizing is that every position in an asset will theoretically have the same bottom-line impact on the whole portfolio on an average day (Clenow, 2013). This mean adjusting for the asset specific volatility profile and point value of said future contract, more on the theoretic framework behind futures can be found in 2.1. Otherwise, if one simply invested the same notional dollar amount in each trade, e.g. same percentage in all instruments, the profile of the portfolio would be highly affected by the most volatile instrument. So the portfolio would basically be made up nearly entirely by the highly volatile instruments whereas the less volatile would be given very small position sizes. It would also inherit the high volatility of said instruments and therefore be considered to be far too risky in its nature as well as not favorable to diversification effects. This is because the instruments in the portfolio have very different volatility profiles but also highly different point values.

Therefore, the *Fixed Fraction* method takes the volatility of each instrument into consideration, as well as point value and also a risk coefficient determining how much each position theoretically should affect the portfolio on an average day. This is not the case because the volatility of the instrument is always changing; therefore it is only theoretically true that each position has the same impact on the portfolio as a whole.

The volatility of the instruments can be determined using a variety of approaches, the most common one is just to simply calculate its standard deviation. But in this study, the *average true range* measure (ATR), see 2.5.2, will be used to determine the volatility contribution to the position size using the *Fixed Fraction* method. This measure represents how big a normal daily move is for an instrument, based on historical movements. A study conducted by Gustafson (2002) also compared the results of using ATR or standard deviation, and the author came to the conclusion that using ATR as a volatility measure generated more trading signals than using standard deviation.

The formula for the number of contracts that should be bought according to the *Fixed Fraction* method is the following:

$$Contracts = \frac{Equity * Risk\ Factor}{ATR_{100} * Point\ Value} \tag{4.1}$$

Where *Equity* is the current value of the whole portfolio, cash held and the value of all active trades. The R*isk Factor* governs how much each position, in theory, should affect the bottom line of the portfolio on a day to day basis and how much damage or profit the position can potentially do to the portfolio as a whole (Clenow, 2013). The *Risk Factor* is set at 0.1%, i.e.

0.1% effect on the portfolio, which is a rather conservative risk level. The low underlying *Risk Factor* means that a large amount of cash will be held, and the volatile part consisting of unrealized profit on active positions will be lower due to said conservative risk level. The cash held will be available to use when taking new positions and resize the position sizes of the alternative position sizing methods.

The average true range will be based on the last 100 trading days. And the *Point Value* is the same as contract size for our futures contracts, i.e. what one contract in the futures contract represent in real world terms of the underlying asset. For more on point value, see the futures section of the theoretical framework chapter 2.1.

4.3 Choice of portfolio allocation methods

This section is central to the study conducted, namely how the performance of the trend following strategy, the *Core strategy*, on the well diversified portfolio changes depending on the choice of portfolio allocation method, i.e. how big positions that should be taken on different assets regarding the criteria's of the different methods. The methods used are described in the subsections below, and the methods have been chosen because they either; reflect the specific aspects that come into play when dealing with the CTA framework and a trend following strategy, or the method have lately experienced an upswing in the literary discussion in the field of portfolio optimization, or are more classical risk managing optimization techniques, and some are of a more novel approach based on conversations with people working within the CTA industry:

- Equity Momentum
- Equity SMA
- Equity Core
- Target Volatility
- Correlation Threshold
- Corretation Asset-Portfolio
- Omega Optimization
- Max Drawdown Minimize
- Max Drawdown Equal Contribution
- Dynamic Stops Risk
- Dynamic Stops Lock-In

In common for all the portfolio allocation methods, including the *Fixed Fraction* method, is that positions will be taken according to the trend following *Core strategy*, but the position size taken will differ for the different allocation methods. When a position change is signaled, either by the *Core strategy* or a reweighing signal from a portfolio allocation method, the change will be on the next day's opening price, because no intraday trading is allowed. The allocation methods will be tested both for just signaling new weights for new positions, and for also reweighing already active positions. The different allocation methods will as mentioned determine whether a new, or already active position, should be reweighted and this is determined by either the performance of the portfolio as a whole, sector the instrument belongs to or the performance of the instrument itself. Where applicable, the instrument-level approach and the sector-level approach will be tested. The results from just using the *Fixed Fraction* method (see 4.2), will be the reference for the comparison to the other allocation methods. The position sizes determined by the *Fixed Fraction* method will be the baseline for the other methods but resized according to the risk level signaled for. Most methods in this study uses three risk levels for reweighing positions: 50 percent of the *Fixed Fraction* weight, 100 percent of the *Fixed Fraction* weight and 150 percent of the *Fixed Fraction* weight. The *Omega*, *Target Volatility* and *Drawdown* position sizing methods do not use the three static risk levels, but sets the risk level to be somewhere in the interval 50 percent to 150 percent, due to the nature of these methods, and the *Dynamic Stops* method do not use risk levels at all. If the past performance of a sector is determined to be good, all new or already active positions on instruments belonging to that sector will be moved up one risk level, I.e. if the current risk level is 100 percent of *Fixed Fraction* and the allocation method signals for good past performance of the sector, all new and already active positions on instruments belonging to that sector will now be reweighted upwards towards 150 percent of *Fixed Fraction*. And if the allocation method signals for a bad past performance of the sector, all new or already active positions on instruments belonging to that sector will be moved down one risk level. And also the same procedure but on an instrument level where the past performance of the instrument itself will determine whether a position on it should be reweighted. Different reweighting periods will also be used for some of the position sizing methods, i.e. different length between when positions are reweighted.

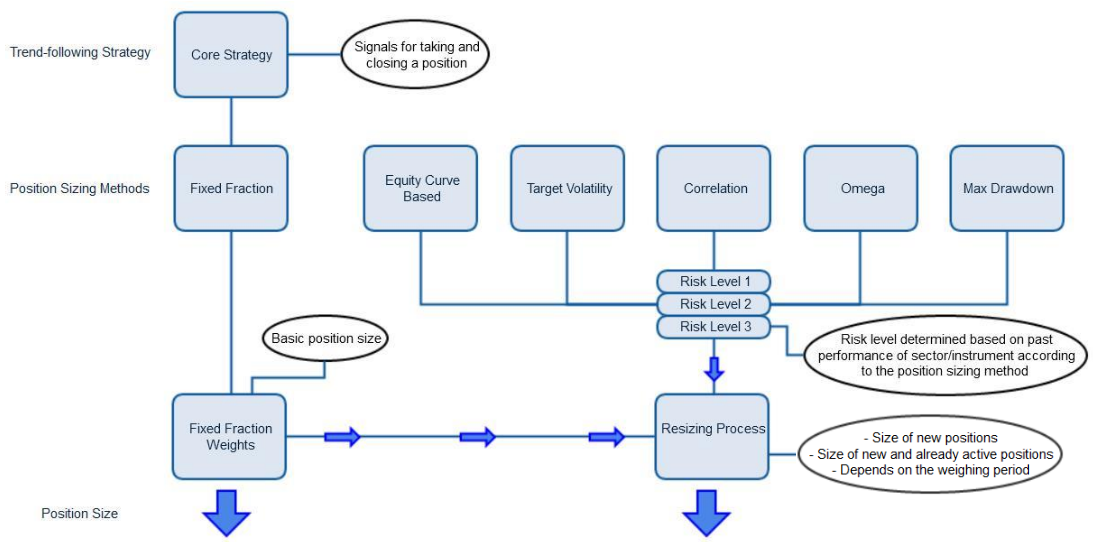

Figure 4.1: How the *Core strategy*, *Fixed Fraction* and the position sizing methods relate to each other, and produce the final positions to be taken.

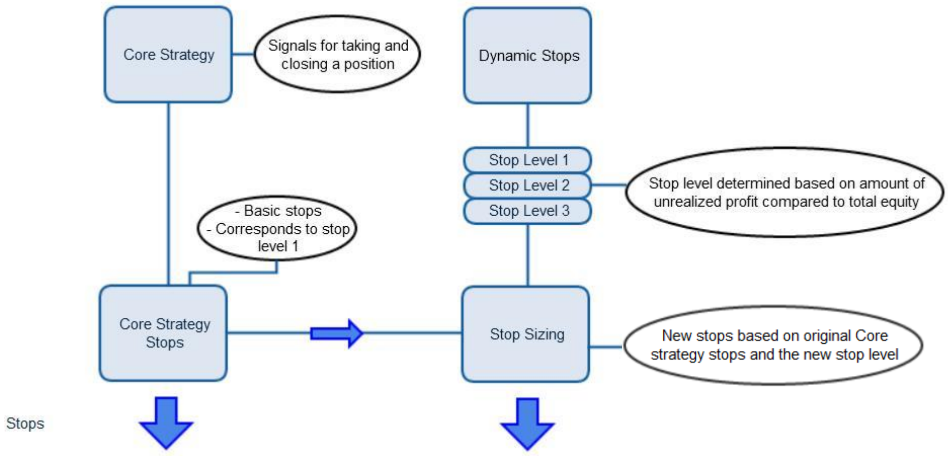

Figure 4.2: How the *Core strategy*, *Fixed Fraction* and the dynamic stop methods relate to each other, and produce the final trailing stops to be used.

Methods and sub-methods

Some of these methods could be implemented in two or three different ways. In some cases we were unwilling to decide between two variants— for example, whether to let *Dynamic Stops* depend on open equity or open profit. In these cases, both variants where implemented and simulated, and results were reported as if these where two different methods.

Parameters

All of these methods have parameters, time between reweighing, whether to increase or decrease open positions when the risk level changes and so on. A set of parameters are then chosen according to general guidelines. For instance, *time between reweighing* is set to 50 days. For every parameter, a sensitivity analysis is also carried out, a few possible parameter values where determined and simulations where carried out for each option. Multiple parameters means the amount of simulations multiply; each new parameter with two values doubles the amount of simulations, giving between three and 40 simulations for any particular method. The advantage of this is that it gives an indication of the stability of results, while avoiding over-fitting that would no doubt have occurred had each parameter been optimal. A summary of parameters for each sizing method can be found in Table 4.2.

Parameters	Values
Equity Momentum	
Time between each reweighing	(5/ 20/50/100/150)
Reweighing active positions	(yes/no)
Equity curve unit of analysis	(symbol/sector)
Total number of simulations:	**20**
Equity SMA	
Length of the fast respectively slow SMA	{5,10}, {5,20}, {5,50}, {5,100}, {10,20}, {10,50}, {10,100}, {20,50}, {20,100}, {50,100}
Reweighing active positions	(yes/no)
Equity curve unit of analysis	(symbol/sector)
Number of simulations:	**40**
Equity Core	
Reweighing active positions	(yes/no)
Equity curve unit of analysis	(symbol/sector)
Number of simulations:	**4**
Target Volatility	
Target Volatility	(8%, 10%, 12%),
Time between each reweighing	(5/ 20/50/100/150)
Reweighing active positions	(yes/no)
Number of simulations:	**30**
Correlation Threshold	
ρ_L- threshold	{-0.2}/{0}/{0.2}
Time between each reweighing	(5/ 20/50/100/150)
Reweighing active positions	(yes/no)
Number of simulations:	**30**
Correlation Asset-Portfolio	
Time between each reweighing	(5/ 20/50/100/150)
Reweighing active positions	(yes/no)
Number of simulations:	**10**
Max Drawdown Minimize	
Time between each reweighing	(5/ 20/50/100/150)
Reweighing active positions	(yes/no)
Number of simulations:	**10**
Max Drawdown Equal Contribution	
Time between each reweighing	(5/ 20/50/100/150)
Reweighing active positions	(yes/no)
Equity curve unit of analysis	(symbol/sector)
Number of simulations:	**20**
Omega	
L-daily profit target	(0.0001/0.0005/0.001)
Time between each reweighing	(5/ 20/50/100/150)
Reweighing active positions	(yes/no)
Number of simulations:	**30**
Dynamic Stops Risk	
Threshold values	{1%, 3%} {3%, 5%} and {5%, 10%}.
Number of simulations:	**3**
Dynamic Stop Lock-In	
Threshold values	{0.03%, 0.05%} {0.05%, 0.1%} and {0.1%, 0.15%}
Number of simulations:	**3**
Total number of simulations	**200**

Table 4.2: Parameters and number of simulations for all sizing methods.

Symbol or sector

In the case of some sizing methods, apart from weighing the symbols, simulations where carried out where the five sectors (agriculture, energy/metal, currencies, rates, equities) where analyzed and weighed as units. *Symbol level* sizing is the standard in all trials, but sensitivity analysis was carried out for the *sector level* as well.

Time between reweighing

All position sizing methods— every method except *Dynamic Stops*— updates the size of positions taken according to new data; be it the profits, volatility, correlation or maximum drawdown. It is not self-evident how often this should be done. Updating weights often makes them more accurately reflect all known data, but might also lead to excessive trading and might not be feasible to implement for smaller hedge funds and investors. Each method is tried for 50 days, and in the sensitivity analysis, an array of five different lengths between reweighing- 5, 20, 50, 100 and 150 days- is used.

Reweighing of active positions

Once the weights are adjusted, it needs to be decided what to do with already open positions. If, one day, 1000 Cocoa futures contracts are entered with a position size of 1, and then two days later the position size for Cocoa suggested by the sizing algorithm is increased to 1.5, should the 500 additional contracts be purchased immediately? Or should this change in position size only be taken into account when a new position is entered? All configurations of all position sizing methods are simulated with and without *reweighing of active positions*. This may greatly affect the result – especially when the *time between reweighing* is small, when the great majority of trades might consist of adjusting the size of open positions.

Other parameters

Most of these methods have method-specific parameters as well; *Target volatility* relies specified desired annual volatility, *Dynamic stops* require values for the thresholds, and *Omega Optimization* uses a daily profit target. For these parameters, a range of reasonable values was determined by looking at the first year of trading data, and calculating e.g. realized volatility. Then three values was chosen, meaning to cover this reasonable range, and simulations where carried out using all three values. For our example of *Target volatility*, it was noted that realized volatility of the *Core strategy* tends to vary around 10-percent mark, and so the target volatility parameter was set to 0.1, with sensitivity analysis ranging from 0.8 to 0.12. Note that this constitute a form of data snooping— at the start of the simulation, parameters are set using information not available during the first year. However, this is a fairly innocent form of snooping, since the purpose is not to find optimal method parameters, but rather a range for reasonable ones.

Active symbols

Some symbols have a starting date later than 1990. In these cases, the symbols are allowed to be traded (and sized) as soon as they are available. However, some of these methods require a vector of past returns. In these cases, the symbols where traded for 100 days, saving the resulting returns, before the symbol was included in the sizing algorithm.

Optimization algorithms

Both *Omega Optimization* and one of the *Maximum Drawdown* methods use position sizes that are solutions to minimization/maximization problems. These non-linear, bounded problems can be solved approximately using a variety of algorithms. For the purposes of this study, BOBYQA (Bounded Optimization BY Quadratic Approximation) was used, a heuristic optimization method suited for non-linear, bounded problems, developed by Powell (2009). Specifically, a publically available C# implementation of BOBYQA was retrieved (Gustafsson, 2012). The functioning of this algorithm was verified by comparing resulting Omega measure with the Omega measure for a *Fixed Fraction* portfolio, and for and the Omega measure for linear approximation: for each symbol, calculate the portfolio omega without this particular symbol. If this is higher, maximize the position, if it is lower, minimize it. Since BOBYQA did consistently better than both *Fixed Fraction* and linear approximation, it was verified to work within this context.

4.3.1 Equity curve based

This portfolio allocation method has a more novel approach and was developed by us out of conversations with people working within the CTA industry. The method is divided in three parts, varying in complexity, but are all based on the behavior of the equity curve of the five sectors, or the equity curve of the instruments themselves for the instrument-level approach as opposed to the sector-level approach. The equity curve is a time series of the profits/losses of all closed positions and current value of active positions at any given time for all instruments that belong to the same sector. It represents the value of a sector specific portfolio, or simply a portfolio of only the individual instruments for the instrument-level approach. The idea is to capitalize on any possible trends in the equity curve itself by determining the risk level for the sectors/instruments depending on the movements of the equity curve.

Equity curve based method 1: Momentum

The first and simplest sub-method is simply to observe the equity curve for the sector an instrument belongs to, or the equity curve for the instrument, depending on the approach. If the value of the equity curve is higher than it was the last weighing period, that sector/instrument is assigned on higher risk level, maximum 150% Fixed Fraction position size. Consequently, if the value of the equity curve is lower, the sector/instrument is demoted one risk level.

- Each day: Calculate the current value for all closed and open positions for each individual instrument, generating an equity curve for the individual instruments and sectors.
- At each weighing day: The instrument/sector is assigned a new risk-level depending on whether the current value of the equity curve has increased or decreased since the last weighing day.
- The position sizes for new positions in the instrument/sector are updated based on the new risk-level, and old positions are resized if resizing is active.

Equity curve based method 2: fast/slow SMA-crossover

For the second sub-method, a more theoretical approach is used to recognize a possible trend, and change risk level depending on if an upward or downward trend in the equity curve is detected. In this part two simple moving averages with different time-spans are used, one slowly-changing and one quickly-changing SMA, to determine if the general movement of the equity curve is changing. See more about this in the simple moving average and the trend filter sections 2.3.3 and 2.3.5. The changes of the risk levels will occur when the two SMA indicators cross each other. A crossover by the faster changing SMA will signal for a change to an upward movement of the equity curve and the highest risk level, 150 percent of Fixed Fraction position size, is assigned the sector/instrument the equity curve belongs to. Consequently, a cross under, the value of the slow SMA is higher than the faster changing SMA, signals for a downward trend and the lowest risk level, 50% of Fixed Fraction position size, is assigned that sector/instrument. Note that the middle risk level, 100 percent of Fixed Fraction position size, will not be used because the SMA indicators can only crossover and cross under maximum one time each making it impossible to have more than two risk levels for this sub-method.

- Each day: Calculate the current value for all closed and open positions for each individual instrument, generating an equity curve for the individual instruments and sectors.
- The slow and the fast SMA-indicators for the equity curve for the individual instrument/sector are calculated.
- New risk-level for the instrument/sector is assigned based on whether the fast SMA cross over or under the slow SMA.
- The position sizes for new positions in the instrument/sector are updated based on the new risk-level, and old positions are resized if resizing is active.

Equity curve based method 3: Core strategy on equity curve

The last sub-method for the equity curve based portfolio allocation method uses a version of the *Core strategy* also on the equity curve. The changes of the risk levels will occur when the *Core strategy* on the equity curve signals for an “entry in a long position” on the equity curve, corresponding to the higher risk level, or an “entry in a short position” on the equity curve, corresponding to the lowest risk level. When the *Core strategy* signals for a closing of the position in the equity curve, the sector/instrument is assigned the middle risk level. I.e.

when the *Core strategy* is “out of market on the equity curve”, the sector/instrument is assigned the middle risk level.
The method is implemented as follows:

- Each day: Calculate the current value for all closed and open positions for each individual instrument, generating an equity curve for the individual instruments and sectors.
- New risk-level for the instrument/sector is assigned based on the signal for a long position, short position or a closing of the position on the equity curve for the individual instruments and sectors.
- The position sizes for new positions in the instrument/sector are updated based on the new risk-level, and old positions are resized if resizing is active.

4.3.2 Target volatility

The levels of target volatility were selected from previous research on target volatility, a level of 10 percent was seen as reasonable starting point (Morningstar, 2011), and levels 8 percent and 12 percent were added to give a cursory indication of how the method results might vary by changing the target volatility parameter.

- Each day: Update the time series of instrument returns.
- If reweighing day, calculate the realized volatility for the portfolio.
- Retrieve weights for each symbol, and use these when taking new positions.
- Resize old positions if resizing is active.

4.3.3 Correlation

Correlation between symbols is a hidden risk for any trading strategy: If two symbols are highly correlated (as, for example, crude oil and gasoil might be) having one position in each of them is really quite similar to having a position of twice the size in one of them – a position of twice the risk the trader originally decided upon as proper. The trading rules described by Faith would handle this by having limits on the number of positions on highly correlated symbols, and another limits for symbols with low correlation (Faith, 2005). By decreasing correlation between symbols, diversification might increase and so improve risk-adjusted return. Ideally, we would want to minimize internal correlation in the portfolio. The problem with this is that there exists no single-valued measure of internal correlation, and so straightforward optimization is not an option.

Correlation method 1: Threshold

Tomasini (2009) proposes a position sizing method governed by the pairwise correlation with the other symbols –specifically, by the number of low correlations. The portfolio is then divided into three groups, one with a large amount of low correlations, one with an average amount, and one with few or no low correlations. These groups are then allowed to take large, average and small position sizes respectively. This method depends on a limit below

which the correlation is considered low, ρ_L- Tomasini suggests that anything between -0.2 and 0.2 might be a suitable limit. (Tomasini, 2009)
The method is implemented as follows:

- Each weighing day:
  - For each symbol:
    - Calculate pairwise correlation with every other symbol, using the last 100 days of returns.
    - Count the number of correlations $<\rho_L$.
  - Sort the symbols according to the number of low correlations.
  - Divide the symbol into three groups of equal size.
  - Give the symbols with the largest amount size 1.5, the middle size 1 and the group with the lowest amount 0.5.
- Retrieve weights for each symbol, and use these when taking new positions.
- Resize old positions if resizing is active.

Correlation method 2: Asset-Portfolio

A problem that might arise with the above method is that all symbols might have a similar amount of low correlations. Another approach to decreasing overall internal correlation is to look at correlation between one symbol and the portfolio of the rest of the symbols.

- Each weighing day:
  - For each symbol:
    - Calculate pairwise correlation with the rest of the portfolio, using the last 100 days of returns.
  - Sort the symbols according to correlation.
  - Divide the symbol into three groups of equal size.
  - Give the symbols with the largest correlation size 1.5, the middle size 1 and the group with the lowest correlation 0.5.
- Retrieve weights for each symbol, and use these when taking new positions.
- Resize old positions if resizing is active.

4.3.4 Omega Optimization

The idea of omega optimization is simple – Maximize the Omega measure with respect to portfolio weights. Implemented on a futures trading strategy, there are no portfolio weights in this sense, so this method have to be is slightly modified. Each positions size is allowed to vary between $w = 0.5$ and $w = 1.5$, where $w = 1$ is the size given by *Fixed Fraction*, in accordance with our method.

$$\max \Omega(\mathrm{L}) = \max \frac{\Sigma_{i=1}^{n}\Sigma_{j=1}^{S} w_j\left(R_{ij} - L\right) * I_i}{\Sigma_{i=1}^{n}\Sigma_{j=1}^{S} w_j\left(R_{ij} - L\right) * (1 - I_i)} \tag{4.2}$$

$$w.r.t \quad 0.5 \leq w_j \leq 1.5 \; j = 1,2 \dots 50$$

$$I_i = I(\Sigma_j R_{ij} \geq L)$$

In this notation, R_{ij} is the return of instrument j on day i, w_j is the weights of instrument j, and I_i equals one if the portfolio return for day i exceeds the target level L. This optimization problem can be solved heuristically using the BOBYQA method.
The method is implemented as follows:

- Each day: Calculate and save weight-neutral daily profits of each symbol.
- Each weighing day:
  - Optimize Omega w.r.t weights using the BOBYQA-algorithm.
- Retrieve weights for each symbol, and use these when taking new positions.
- Resize old positions if resizing is active.

4.3.5 Max Drawdown

The current drawdown of a portfolio $DD(T)$ at time T is defined as the decline from the historical maximum:

$$DD(T) = \max\left\{0, \max_{t\in(0,T)} X(t) - X(T)\right\} \tag{4.3}$$

And the maximum drawdown $MDD(T)$ is the highest drawdown to date:

$$MDD(T) = \max_{\tau\in(0,T)} [DD(\tau)] \tag{4.4}$$

Drawdown is an alternative measure of risk of a trading strategy, which makes it suitable to be used as a basis of position sizing.

Max Drawdown method 1: Minimization

This first method concerns itself with minimizing the maximum drawdown for the past 100 days. It uses the same BOBYQA-implementation that was used for *Omega Optimization*.

- Each day: calculate and save weight-neutral daily profits of each symbol
- Each weighing day:
  - Choose new weights (between 0.5 and 1.5), so that they minimize the portfolio maximum drawdown of the past 100 days
- Retrieve weights for each symbol, and use these when taking new positions.
- Resize old positions if resizing is active.

Max Drawdown method 2: Equal contribution

Another approach to maximum drawdown follow a similar logic to that of *Target Volatility*— If equal risk contribution is a desirable characteristic of trading strategies, and max drawdown is a measure of risk, it should follow that weighing symbols according to maximum drawdown might improve performance.

The method is implemented as follows:

- Each day: Calculate weight-neutral daily profits of each symbol.
- Each weighing day:
  - Calculate maximum drawdown for each individual symbol (or all symbols in one sector).
  - Calculate the average of these maximum drawdowns.
  - The new weight is equal to average maximum drawdown divided by the maximum drawdown of the symbol (or sector).
- Retrieve weights for each symbol, and use these when taking new positions.
- Resize old positions if resizing is active.

4.3.6 Dynamic Stops

In common with the *Equity curve-based* allocation methods, this method also has a more novel approach and was derived from conversations with our cooperating CTA. The general idea of this allocation method is to take a portfolio perspective considering the overall current performance of the whole portfolio, made up by the different sectors and futures contracts, and investigate whether the portfolio has a large amount of unrealized profits. The idea is to try and lock in the unrealized profit so that the main part of it is capitalized upon, in case the market shifts direction. This will be done by dynamically changing the size of the *Core strategy*'s stops, i.e. exit conditions. The original stops can be found in 4.2, and they are three ATR units from the highest or lowest price, depending on whether the trade is a long or short position, since a position was taken in the asset. If the total amount of unrealized profit is deemed to be to high compared to the total equity (cash and the value of active trades) the stops will be made easier to reach by reducing the size of them. Going from three ATR units to two ATR units, and finally one ATR unit if the amount of unrealized profit is still very high. Hence making it easier for the *Core strategy* to exit a trade and capitalize on the unrealized profit. By decreasing the size of the stops for *Core strategy*, the positions in the individual futures contracts will be easier to exit and the profit made so far will be locked in.

Dynamic Stops method 1: Lock-in

This sub-method of the *Dynamic Stops* portfolio allocation method takes the profit made so far from when a position was open into consideration and will make it easier to lock-in that profit. In order to determine whether the portfolio has a large amount of unrealized profit, we will use the following definition for unrealized profit: The unrealized profit for an individual asset in the portfolio is the difference between the current value of the position and the value it had when the position in the asset was taken. I.e. it is the eventual overall profit to be made by closing the position at the current price.

$$Unrealized\ profit_t = \sum_{i=1}^{N} number\ of\ contracts_{i,t} * (P_{i,t} - P_{i,0}) \qquad (4.5)$$

Equation 4.5 is an expression for the unrealized profit for the whole portfolio at time t. N is the total amount of assets, $number\ of\ contracts_{i,t}$ is the number of contracts in asset i at time t, $P_{i,t}$ is the closing price for asset i at time t and $P_{i,0}$ is the price for asset i when the position was taken.

- Each day: Calculate the unrealized profit.
- If the unrealized profit compared to the current total value of the overall portfolio is above the lowest threshold, the stops for all active positions are decreased to 2 ATR units, and 1 ATR unit if it is above the highest threshold.

Dynamic Stops method 2: Risk.

This sub-method of the *Dynamic Stops* portfolio allocation method takes the distance to current stop-levels into consideration. For this sub-method, unrealized profit is defined as: The unrealized profit for an individual asset in the portfolio is the distance between its current value and the value it has at the current stop-level for that asset. I.e. it is the unrealized profit to be made by closing the position now as opposed to waiting until it hits the current stop-level.

$$Open\ Equity_t = \sum_{i=1}^{N} number\ of\ contracts_{i,t} * (P_{i,t} - Stop_{i,t}) \qquad (4.6)$$

Here $Stop_{i,t}$ is the price where the current stop is for asset I at time t.

- Each day: Calculate the unrealized profit.
- If the unrealized profit compared to the current total value of the overall portfolio is above the lowest threshold, the stops for all active position is decreased to 2 ATR units, and 1 ATR unit if it is above the highest threshold.

4.3.7 Standard parameters

The specific set of parameters chosen for each sub-method to be representative for the performance of the sub-methods as a whole are:

- **Equity Momentum:** 50 days reweighing time, symbol level and no reweighing of active positions.
- **Equity SMA:** 10 days look back period for the fast SMA and 50 days for the slower SMA, symbol level and no reweighing of active positions.
- **Equity Core:** Symbol level and no reweighing of active positions.
- **Target Volatility:** 50 days reweighing time, target volatility of 0.1 and no reweighing of active positions.
- **Correlation Threshold:** 50 days reweighing time, 0.0 as what is considered low correlation and no reweighing of active positions.
- **Correlation Asset-Portfolio:** 50 days reweighing time, symbol level and no reweighing of active positions.

- **Max Drawdown Minimization:** 50 days reweighing time and no reweighing of active positions.
- **Max Drawdown Equal Contribution:** 50 days reweighing time, symbol level and no reweighing of active positions.
- **Omega:** 50 days reweighing time, loss threshold of 0.0005 and no reweighing of active positions.
- **Dynamic Stops Lock-In:** Low threshold value of 3% and high threshold value of 5%.
- **Dynamic Stops Risk:** Low threshold value of 3% and high threshold value of 0.05% and high threshold value of 0.1%.

These specific parameters for each sub-method were chosen because they are in the middle of the range the specific parameters are allowed to vary between, and symbol level and not reweighing active positions are deemed to be the standard values for all methods where those factors are present.

4.4 Methods for comparing the performance of the portfolio allocation methods

These portfolio allocation methods will be backtested for the period 1990-2012 and then evaluated using a number of performance indicators. Apart from annualized return, the comparison will be made using standard deviation, maximum drawdown, skewness, recovery factor, payoff ratio, profit factor, the *Sharpe Ratio* and correlation with S&P 500. The latter because of the low correlation with equity markets CTAs have traditionally enjoyed, we want to be certain this advantage is not compromised by any of the portfolio strategies. *Sharpe Ratio* is important to gauge risk adjusted return, although as several authors have pointed out, the risk profile is (and should be) different for a hedge fund than for a mutual fund, and this is not necessarily captured by classical mean-variance analysis. Because of this, a few industry-specific measures of risk-adjusted return will be used: *Profit Factor* (defined as gross profits over gross losses), *Payoff Ratio* (average win per trade divided by the average loss per trade), and *Recovery Factor* (net profit for the strategy divided by the maximum drawdown). A high *Recovery Factor* means that the strategy has overcome a drawdown, but a high historical drawdown may still be unsatisfactory for a risk-averse investor.

Each of these performance measures will then be compared to a baseline defined by the *Fixed Fraction method* results, in order to gauge whether a portfolio allocation method constitutes an improvement. Each of the performance measures will be qualitatively weighed together in order to group the allocation methods into improving and non-improving. The objective is to reach a definite conclusion as to which portfolio methods are advisable to use, while at the same time having maximum transparency as to how the conclusion was reached.

Note that many of these methods will have the same win ratio, due to them using the same underlying strategy, and also that *Payoff Ratio* and *Profit Factor* depend on each other with the following relation.

$$Payoff\ Ratio\ =\ (1 - win\,ratio) * \frac{Profit\ Factor}{win\,ratio} \tag{4.7}$$

Constant win ratio yields:

$$Payoff\ Ratio\ =\ k * Profit\ Factor \tag{4.8}$$

In other words, strategies exhibiting a higher payoff ratio will also exhibit a higher profit factor.

4.5 Reliability

This study uses historical intraday market data that was collected from a database, TickData, and it is available from numerous other sources, meaning that the data used in this study can be reproduced. Together with the thorough description about how the methods were implemented and the different parameter values that were used, it should be possible to replicate and reproduce the results from this study. The results are also complimented by the figures and tables presented in the appendix, which offer deeper understanding of each methods result with results from individual simulations that can be used as a comparison for further studies. So the possibility of achieving the same results based on the instructions given in this thesis should be high and the results should therefore have high reliability.

4.6 Validity

Certain decisions have been made in this study in order to increase the validity of the study. The time period used in this study is chosen in order to include both periods of distress and prosperous periods for the futures market. The time period will give a good amount of data points covering periods of different performance of the market as a whole, so the results will not be one sided and based on a particularly good or bad historical time period. The data is also from several different futures contracts, resulting in a well-diversified portfolio that allows the possibility to draw valid results. All of these contracts also have high liquidly and are traded regularly on the market. The *Core strategy* used in this study is also replicated from the works of Clenow (2013) whom in turn bases the trend following strategy on previous well documented and tested trend following strategies. This *Core strategy* is deemed to be a good proxy for a trend following hedge fund, showing similar characteristics as the BTOP50 index, and therefore increases the validity of this study. One simplification made in this study is that no commission costs or slippage are considered. It can be argued that this decreases validity slightly.

4.7 Limitations

This study uses a valid trend following strategy, but it would have been interesting to investigate the performance of the position sizing methods on other trend following methods as well. But that would also have been more time consuming and limit the number of position sizing methods investigated in this study. There are also other possible position sizing methods that could have been investigated and the ones used in this study could possibly have been designed in another way. The choices of the included methods and there designs were decided upon by trying to capture different aspects and show if certain areas of position sizing were better or worse than the results from *Fixed Fraction*. The parameters for these methods were also deliberately chosen without precision, not trying to over-optimize the results. The length for the lookback period for e.g. ATR, correlation and volatility were all set to the same length. It is discussable if these lookback periods should have been different from each other and which ones should then have been longer, and also how long. But the purpose here was again to use simple values in order to focus more on the performance of different position sizing methods compared to *Fixed Fraction*, rather than finding the optimal parameter values for the different methods based on the data and time period. The time period was also limited to 1990-2012 due to the shortcoming of available futures contracts before 1990, most of the futures contracts used in this study dates back to 1990 or later, only a few of them have available data before 1990.

5. Results

The results section is structured as follows. First, the performance of the Core strategy (using Fixed Fraction weights) during the period of simulation is presented, giving a baseline to performance. Then, each of the methods is presented, with a comparison with Fixed Fraction, a sensitivity analysis of performance and a year-by-year breakdown of returns. Finally, a summary of the results is made.

5.1 Fixed Fraction

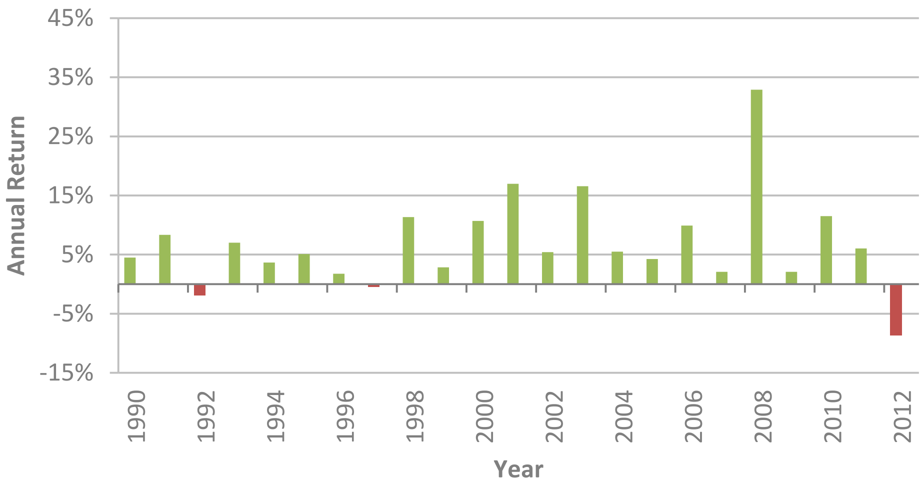

Figure 5.1: Year-by-year breakdown of *Fixed Fraction* returns.

APR	Std. Dev	Max Drawdown	Skew	S&P Correlation
6.57%	9.10%	17.44%	0.223	-0.198
Recovery Factor	**APR/MDD**	**Payoff Ratio**	**Profit Factor**	**Sharpe Ratio**
3.758	0.377	1.832	1.333	0.472
Total return	**Trades**	**Winning Trades**	**Winning %**	**Avg. Bars Held**
332%	3064	1288	42.0%	32

Table 5.1: General characteristics and performance measures of the Core strategy with *Fixed Fraction* weights.

The Figure 5.1 is a yearly breakdown of returns. The *Core strategy* exhibits large returns 2008, ending in a drawdown 2012. This is similar to how the BTOP50 CTA index has performed, although more extreme and this is indicative of that our *Core strategy* is a valid proxy for a trend following hedge fund. Figure 5.2 compares the equity curves of BTOP50, S&P500 and the *Core strategy*, showing that it behaves more like the hedge fund index than S&P 500, a proxy for traditional equity markets. It also exhibits similar characteristics as Clenows results (Clenow, 2013).

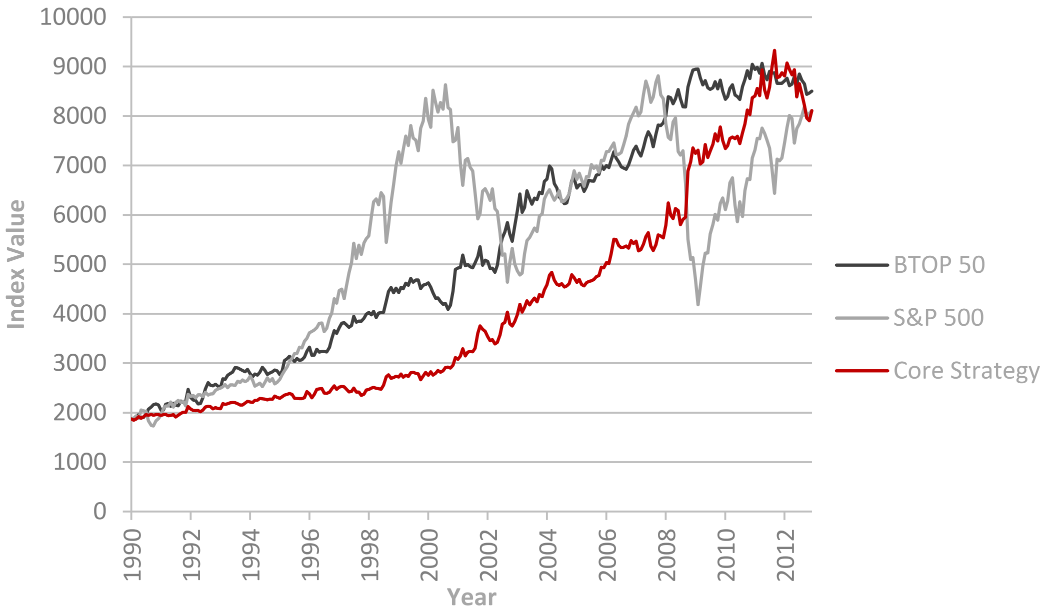

Figure 5.2: Comparison between the *Fixed Fraction* equity curve, BTOP50 (2014) and S&P 500 (2014). (The Core strategy and the S&P series is normalized in order to be equal to BTOP50 at its inception). Source: Yahoo Finance and barclayhedge.com

5.3 Equity curve based

The results presented below are the results from the *Equity curve based* sizing method; firstly the results from the momentum sub-method will be presented, then the SMA sub-method and lastly the core sub-method.

Equity Momentum

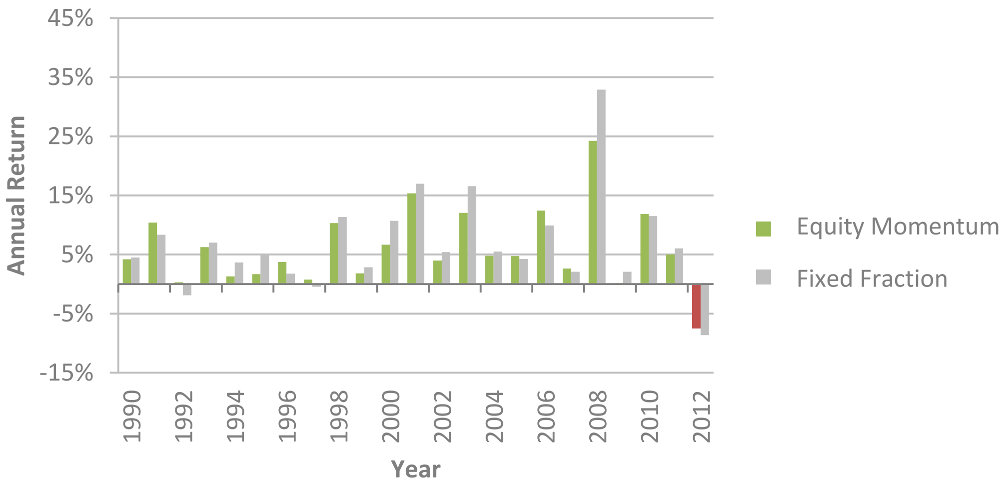

Figure 5.3: Year-by-year breakdown of *Equity Momentum* returns (green/red) compared with *Fixed Fraction* returns (grey).

The yearly returns for this sub-method with its standard parameters are green if they are positive and red for negative yearly returns. The standard parameters used for this sub-method were: 50 days reweighing time, symbol level and no reweighing of active positions. As a comparison, the original returns for the *Fixed Fraction* sizing method are presented next to them in grey. One noteworthy aspect is that the yearly returns for this sub-method have been positive, although some fairly small, for all years except the last year. Overall the yearly returns are smaller for this sub-method compared to the *Fixed Fraction* yearly returns, but with a higher negative return for the last year. For a comparison of the equity curve for this sub-method with its standard parameters with the original equity curve for the *Core strategy* using the *Fixed Fraction* sizing method, see Appendix I were also the equity curves for the other methods are presented.

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Equity Momentum	**5.77%**	**15.08%**	**4.19**	**0.38**	**1.82**	**1.33**	**0.40**
Sensitivity Analysis:							
—min	4.36%	11.35%	3.05	0.29	1.74	1.27	0.31
—mean	6.22%	16.60%	3.95	0.38	1.93	1.32	0.41
—max	7.44%	19.78%	5.02	0.43	2.56	1.34	0.52
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.2: Performance and sensitivity analysis for *Equity Momentum*, compared to *Fixed Fraction*.

20 simulations were conducted for this sub-method by varying the time between reweighing the position sizes, whether to reweigh already active positions or not, and on a symbol- and sector-level. The first row in Table 5.2 is the performance for this sub-method with its standard parameters; the last row is the performance for the original *Fixed Fraction* sizing method. Both the *annual percentage returns (APR)* and the *Max Drawdown (MDD)* are lower for this sub-method, and the *recovery factor* is higher than for the *Fixed Fraction* sizing method. The mean values for the performance measures for all 20 simulations are presented in the sensitivity analysis with respective lowest and highest value for each performance measure from these 20 simulations, note that these values are not connected to each other but are simply just the average, low and high value of each performance measure. Here the mean values for the *APR* and the *MDD* are both lower than the *Fixed Fraction* values but the *APR/MDD* is approximately the same and the *Payoff ratio* is slightly higher. The differences between the highest and lowest values for the different performance measures are relatively big with a fairly poor minimum *APR/MDD* of 0.29.

Equity SMA

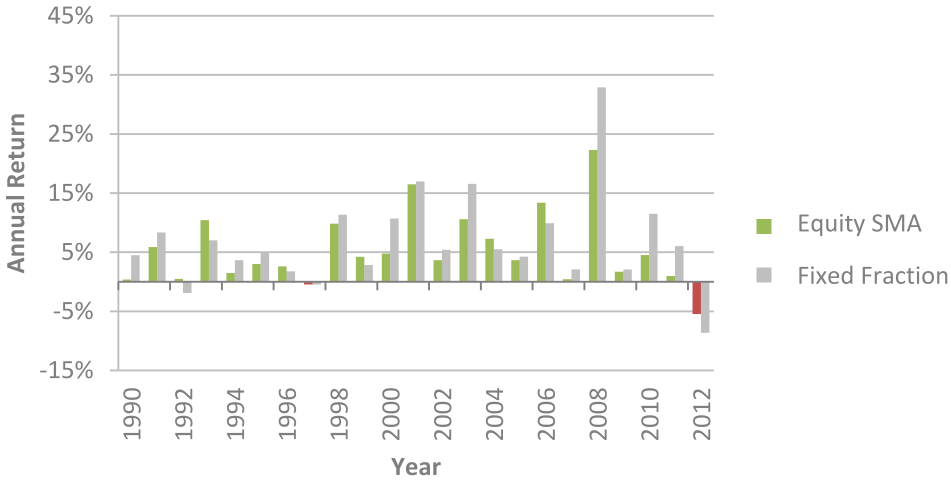

Figure 5.4: Year-by-year breakdown of *Equity SMA* returns (green/red) compared with *Fixed Fraction* returns (grey).

The yearly returns for this sub-method have not been positive for all years, there is a small negative return in 1997 just like for *Fixed Fraction*.

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Equity SMA	**5.14%**	**12.08%**	**5.06**	**0.43**	**1.88**	**1.37**	**0.38**
Sensitivity Analysis:							
—min	4.09%	12.08%	2.26	0.17	1.71	1.18	0.25
—mean	5.79%	17.80%	3.73	0.33	2.10	1.30	0.37
—max	8.96%	36.50%	5.06	0.49	3.09	1.38	0.61
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.3: Performance and sensitivity analysis for *Equity SMA*, compared to *Fixed Fraction*.

40 simulations were conducted for this sub-method with the following parameters as the sub-methods standard parameters: 10 days look back period for the fast SMA and 50 days for the slower SMA, symbol level and no reweighing of active positions. The performance of this sub-method with its standard parameters is fairly good from a low *MDD* perspective but the *APR* is also lower than for *Fixed Fraction*. The *Recovery Factor* and *APR/MDD* is better, much due to the fact of the low *MDD*. But the mean values for this sub-method are not that good with a higher *MDD* and still a rather small *APR* and a not so good *APR/MDD*. The high and low values are also quite extreme with a maximum *APR* of 8.96% and maximum *MDD* of 36.50% the biggest observed *MDD* for all methods. The lowest *APR/MDD* is also the worst for all methods and this sub-method is heavily represented among the simulations with the worst *APR/MDD* 17 out of the worst 20 simulations based on *APR/MDD* are simulations from the Equity SMA method. But it does also have one simulation with a rather high *APR/MDD* and one with a rather high *Recovery Factor*.

Equity Core

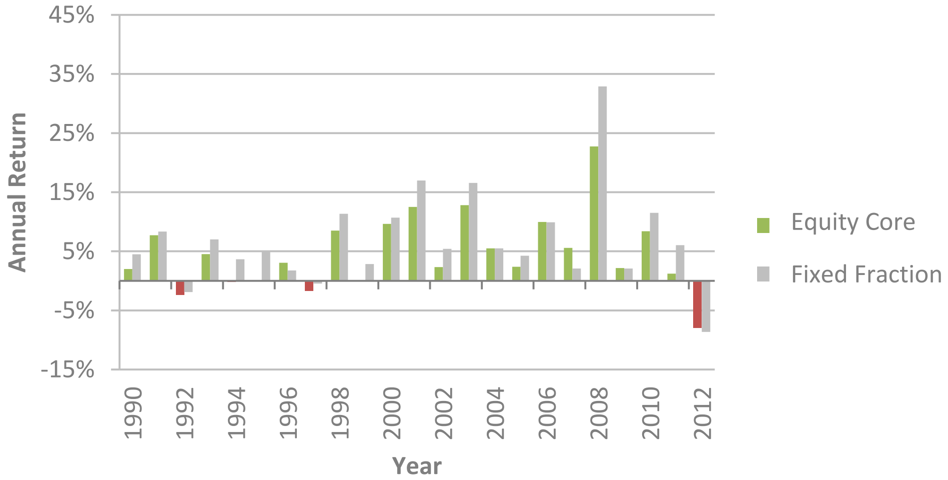

Figure 5.5: Year-by-year breakdown of *Equity Core* returns (green/red) compared with *Fixed Fraction* returns (grey).

Here, the same pattern is not observed. This sub-method, like the *Fixed Fraction* sizing method, makes negative returns for 1992 and 1997 apart from the last year. The overall returns are also lower than the Fixed Fraction yearly returns for the most part.

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Equity Core	**4.54%**	**15.30%**	**3.63**	**0.30**	**1.78**	**1.29**	**0.28**
Sensitivity Analysis:							
—min	4.54%	14.24%	3.22	0.30	1.78	1.28	0.28
—mean	5.35%	16.30%	3.69	0.33	2.11	1.31	0.34
—max	5.85%	18.09%	4.39	0.40	2.72	1.34	0.37
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.4: Performance and sensitivity analysis for *Equity Core*, compared to *Fixed Fraction*.

4 simulations were conducted for this sub-method with the following parameters as the sub-methods standard parameters: Symbol level and no reweighing of active positions. The performance of this sub-method with its standard parameters is not that well where both *APR* and *MDD* are lower than for *Fixed Fraction*, and the *APR/MDD* measure is rather low. The same pattern can be observed in the sensitivity analysis were the *MDD* is lower than for *Fixed Fraction* but not that much lower and one simulation has a slightly higher *APR/MDD* and *Recovery Factor* than *Fixed Fraction* has.

5.4 Target Volatility

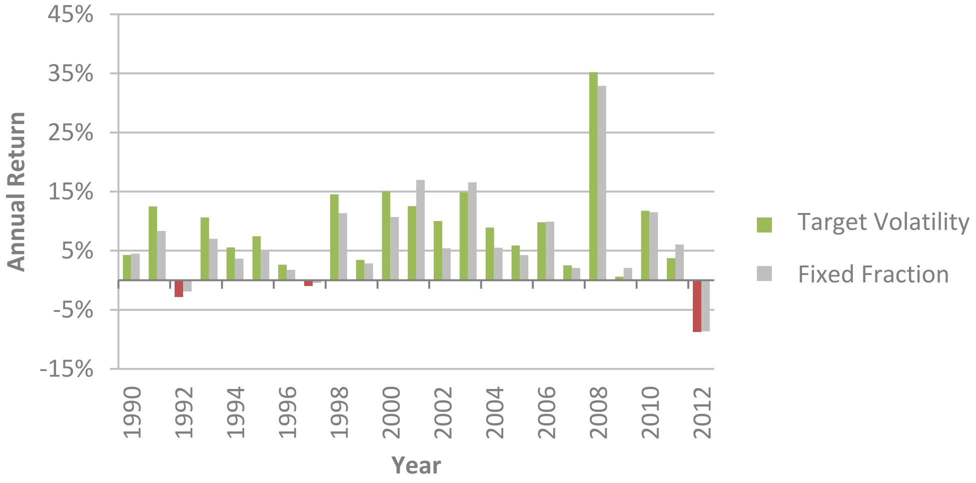

Figure 5.6: Year-by-year breakdown of *Target Volatility* returns (green/red) compared with *Fixed Fraction* returns (grey).

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Target Volatility	**7.48%**	**15.11%**	**4.65**	**0.50**	**1.84**	**1.34**	**0.50**
Sensitivity Analysis:							
—min	6.07%	11.72%	3.40	0.40	1.82	1.30	0.45
—mean	7.88%	15.25%	4.86	0.52	1.89	1.36	0.54
—max	9.25%	20.58%	6.11	0.61	1.97	1.43	0.64
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.5: Performance and sensitivity analysis for *Target Volatility*, compared to *Fixed Fraction*.

Target Volatility with standard parameters has a higher return and lower drawdown, and better performance indicators than *Fixed Fraction*. More importantly, the sensitivity analysis shows lowest values for each performance indicator are similar to *Fixed Fraction*, while the mean and max values are higher. In other words, target volatility does not seem to be able harm performance as much as it could help it. *APR/MDD, Payoff Ratio* and *Profit Factor* seem to improve.

In the year-by-year breakdown graph, we see overall higher returns in years with positive returns, and also slightly higher negative returns in years where *Fixed Fraction* yielded negative returns.

5.5 Correlation

Correlation Threshold

Figure 5.7: Year-by-year breakdown of *Correlation Threshold* returns (green/red) compared with *Fixed Fraction* returns (grey).

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Correlation Threshold	**7.15%**	**17.91%**	**3.71**	**0.40**	**1.85**	**1.34**	**0.50**
Sensitivity Analysis:							
—min	6.19%	16.53%	3.18	0.32	1.78	1.30	0.40
—mean	7.21%	18.55%	3.62	0.39	1.85	1.33	0.49
—max	8.33%	20.85%	4.14	0.45	2.02	1.38	0.58
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.6: Performance and sensitivity analysis for *Correlation Threshold*, compared to *Fixed Fraction*.

Correlation Threshold with standard parameters yields numbers very similar to those of *Fixed Fraction*, no performance indicator being improved by a huge amount. Sensitivity analysis shows performance indicators have both been improved and worsened, with the mean of all simulations having very similar numbers to those of *Fixed Fraction*, having slightly higher *APR* and slightly higher max drawdown, suggesting a slightly riskier strategy, with no discernible edge over *Fixed Fraction* suggested by the data. This is corroborated by the year by year breakdown, with higher positive and higher negative returns.

Correlation Asset-Portfolio

Figure 5.8: Year-by-year breakdown of *Correlation Asset-Portfolio* returns (green/red) compared with *Fixed Fraction* returns (grey).

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Correlation Asset-Portfolio	**6.74%**	**18.05%**	**3.66**	**0.37**	**1.84**	**1.34**	**0.49**
Sensitivity Analysis:							
—min	6.16%	15.63%	3.22	0.32	1.81	1.32	0.43
—mean	6.81%	18.01%	3.71	0.38	1.84	1.34	0.50
—max	7.19%	19.42%	4.46	0.44	1.87	1.36	0.53
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.7: Performance and sensitivity analysis for *Correlation Asset-Portfolio*, compared to *Fixed Fraction*.

Correlation Asset-Portfolio has almost exactly the same numbers as *Fixed Fraction*, both in with standard parameters and in the sensitivity analysis, the numbers placing themselves on a narrow band around their Fixed Fraction values.

5.6 Omega Optimization

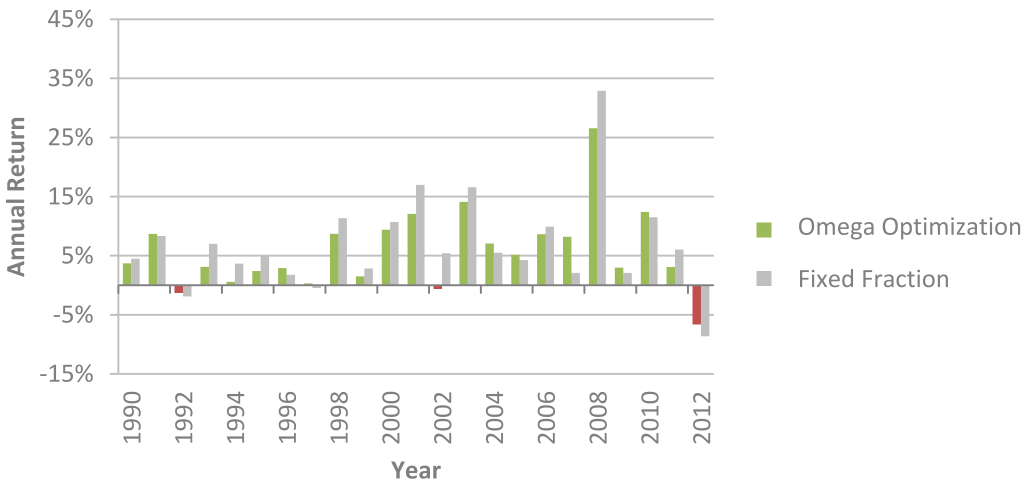

Figure 5.9: Year-by-year breakdown of *Omega* returns (green/red) compared with *Fixed Fraction* returns (grey).

The structure of the yearly returns for this method is fairly similar to the *Fixed Fraction* yearly returns, but the yearly returns are for the most part slightly small with a few exceptions.

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Omega	**5.58%**	**14.46%**	**4.35**	**0.39**	**1.91**	**1.39**	**0.42**
Sensitivity Analysis:							
—min	4.87%	12.98%	3.50	0.31	1.83	1.30	0.34
—mean	5.40%	15.16%	4.13	0.36	1.99	1.35	0.39
—max	5.64%	17.35%	5.34	0.41	2.30	1.39	0.42
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.8: Performance and sensitivity analysis for *Omega*, compared to *Fixed Fraction*.

30 simulations were conducted for this sub-method with the following parameters as the sub-methods standard parameters: 50 days reweighing time, loss threshold of 0.0005 and no reweighing of active positions. The performance of this method with its standard parameters is close to the original *Fixed Fraction* sizing method from an *APR/MDD* perspective with a lower *APR* and *MDD*, but with a higher *Recovery Factor*. The maximum *APR* from the simulations is lower than the original Fixed Fraction, but the maximum and mean *Recovery Factor, Payoff ratio and Profit Factor* are higher. The maximum *APR/MDD* is also just slightly higher than the Fixed Fraction counterpart, but the lowest value is not that much lower. So the *APR/MDD* measure is more stable around the *Fixed Fraction* value than for instance the Equity SMA sub-methods *APR/MDD* values.

5.7 Max Drawdown

Max Drawdown Minimize

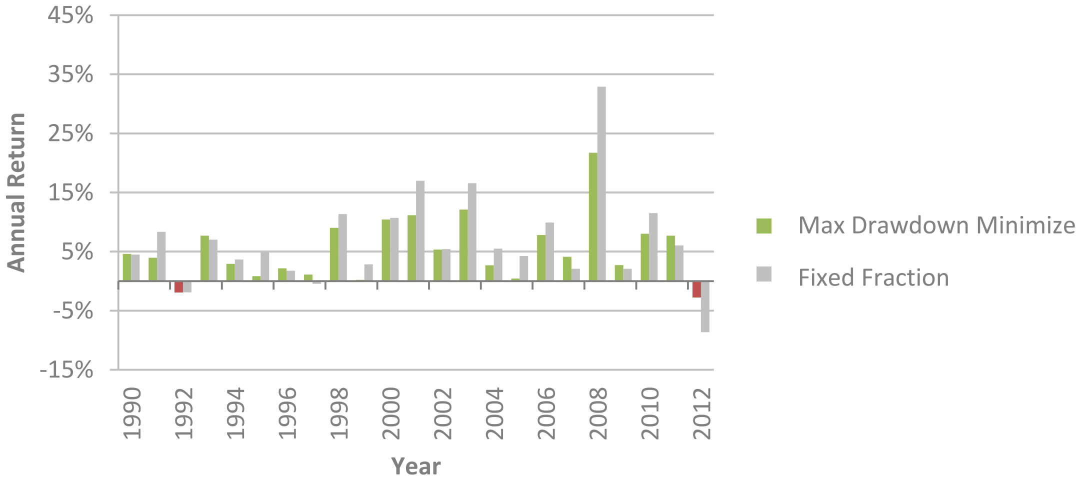

Figure 5.10: Year-by-year breakdown of *Max Drawdown Minimize* returns (green/red) compared with *Fixed Fraction* returns (grey).

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Max Drawdown Minimize	5.17%	10.34%	6.12	0.50	1.94	1.41	0.43
Sensitivity Analysis:							
—min	4.54%	9.53%	4.47	0.36	1.85	1.34	0.33
—mean	4.93%	11.31%	5.48	0.44	1.92	1.37	0.39
—max	5.30%	12.94%	6.75	0.51	2.01	1.41	0.44
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.9: Performance and sensitivity analysis for *Max Drawdown Minimize*, compared to *Fixed Fraction*.

Max Drawdown Minimize seems to lower the rate of returns, but also risk as being realized in max drawdown. *Recovery Factor* and *APR/MDD* improves for almost all simulations (since both of these are dependent on drawdown, and drawdown is lowered with this method, this is hardly surprising). The *Payoff Ratio* and *Profit Factor* are improved somewhat for all simulations. The year-by-year breakdown also suggests a risk-averse strategy, with lower returns most years, but also much lower negative returns. Note however, that *Max Drawdown Minimize* yields a lower return for all simulations, which may not be desirable.

Max Drawdown Equal Contribution

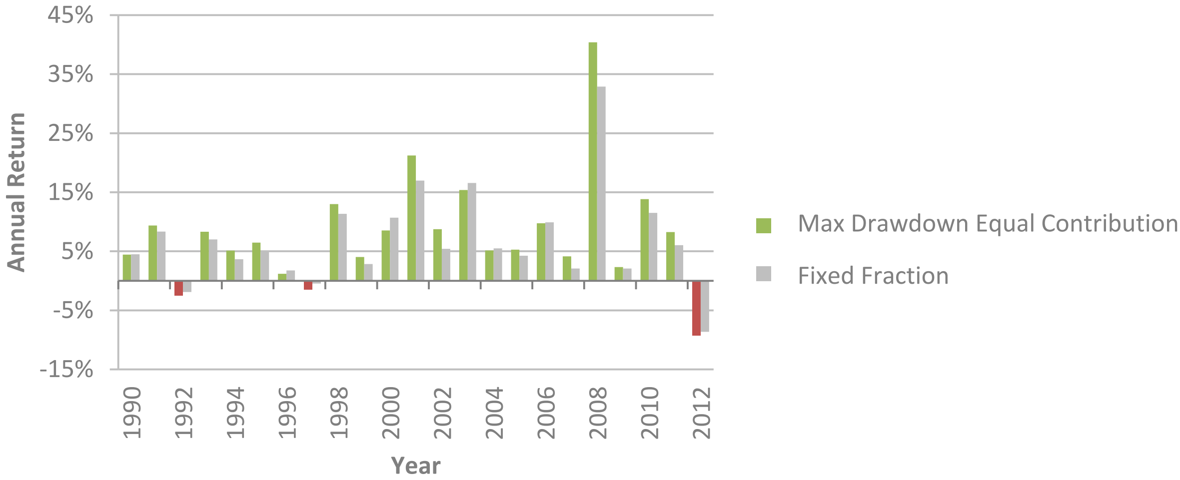

Figure 5.11: Year-by-year breakdown of *Max Drawdown Equal Contribution* returns (green/red) compared with *Fixed Fraction* returns (grey).

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Max Drawdown Equal Contribution	**7.53%**	**17.95%**	**3.82**	**0.42**	**1.86**	**1.36**	**0.35**
Sensitivity Analysis:							
—min	7.14%	17.64%	3.46	0.37	1.84	1.35	0.32
—mean	7.41%	18.43%	3.69	0.40	1.86	1.36	0.34
—max	7.65%	19.23%	3.90	0.43	1.88	1.36	0.36
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.10: Performance and sensitivity analysis for *Max Drawdown Equal Contribution*, compared to *Fixed Fraction*.

Max Drawdown Equal Contribution increases the *APR* somewhat, *Payoff Ratio* and *Profit Factor* being somewhat higher. This result is stable for all simulations. *Max Drawdown* also increases somewhat for all simulations. In the year-by-year breakdown, *Max Drawdown Equal Contribution* outperforms especially in the years where *Fixed Fraction* already does very well, such as 2001 and 2008, having slightly worse negative returns in 1992, 1997 and 2012.

5.8 Dynamic Stops

Dynamic Stop Risk

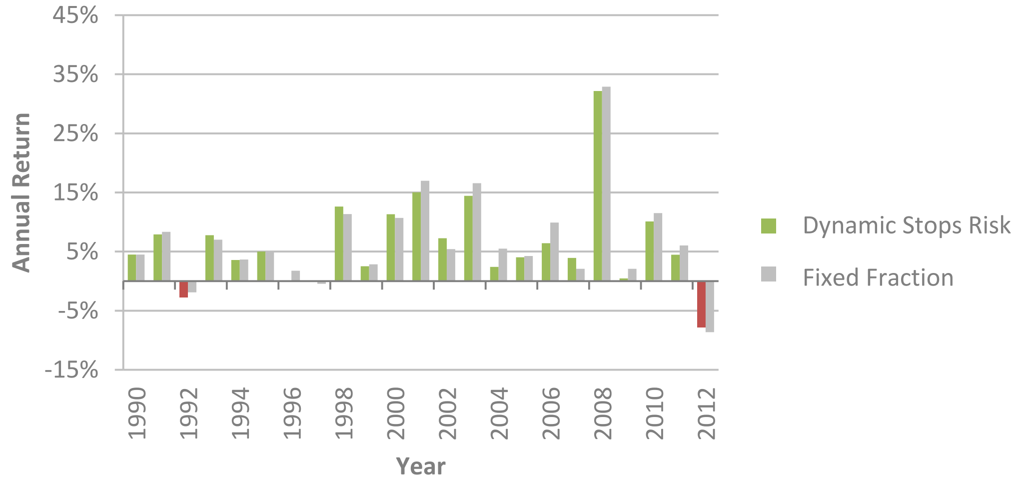

Figure 5.12: Year-by-year breakdown of *Dynamic Stop Risk* returns (green/red) compared with *Fixed Fraction* returns (grey).

The yearly returns are just slightly smaller for the more prosperous years, but are also not as negative for the years with negative yearly returns compared to the *Fixed Fraction* yearly returns.

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Dynamic Stop Risk	**6.06%**	**16.52%**	**3.86**	**0.37**	**1.85**	**1.29**	**0.44**
Sensitivity Analysis:							
—min	5.17%	14.53%	3.86	0.36	1.79	1.24	0.36
—mean	5.88%	15.74%	4.03	0.37	1.82	1.28	0.42
—max	6.40%	16.52%	4.16	0.40	1.85	1.32	0.46
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.11: Performance and sensitivity analysis for *Dynamic Stop Risk*, compared to *Fixed Fraction*.

Three simulations were conducted for this sub-method with the following parameters as the sub-methods standard parameters: Low threshold value of 3% and high threshold value of 0.05% and high threshold value of 0.1%. The performance of this sub-method with its standard parameters is fairly similar to the *Fixed Fraction* performance with slightly lower *APR* and *MDD*. The maximum, minimum and mean values for the different performance measures are also fairly close to original *Fixed Fraction* performance results but with a higher *Recovery Factor*, even the minimum value is higher than for *Fixed Fraction*.

Dynamic Stop Lock-In

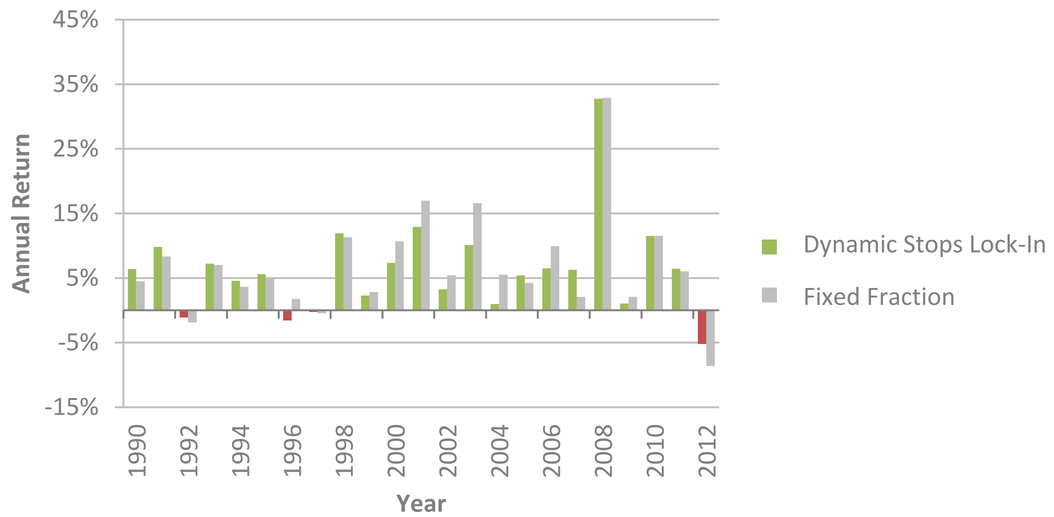

Figure 5.13: Year-by-year breakdown of *Dynamic Stop Lock-In* returns (green/red) compared with *Fixed Fraction* returns (grey).

The yearly returns are also here just slightly smaller for the more prosperous years, but also negative for one year were the yearly returns are positive for *Fixed Fraction*. The last year is also less negative than for *Fixed Fraction* and compared to the *Dynamic Stop Risk* sub-method.

	APR	Max Drawdown	Recovery Factor	APR/ MDD	Payoff Ratio	Profit Factor	Sharpe Ratio
Dynamic Stop Lock-In	**6.04%**	**13.06%**	**5.11**	**0.46**	**1.79**	**1.29**	**0.46**
Sensitivity Analysis:							
—min	5.85%	11.83%	4.41	0.44	1.71	1.27	0.46
—mean	6.19%	13.40%	5.05	0.46	1.78	1.29	0.48
—max	6.67%	15.32%	5.65	0.49	1.82	1.33	0.51
Fixed Fraction	6.57%	17.44%	3.76	0.38	1.83	1.33	0.47

Table 5.12: Performance and sensitivity analysis for *Dynamic Stop Lock-In*, compared to *Fixed Fraction*.

3 simulations were conducted for this sub-method with the following parameters as the sub-methods standard parameters: Low threshold value of 3% and high threshold value of 5%. The performance of this sub-method with its standard parameters is better than *Fixed Fraction* from both an *APR/MDD* and *Recovery Factor* perspective. The *APR* is lower but the *MDD* is also much lower than for *Fixed Fraction*, which also is indicated by the less negative yearly return for this sub-method. The same pattern can be recognized in the sensitivity analysis, the *APR* is slightly smaller than for *Fixed Fraction* but the *MDD* is quite a bit smaller even for the maximum value. The *APR/MDD* and *Recovery Factor* are also quite much higher than for *Fixed Fraction*, even for the minimum value.

5.9 Review of results

In Table 5.13 presented below gives an overview of how each of the methods performed using standard parameters, that is a 50-day weighing window, no reweighing of active positions and symbol level. Other parameters are given in parenthesis (see 4.8 for more).

	APR	Annual standard deviation	Max Draw-down	Skew	S&P Corr.
Fixed Fraction	6.57%	9.10%	17.44%	0.223	-0.198
Correlation Threshold (0.0)	7.15%	9.81%	17.91%	0.178	-0.195
Correlation Asset-Portfolio	6.74%	9.02%	18.05%	0.211	-0.194
Equity Core (symbol)	4.54%	7.82%	15.30%	0.291	-0.192
Equity Momentum (symbol)	5.77%	8.52%	15.08%	0.313	-0.182
Equity SMA, (50x10, symbol)	5.14%	7.18%	12.08%	0.000	-0.201
Max Drawdown EC (symbol)	7.53%	10.31%	17.95%	0.247	-0.204
Max Drawdown Minimize	5.17%	6.28%	10.34%	0.165	-0.187
Omega (0.05%)	5.58%	7.37%	14.46%	0.250	-0.180
Dynamic Stop Risk (0.05 %, 0.1%)	6.06%	8.59%	16.52%	0.157	-0.221
Dynamic Stop Lock-In (3 %, 5 %)	6.04%	8.04%	13.06%	0.153	-0.200
Target Volatility (10 %)	7.48%	10.41%	15.11%	0.288	-0.185

Table 5.13: General characteristics of each sizing method, with standard parameters.

There is a difference in risk-reward balance (e.g. *Max Drawdown Minimize* and *Dynamic Stop Lock-In* have a lower rate of return but also lower standard deviation and max drawdown). All methods retain a low correlation to S&P 500, which is necessary. All methods except *Equity SMA* have a positive skew, which is desirable considering a large amount of small losses and few and significant gains is how the strategy is supposed to work.

Figure 5.14: Averages of performance indicators (Profit Factor, Payoff Ratio, Recovery Factor, APR/MDD) for each of the position sizing methods.

In Figure 5.14 above, the performance measures of all simulations are summarized. Each diagram displays the mean of the performance measure for each method, sorted by value. So these results are based on the mean values from all simulations and not the standard values for each method. *Max Drawdown Minimize* and *Target Volatility* outperform *Fixed Fraction* in all measures, and many of the methods outperform *Fixed Fraction* in more than one measure. The exact values of these performance measures, both the average and for individual simulations, can be found in Appendix IV.

Note that if win rate is held constant, *Payoff Ratio* is equal to *Profit Factor* times a constant. Since all methods use the same underlying strategy, these performance measures are closely correlated and therefor very similar. But for methods with frequent reweighing (*Equity SMA* and *Equity Core* being the extremes, since these may reweigh positions more often than every five days) win rate may change, and for these methods it is lower. This explains how *Equity SMA* and *Equity Core* can have a much higher *Payoff Ratio* while still having a lower *Profit Factor*- the win ratio is lower, is some cases as low as 30%.

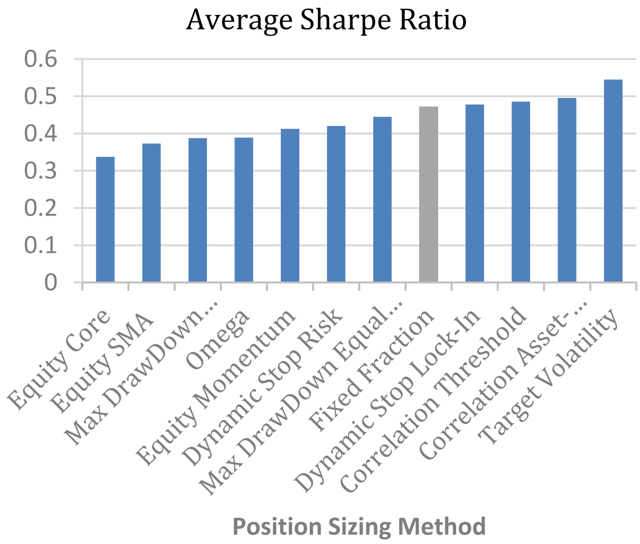

Figure 5.15: Averages Sharpe Ratio for each of the position sizing methods.

When also considering the *Sharpe Ratio,* as shown in Figure 5.15 above, it is again notable that *Target Volatility* has performed better than *Fixed Fraction*. The average *Sharpe Ratio* based on all simulation of each method show that the *Sharpe Ratio* for *Target Volatility* is well above *Fixed Fraction*, also *Dynamic Stop Lock-In, Correlation Threshold* and *Correlation Asset-Portfolio* are slightly above *Fixed Fraction*. The *Equity curve-based*, *Omega* and *Max Drawdown* do not show particularly good results compared to *Fixed Fraction* according to this performance measure.

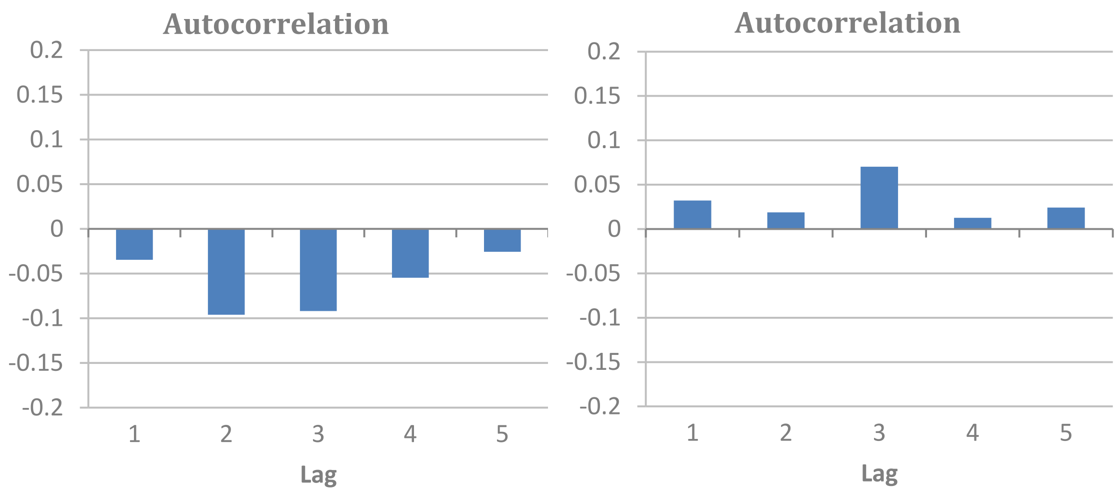

Figure 5.16: Autocorrelation for up to 5 lags, based on monthly returns for Dow jones-UBS Commodity Index (left) and the *Core strategy* with *Fixed Fraction weights* (right). Source: Yahoo Finance.

Autocorrelation may explain how the methods reliant on past equity does not outperform *Fixed Fraction*. Burghardt and Liu (2012) showed how trend following strategies, while being dependent on autocorrelation in markets to produce returns, tend to have negative autocorrelation for their own equity curves. For CTAs, past returns is not indicative of future returns. In the short term the reverse tends to be true. Figure 5.16 shows the autocorrelation for the equity curve of *Fixed Fraction*, compared with the autocorrelation of Dow Jones-UBS commodity index. Indeed, the *Core strategy* exhibit weakly negative autocorrelation, suggesting short term past returns is not an attractive way of constructing position sizes.

5.9.1 The Risk-Return Tradeoff

There exists a problem in comparing the different sizing methods to each other directly, seeing as how some methods produce higher returns, some seem to have lower risk. The most glaring example of this is *Max Drawdown Minimize*, which is systematically risk averse, lowering both returns and *Max Drawdown* significantly. Since a potential investor using one of these strategies could account for this by increasing leverage, it makes sense to compare the methods by resizing using a measure of risk, like *Max Drawdown* or annual volatility. For *Max-Drawdown*-adjusted APR, the annual return is divided by *Max Drawdown* and multiplied by *Max Drawdown* of *Fixed Fraction*. These adjusted returns should give a further indication of the risk-adjusted return for each method.

In Table 5.14 the results of this analysis are summarized. This is very similar to the results arrived at earlier, with *Target Volatility* yielding the best results, with *Max Drawdown Minimize* and *Dynamic Stop Lock-In* also constituting an improvement over *Fixed Fraction*.

	Mean of Max Drawdown-adjusted APR	**Mean of Volatility-adjusted APR**	**Mean of Volatility-adjusted MDD**
Equity Core	5.77%	5.39%	16.42%
Equity SMA	5.81%	5.51%	16.90%
Omega	6.24%	6.44%	18.09%
Dynamic Stop Risk	6.50%	6.24%	16.75%
Equity Momentum	6.57%	5.91%	15.77%
Fixed Fraction	6.57%	6.57%	17.44%
Correlation Asset-Portfolio	6.63%	6.93%	18.31%
Correlation Threshold	6.80%	6.42%	16.52%
Max Drawdown Equal Contribution	7.03%	6.67%	16.59%
Max Drawdown Minimize	7.68%	6.99%	16.02%
Dynamic Stop Lock-In	8.09%	7.04%	15.20%
Target Volatility	9.11%	6.96%	13.44%

Table 5.14: Average Max Drawdown-adjusted APR, and volatility-adjusted APR and Max Drawdown for each sizing method.

6. Analysis

The purpose of this study was to try several different position sizing methods and to determine if any of them might improve the performance of a trend following strategy. It was not to decide on which singular method would improve results the most. A conservative approach is used in stating the judgment over each method, where a method should have done better on all performance indicators, and not done significantly worse than *Fixed Fraction* in its worst simulation, in order to be said to have improved performance.

None of the *Equity curve-based* methods can be said to reliably improve performance of our trend following strategy. This is despite them having higher average payoff ratio than any other class of method. They have lower win ratio and are also highly sensitive for choice of parameters. This means choosing the wrong set of parameters makes the strategy perform significantly worse than *Fixed Fraction*, and most sets of parameters give adverse results. An *Equity curve-based* method of sizing positions is more likely to do harm than good and is best avoided. An answer to why this might be the case is that the autocorrelation of the equity curve of *Fixed Fraction* was slightly negative. This corroborates the result of Burghardt & Liu (2012) that the returns of trend following CTAs are often negatively autocorrelated. If returns have negatively autocorrelation, sizing up positions based on past high returns is ill advised.

Correlation methods do not exhibit difference in results compared to *Fixed Fraction*. The reason for this is not necessarily that using internal correlation for sizing positions is an inherently flawed idea; it might well be that there is a better method to rank correlations. As it was implemented in this study, however, the *Correlation* methods did not seem to improve performance in any meaningful way.

Omega Optimization does not seem to improve performance indicators in a reliable way. This result appear to be in contrast with the results of Harris & Mazibas (2013), that seemed to show improvement when *Omega Optimization* was implemented. There are two ways in which their study was conducted differently, which might serve to explain this discrepancy: Firstly, Harris & Mazibas constructed a fund of funds, rather than following a strategy for buying individual instruments. Secondly, their *Omega Optimization* was done in a way similar to classic portfolio optimization: By allocating a fixed set of capital to funds, with no upper or lower limits for the position taken in each individual asset. This means our failure to find any benefit with *Omega Optimization* might stem from failure of this particular implementation, as well as omega not working within the context of a trend following futures strategy. (Harris & Mazibas, 2013)

The *Maximum Drawdown methods*, especially *Maximum Drawdown Minimize*, seem to hold some promise. *Maximum Drawdown Minimize* is really a variation of the Conditional Drawdown Minimization, which Harris & Mazibas (2013) used with great effect when constructing fund-of-funds. *Maximum Drawdown Minimize* had very high performance indicators, but suffers from one serious drawback – returns are notably lower than for *Fixed*

Fraction. A fund manager might want to modify standard position size if implementing the *Max Drawdown Minimize* method.

Dynamic Stop Lock-In seems to constitute an improvement over *Fixed Fraction*. Similar to *Max Drawdown Minimize, Dynamic Stop Lock-In* seems to be systematically risk averse, having lower APR but also notably lower Max Drawdown, but with an improvement in performance measures. *Dynamic Stop Lock-In* manages to lower the *Max Drawdown* caused by fluctuations in the underlying markets and diminishing trends, by making it easier to close positions when the markets starts to turn and the trend following strategy becomes less profitable, especially successful during the large drawdown in 2012. The downside is that it also causes overall yearly losses, although small, when the original strategy does not. *Dynamic Stop Risk*, however, despite being very similar in its method, does not seem to improve anything at all.

Target Volatility perhaps produced the most promising results. On average, this position sizing method offers a noteworthy improvement over *Fixed Fraction*. And— perhaps more importantly— *Target Volatility,* regardless of method parameters, never seem to perform worse than *Fixed Fraction*. This is intriguing, as the *Core strategy* already takes into account volatility (albeit measured by the average true range of each symbol). The success of *Target Volatility* might be seen as a refinement of the volatility sizing already in place, using a different volatility measure and applied at the portfolio level.

In so far as a recommendation can be made on the basis of these results, it is for a CTA to use *Target Volatility*, possibly in conjunction with *Max Drawdown Minimize*. There is in fact good reason to believe that these two methods can be used in conjunction to great effect. *Target Volatility* is squarely an improvement over *Fixed Fraction*, but does not affect relative sizes, every symbol is either weighed up or down at the same time. *Target Volatility* increases exposure to periods of low volatility but negative returns— in these periods this method actually increase position sizes. *Maximum Drawdown Minimize* prevents this type of situations, but is biased towards small positions and so have low absolute return. If used in conjunction, these methods might complement each other.

7. Discussion

In the beginning of this thesis we presented the following research questions that we were to investigate and find answers to:

1. Which, if any, of the investigated position sizing methods give better returns in relation to risk, compared to Fixed Fraction?

Based on the results presented in this study and the analysis of these results, it can be observed that three methods gave promising results but especially one alternative position sizing method consequently exhibited better returns to risk values for all performance indicators, namely *Target Volatility*. Not only does it generate better performance indicators than *Fixed Fraction* for the methods standard parameter values and mean values based on all simulation, but the performance indicators are consequently higher than for *Fixed Fraction* even for the minimum values of these performance indicators from all simulations, except for the lowest sharp ratio which is just slightly lower than for *Fixed Fraction*. This insensitivity to the values of the different parameter used in this study is a strong indicator for that *Target Volatility* gives better returns in relation to risk, compared to F*ixed Fraction*. The M*ax Drawdown Minimize* position sizing method also consequently generates better returns to risk values than *Fixed Fraction* for all performance indicators except *Sharpe Ratio*. One difference is that one out of the twenty simulations gives a slightly smaller *yearly return (APR) over Maximum Drawdown (MDD)* value than for *Fixed Fraction*, but apart from that the method gives better performance indicator values for all simulations compared to *Fixed Fraction*. The lower *Sharpe Ratio* is perhaps worrying, but the results from the other performance indicators still suggests that M*ax Drawdown Minimize* gives better returns in relation to risk than *Fixed Fraction*. The *Dynamic Stop Lock-In* position sizing method also consequently gives better returns in relation to risk for the *APR/MDD* and *Recovery Factor* indicators, the mean *Sharpe Ratio* is also higher, but lower values for *Profit Factor* and *Payoff Ratio* compared to *Fixed Fraction*. The other methods do not consequently give better returns in relation to risk and the performance indicators for the standard parameters and mean values of simulations are equal to or worse than for *Fixed Fraction*.

2. Do the investigated position sizing methods still have the low correlation with equity markets traditionally associated with managed futures?

Yes, the correlation to the S&P 500 index is negative for *Fixed Fraction* and the correlation is still negative to the S&P 500 index for all of the 200 simulations from the different position sizing methods. So the position sizing methods still have the low correlation with the equity markets traditionally associated with managed futures.

3. Are these position methods feasible to implement?

The difference between the choice of *time to reweighing*, *reweighing of active positions or not*, and *symbol or sector level* does not seem to systematically influence performance. The *time to reweighing* variable do not have a great effect on the *APR/MDD* performance indicator, based on the mean value for all simulations. The same goes for *reweighing of active positions or not*, and *symbol or sector level*. So the results of the performance methods do not seem to be that heavily dependent on these choices of parameter values and the possible implications problem they may bring. It should also be noted that with less assets under management, position sizes cannot be adjusted with the same precision, this will have to be taken into consideration when implementing the described position sizing methods. Based on this, there are no reasons to believe these methods should not be possible to implement.

A large *Max Drawdown* can be devastating for a CTA, causing its investors to lose faith in the managers and abandon the fund. It may also deter future investors from investing. Even though the managers of the fund are highly convinced that their fund will be profitable in the future, it is important to pay attention to *Max Drawdown* for the survival of the fund (Clenow, 2013). This is the reason why we have included *Max Drawdown* in the evaluation of the methods, because even though a method may have a great *APR* it cannot come at the cost of a high *Max Drawdown*. The *APR/MDD* values in this study may seem small, but it is important to note that the study's time period includes both periods of distress as well as prosperous periods for trend following strategies, and the deliberately low *Risk Factor* (0.001) in the underlying *Fixed Fraction* method limits potential high *APRs*, but it also makes the method less risk and prone to extensively large *Max Drawdowns*.

This low *Risk Factor* that limits potential high *APRs* plays a significant part in the methods observed low *Sharpe Ratios*. A higher *Risk Factor* would likely contribute to higher *Sharpe Ratios*, but at the cost of greater risk.

8. Conclusion

This chapter includes a review of the results from this study with conclusions drawn from the analysis with recommendations based on the purpose of this study. A brief section about sustainability and the impact of our study from a sustainability perspective is also discussed. Finally, the last section of this chapter is devoted to propositions and recommendations of further research.

8.1 Summary of results

In this study, a total of 200 simulation were conducted for 11 alternative position sizing methods and sub-methods with varying set of parameters including *time to reweighing*, *reweighing of active positions or not*, and *symbol or sector level*. The result from these simulations were then compared to the benchmark, which was using *Fixed Fraction* as position sizing method to the *Core strategy* developed by Clenow (2013). The purpose was to determine whether a trend following hedge fund could improve its performance by changing its position sizing method.

The conclusion that could be drawn from the analysis of the results from these simulations were that some methods exhibited results that improved the performance of strategy from a return over risk perspective, some position sizing methods more consequently than others. The final recommendation for a CTA is to use *Target Volatility* over simple *Fixed Fraction* as position sizing method, possibly in conjunction with *Max Drawdown Minimize*. There is in fact good reason to believe that these two methods can be used in conjunction to great effect. *Target Volatility* is squarely an improvement over *Fixed Fraction*, but does not affect relative sizes, every symbol is either weighed up or down at the same time. *Target Volatility* is exposed to periods of low volatility but negative returns – in these periods this method actually increase position sizes. *Maximum Drawdown Minimize* prevents this type of situations, but is biased towards small positions and so have low absolute return. If used in conjunction, these methods might complement each other. The investigated sizing methods also preserve the low correlation with equity markets traditionally associated with managed futures, and there are no reasons to believe these methods should not be possible to implement.

This study investigated the relatively unexplored combination of trend following trading strategies and alternative portfolio optimization. The performance of the *Core strategy* where, unsurprisingly, similar to the results demonstrated by Clenow (2013). The failure of the *Omega* method to yield any improvement in performance might be viewed as a contradiction to the results of Harris & Mazibas (2013), who observed such findings. However, their study was concerned with constructing a fund-of-funds portfolio, so the results of this study might only suggest that the previously demonstrated advantages of Omega Optimization fail to translate into the context of weighing individual futures in a strategy portfolio. However, these results speak more directly against the method suggested by Tomasini (2010), *Correlation Threshold*, as this method was intended to work in precisely this context, and did not exhibit any discernable difference over *Fixed Fraction*.

8.2 Sustainability

In 1987, the Brundtland Commisions of the United Nation defined sustainability as "meeting the needs of the present without compromising the ability of future generations to meet their own needs." In order to be sustainable, three different aspects of sustainability need to be taken into consideration: Environmental-, Social-, and Economic-impact. (Brundtland, 1987)

The findings of this study do not have a negative impact on sustainability from neither an environmental, social or economic perspective. Investments in futures describe in this study are merely speculative, and positions in for instance crude oil are not related to the physical commodity, but a speculation based on a belief in future positive or negative price movements. The findings of this study are in line with previous research that the returns from a trend following hedge fund strategy have low correlation with the equity market and are therefore an important alternative investment source, particularly for pension funds in order to better diversify their portfolio. So by being able to use more efficient position sizing method, a hedge fund will be able to present better returns over risk and have a positive impact on sustainability from an economic perspective.

8.3 Further research

One major area of further research would be an attempt to replicate these results using another strategy. One methodological limitation of this study is the focus on a single trend following strategy, whereas an actual CTA fund would have several strategies trading at once. Simulating position sizing for e.g. simple SMA-crossover strategies, simple breakouts, or mean-reverting strategies could improve the validity of the findings in this study.

Another way forward is to conduct more through investigations of each individual position sizing method, focusing more on parameter estimation or constructing a different implementation. For instance, the *Correlation methods* simulated in this study used a ranking of symbols, from high to low correlation. Perhaps this is the wrong way to go. Would a *Correlation* method more like the one described by Covel (2007) with limits on the number of positions in highly correlated symbols, give better performance? Leniency with method parameters could perhaps yield better results for *Omega Optimization*. *Target Volatility* gave promising results in this study, but has a weakness towards periods with repeated losses and low volatility. Is there a way of lowering this exposure, while retaining the high performance? These are things further research would have to take into consideration.

A final way of letting these results inform future studies is to combine strategies. The effect achieved from *Target Volatility* might add to the effect achieved by *Max Drawdown Minimize*. A combination of these two strategies, or another subset of strategies, might prove the most promising choice of position sizing method for a CTA.

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Appendix

Appendix I: Equity Curves for standard parameters, compared with Fixed Fraction

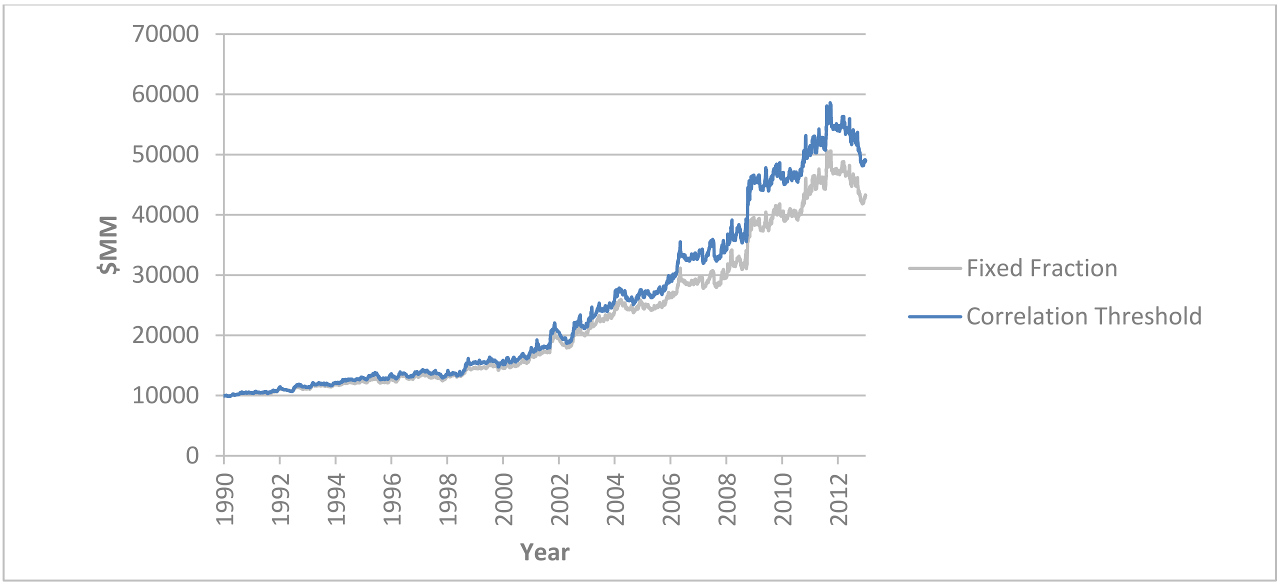

Figure A1: Equity curve for the *Correlation Threshold* sizing method with standard parameters (blue) compared to the equity curve for *Fixed Fraction* (grey).

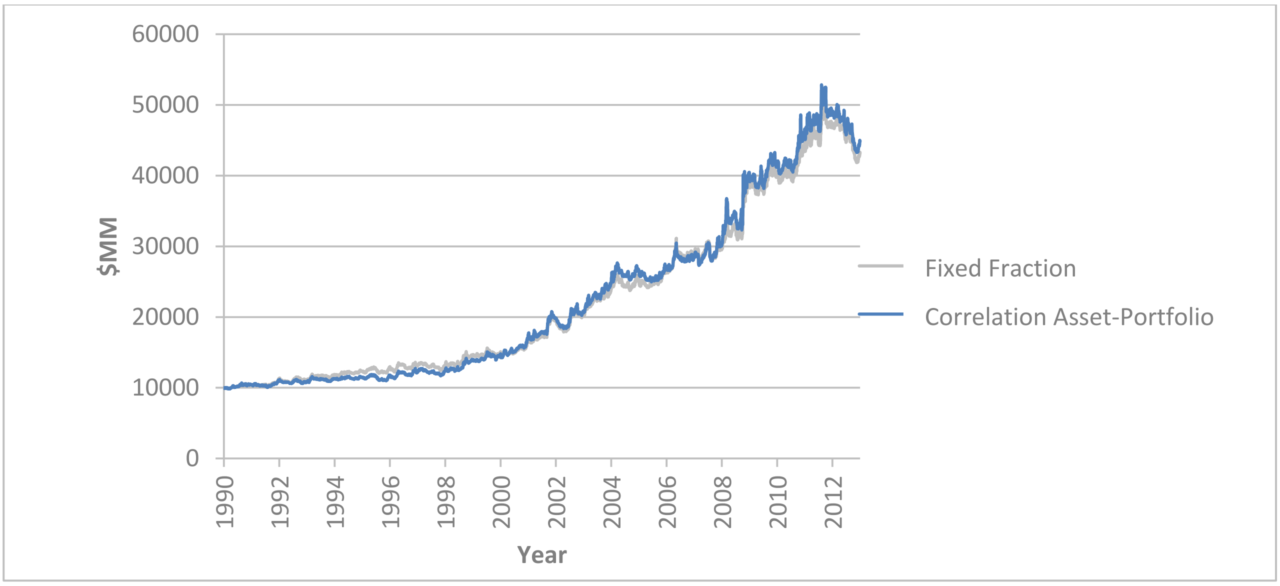

Figure A2: Equity curve for the *Correlation Asset-Portfolio* sizing method with standard parameters compared to the equity curve for *Fixed Fraction*.

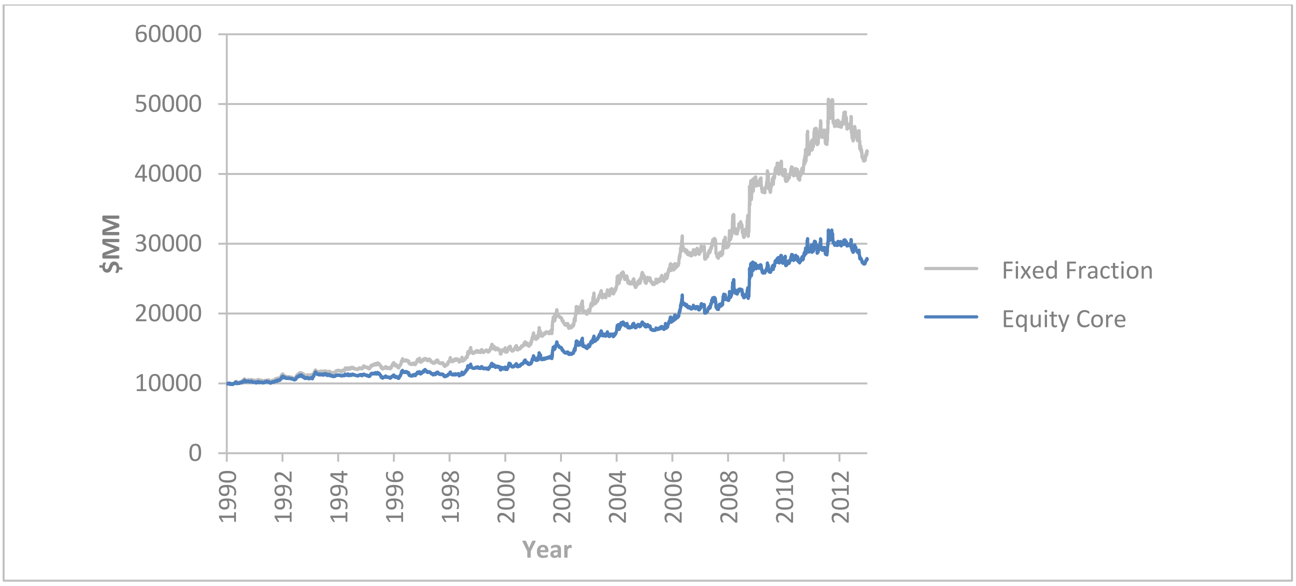

Figure A3: Equity curve for the *Equity Core* sizing method with standard parameters compared to the equity curve for *Fixed Fraction*.

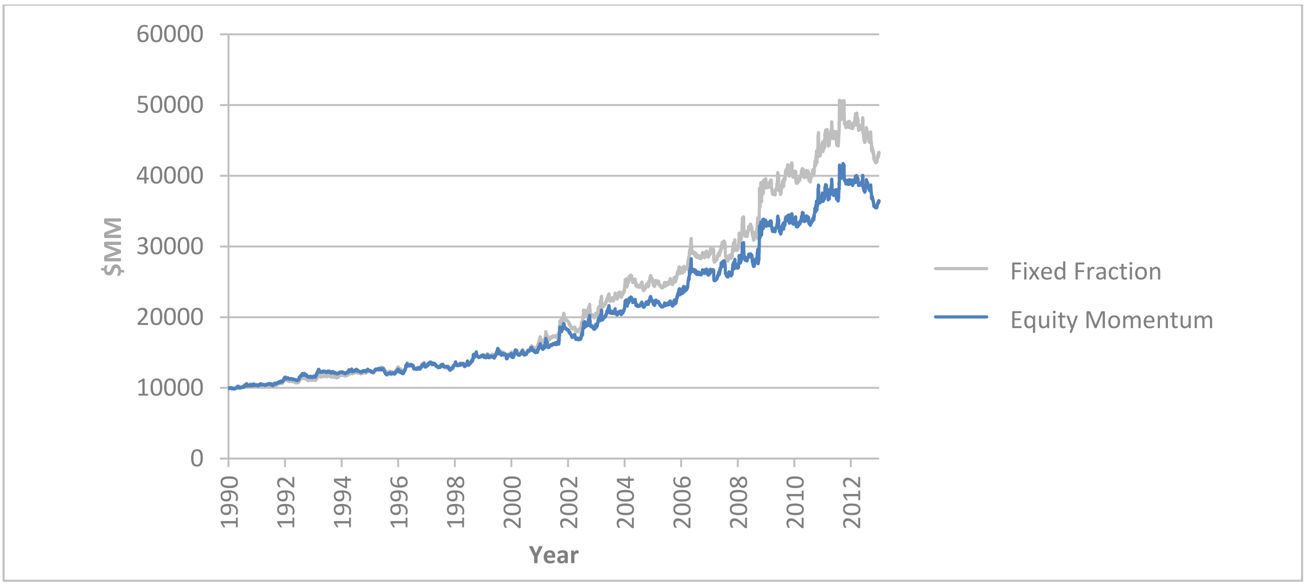

Figure A4: Equity curve for the *Equity Momentum* sizing method with standard parameters compared to the equity curve for *Fixed Fraction*.

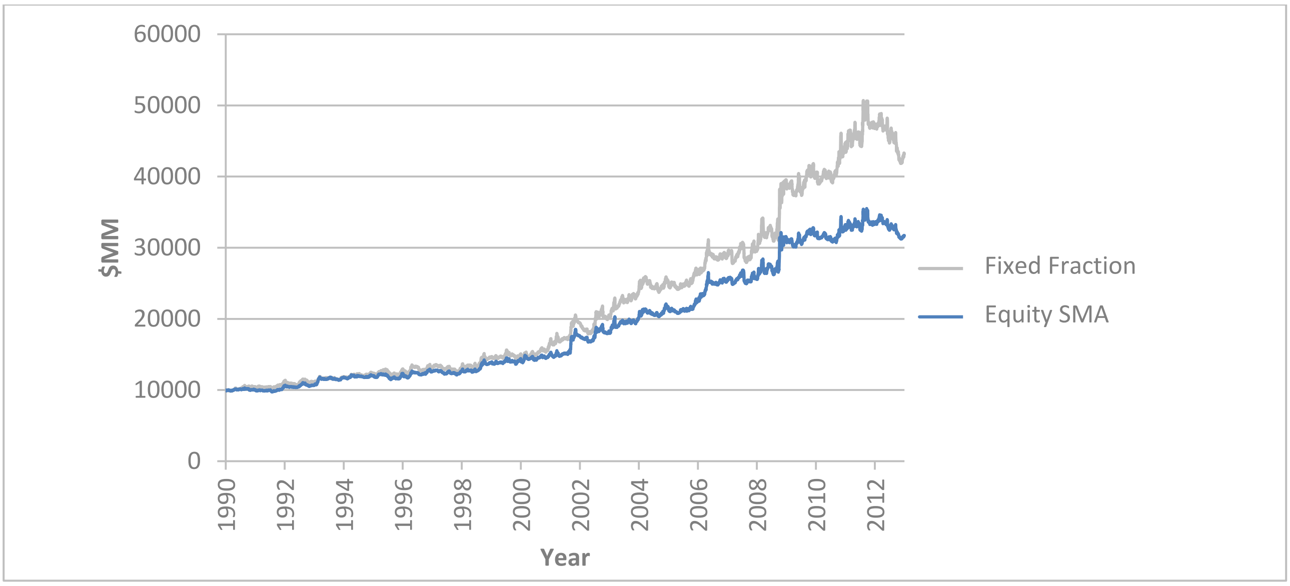

Figure A5: Equity curve for the *Equity SMA* sizing method with standard parameters compared to the equity curve for *Fixed Fraction*.

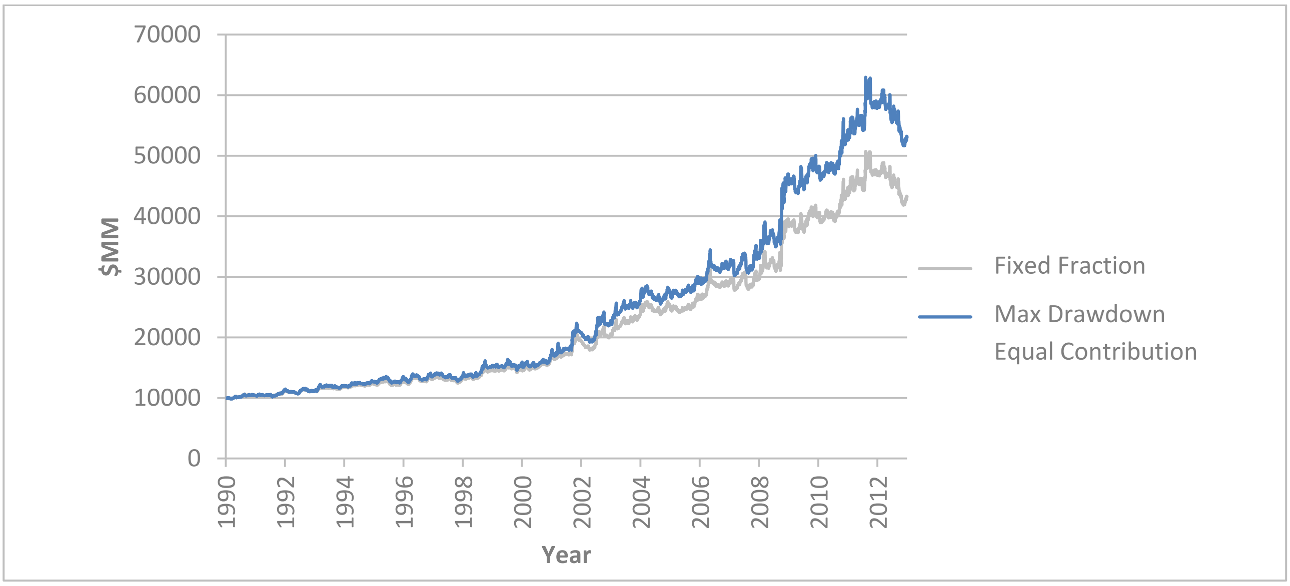

Figure A6: Equity curve for the *Max Drawdown Equal Contribution* sizing method with standard parameters compared to the equity curve for *Fixed Fraction*.

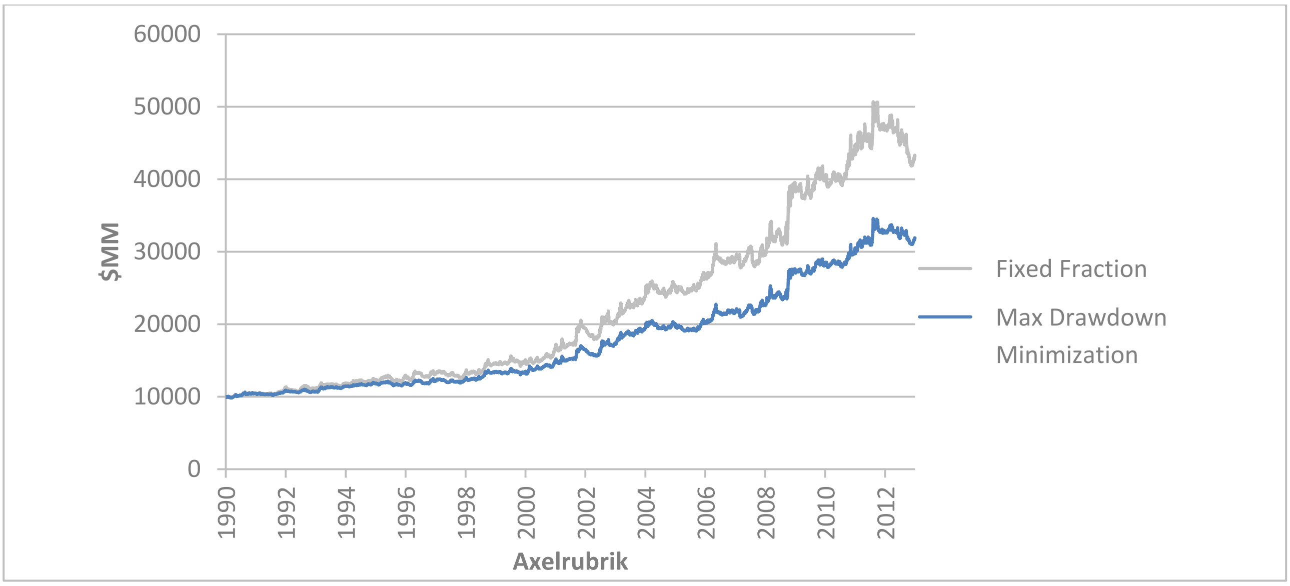

Figure A7: Equity curve for the *Max Drawdown Minimization* sizing method with standard parameters compared to the equity curve for *Fixed Fraction*.

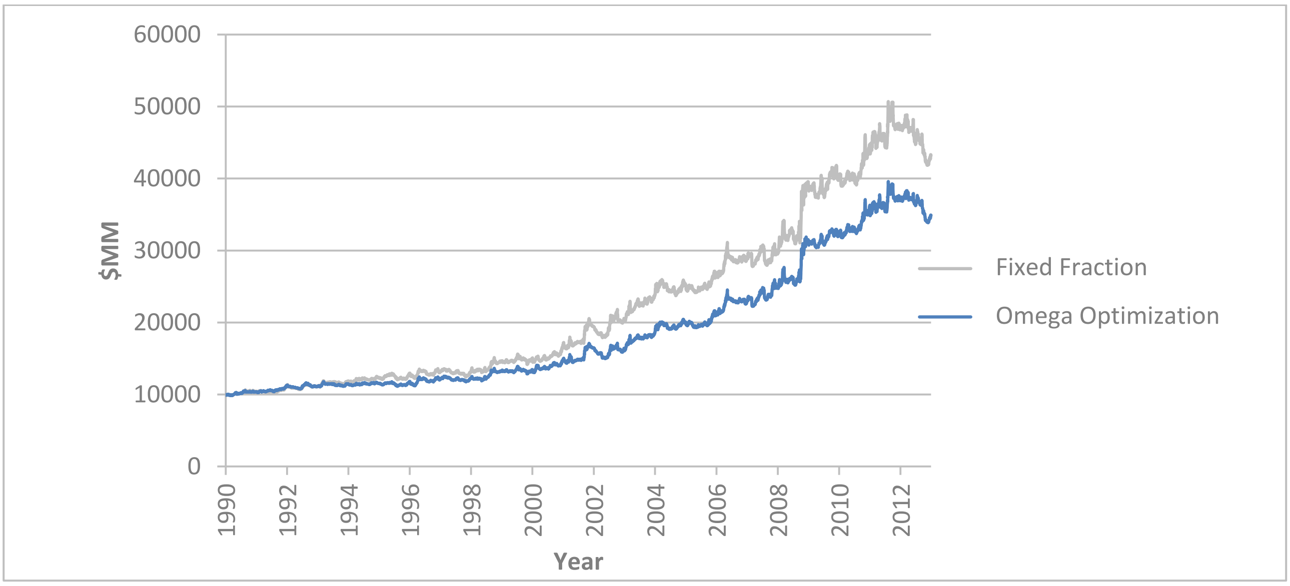

Figure A8: Equity curve for the *Omega* sizing method with standard parameters compared to the equity curve for *Fixed Fraction*.

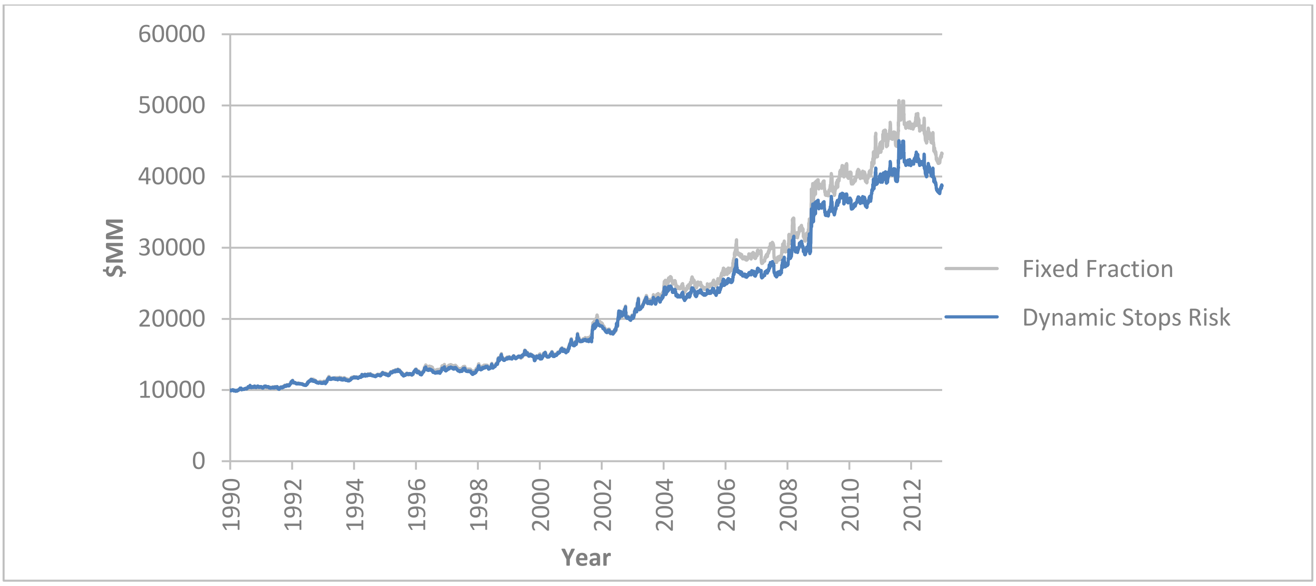

Figure A9: Equity curve for the *Dynamic Stops Risk* sizing method with standard parameters compared to the equity curve for *Fixed Fraction*.

Figure A10: Equity curve for the *Dynamic Stops Lock-In* sizing method with standard parameters compared to the equity curve for *Fixed Fraction*.

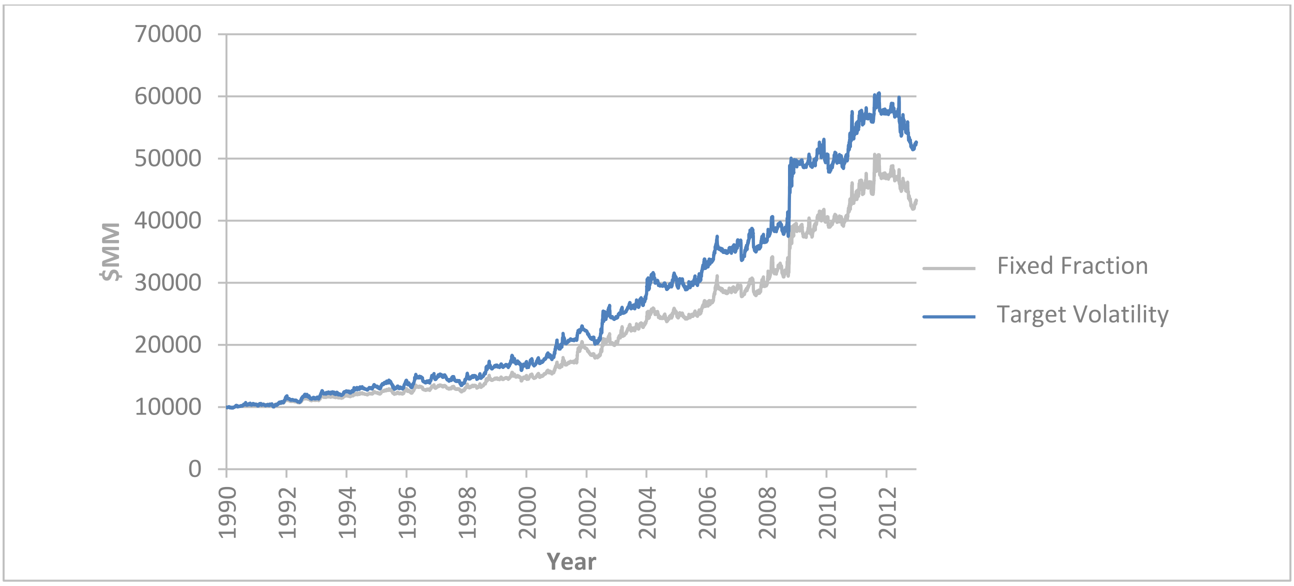

Figure A11: Equity curve for the *Target Volatility* sizing method with standard parameters compared to the equity curve for *Fixed Fraction*.

Appendix II: Review of results; mean values for the different sizing methods

	Recovery Factor (mean)	APR/ MDD (mean)	Payoff Ratio (mean)	Profit Factor (mean)	Sharpe Ratio (mean)
Fixed Fraction	3.76	0.38	1.83	1.33	0.47
Correlation Asset-Portfolio	3.71	0.38	1.84	1.34	0.50
Correlation Threshold	3.62	0.39	1.85	1.33	0.49
Dynamic Stop Lock-In	5.05	0.46	1.78	1.29	0.48
Dynamic Stop Risk	4.03	0.37	1.82	1.28	0.42
Equity Core	3.69	0.33	2.11	1.31	0.34
Equity Momentum	3.95	0.38	1.93	1.32	0.41
Equity SMA	3.73	0.33	2.10	1.30	0.37
Max Drawdown Equal Contribution	3.69	0.40	1.86	1.36	0.44
Max Drawdown Minimize	5.48	0.44	1.92	1.37	0.39
Omega	4.13	0.36	1.99	1.35	0.39
Target Volatility	4.86	0.52	1.89	1.36	0.54

Table A1: Mean values of performance measures for the different sizing methods

Appendix III: APR/MDD, All methods

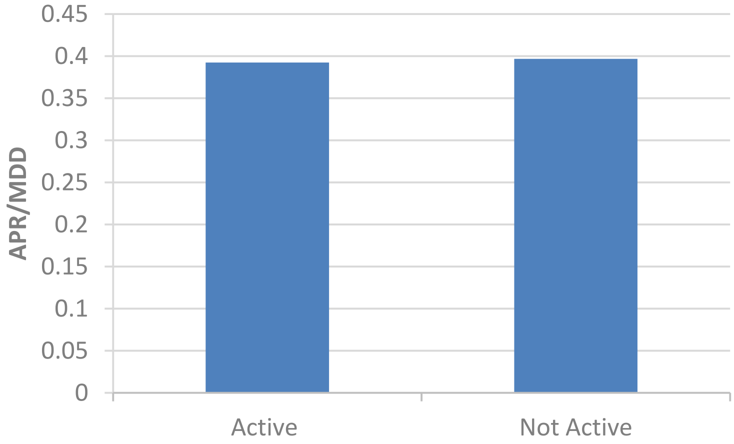

Figure A12: Mean of APR/MDD of all methods, Active compared with No Active reweighing.

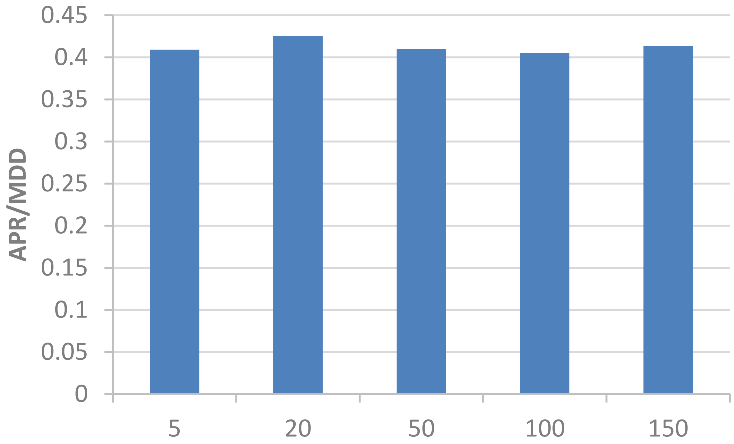

Figure A13: Mean of APR/MDD of all methods, divided by days between reweighings.

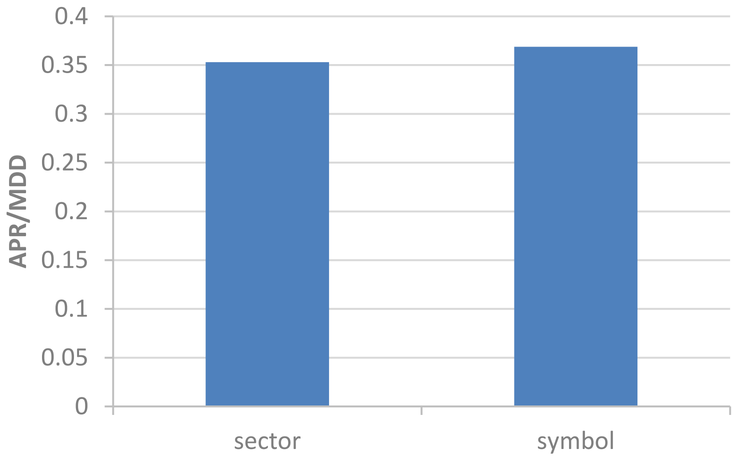

Figure A14: Mean of APR/MDD of Equity Based and Max Drawdown Equal Contribution, sector versus symbol level sizing.

Appendix IV: All simulations, sorted by method

Correlation Asset-Portfolio

Time to Reweighing/Reweighing of active positions/Level	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
5/Not active/Symbol	7.19%	17.44%	1.87	1.36	3.95	0.41	0.52
5/Active/Symbol	6.86%	15.63%	1.82	1.34	4.46	0.44	0.51
20/Not active/Symbol	7.10%	18.67%	1.85	1.34	3.58	0.38	0.52
20/Active/Symbol	7.05%	16.79%	1.84	1.34	4.06	0.42	0.53
50/Not active/Symbol	6.74%	18.05%	1.84	1.34	3.66	0.37	0.49
50/Active/Symbol	6.89%	17.61%	1.83	1.33	3.80	0.39	0.51
100/Not active/Symbol	6.53%	18.70%	1.82	1.33	3.47	0.35	0.47
100/Active/Symbol	6.92%	18.50%	1.86	1.33	3.59	0.37	0.51
150/Not active/Symbol	6.16%	19.27%	1.81	1.32	3.22	0.32	0.43
150/Active/Symbol	6.65%	19.42%	1.84	1.33	3.34	0.34	0.48

Table A2: All simulations, Correlation Asset-Portfolio.

Correlation Threshold

Time to Reweighing/Reweighing of active positions/Level	Threshold	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
5/Not active	-0.2	8.18%	18.15%	1.86	1.36	3.90	0.45	0.56
5/Active	-0.2	7.39%	18.51%	1.83	1.30	3.66	0.40	0.50
5/Not active	0	6.33%	19.00%	1.82	1.32	3.30	0.33	0.43
5/Active	0	7.35%	18.85%	2.02	1.32	3.56	0.39	0.49
5/Not active	0.2	7.13%	18.23%	1.85	1.35	3.68	0.39	0.48
5/Active	0.2	7.47%	20.85%	1.84	1.31	3.18	0.36	0.50
20/Not active	-0.2	8.12%	18.64%	1.86	1.36	3.77	0.44	0.56
20/Active	-0.2	7.38%	17.64%	1.82	1.32	3.89	0.42	0.49
20/Not active	0	6.19%	18.62%	1.79	1.31	3.34	0.33	0.41
20/Active	0	6.93%	19.21%	1.96	1.32	3.37	0.36	0.47
20/Not active	0.2	6.19%	19.18%	1.78	1.30	3.26	0.32	0.40
20/Active	0.2	7.17%	18.70%	1.88	1.32	3.56	0.38	0.48
50/Not active	-0.2	6.94%	19.62%	1.80	1.31	3.34	0.35	0.46
50/Active	-0.2	7.20%	19.51%	1.83	1.31	3.41	0.37	0.48
50/Not active	0	7.15%	17.91%	1.85	1.34	3.71	0.40	0.50
50/Active	0	6.79%	19.49%	1.90	1.32	3.31	0.35	0.45
50/Not active	0.2	6.82%	16.80%	1.82	1.32	3.97	0.41	0.45
50/Active	0.2	6.93%	18.41%	1.87	1.33	3.59	0.38	0.46
100/Not active	-0.2	6.88%	19.61%	1.79	1.30	3.31	0.35	0.46
100/Active	-0.2	6.78%	20.14%	1.81	1.30	3.19	0.34	0.44
100/Not active	0	7.32%	17.98%	1.85	1.35	3.74	0.41	0.50
100/Active	0	7.56%	18.31%	1.91	1.35	3.73	0.41	0.52
100/Not active	0.2	7.34%	17.63%	1.84	1.34	3.85	0.42	0.50
100/Active	0.2	7.42%	18.21%	1.87	1.35	3.74	0.41	0.50
150/Not active	-0.2	8.33%	19.51%	1.90	1.38	3.59	0.43	0.57
150/Active	-0.2	8.29%	19.72%	1.89	1.37	3.53	0.42	0.58
150/Not active	0	7.38%	17.02%	1.85	1.35	4.04	0.43	0.51
150/Active	0	7.20%	16.53%	1.87	1.34	4.14	0.44	0.49
150/Not active	0.2	6.95%	17.46%	1.81	1.32	3.82	0.40	0.46
150/Active	0.2	7.32%	17.02%	1.84	1.34	4.05	0.43	0.49

Table A2: All simulations, Correlation Threshold.

Dynamic Stop Lock-In

Low Threshold/ High Threshold	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
0.01/0.03	5.85%	11.83%	1.71	1.27	5.65	0.49	0.46
0.03/0.05	6.04%	13.06%	1.79	1.29	5.11	0.46	0.46
0.05/0.1	6.67%	15.32%	1.82	1.33	4.41	0.44	0.51

Table A3: All simulations, Dynamic Stop Lock-In.

Dynamic Stop Risk

Low Threshold/ High Threshold	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
0.0003/0.0005	5.17%	14.53%	1.79	1.24	4.16	0.36	0.36
0.0005/0.001	6.06%	16.52%	1.85	1.29	3.86	0.37	0.44
0.001/0.0015	6.40%	16.17%	1.82	1.32	4.07	0.40	0.46

Table A4: All simulations, Dynamic Stop Risk.

Equity Core

Reweighing of active positions/Level	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
Not active/Sector	5.63%	14.24%	1.82	1.31	4.39	0.40	0.37
Not active/Symbol	4.54%	15.30%	1.78	1.29	3.63	0.30	0.28
Active/Sector	5.38%	18.09%	2.10	1.28	3.22	0.30	0.33
Active/Symbol	5.85%	17.56%	2.72	1.34	3.51	0.33	0.36

Table A5: All simulations, Equity Core.

Equity Momentum

Time to Reweighing/Reweighing of active positions/Level	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
5/Not active/Sector	5.81%	19.78%	1.74	1.27	3.05	0.29	0.38
5/Not active/Symbol	4.36%	11.35%	1.83	1.33	5.02	0.38	0.31
5/Active/Sector	7.36%	19.58%	1.99	1.30	3.48	0.38	0.49
5/Active/Symbol	7.44%	18.63%	2.30	1.31	3.67	0.40	0.52
20/Not active/Sector	6.33%	14.65%	1.83	1.33	4.49	0.43	0.44
20/Not active/Symbol	5.17%	13.64%	1.84	1.34	4.46	0.38	0.37
20/Active/Sector	6.55%	17.38%	2.22	1.31	3.75	0.38	0.41
20/Active/Symbol	6.47%	16.36%	2.56	1.34	4.29	0.40	0.43
50/Not active/Sector	5.97%	17.68%	1.79	1.30	3.58	0.34	0.39
50/Not active/Symbol	5.77%	15.08%	1.82	1.33	4.19	0.38	0.40
50/Active/Sector	5.77%	18.12%	1.93	1.29	3.34	0.32	0.36
50/Active/Symbol	5.99%	17.82%	2.10	1.32	3.50	0.34	0.40
100/Not active/Sector	6.99%	17.07%	1.84	1.34	4.25	0.41	0.46
100/Not active/Symbol	6.06%	16.22%	1.82	1.32	3.97	0.37	0.40
100/Active/Sector	6.61%	17.08%	1.85	1.32	3.88	0.39	0.44
100/Active/Symbol	5.93%	16.82%	1.84	1.31	3.75	0.35	0.38
150/Not active/Sector	6.73%	16.35%	1.83	1.33	4.15	0.41	0.43
150/Not active/Symbol	6.18%	15.35%	1.82	1.32	4.26	0.40	0.41
150/Active/Sector	6.62%	17.53%	1.83	1.32	3.75	0.38	0.41
150/Active/Symbol	6.30%	15.43%	1.85	1.32	4.27	0.41	0.42

Table A6: All simulations, Equity Momentum.

Equity SMA

Reweighing of active positions/Level	Fast SMA/Slow SMA	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
Not active/Sector	5/10	6.36%	19.73%	1.76	1.28	3.21	0.32	0.41
Not active/Symbol	5/10	5.25%	15.87%	1.80	1.31	3.74	0.33	0.35
Active/Sector	5/10	5.70%	19.64%	1.76	1.18	3.12	0.29	0.34
Active/Symbol	5/10	6.34%	23.84%	1.94	1.21	2.53	0.27	0.39
Not active/Sector	10/20	5.43%	18.17%	1.74	1.27	3.27	0.30	0.35
Not active/Sector	5/20	5.51%	18.65%	1.73	1.26	3.21	0.30	0.36
Not active/Symbol	5/20	4.42%	14.34%	1.79	1.30	3.86	0.31	0.31
Not active/Symbol	10/20	4.09%	15.21%	1.77	1.29	3.42	0.27	0.25
Active/Sector	10/20	8.47%	17.45%	2.10	1.34	4.91	0.49	0.57
Active/Sector	5/20	6.35%	36.50%	1.99	1.24	2.26	0.17	0.37
Active/Symbol	10/20	8.51%	20.57%	2.35	1.33	3.39	0.41	0.58
Active/Symbol	5/20	8.96%	21.96%	2.37	1.33	3.19	0.41	0.61
Not active/Sector	10/50	5.35%	14.31%	1.79	1.30	4.28	0.37	0.36
Not active/Sector	20/50	5.49%	15.24%	1.81	1.32	4.02	0.36	0.37
Not active/Sector	5/50	5.30%	15.57%	1.78	1.29	3.86	0.34	0.34
Not active/Symbol	20/50	5.46%	12.90%	1.88	1.37	4.84	0.42	0.38
Not active/Symbol	5/50	5.47%	13.61%	1.89	1.37	4.61	0.40	0.41
Not active/Symbol	10/50	5.14%	12.08%	1.88	1.37	5.06	0.43	0.38
Active/Sector	5/50	6.17%	17.30%	2.38	1.29	4.17	0.36	0.39
Active/Sector	20/50	5.74%	21.70%	2.28	1.26	3.35	0.26	0.34
Active/Sector	10/50	4.97%	19.12%	2.20	1.23	3.91	0.26	0.28
Active/Symbol	5/50	8.15%	17.50%	2.84	1.38	4.09	0.47	0.55
Active/Symbol	10/50	7.71%	17.61%	2.86	1.36	3.98	0.44	0.51
Active/Symbol	20/50	6.91%	18.02%	2.78	1.32	3.70	0.38	0.45
Not active/Sector	20/100	5.44%	14.04%	1.83	1.33	4.63	0.39	0.36
Not active/Sector	50/100	5.57%	14.73%	1.80	1.31	4.28	0.38	0.36
Not active/Sector	10/100	4.87%	14.22%	1.77	1.29	4.08	0.34	0.31
Not active/Sector	5/100	4.28%	15.88%	1.71	1.24	4.03	0.27	0.25
Not active/Symbol	50/100	4.73%	15.43%	1.77	1.29	3.71	0.31	0.30
Not active/Symbol	20/100	4.64%	15.19%	1.78	1.30	3.72	0.31	0.30
Not active/Symbol	5/100	4.46%	15.08%	1.78	1.30	3.68	0.30	0.29
Not active/Symbol	10/100	4.25%	15.85%	1.76	1.28	3.36	0.27	0.26
Active/Sector	5/100	5.50%	18.38%	2.31	1.28	3.19	0.30	0.33
Active/Sector	20/100	5.48%	21.19%	2.24	1.28	3.22	0.26	0.33
Active/Sector	50/100	5.63%	22.67%	2.05	1.28	3.28	0.25	0.34
Active/Sector	10/100	4.98%	21.84%	2.30	1.25	3.21	0.23	0.29
Active/Symbol	5/100	6.68%	17.38%	3.09	1.35	3.89	0.38	0.44
Active/Symbol	10/100	6.56%	18.34%	3.01	1.34	3.97	0.36	0.43
Active/Symbol	20/100	5.98%	16.83%	2.95	1.34	3.86	0.36	0.38
Active/Symbol	50/100	5.29%	17.97%	2.48	1.30	3.26	0.29	0.33

Table A7: All simulations, Equity SMA.

Max Drawdown Equal Contribution

Time to Reweighing/Reweighing of active positions/Level	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
5/Not active/Sector	7.27%	18.79%	1.86	1.35	3.59	0.39	0.33
5/Not active/Symbol	7.65%	17.85%	1.87	1.36	3.87	0.43	0.36
5/Active/Sector	7.25%	18.95%	1.87	1.35	3.55	0.38	0.33
5/Active/Symbol	7.65%	17.98%	1.88	1.36	3.83	0.43	0.36
20/Not active/Sector	7.27%	18.81%	1.87	1.36	3.58	0.39	0.33
20/Not active/Symbol	7.59%	17.84%	1.87	1.36	3.86	0.43	0.36
20/Active/Sector	7.25%	18.85%	1.87	1.35	3.57	0.38	0.33
20/Active/Symbol	7.64%	17.87%	1.87	1.36	3.86	0.43	0.36
50/Not active/Sector	7.22%	19.01%	1.86	1.35	3.52	0.38	0.50
50/Not active/Symbol	7.53%	17.95%	1.86	1.36	3.82	0.42	0.52
50/Active/Sector	7.20%	18.86%	1.85	1.35	3.56	0.38	0.50
50/Active/Symbol	7.54%	17.88%	1.87	1.36	3.84	0.42	0.52
100/Not active/Sector	7.24%	19.12%	1.86	1.36	3.49	0.38	0.50
100/Not active/Symbol	7.55%	17.90%	1.87	1.36	3.83	0.42	0.52
100/Active/Sector	7.14%	19.23%	1.84	1.35	3.46	0.37	0.49
100/Active/Symbol	7.54%	18.09%	1.86	1.36	3.78	0.42	0.52
150/Not active/Sector	7.30%	19.15%	1.86	1.36	3.50	0.38	0.51
150/Not active/Symbol	7.57%	17.64%	1.87	1.36	3.90	0.43	0.52
150/Active/Sector	7.28%	18.96%	1.86	1.36	3.55	0.38	0.51
150/Active/Symbol	7.53%	17.77%	1.87	1.36	3.87	0.42	0.52

Table A8: All simulations, Max Drawdown Equal Contribution.

Max Drawdown Minimize

Time to Reweighing/Reweighing of active positions	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
5/Not active	4.86%	10.01%	1.88	1.37	6.10	0.49	0.12
5/Active	5.30%	12.94%	2.01	1.35	4.78	0.41	0.18
20/Not active	4.90%	9.53%	1.90	1.38	6.75	0.51	0.12
20/Active	4.99%	10.43%	1.99	1.36	6.26	0.48	0.14
50/Not active	5.17%	10.34%	1.94	1.41	6.12	0.50	0.43
50/Active	4.68%	11.43%	1.89	1.34	5.16	0.41	0.35
100/Not active	4.98%	11.67%	1.90	1.39	5.17	0.43	0.40
100/Active	5.21%	11.82%	1.90	1.39	5.23	0.44	0.42
150/Not active	4.54%	12.08%	1.85	1.35	4.73	0.38	0.33
150/Active	4.66%	12.86%	1.88	1.35	4.47	0.36	0.35

Table A9: All simulations, Max Drawdown Minimize.

Omega

Time to Reweighing/ Reweighing of active positions	Profit Target	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
5/Not active	0.0001	4.87%	14.91%	1.83	1.33	3.91	0.33	0.34
5/Active	0.0001	5.37%	15.98%	2.30	1.31	3.82	0.34	0.35
5/Not active	0.0005	5.02%	14.58%	1.84	1.34	4.08	0.34	0.36
5/Active	0.0005	5.63%	16.44%	2.29	1.32	3.78	0.34	0.38
5/Not active	0.001	4.88%	14.47%	1.83	1.33	4.06	0.34	0.34
5/Active	0.001	5.27%	16.25%	2.29	1.30	3.71	0.32	0.34
20/Not active	0.0001	5.15%	15.01%	1.87	1.36	4.01	0.34	0.38
20/Active	0.0001	5.37%	16.96%	2.28	1.34	3.57	0.32	0.37
20/Not active	0.0005	5.14%	15.19%	1.87	1.36	3.94	0.34	0.38
20/Active	0.0005	5.53%	16.38%	2.30	1.35	3.77	0.34	0.39
20/Not active	0.001	5.21%	15.15%	1.87	1.36	3.99	0.34	0.38
20/Active	0.001	5.45%	17.35%	2.30	1.34	3.50	0.31	0.38
50/Not active	0.0001	5.54%	14.37%	1.90	1.38	4.37	0.39	0.42
50/Active	0.0001	5.59%	15.66%	2.12	1.37	3.96	0.36	0.40
50/Not active	0.0005	5.58%	14.46%	1.91	1.39	4.35	0.39	0.42
50/Active	0.0005	5.57%	15.44%	2.14	1.37	4.02	0.36	0.40
50/Not active	0.001	5.47%	14.34%	1.89	1.38	4.34	0.38	0.41
50/Active	0.001	5.60%	15.34%	2.14	1.37	4.06	0.37	0.40
100/Not active	0.0001	5.64%	16.01%	1.90	1.38	3.88	0.35	0.42
100/Active	0.0001	5.48%	16.23%	1.95	1.35	3.74	0.34	0.40
100/Not active	0.0005	5.58%	15.75%	1.90	1.38	3.93	0.35	0.41
100/Active	0.0005	5.55%	16.17%	1.96	1.36	3.78	0.34	0.40
100/Not active	0.001	5.55%	16.00%	1.89	1.38	3.85	0.35	0.41
100/Active	0.001	5.54%	15.62%	1.96	1.36	3.93	0.35	0.41
150/Not active	0.0001	5.26%	12.98%	1.86	1.35	4.84	0.41	0.38
150/Active	0.0001	5.55%	14.04%	1.92	1.36	5.34	0.40	0.41
150/Not active	0.0005	5.29%	13.05%	1.86	1.35	4.82	0.41	0.39
150/Active	0.0005	5.49%	13.97%	1.91	1.36	4.82	0.39	0.40
150/Not active	0.001	5.23%	13.02%	1.86	1.35	4.81	0.40	0.38
150/Active	0.001	5.49%	13.66%	1.91	1.36	4.84	0.40	0.40

Table A10: All simulations, Omega.

Target Volatility

Time to Reweighing/Reweighing of active positions	Target Volatility	APR	Max Drawdown	Payoff Ratio	Profit Factor	Recovery Factor	APR/MDD	Sharpe Ratio
5/Not active	0.08	7.85%	13.72%	1.97	1.43	5.30	0.57	0.60
5/Active	0.08	6.07%	12.00%	1.84	1.30	5.54	0.51	0.45
5/Not active	0.1	8.22%	13.81%	1.91	1.39	5.58	0.60	0.59
5/Active	0.1	7.63%	16.37%	1.84	1.32	4.27	0.47	0.54
5/Not active	0.12	8.67%	14.96%	1.89	1.38	5.02	0.58	0.60
5/Active	0.12	7.85%	19.54%	1.83	1.30	4.74	0.40	0.52
20/Not active	0.08	7.47%	13.07%	1.93	1.40	5.49	0.57	0.56
20/Active	0.08	7.40%	13.00%	1.92	1.38	5.62	0.57	0.57
20/Not active	0.1	8.69%	14.28%	1.96	1.43	5.22	0.61	0.62
20/Active	0.1	8.44%	14.33%	1.91	1.39	5.29	0.59	0.61
20/Not active	0.12	8.98%	15.74%	1.92	1.40	4.71	0.57	0.61
20/Active	0.12	9.25%	15.39%	1.91	1.39	5.00	0.60	0.64
50/Not active	0.08	6.52%	12.57%	1.85	1.35	5.43	0.52	0.46
50/Active	0.08	7.06%	11.72%	1.97	1.39	6.11	0.60	0.53
50/Not active	0.1	7.48%	15.11%	1.84	1.34	4.65	0.50	0.50
50/Active	0.1	8.11%	14.52%	1.95	1.38	5.06	0.56	0.56
50/Not active	0.12	8.30%	17.73%	1.84	1.34	4.01	0.47	0.54
50/Active	0.12	8.90%	17.23%	1.93	1.38	4.29	0.52	0.58
100/Not active	0.08	6.43%	12.51%	1.85	1.34	5.46	0.51	0.47
100/Active	0.08	6.78%	12.40%	1.91	1.36	5.67	0.55	0.50
100/Not active	0.1	7.69%	15.36%	1.84	1.34	4.65	0.50	0.52
100/Active	0.1	7.89%	15.15%	1.90	1.35	4.80	0.52	0.53
100/Not active	0.12	8.48%	18.21%	1.83	1.33	3.95	0.47	0.54
100/Active	0.12	8.75%	17.98%	1.90	1.34	4.08	0.49	0.55
150/Not active	0.08	6.75%	14.07%	1.85	1.34	4.87	0.48	0.47
150/Active	0.08	7.10%	13.43%	1.89	1.37	5.36	0.53	0.51
150/Not active	0.1	7.85%	17.37%	1.84	1.34	4.04	0.45	0.52
150/Active	0.1	8.14%	16.22%	1.88	1.36	4.44	0.50	0.55
150/Not active	0.12	8.59%	20.58%	1.82	1.32	3.40	0.42	0.54
150/Active	0.12	8.92%	19.20%	1.87	1.34	3.74	0.46	0.56

Table A11: All simulations, Target Volatility.