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A Quantitative Framework for Constructing a Multi-Asset CTA with a Momentum-Based Approach

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Civilingenjörsprogrammet i system i teknik och samhälle

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Abstract

Commodity Trading Advisors (CTAs) have gained popularity due to their abilities to generate an absolute return strategy. Little is known about how CTAs work and what variables are important to tune in order to create a profitable strategy. Some investors use CTA-like strategies to leverage their portfolio and create positive returns in times when the spot market is falling. The report is written for Skandinaviska Enskilda Banken and aims to give the bank and readers an understanding on how changes of parameters in a CTA strategy change the outcome of it with focus on three main measurements: Sharpe ratio, drawdown and total return.

The foundation of CTAs is that they rely on signals from some given sets of assets and make investments decisions solely based on them. CTAs can be rule-based with a binomial signal, or they can use a continual signal, like in the report. The thesis aims to recreate a CTA using a continuous momentum signal and with the signal, invest accordingly. Some different variables were tested, most importantly the report focuses on the weights of the assets and investigates of the momentum signal is good as it is or if a risk parity weighting is needed on top of the signal in order to generate a return that matches the expectations of a low drawdown and a high Sharpe ratio.

Beyond the weight allocation, different lookback periods of both the signal and weight were tested. A shorter lookback generated a quicker return that was more sensible to short trends on the market. Which in some cases was profitable but it also lost more of it accumulated return when the trend was "false". The equally weighted signal that only takes the trend into account when allocating the weights of the assets was more volatile it its returns and benefited from a long signal. The CTA results presented can only be seen as an index since it is rebalanced every rebalancing point, the frequency of those points was examined and the strategy was performing well if rebalanced once a week or once a month, every day and once a year did not yield a better result.

As expected, the CTA benefits from trend on the market, no matter the direction of it. The best periods for the CTA were when the market was very volatile, mainly 2008 and 2022. When there is no clear trend, the CTA reacts too slowly and often loses money. One important conclusion is that the CTA never should be used as an investment strategy on its own, rather as a hedging strategy that allocates a fraction of a total long-only portfolio.

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I en tid då de finansiella marknaderna snabbt kan skifta är risken stor för att förlora en stor del av sitt placerade innehav på bara några veckor eller månader. Då många instrument korrelerar och faller samtidigt, räcker inte alltid en diversifiering av tillgångar för att skydda sig mot risk vid nedgång. Ett alternativ för finansieringsinstitut med möjlighet att handla så kallat over-the-counter, det vill säga handel med värdepapper via ett nätverk av mäklare och handlare på en stängd marknad, är att kortsälja, även kallat att blanka, tillgångar. Detta innebär att man säljer en lånad tillgång för ett förbestämt pris och köper tillbaka och återlämnar tillgången ett förbestämt datum i framtiden. Detta genererar en vinst vid nedgång på tillgångens pris på överlämningsdagen jämfört med vad priset vid försäljningsdagen låg på. Att kortsälja en tillgång är mycket riskabelt och förlusten kan i teorin bli oändligt stor om tillgången går upp till extrema prisnivåer och därför måste risken kalkyleras noga innan en sådan affär sker.

Att sätta upp handelsregler för när en aktör, till exempel en fondförvaltare, bör köpa eller kortsälja tillgångar kan eliminera risk och genererar avkastning både när marknaden rör sig upp och ned om de görs på ett ansvarsfullt och bra sätt. En metod som har börjat användas flitigt under de senaste årtionden baserar sina beräkningar på momentum. Momentum kan enkelt beskrivas som att om priset på en tillgång ökar är det troligt att priset fortsätter öka och tvärt om när priset går ned. Detta är främst ett psykologiskt fenomen bland både professionella och amatörmässiga investerare och beror på riskavert individen är. I grupp har människor lätt att göra vad andra gör och likaså aktörer på de finansiella marknaderna, därav har momentum blivit väletablerat inom finans. Att följa momentum och investera därefter har i denna avhandling undersökts och detta genom att efterlikna regler som en CTA kan tänka sig ha. En CTA, eller *Commodity Trading Advisor*, är en strategi som härstammar från då råvaruhandelns futures användes för att hedga sig mot fallande råvarupriser. En vetebonde kunde då köpa en future som garanterade bonden att få sälja sitt vete till ett förbestämt pris i framtiden som en försäkring mot att vetepriset vid skördetid går ned från dagens pris. Futureskontrakt är standardiserade och handlas på den öppna marknaden och CTA:er handlade då kontrakten med förbestämda regler som beslutade om fondförvaltaren skulle köpa eller sälja dem. Dessa regler kan implementeras för att handla tillgångar även idag och i rapporten är den replikerade CTA:en inte begränsad till enbart futureskontrakt. Den replikerade CTA:en bestod av en portfölj med 64 globalt diversifierade tillgångar från alla primärmarkander: aktiemarknaden, räntemarknaden, valutamarknaden och råvarumarknaden. Med hjälp av olika regler kunde algoritmen köpa eller sälja tillgångar beroende på trendsignalen som genererades. Trendsignalen mätte trend för varje tillgång med olika lång återblickstid och vägde tillgångarna med att antal olika vikter som alternerades i rapporten. Fler variabler användes även för att undersöka effekten av att begränsa portföljen till de tillgångar som under ett ombalanseringstillfälle har en trendsignal över ett visst tröskelvärde och även att variera längden på perioden mellan varje ombalanseringstillfälle.

En kortare återblickstid genererade en avkastning som tog upp korta trender på marknaden, i vissa fall var detta lönsamt men då trenden visade sig vara "falsk" förlorade den också mer pengar. Riskparitetvikt, lika vikt och Markowitzvikt undersöktes och även om de två sistnämnda ofta gav en bättre ackumulerad avkastning var den inte lika stabil och förlorade ofta mycket på när det inte fanns en stabil trend på marknaden. För den likaviktade portföljen var långa signaler fördelaktigt då avkastningen annars blev för volatil. Olika ombalanseringspunkter gjorde en stor skillnad för utfallet av strategin, bäst resultat oavsett vikt visade sig att en ombalansering en gång i månaden eller en gång i vecka, gärna tisdag, onsdag eller torsdag, gav. Resultatet visade på att algoritmen genererar bäst avkastning då det sker en stark trend på marknaden och extremt volatila år så som 2008 och 2022 genererade de absolut starkaste åren för strategin. Resultaten som presenterades kan endast ses som ett index för att jämföra strategier mot varandra. På så sätt kunde de bästa variablerna hittas. De bästa variablerna beror på tillämpningen och om en fondförvaltare vill addera inslag av CTA i en annars enbart lång portfölj för att skydda sig mot risk skulle riskparitetsvikter vara att föredra. Vidare forskning bör undersöka om algoritmen bör ändra återblickstid beroende på volatiliteten på marknaden och inte hålla en konstant längd.

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Glossary

absolute return strategy a strategy that can generate return both in bull and bear market since it can take on both long and short positions. 36

American option an option that can be exercised any day until the expiration date. 6

credit rating a measurement of the creditworthiness of a borrower. The biggest issuers of credit rating include Standard & Poor and Moody's. A credit score puts the borrower in either High Yield (HY) or Investment Grade (IG), IG signals that an issuer of a bond has a low risk of defaulting. 5

European option an option that can be exercised only on the expiration date. 6, 13

market maker a person or company who quotes both sides of a security, meaning they provide both bids and offers. They profit from the spread which is the difference between the current best bid and lowest offer. 4

over-the-counter a trading process of financial contracts that takes place in a broker-dealer network and not a centralized exchange. 2, 21

quantitative easing a form of monetary policy in which central banks purchases securities from the open market in order to lower interest rates and increase the monetary supply. Often used to reduce interest rates further down the yield curve or when interest rates cannot be reduced any further. 1

quantitative tightening a form of monetary policy used in contractionary purpose in which central banks sells securities to the open market and therefore reduces the financial assets it holds on its balance sheet. This leads to a lower supply and higher interest rates, something that can be used as a complementary action to increasing interest rates. 1

yield curve a graph showing how the yields on debt instruments vary as a function of their years remaining to maturity. 1

Chapter 1

Introduction

One of the seminal achievements in modern portfolio theory is the theory formulated by Harry Markowitz in the 1950s. Markowitz underscored the significance of diversification in a portfolio and demonstrated that selecting assets with minimal correlation would lead to an optimized portfolio [2][7]. This optimization entails maximizing returns while considering the associated level of risk[1], achieved through the simulation of feasible portfolios involving specific assets [25]. Markowitz's [2] theory has served as the benchmark in the industry for several decades, inspiring the development of numerous portfolio allocation strategies.

Over the past turbulent decades, characterized by significant events such as the extensive 2008 financial crisis, a prolonged period of negative interest rates in which the Riksbank of Sweden [2] was one of the pioneers [15], an ephemeral recession caused by Covid-19 [19], and subsequent market fluctuations, including a short-lived boom on the market followed by a supply crisis as an effect of the Ukraine war which resulted in extreme global inflation, the Riksbank has demonstrated proactive and innovative measures to manage economic growth and achieve its annual inflation goal of 2%. Beyond adjusting the interest rate, the Riksbank has also implemented strategies such as quantitative easing (QE) and quantitative tightening (QT) as tools to exert control over the whole yield curve. QE, involving the purchase of securities, such as government and covered bonds, has a softening effect on longer-term interest rates by reducing their demand, increasing their prices, and consequently lowering interest rates [16]. In contrast, QT, introduced in April 2023, aims to achieve the opposite effect by selling existing securities or allowing them to expire at maturity [24].

Given the rapidly evolving trends in the fixed-income market, the sole use of Markowitz's theory might be insufficient during volatile periods. The need for a trend-following strategy that can generate returns even during market downturns has become more important than ever. The market is influenced by uncontrollable factors, and the need to identify them and invest accordingly is indispensable to hedge against changing prices.

We observe two different CTA following indices and compared to the S&P500,

[1] Risk will be used ambiguously to the standard deviation of the return of a specific asset. Return in this case (when used to describe the return of a portfolio) is the mean of the return of that portfolio.

[2] Here after only mentioned as the Riksbank.

they have performed well during times when the stock market has fallen. We can also observe a negative correlation between them and the S&P during the same period.

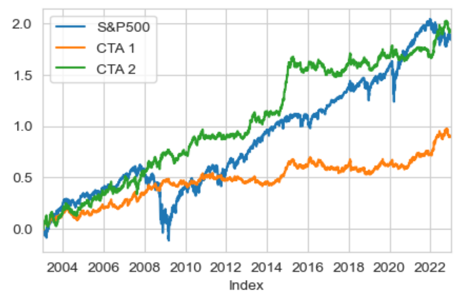

Figure 1.1: Aggregated return of two CTA indices and the S&P500

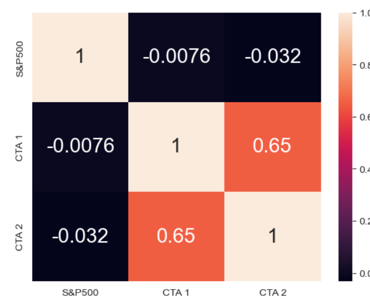

Figure 1.2: Correlation matrix of two CTA indices and the S&P500

Since the need for these portfolios is great, several market participants have already implemented these strategies and to stay ahead of those players, an understanding of the dynamics and signals generated is needed for financial intermediaries, for example banks, that the society relies on.

1.1 CTA trading

The term commodity trading advisor (CTA) refers to professional fund managers registered with the Commodity Futures and Trading Commission, the responsible body for the futures market in the US. They can take on speculative positions on futures by buying or short-selling [3] them [7]. The name originates from the historical practice of CTAs trading commodity futures, which served as a means for investors to hedge against the potential risk associated with declining commodity prices [5]. CTAs are generally driven by technical signals, rather than basic portfolio analysis, which means they heavily rely on computer programs to generate a buy or sell signal. The CTA trading strategy may be used by other fund managers than CTAs, as long as they obtain a license to trade over-the-counter (OTC). The manager must be able to take on short positions in the future and that can be done OTC. The strategy is not limited to futures, other instruments can be traded with the same CTA trading approach. The CTA-inspired trading strategy will in this report be referred to as a CTA. The CTA can be rule-based or follow momentum, but one common factor is the computer-generated signals that eliminate human portfolio analysis and the both long and short positions that the program generates for the assets of the portfolio. CTAs have been very successful in times of market downturns, such as during crises [7] [25], which makes it relevant in the recent period of high amplitude market swings.

[3] Short-selling will be further explained in 1.1.1

1.1.1 The basics of hedge fund strategies

To understand CTAs, one must understand the investment mechanism behind them. Trend-following strategies such as CTAs can be implemented by hedge funds, and therefore the basics of hedge funds will be explained. A key difference between a mutual fund and a hedge fund is the ability of hedge funds to take short positions when investing in an asset [13]. Taking a short position means selling a borrowed asset at a fixed price instead of buying it, generating a profit when the price of the asset falls. The investor then has to buy the asset back at a lower price than what the asset was sold for. If the price of the asset instead increases, the investor loses money since it has to be returned to the initial owner that the asset was borrowed from. The asset is never owned, meaning the hedge fund takes a leveraged position. A mutual fund can only buy assets and sell existing assets [12], referred to as going long on assets. Selling an asset that one does not own is called short-selling an asset. The concept of shorting an asset in a portfolio means that a hedge fund has an absolute return strategy and can generate a profit whether the market goes up or down [12]. The ability to buy and short assets in a portfolio can help to mitigate the sensitivity to market conditions Fung and Hsieh [13] and Strachman [12] argue that in theory, a hedge fund should always make money regardless of the market. CTA strategies can be implemented by hedge funds and other financial intermediaries that allow short-selling, as the mechanism behind CTA requires shorting the assets and therefore leveraging the portfolio.

1.1.2 CTA as a strategy

CTAs can generate returns in both market upturns and downturns [7], and are therefore beneficial to understand to take advantage of the positive effects they offer. To eliminate risk, a diversified portfolio is a good approach, and Derek [25] claims that a CTA must trade instruments in both the commodity market and the financial market to be considered diversified. Many investors understand the importance of diversification to eliminate risk, and including a CTA in a strategy with long-only positions can increase risk-adjusted returns and reduce portfolio risk [7]. A key reason for this result is that CTAs often generate positive returns when stock prices move downward, meaning that the correlation is negative during those periods [7].

CTAs often have an overall lower return than stock indices such as the S&P500, but they reduce drawdown and risk [7]. The strategy can therefore be seen as a complement to long-only investments in stocks and bonds. Especially during longer periods of negative trending markets for various asset classes, as in recent volatile years, a CTA strategy would be beneficial since it can generate returns regardless of whether the trend is going up or down. A CTA collects signals, for example daily, and decides how the portfolio should allocate its capital based on some algorithmic rules. The signals are buy or sell signals, the assets with a weak or negative (depending on how the algorithm ranks them) are sometimes cut, and the strongest signals form a basket that makes up the portfolio [20]. In the next period, which could be the next day or the next year or anything in between, the portfolio is rebalanced [20].

CTAs use trend signals and each investment strategy has its own covert signal. Known is that they can use momentum signals and momentum can be measured with different lookback periods, ranging between daily trend to several years. Normally, CTAs do not disclose their lookback [20] but the performance is sometimes published. Some studies claim that CTAs with longer lookback has had higher returns than the ones with shorter [7]. Derek [25] claims that the most difficult part of constructing a CTA is identifying the significant information. The information includes selecting assets, selecting trend signal and selecting the trading rules that the algorithm should follow. One advantage with CTAs is that it eliminates emotional behaviour that can make a manual trader take irrational decisions. The human factor in crucial in deciding the rules of the algorithm but it will not affect it when the strategy is incorporated [25]. It can calculate risk quickly and make sound decisions based on the market information given.

1.2 Fixed-income market

The economy is made up of several markets such as the equity, fixed-income, commodity, and foreign exchange market. Equity and fixed-income securities differ from the latter since they are claims of securities of a company [17]. A financial asset is a claim of future cash flows generated by the security and the price of the security reflects the value of these cash flows and is set by the market [18]. There are many issuers of fixed-income instruments but two common ones are governments and corporations and the instruments are a form of debt that will yield a fixed return to the owner[18]. This is a form of financing at a lower cost than equity financing to the issuer, as owners of equity require a higher return because of the risk associated with the asset [3]. Other fixed-income securities are asset-backed and can be seen as a pool of interest-bearing instruments that have been repackaged into a new bond, such as mortgage-backed securities issued by banks and covered bonds issued by large financial institutions [18].

The global fixed-income market is one of the largest markets when it comes to size, at the end of 2020 the market size was $123 trillion, but the size is clearly not easy to value [18]. Ilmanen [23] argues that the size of the global fixed-income market is close to $200 trillion. The market for fixed-income instruments plays an important role in financing governments, institutions, banks, and corporations according to Choudhry [14], making it a vital instrument in the modern financial system. The source of the capital in debt instruments comes from both household savings and accumulated retained earnings of firms and the total size of these constitutes the total market size for debt instruments [14]. This money stock is available for market participants who have a demand for money, they have to pay an interest rate as a fee to lend the money from participants with a surplus of money. Financial intermediaries play an important role in borrowing and lending, their function is as brokers or lenders on behalf of clients. They have an important function as market makers [14]. Fixed-income instruments, such as bonds, can be traded on a major exchange and OTC.

We have concluded that fixed-income instruments can be regarded as contractual loans between two parties, the nature of these loans can vary significantly depending on the issuer and the duration of the loan. Typically, the instruments are traded with a duration range of 2 to 30 years [14]. The primary focus will be on government bonds, which are issued by governments. Government bonds are characterized by excellent credit performance with credit rating often obtaining the highest credit ratings such as AAA in major economies which signifies a minimal risk of government bankruptcy [14]. Governments issue benchmark bonds with a time to maturity of a fixed duration of years.

1.3 Problem formulation

The traditional portfolio theory by Harry Markowitz has long been the industry norm, but recent years have demonstrated the necessity for alternate portfolio allocation methodologies, particularly during periods of high volatility in the market. Due to their capacity to make absolute gains in both up and down markets, CTAs have grown in popularity and are a desirable complement to a diversified portfolio. Despite their growth in the use of CTAs, little is known about how they identify signals and provide returns. In contrast to conventional portfolio theories, there is also limited evidence on how CTAs perform when the market is volatile. This research gap offers a chance to construct a CTA strategy and evaluate its effectiveness in various markets using several tuning variables.

The objective of the thesis is to develop a trend-following strategy replicating a CTA and research how well it performs in both bullish and bearish markets and draw conclusions on measurements such as Sharpe ratio, drawdown, and return. Understanding the signals produced by the CTA and how they are recognized, as well as how the CTA performs during times of market volatility, will be the main points of the thesis. The thesis will backtest the CTA approach and evaluate historical data using quantitative methodologies to fill in these research gaps. The findings of this thesis will help to better understand the behavior of CTAs and the value of using them for portfolio management. The results will also shed light on how investors might utilize CTAs to minimize risk during periods of market turbulence and hedge against shifting prices on the market.

1.4 Delimitations

To reach the full depth of the problem formulation and keep within the scope of the course, some limitations will be set. CTAs are in theory always well-diversified portfolios and the dynamic portfolio to be built, replicating a trend-following CTA will be no exception. Diversification is important in order to get proper weights that correspond to each asset in a portfolio. Even if the portfolio includes assets of different markets as well as asset classes, the primary focus and evaluation point for the portfolio are the fixed-income assets and their performances. This is due to the interest of the department where the thesis is written and the fact that it is too wide in range to evaluate all assets in detail. As earlier discussed, fixed-income instruments can be very complex and differ a lot from each other. In the thesis, only government fixed-income instruments will be considered. These instruments can be traded as derivatives and hence diverge in character, for that reason a small set of assets are important for keeping the report within scope. One common denominator among the instruments is the duration, it will be set to bonds ranging between 2 and 10 years in expiry.

The exact instruments that make up the CTA portfolio will not be disclosed due to competitive reasons, nor will the exact formula for calculating the trend signal. A framework of how the signal is detected will be given for ensuring the technical level of the thesis, as well as a description of common qualities of the traded instruments. The portfolio will be made up of several asset classes and the asset classes will be outlined, since the thesis heavily focuses on the performance of fixed-income instruments, no large weight will be put into describing the assets from other asset classes. The diversification is solely used as a market performance reflection and the instruments themselves, apart from fixed-income instruments, are not of importance.

The strategy developed is neither meant to be an investment strategy for the bank nor a recommendation for anyone reading the paper. It will only be used as an information provider to predict other patterns in the market. Since all the trades are centralized to the bank and another party, the thesis will only cover OTC trading and not any traded on an open exchange. All derivatives covered in the thesis are European options, meaning they can be exercised only on the expiration date. American options, Asian, or anything else than European vanilla options will not be covered.

Chapter 2

Theory

2.1 Concepts used for financial evaluation

2.1.1 Return

Return on an asset for a period t_i is seen as the price difference in percent between those periods in time.

$$r_t = \frac{P_t - P_{t-1}}{P_t}$$

This is valid for all assets that are quoted in price. The return on assets quoted in yield is explained in in the sub chapter below.

Return on assets quoted in yield

The asset selection mostly consists of instruments quoted in price but some are not available on the futures market and fixed-income instruments, such as the swaps, are priced in yield. This means their return cannot be calculated as the percentage of change from one day to another. A shorter explanation of how the relation between price and interest rate will be given in order to calculate a proper return that is comparable to the other assets, quoted in price.

The price-yield relation is inverse and has a convex shape which gets more convex the higher the yield [6]. The inverse price yield relationship follows naturally from the expression of the price of a bond [6].

$$\mathrm{P} = C\left[\frac{1-1/(1+r)^n}{r}\right] + \frac{M}{(1+r)^n}$$

Where:

C = annual coupon

r = yield of the bond

n = years to maturity

M = face value to be repaid upon maturity

The instruments concerned about this price model do not generate a coupon and the price can be expressed as:

$$\mathrm{P} = \frac{M}{(1+r)^n}$$

One can deduct a linear curve with the negative maturity representing the slope. Close to the par value, here set to an example of \$ 100 but normally for the illustrative example but normally \$ 100 M, the curve follows the real price-yield curve very well.

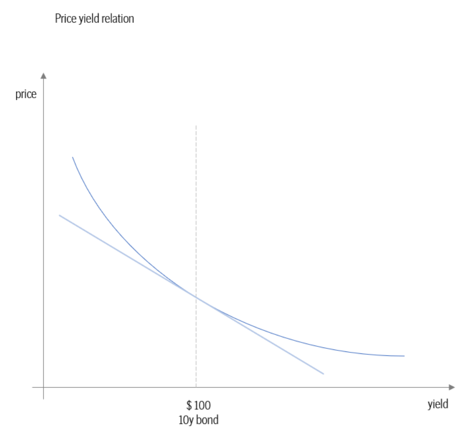

Figure 2.1: Example of a price yield inverse relation of a 100\$ 10-year bond

To get a representative return on the yield quoted instruments, the Bloomberg tool mid risk for bonds was used. It assumed all instruments with the same time to maturity followed the same curve and the further the yield was from pair, the bigger the constant added to the return was. With The formula for the return that was used followed:

$$\mathrm{r}_i = D(y_i - y_{i-1}) + C_y$$

Where:

C_y = constant unique for each time to maturity

y_i = yield of the bond day i

n = years to maturity

2.1.2 Risk

All assets that are not risk-free come with risk, they can be referred to as risky assets. The risk depends on the price volatility and a higher volatility implies a higher degree of risk.

For a single asset, the risk is the standard deviation of the return $\sigma(r)$ but since the correlation between assets often not is 0, the risk for a whole portfolio takes the covariance matrix into account.

The total risk of a portfolio is dependent on the covariance matrix Σ as well as the weights of each asset [10]. If we have N risky assets and let the weight vector be $x = [x_1, \ldots, x_N]^T$, the total risk of the portfolio is described as:

$$\sigma(x) = \sqrt{x^T \Sigma x}$$

2.1.3 Sharpe ratio

The Sharpe ratio is used to evaluate an investment in an asset or a portfolio, it measures the ratio between return and risk. If a risk-free rate is considered, it will be substituted from the return since a total investment in the risk-free asset would return r_f, the return on a risky asset can therefore be seen as the difference between the real return and r_f [11]. The Sharpe ratio is defined as:

$$SharpeRatio = \frac{\text{return on portfolio - risk-free rate}}{\text{risk of portfolio}} = \frac{r_p - r_f}{\sigma p}$$

Where:
r_p = return of portfolio
r_f = risk-free rate
σp = standard deviation of the portfolio's excess return

2.1.4 Drawdown

Drawdown is defined as the largest decrease of value of the portfolio since the last peak, often constrained with a certain lookback period. It refers to the decline in value of an individual investment or an investment portfolio from its highest point within the designated lookback period to its current value. Drawdown is measured in percentage in the decrease between these two measurements. The yearly drawdown of the S&P 500 between 1998 and 2021 is shown in figure 2.2.

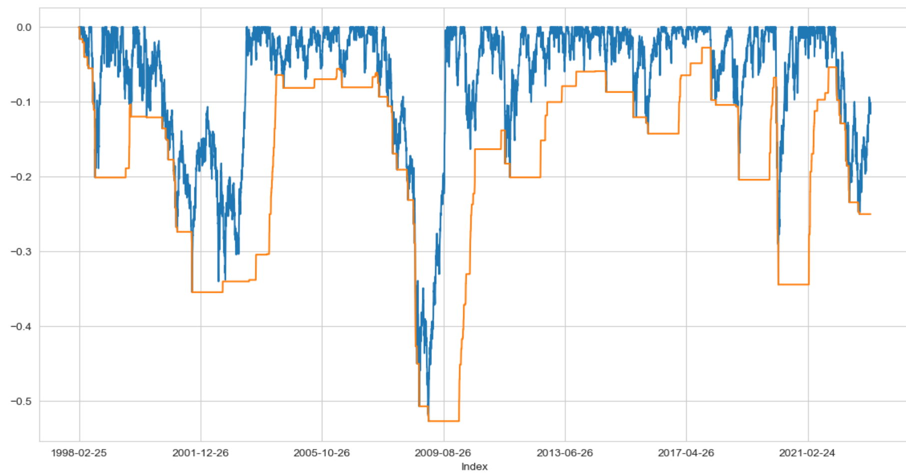

Figure 2.2: Example of a drawdown plot

2.2 Derivatives

The most common instruments traded such as currencies, equities, fixed-income and commodity make up the financial system and their prices are easily digested. They either represent a claim on assets of corporations, claims of natural resources or a monetary unit. These instruments all trade on the spot market, meaning they are traded with an exchange of cash in order to get the security with immediate delivery. These are not the only instruments that make up the global financial markets, derivatives are essential to transfer risk between two parties and they derive their price from an underlying asset on the spot market [17]. Their nature is somewhat more complex but futures, options, and swaps all go under the concept of financial derivatives. The three types of derivatives are used in completely different ways in the report but will be presented in order to understand the instruments as well as get a good understanding of how trend will be measured.

2.2.1 Futures

A future is a type of forward commitment which binds two parties to trade at a set date in the future. A future is a standardized contract that can be traded on the futures exchange and the contract itself is an agreement between the buyer and the seller. A future is a type of forward commitment that binds the buyer and seller to trade a specified asset, the underlying, for a predetermined price at a given date in the future [17]. Futures were the foundation of CTA but the assets in the CTA of the report consists of different type of contracts, some of them are futures and that makes the pricing easier specifically for rates, which otherwise, are quoted in yield. The pricing of futures is not relevant to the scope of the thesis.

2.2.2 Swaps

A swap is, like a future, a forward commitment between two parties. It binds two parties to swap an asset at a certain date in the future [17]. In this report, the only swaps considered are interest rate swaps from the Swedish, European, and American markets and the swap is quoted in yield, not an amount of a currency. The yield, or interest rate, is the price the buyer must pay in order to trade either a fixed interest rate to a floating one or the opposite. Therefore the swap can be used as an instrument to change debt from a fixed interest rate to a floating one or, the contrary, from a floating rate to a fixed rate. The swaps covered are seen as assets that may be included in the CTA.

2.2.3 Options

Options differ from the two, already mentioned, derivatives since it gives the buyer the right but not the obligation to trade an asset at a set date in the future. The seller must buy or sell the asset at this date if the buyer decides to exercise the option [17]. For this, the buyer pays the seller a premium no matter if the option is exercised or not. This premium is the price of the option and reflects the fair market price [17]. Options give the investor a non-linear exposure to the underlying asset because of the non-linear payoff, the different payoffs are described under the different option types for both the buyer and seller. The buyer of an option takes a long position and is sometimes referred to as *the long*, the seller takes on a short position and can therefore be referred to as *the short*. When trading an option, the strike price, K, is decided between the buyer and the seller. This price is the level that the asset will be traded at if exercised.

Call option

A call option gives the buyer the right, but not the obligation, to buy a certain asset at a set price at a set date in the future. If the buyer exercises the option on the expiration date, the seller must sell the option for the price K.

The payoff for the long call (buyer of a call option) is:

$$\mathrm{c}_T = max(0, \mathrm{S}_T - K)$$

The long position pays a premium c_0 to the seller. We denote the profit of the buyer:

$$\Pi_{long} = max(0, \mathrm{S}_T - K) - c_0$$

Where:

T = Expiration date

S_T = Price of underlying asset at time T

c_0 = Premium of the call option

The short call's payoff is the negative payoff of the long:

$$-\mathrm{c}_T = -max(0, \mathrm{S}_T - K)$$

We denote the profit of the seller:

$$\Pi_{short} = -\Pi_{long} = -max(0, \mathrm{S}_T - K) + c_0$$

Put option

A put option gives the buyer the right, but not the obligation, to sell a certain asset at a set price at a set date in the future. If the buyer exercises the option on the expiration date, the seller must buy the option for the price K.

The payoff for the long put (buyer of a put option) is:

$$\mathrm{p}_T = max(0, K - \mathrm{S}_T)$$

The long position pays a premium p_0 to the seller. We denote the profit of the buyer:

$$\Pi_{long} = max(0, K - \mathrm{S}_T) - p_0$$

The short put's payoff is the negative payoff of the long:

$$-\mathrm{p}_T = -max(0, K - \mathrm{S}_T)$$

We denote the profit of the seller:

$$\Pi_{short} = -\Pi_{long} = -max(0, K - \mathrm{S}_T) + p_0$$

Straddle

An option can be customized in many different ways to suit the investor. One important option combination for the thesis is called a straddle, it will be used to measure trend for an underlying asset. The idea of a straddle is that one buys a call option and a put option with the same strike price, $K_C = K_P$. The buyer will pay $c_0 + p_0$ for the combined option and the profit of the buyer is:

$$\Pi_{long} = max(0, \mathrm{S}_T - K) + max(0, K - \mathrm{S}_T) - c_0 - p_0$$

The profit of the short position is the negative profit of the long position:

$$\Pi_{short} = -max(0, \mathrm{S}_T - K) - max(0, K - \mathrm{S}_T) + c_0 + p_0$$

A profit for the long position often requires a significant price movement since the buyer is paying a double premium to the seller [17]. It can be hard to make money from this type of option and the purpose of the straddle is in this case only to give an idea about the dynamics of the trend signal later introduced.

2.3 Pricing derivatives

In the financial sector, to price vanilla European options, the Black-Scholes model is fundamental for options with underlying assets with $S > 0$. Since the scope of this report focuses on assets of different classes, such as rates, currencies, equities, and commodities and some of these have had a $S > 0$ during the chosen period, some solutions for this problem will be presented in order to measure the options (and therefore the trend) equally.

2.3.1 Black-Scholes model

The Black-Scholes model was presented in 1973 and is is still the norm in modern-day finance. The model was a milestone in option pricing and sets a fair market price on options [4]. Fischer Black and Myron Scholes presented the following relations useful for the report:

Call option price:

$$\mathrm{c}_0 = \mathrm{S}_0 e^{-qt}\Phi(\mathrm{d}_1) - \mathrm{K}e^{-rt}\Phi(\mathrm{d}_2)$$

Put option price:

$$\mathrm{p}_0 = \mathrm{K}e^{-rt}\Phi(-\mathrm{d}_2) - \mathrm{S}_0 e^{-qt}\Phi(-\mathrm{d}_1)$$

Where:

$$\mathrm{d}_1 = \frac{1}{\sigma\sqrt{\mathrm{t}}}\left[\ln\left(\frac{S_0}{K}\right) + t\left(r + \frac{\sigma^2}{2}\right)\right]$$

$$\mathrm{d}_2 = \mathrm{d}_1 - \sigma\sqrt{\mathrm{t}}$$

$\Phi(x)$ is the normal cumulative distribution function (CDF):

$$\Phi(x) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{x} \mathrm{e}^{-\frac{1}{2}z^2} dz$$

S_0 = Price of the underlying asset at time 0

K = Strike price of the option

r = risk-free interest rate, $r \in [0,1]$

q = dividends for the stock

σ = volatility of the stocks return $\sigma \in [0,1]$

t = time to option maturity $t \in [T,0]$ (in years)

Option greeks in the Black-Scholes model

The greeks in the Black-Scholes model are derivatives derived from the price formula. Mostly used are:

Delta:

$$\delta_c = \frac{\partial C}{\partial S}, \delta_p = \frac{\partial P}{\partial S}$$

Gamma:

$$\gamma_c = \frac{\partial^2 C}{\partial S^2} \quad \text{(same for the put option)}$$

Vega:

$$\nu_c = \frac{\partial C}{\partial \sigma} \quad \text{(same for the put option)}$$

Theta:

$$\theta_c = \frac{\partial C}{\partial t} \quad \text{(same for the put option)}$$

To calculate the signals from the different assets of the portfolio, we will use the delta function. The delta is a property of the Black-Scholes model and is calculated by taking the first derivative of the option price with respect to the underlying price S.

$$\delta_c = \frac{\partial c}{\partial S} = \mathrm{e}^{-\mathrm{qt}}\Phi(\mathrm{d}_1)$$

$$\delta_p = \frac{\partial p}{\partial S} = -\mathrm{e}^{-\mathrm{qt}}\Phi(-\mathrm{d}_1)$$

Dividends are not relevant for the instruments within the scope of this report. Without dividends $q = 0 \to e^{qt} = 1$:

$$\delta_c = \Phi(\mathrm{d}_1)$$
$$\delta_p = -\Phi(-\mathrm{d}_1) = \Phi(\mathrm{d}_1) - 1$$

These measurements can also be interpreted as the elasticity of the option price with respect to the stock price. The d_1 function is later put into the CDF.

2.3.2 Bachelier

To cope with negative prices on the commodity futures market and negative interest rates, the Black-Scholes model is not sufficient. The problem with negative interest rates and the Black-Scholes model is the calculation of d_1. Recall:

$$\mathrm{d}_1 = \frac{1}{\sigma\sqrt{\mathrm{t}}}\left[\ln\left(\frac{S}{K}\right) + t\left(r + \frac{\sigma^2}{2}\right)\right]$$

$$\mathrm{d}_2 = \mathrm{d}_1 - \sigma\sqrt{\mathrm{t}}$$

The $ln(x)$ function is only defined for $x > 0$. For swap rates, S_T and K have been on levels below 0, making a need for an extension of the Black-Scholes model indispensable where negative prices are allowed [22]. The Bachelier model [1] was presented way ahead of its time, introducing Brownian motions 5 years before Einstein as well as a method of pricing options to a fair price 73 years before Black and Scholes. Yet, Bachelier has gained popularity in the last couple of years, more than 100 years after his model was presented. The Bachelier model is defined for all S_T and K, in comparison to the Black-Scholes model where S_T/K has to be *greater* than 0.

The Bachelier model assumes the T[1]-forward price of an asset (the underlying) follows an arithmetic Brownian motion with volatility σ_N whereas the Black-Scholes model assumes a geometric Brownian Motion with volatility σ_{BS}. σ_N measures the absolute change in the forward price, σ_{BS} measures the relative change in the forward price [22]. Meaning:

$$dF_t = \sigma_N dW_t$$
$$\frac{\mathrm{d}F_t}{\mathrm{d}F_t} = \sigma_{BS} dW_t$$

The dynamics of the forward price will not be presented in detail, but important is that the volatility is measured differently. In the code, σ_N will be calculated as $\sigma_N = S_0\sigma_{BS}$, other variables are used in the same way.

Bachelier derived the following relations for fair market prices for options.

Call option price:

$$\mathrm{c}_B = (\mathrm{S}_0 - \mathrm{K})\Phi(\mathrm{d_N}) + \sigma_N\sqrt{T-t}\phi(\mathrm{d_N})$$

Put option price:

$$\mathrm{p}_B = (\mathrm{K} - \mathrm{S}_0)\Phi(-\mathrm{d_N}) + \sigma_N\sqrt{T-t}\phi(-\mathrm{d_N})$$

Where:

$$\mathrm{d}_N = \frac{S_0 - K}{\sigma_N\sqrt{T-t}}$$
$$-\mathrm{d}_N = \frac{K - S_0}{\sigma_N\sqrt{T-t}}$$

Note that $\phi(x)$ is the probability density function of the normal distribution.

Similarly to the Black-Scholes model, the delta functions are the following:

$$\delta_c^B = \frac{\mathrm{d}c_B}{\mathrm{d}S_0} = \Phi(\mathrm{d_N})$$
$$\delta_p^B = \frac{\mathrm{d}p_B}{\mathrm{d}S_0} = -\Phi(-\mathrm{d_N}) = \Phi(\mathrm{d_N}) - 1$$

Since investors assumed that prices always will be strictly positive, the Black-Scholes model has been the industry standard since its introduction [22]. The fixed-income market was the first to switch to the Bachelier formula during the mid-2010s when interest rates went below zero, followed by the commodity derivatives market with negative oil futures [22].

[1] T is the expiration date

2.3.3 Shifting

Shifting is another methodology for adjusting the Black-Scholes model for negative prices. The problem can be solved by adding a positive shift α, representing the most negative level of the asset, to the forward price s.t.:

$$dF = \sigma(F+\alpha)dW_t$$

One of the main points of criticism for this method is that one has to know beforehand the level of α for the model to work properly [21]. For the data considered in the report, all prices are known. On the other hand, if the model should be able to function in real-time, this method might not be optimal.

2.4 Asset weighting

To construct a portfolio we must allocate weights to the different assets. The weight can be allocated with several methods and different methods are good for different purposes. Each asset has different properties when it comes to risk and periodical return, and therefore the different weights of each asset in a portfolio

2.4.1 Risk parity

The concept of risk parity portfolios was first introduced by Qian [8] in 2005. Since investing in a CTA includes taking on risky positions (by shorting assets) the risk parity portfolio will be used to examine if risk can be reduced by asserting a risk-adjusted weight to each asset in the portfolio. A risk parity portfolio limits the individual asset losses and are expected to generate exceptional return on the total portfolio [8].

Consider a portfolio with N risky assets with respective weights $x = [x_1, \ldots, x_N]$. We do not allow shorting ($x_i \geq 0$) and we assume total capital allocation in the portfolio s.t. $\sum_i^N x_i = 1$. We denote the variance of asset i σ_i^2, the covariance between asset i and j σ_{ij} and the covariance matrix Σ. We let $\sigma(x) = \sqrt{x^T\Sigma x}$ denote the risk of the portfolio. If we develop the notion for risk further we get that $\sqrt{x^T\Sigma x} = \Sigma_i x_i^2\sigma_i^2 + \Sigma_i\Sigma_{i\neq j}x_ix_j\sigma_{ij}$. The marginal risk contribution for asset i is defined as the following:

$$\partial_{x_i}\sigma(x) = \frac{\partial\sigma(x)}{\partial x_i} = \frac{x_i\sigma_i^2 + \Sigma_{i\neq j}x_j\sigma ij}{\sigma(x)}$$

The marginal risk contribution can be used to describe the total contribution of risk from an asset in the portfolio in the same manner as Maillard, Roncalli, Teiletche [10] as $\sigma_i(x) = x_i \times \partial_{x_i}\sigma(x)$

The definition of risk parity can then be written as:

$$x_i \times \partial_{x_i}\sigma(x) = x_j \times \partial_{x_j}\sigma(x), \forall i, j$$

Meaning, the risk contribution is the same for all assets in the portfolio. The problem can be written as [10]

$$x^* = \left\{ x \in [0,1] : \sum x_i = 1, x_i \times \partial_{x_i} \sigma(x) = x_j \times \partial_{x_j} \sigma(x), \forall i,j \right\}$$

The equation has no closed-form solution and solving for optimal weights requires a numerical solution.

$$\begin{aligned} x^* = & \arg\min_x \sum_{i=1}^{N} \sum_{j=1}^{N} \left(x_i(\Sigma x)_i - x_j(\Sigma x)_j \right) \\ \text{s.t.} \quad & 1^T x = 1 \\ & 0 \leq x \leq 1 \end{aligned} \tag{2.1}$$

2.4.2 Equal weighting

In with equal weight, the weights of the assets are the same in the portfolio, the definition can be written as $x_i = x_j, \forall i, j$. This method does not require any optimization and as long as N stays equal, the weight will not change.

$$x_i = \frac{1}{N} \sum_{i=1}^{N} x_i = \frac{1}{N}$$

2.4.3 Markowitz's efficient frontier

Though Markowitz himself claims [9] that the epithet 'father of modern portfolio theory' is ill-founded, one can say with confidence that his findings changed the view of diversification and its importance in asset selection. The portfolio theory he published in 1952 presented a mathematical foundation for creating a diversified strategy and we will consider one of the feasible portfolios in Markowitz's theory: the portfolio on the efficient frontier which maximizes the Sharpe ratio.

Like in the case of the risk parity portfolio, we consider N risky assets and respective weights $x = (x_1, \ldots, x_N)$. We do not allow shorting $[x_i \geq 0]$ and we assume total capital allocation in the portfolio s.t. $\sum_i^N x_i = 1$. We denote the variance of asset i σ_i^2, the covariance between asset i and j σ_{ij} and the covariance matrix Σ. We let $\sigma(x) = \sqrt{x^T \Sigma x}$ denote the risk of the portfolio. Besides this, we consider $R = [R_1, \ldots, R_N]^T$ the single-period returns, $E[R] = \alpha = [\alpha_1, \ldots, \alpha_N]^T$ the mean of returns. The expected return for the whole portfolio for a single period $\alpha = E[R] = x^T \alpha$.

Markowitz claims that an efficient portfolio is a portfolio that generates a maximum return for a given risk. He identifies a set of efficient portfolios in the feasible set of portfolios (all linear combinations of weights x in a portfolio). The set will be referred to as the efficient set and represent the portfolios that maximize return for a given risk. We can evaluate all feasible portfolios by changing the weights x to find the portfolios that are a part of the efficient set.

To find the set of efficient portfolios, for each given target of risk $t \in [0, \infty)$, find the optimal portfolio by optimizing:

$$\begin{aligned} \max_{x} \quad & x^T \alpha \\ \text{s.t.} \quad & x^T \Sigma x = t \\ & 1^T x = 1 \end{aligned} \tag{2.2}$$

Optimal portfolio

There are different ways of selecting the optimal portfolio and the portfolio depends completely on the application or the preferences of the fund manager. The efficient frontier consists of a set of portfolios with maximal return for a given risk level. In this thesis, the optimal portfolio will be the portfolio on the efficient frontier with the highest Sharpe ratio, since a given risk level is not set and the Sharpe ratio will be used for the evaluation of strategies. To find the portfolio in the efficient set with the highest Sharpe ratio, the optimization becomes:

$$\begin{aligned} \max_{x} \quad & \frac{x^T \alpha - r_f}{\sqrt{x^T \Sigma x}} \\ \text{s.t.} \quad & 1^T x = 1 \end{aligned} \tag{2.3}$$

2.5 Trend signal and asset allocation

The trend signal uses the earlier presented theory on derivatives and asset allocation. The combined signal will be presented briefly. The signal is trend-following and has to generate profit in persistent bear and bull markets, hence, the straddle will be used to measure the trend. A perpetual trend will generate a higher absolute value of the delta signal and the sign of the signal will indicate the direction of the trend. For a straddle with $\text{price}_{\text{straddle}} = C + P > 0$, the payoff will be negative if S is *close enough* to K. A certain trend will therefore be required in order for the straddle to be profitable.

$$\delta_C = \mathrm{N}(\mathrm{d}_1)$$

$$\delta_P = -\mathrm{N}(-\mathrm{d}_1) = \mathrm{N}(\mathrm{d}_1) - 1$$

$$\delta_{Straddle} = \delta_C + \delta_P = 2\mathrm{N}(\mathrm{d}_1) - 1$$

$\delta_{Straddle}$ will hereafter be presented as $\delta_i^{lb}(t)$ with t a given day on the interval $[0, T]$, i the ith asset in a portfolio and lb the look back period of the data for the calculation. Since $\delta_C \in [0, 1]$ and $\delta_P \in [-1, 0]$, this is a continuous function $\delta_i^{lb}(t) \in [-1, 1]$

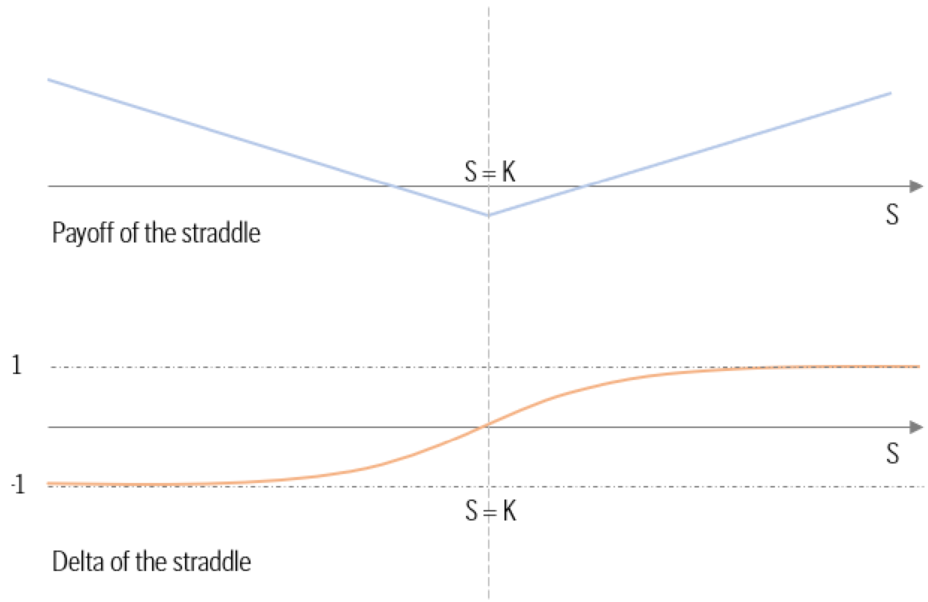

Figure 2.3: Payoff and delta of a straddle

The measurement for trends, the delta, is an element of the Black-Scholes model.

The portfolio constructed will be centered around the daily trend signals for each asset. To get a fair weight of the signals in order to eliminate unnecessary risk, the optimal weight will be included in the signal.

The basic structure of the signal will be:

$$signal_i(t) = w_i(t)\delta_i^{lb}(t) / \sum_{j=1}^{N} |w_j(t)\delta_j^{lb}(t)|$$

Where N is the number of assets in the portfolio, w_i some optimized weight, i the specific asset, $t \in [0,T]$, $\delta_i^{lb}(t) \in [-1,1]$, lb the look back of the delta signal. This leads to a total asset allocation for each $t \in (0,T)$ since the signal is normalized.

$$\sum_{i=1}^{N} |signal_i(t)| = 1$$

Chapter 3

Method

3.1 Data collection

3.1.1 Asset selection

In the process of the asset selection, it was important to diversify the portfolio, this was done by picking assets from different markets and from different global areas. It was important that the asset classes covered the four main markets when it comes to over-the-counter trading: fixed-income, foreign exchange, commodities, and equities. Fixed-income was divided into three main areas: rate futures, interest rate swaps, and credits. That led to a total of six asset classes. For each asset class, at least two different geographies were chosen as the home market of the assets concerned. By researching other CTA strategies, some clues were given for what assets should be chosen and the selection was inspired by many different strategies but with a focus on fixed-income instruments, making up more than 40% of the number of assets. The assets are summarized in the two tables below.

Table 3.1: Description of asset classes of the assets in the portfolio

Asset class	Number of assets	Priced	Short description
Equities	13	price	Equity indexes tracking between 25 and 2000 assets in a specific region or field
Credits	4	price	Credit indexes
Rates	14	price	Interest rate futures ranging between 2 and 10 years
Swaps	9	yield	Interest rate swaps, the rate to pay to switch between moving and fixed interest rate ranging between 2 and 10 years
Commodity	11	price	Global price of different commodities
Currencies	13	price	Currency pairs with global range

Figure 3.1: Correlation between the returns of the asset classes

The assets can also be divided into different geographical areas. The four different classes are Europe, North America and South America, Asia and Oceania, and a global market. The global market consists of the commodity assets since the price of them is the global price. There exist geographically specific commodity assets but since the assets will be the same no matter the grouping, those assets will not be used and instead a global class was created.

Table 3.2: Description of asset classes of the assets in the portfolio

Geographical asset class	Number of assets	Region
Europe	25	European assets and currencies influenced by the European market
South and North America	12	Ibid as previous with North, Central and South America
Asia and Oceania	16	Ibid as previous with Asia and Oceania
Global	11	Globally priced assets, commodities in this case

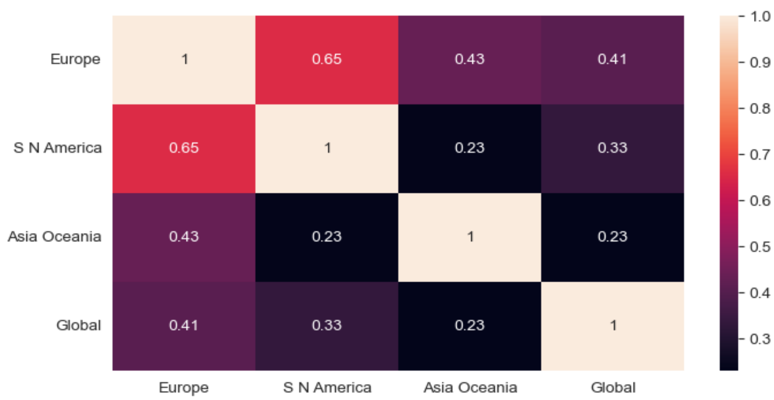

Figure 3.2: Correlation between the returns of the asset classes

3.1.2 Financial data

All financial data was collected from Bloomberg and the price was the closing price and the mid of the spread, meaning, the price between the best bid and lowest offer. For the assets quoted in yield, the mid-price was also considered which made the collection easier since the price-yield relationship is inverse and a higher yield means a lower price and vice versa. One data point was collected for each asset for each day for the days within the chosen period of time. The period considered was 2003-01-01 to 2022-12-31, exactly 20 years of data.

3.1.3 Data preparation

All data was prepared and analyzed using Python and the library Pandas. Since the data was prepared from Bloomberg with the desired prices each day, the data did not need any cleaning. The only preparation was to section the data into the right time frame. The optimization was performed with the SciPy optimization package and the method for optimizing was Sequential Least Squares Programming (SLSQP) with the equal weight as starting weights.

3.2 Delta

The delta signal was calculated for three different lookback periods, one quite short, one medium with double the lookback of the short, and one long double as long as the medium one. For each day within the lookback, a delta value was calculated and the delta signal of day t was the average of $delta_{t-LB}$ to $delta_t$ to capture the momentum trend. This was performed for each asset in the portfolio and each delta signal is independent from the other signals. The delta signal, or the trend signal, was calculated with the Black-Scholes formula for delta. The delta signal was calculated per day as the delta of a straddle, meaning, $2\Phi(d_1) - 1$.

With the swaps, assets that had a negative yield during the time period, the Bachelier formula for delta was used and delta was calculated as $2\Phi(d_N) - 1$ where d_N is from the calculation of the option price in the Bachelier formula.

Figure 3.3. shows the delta signals for all 64 assets for a shorter time period within the time period considered. Figure 3.4 shows an example of an asset in the portfolio with different lookback periods. The shorter lookback generates a quicker responding trend signal that is more sensitive to changes in the price whereas the longer one takes longer to react.

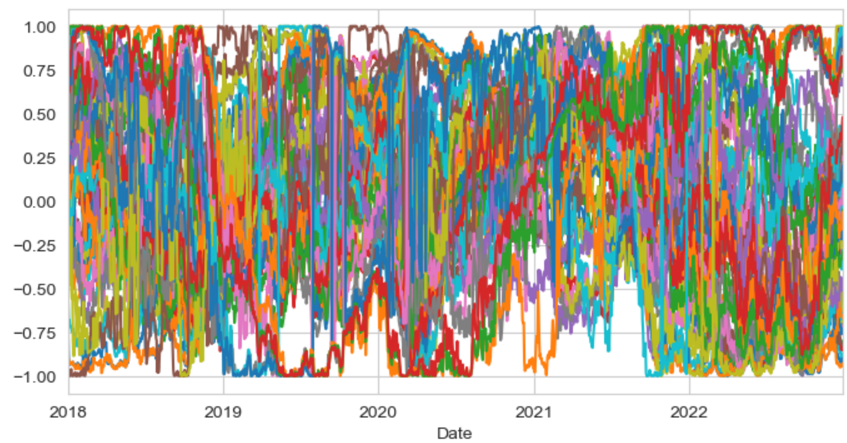

Figure 3.3: Delta signal for all assets 2018-2022

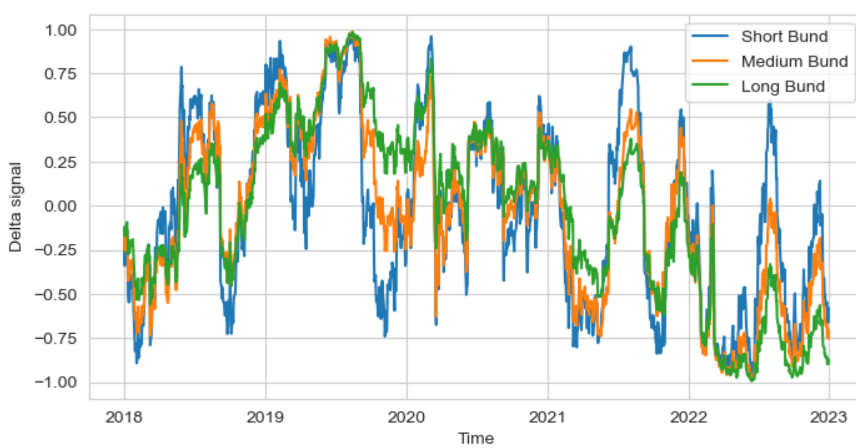

Figure 3.4: Delta signal for the Bund 10y for different lookback periods

Adjusting for negative future and swap prices

When testing the different methods for adjusting the Black and Scholes model for negative prices, the Bachelier model and shifting method were compared to the original model. The three methods gave almost the same result for all assets that were tested. A plot for a shorter period is shown below, showing almost identical delta signals for each day. The instrument in this example is the Australian 3-year government bond.

Figure 3.5: Plot of delta with three different methods

To understand which method to use as substitution for the Black-Scholes model, the correlations and mean error were examined. The time period was the same as the rest of the data, i.e. 2003-2022. The correlation was calculated by the built-in methods for Pandas dataframes in Python and the difference was the mean of the absolute value of the difference between Black and Scholes delta and the two other methods. This was done for each instrument with negative values but the output shown below is an example of the 3 year Australian government bond.

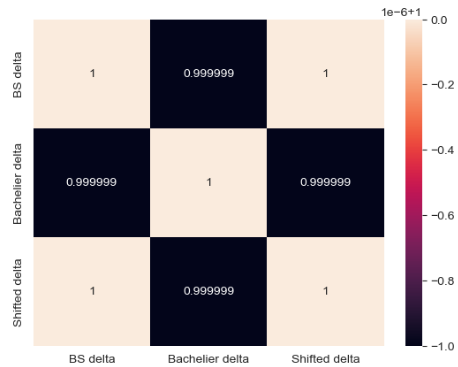

Figure 3.6: Correlation between Black-Scholes delta, shifted delta and Bachelier delta

Table 3.3: Difference in delta for substitutes to the Black-Scholes delta

Method	**Mean of absolute difference in delta**
Bachelier	$1.502 \cdot 10^{-3}$
Shifted	$9.550 \cdot 10^{-7}$

The correlation is slightly higher between the Bachelier delta and the Black-Scholes delta, but neglectable. The mean difference is also larger for Bachelier than for the shifted delta. One main concern about the shifted delta is that one need to know the most negative value in order to use the method. For the historical data, that level is known and the shift α was set to the lowest level of the price + 0.001 in order for S and K to stay above 0. In this case, it worked fine but one cannot know beforehand what that level will be. There might be levels in the future lower than the level of α and the model would have to be revised, making it less efficient and sensitive to crashes. For that reason, the Bachelier delta is preferred and was the method used.

3.3 Weights

3.3.1 Risk parity

A risk parity optimization was performed each day so that whenever a re-balancing point would appear, the optimal weights would not have to be calculated again. Re-balancing could in the result differ between dates within the week, months, or other dates.

After careful consideration, another constraint was added to the risk parity optimization problem. The portfolio consists of 64 assets and when trying out the algorithm to construct a risk parity portfolio, some assets with low risk or negative correlation with the other assets allocated a majority of the portfolio weight on some days.

Since their return was low, an asset allocation like that would not generate a good return, even if the risk is low. An equally weighted portfolio would allocate 1.5623 % of the weight to each asset, and 5% was decided to be the maximum portfolio allocation per asset. The constraint that was added was $x_i \leq 0.05$.

To get a better understanding of both parts of the signal, where delta has to be defined on [-1,1], negative weights, or shorting, was not allowed. Shorting an asset would lead to the strategy going against itself since the sign of delta is to decide if the asset should be shorted or not, a negative weight would change the sign of delta and the trend signal would be useless.

This resulted in three constraints.

$$
\begin{aligned}
x^* = & \arg\min_x \sum_{i=1}^{N} \sum_{j=1}^{N} \left(x_i(\Sigma_{lb}x)_i - x_j(\Sigma_{lb}x)_j \right) \\
\text{s.t.} \quad & 1^T x = 1 \\
& 0 \leq x \leq 1 \\
& x \leq 0.05
\end{aligned} \tag{3.1}
$$

The graphs below show the weights for different lookback periods for the portfolio with all assets.

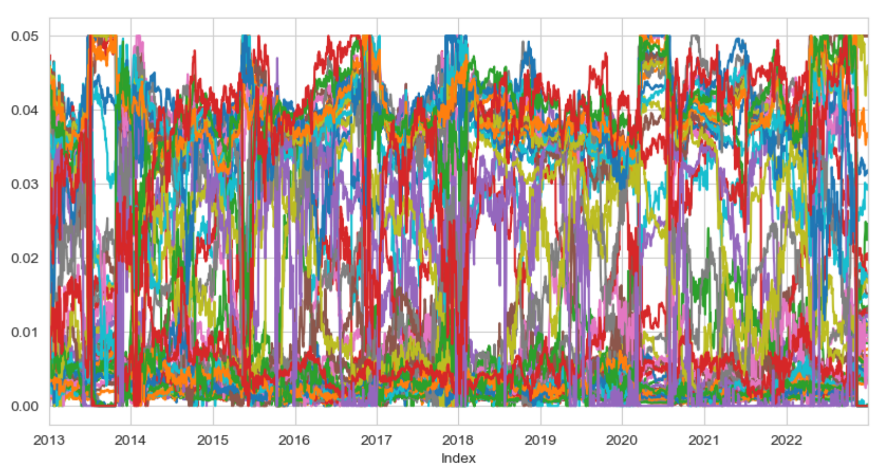

Figure 3.7: Weights for all assets with short lookback

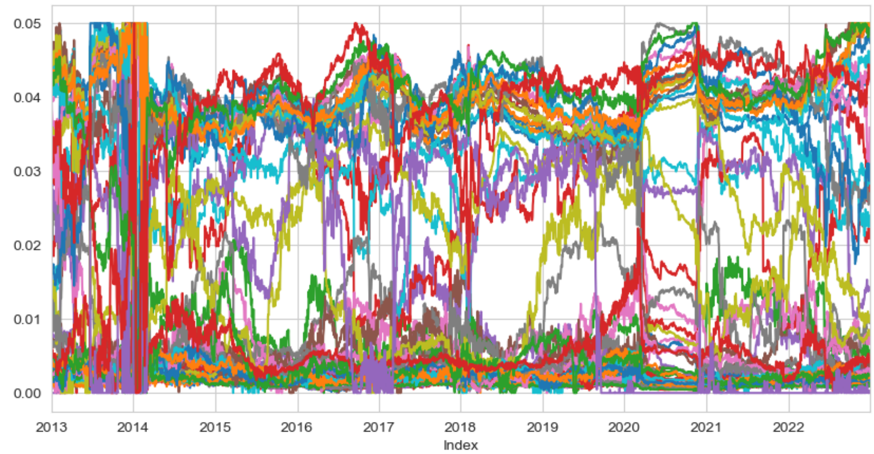

Figure 3.8: Weights for all assets with medium lookback

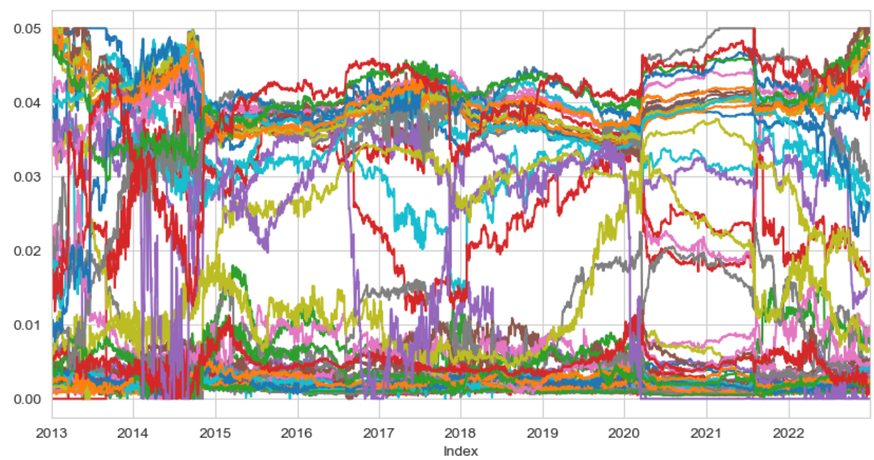

Figure 3.9: Weights for all assets with long lookback

We can clearly see some market patterns reflected in the weights, for example in 2014 and the decrease in interest rates from ECB and FED. In 2017 the interest rate became negative, which can also be seen especially in the shorter lookback risk parity graph. Early in 2020, Covid-19 affected the world and the global market immensely and that is also shown in the graph.

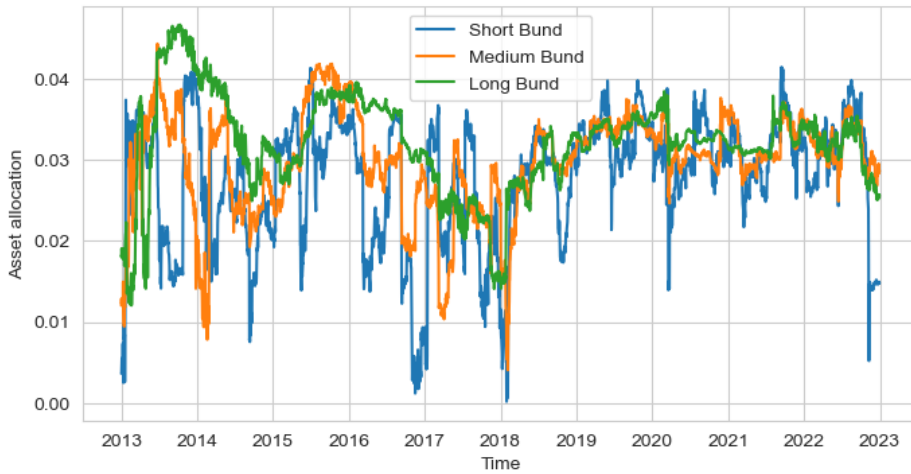

Figure 3.10: Asset allocation for the Bund 10y for different lookback periods

Figure 3.10 shows the difference in the weight assigned to the 10-year German government bond called Bund. A longer lookback generates a more robust weight while the shorter one a more sensitive weight. This was the same for all assets in general, a longer lookback will make the weight less sensitive to changes in prices. This is due to the correlation matrix that was used to calculate risk contribution, a longer lookback will give a correlation matrix that is less sensitive to trend since the time interval is longer and is more likely to capture both upward and downward trends.

Portfolio classes

The portfolio was also divided into an asset class portfolio and a geographical class portfolio. In general, those portfolios can be seen as individual and independent from the other portfolios. This can be described with an example. Let's say that there are six asset classes, each can be seen as its own investment strategy. In one of them, let's say the equity portfolio, the equities take up 100% of the asset allocation and the asset allocation depends only on the different delta signals. There will now be six portfolios with 100% assets allocation each. The risk parity is later used as a second layer for deciding on what portfolios to invest in. The risk parity is performed only on the correlation of the sum of the delta times the next period's return on the specific portfolio. Let's say that for a given day, the optimization gives the equity portfolio 20% of the total capital. That means that we have 20% of the total capital to invest in the equity portfolio and the equity portfolio itself is allocated accordingly to the delta signal only.

There were two strategies like the example, one with asset class portfolios and one with geographical class portfolios. They had six and four portfolios each and were divided as the classes in table 3.1 and 3.2. For this optimization on weight, other constraints were needed since 5% max per asset will not add up to 100%. The constraint that replaced the last constraint from equation 3.1 was a maximum portfolio allocation of the top portfolios of twice the equal weight. For the asset class portfolio that was 33% ($2 \cdot \frac{1}{6} = 0.333$) and for the geographical class the maximum was 50% ($2 \cdot \frac{1}{4} = 0.5$).

This can be summarized to the class weight optimization:

$$
\begin{aligned}
x^*_{class} = &\arg\min_x \sum_{i=1}^{N} \sum_{j=1}^{N} \left(x_i(\Sigma x)_i - x_j(\Sigma x)_j \right) \\
\text{s.t.} \quad & 1^T x = 1 \\
& 0 \leq x \leq 1 \\
& x \leq \frac{2}{N}
\end{aligned}
\tag{3.2}
$$

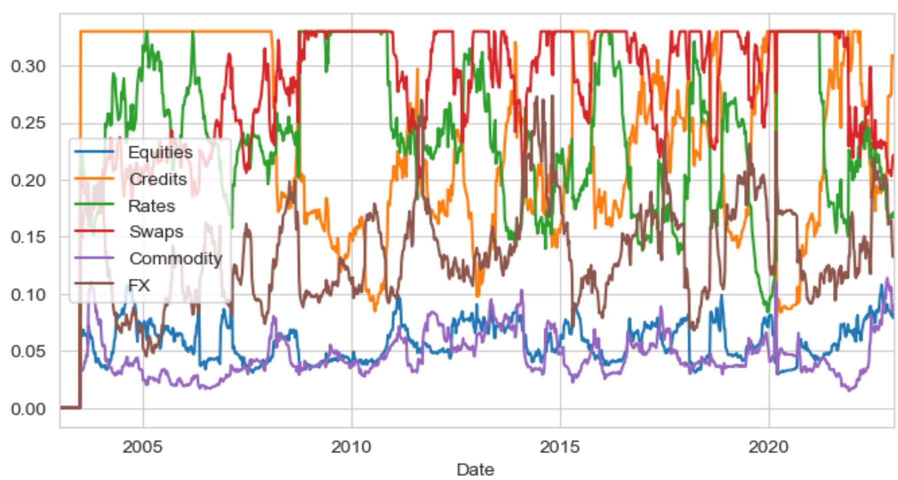

Figure 3.11: Weights for asset class portfolios with medium lookback

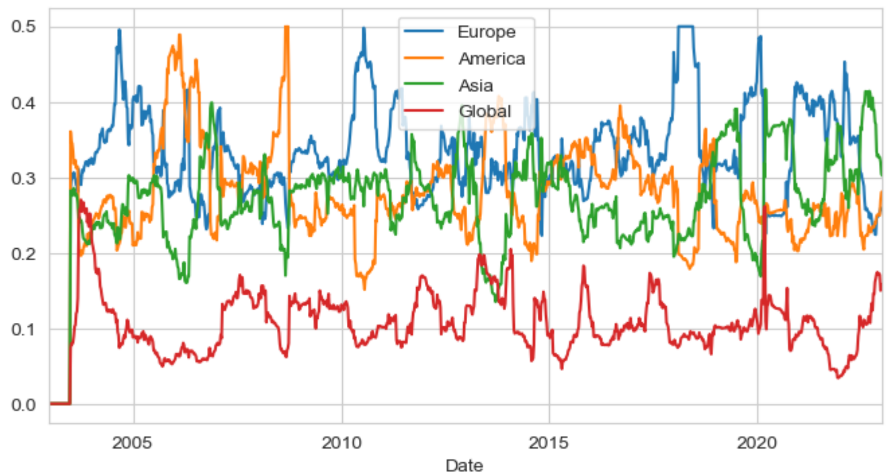

Figure 3.12: Weights for geographical class portfolios with medium lookback

Figures 3.11 and 3.12 show the portfolio allocation of the global (upper level) portfolio containing the sub-portfolios. One can observe that the upper limit sometimes is reached and then the portfolios with that allocation keep a constant weight until the optimization lowers the level at some other day in the future. For the two figures, the medium lookback time was used but all three lookbacks were later examined.

3.3.2 Markowitz weights

The Markowitz weight was calculated for each year within the given time frame, which meant 20 sets of optimal weights. For each year, 1000 portfolios were simulated. The efficient frontier was later calculated and among the sets of portfolios on the efficient frontier, the portfolio with the highest Sharpe ratio was selected as the optimal portfolio. The weights were deduced for each optimization and used as the weight for that selected year. The Markowitz weights were used in order to compare strategies with risk parity weight, equal weights, and Markowitz weights.

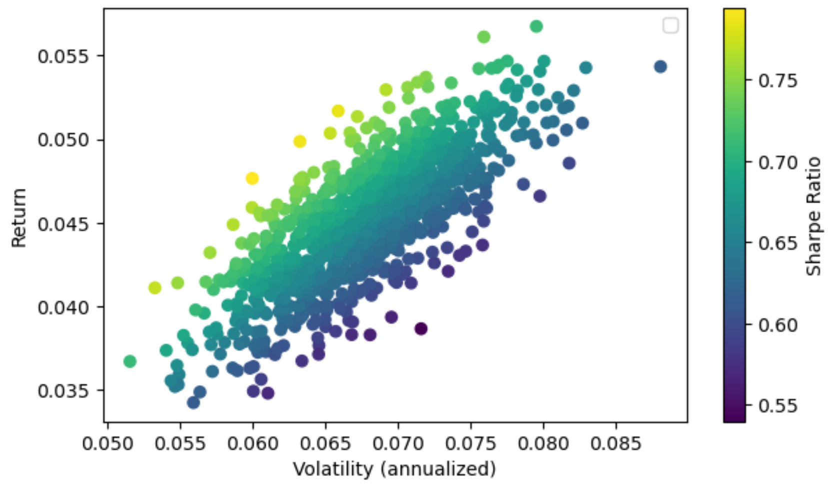

Figure 3.13: Simulated portfolio weights for Markowitz weights

3.4 Signals

At each rebalancing period, the portfolio was rebalanced with a total asset allocation of 100%. That means that the signal had to be normalized at each period such that the sum of the signal for all assets is 1.

$$signal_i(t) = w_i(t)\delta_i^{lb}(t) / \sum_{j=1}^{N} |w_j(t)\delta_j^{lb}(t)|$$

For each set of variables identifying the signal, one lookback length was given. The short signal used the short lookback of the delta and for the covariance matrix of the weight optimization, medium and short for medium and short lookback respectively.

3.4.1 Returns

The returns were calculated as the change in percent between tho days. Meaning $r_i = P_i - P_{i-1}/P_i$. For assets priced in yield, the return was calculated using the relative yield as return times the maturity to take the time frame into account.

To get the return of a strategy, the signal at rebalancing period t_i was multiplied with the return of the next rebalancing period t_{i-1}. This was performed at each rebalancing period and the return was aggregated in order to see the total performance of a strategy.

3.5 Positioning

To get the position of each instrument, the aggregated signal was used. To get the total positioning of the whole signal, the aggregated separate signals were summarized into one. The positioning shows how the investor's position would look like at any moment within the given time interval if the investments start at the first day with total asset allocation at all rebalancing points.

3.5.1 Fixed-income positioning and return

To show an example of what the graphs may look like, we take the rates as an example. There are 14 rate instruments and the example below is with the shortest lookback and daily rebalancing. No normalization of the signal was done since only a subset of the assets are used. That might give a misleading result but the result is only used to show how different variables change the signal, positioning, and return. The proper signal will be used in the result.

Weighted and non-weighted positioning

The weights used were from the calculated risk parity weights only applied to the rates, meaning the total weight was not 100% but the total weight of only those instruments, recall that we use 64 instruments and the weight might therefore be low.

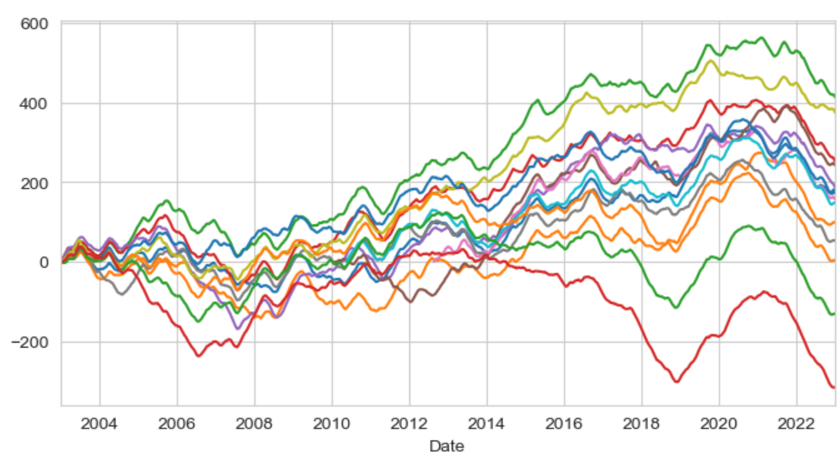

Figure 3.14: Aggregated delta (short lookback) for rates

If we multiply delta with the weight we get the non-normalized signal. The signal is aggregated to get the positions. The same lookback was used for the delta and the weights.

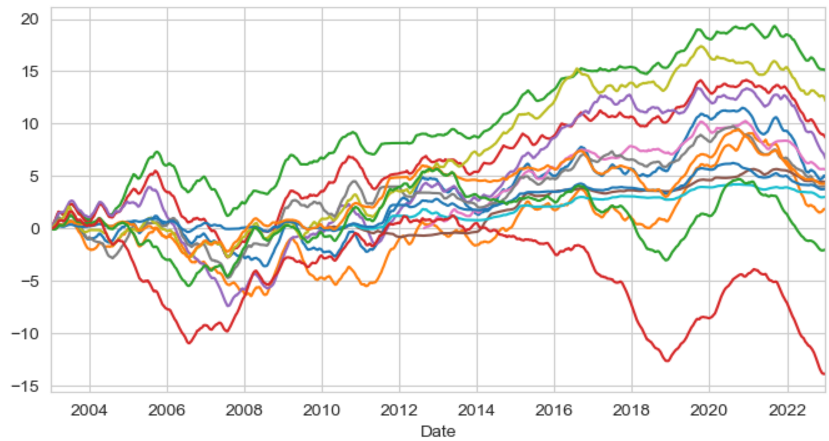

Figure 3.15: Aggregated signal (short lookback) for rates

The weights scale the delta signals and make the signal weaker depending on the specific weight of the specific instrument.

Return with risk parity weights

When the signal is multiplied with the return of the next time period we get the return of that specific asset. Below is a graph of the different aggregated returns for the 14 rates. The weights in this case are the risk parity weights. The return has a tenancy of increasing a lot when the trend is persistent and when the market shows no sign of a long-lasting trend, it often decreases but more slowly.

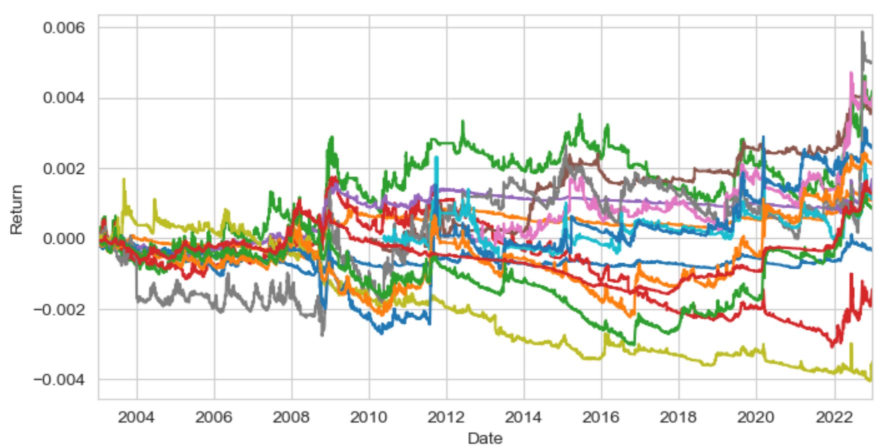

Figure 3.16: Return with risk parity weights for each rate

Figure 3.16 shows the returns on the individual assets and figure 3.17 the sum of the return of all rates with risk parity weights.

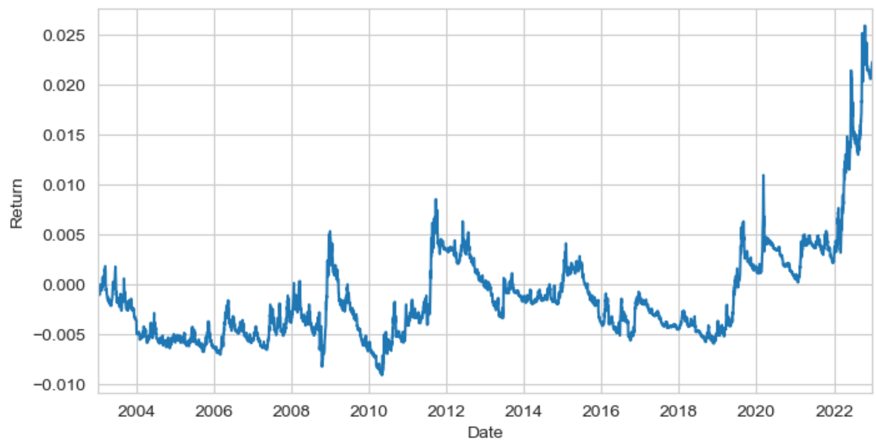

Figure 3.17: Total return with risk parity weights

Return with equal weights

If the risk parity weight is substituted with equal weights, the return looks different, risk parity will benefit assets with low risk, even though they might generate a high return. Equal weight makes no difference between assets and that often leads to equally weighted portfolios performing better.

Figure 3.18 shows the return on the individual assets with only the delta as the signal, to get the equally weighted portfolio, the total return is divided by the number of assets in order to maintain an assets allocation of 100%, as seen in figure 3.19.

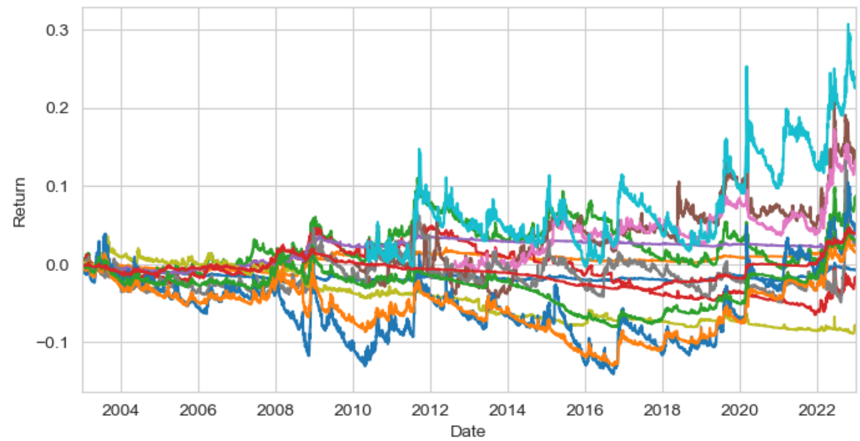

Figure 3.18: Return with no weight scaling for each rate

And by scaling each instrument with the total number of assets, such that the signal is divided by the number of assets we get the equally weighted portfolio.

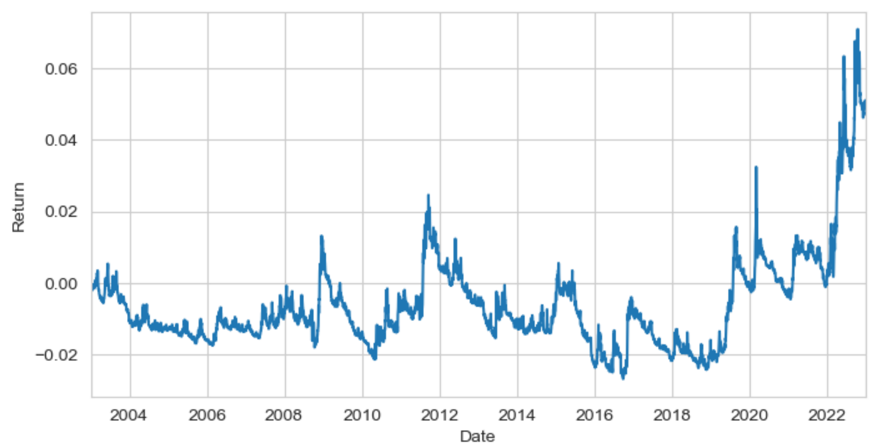

Figure 3.19: Total return with equal weights

Absolute return strategy

We can observe that the return is specifically high during some periods. To illustrate the power of a absolute return strategy, we can examine the return of long-only investing in rates and compare it to the CTA strategy.

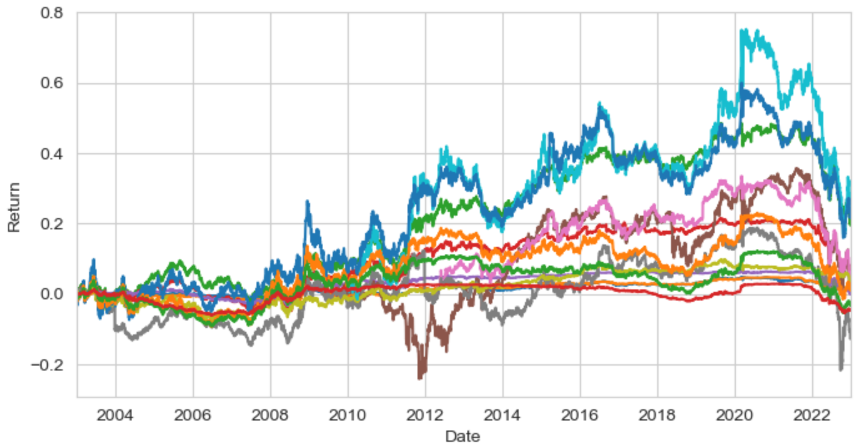

Figure 3.20: Return per instrument

Figure 3.21: Total return for all 14 rates

Overall, a CTA strategy can help generate an absolute return, for example when the market shows a significant trend in any direction. Most obvious for rates are the years 2021 and 2022 where returns on investing long-only decreased substantially and that led to a positive return for the CTA strategy, both for portfolios with risk parity and equal weights.

3.6 Rebalancing

The performance of the strategy can be seen as investing in an index. The investor will hold its positions only until the next rebalancing point and at each point, always invest the total capital in the strategy. There are costs associated with rebalancing, one is transaction cost and another is the fact that depending on the position (long or short), the investor might have to pay for a widespread for some more illiquid instruments. This will not be considered and the CTA strategy should not be seen as a way of investing, but simply as an index tracking different strategies with different variables. Different frequencies of rebalancing will be tested to see what makes up the best strategy.

Chapter 4

Results

In order to evaluate the strategies, some given measurements are used. The measurements used are Sharpe ratio, drawdown and total return. The Sharpe ratio is measured for the whole time interval, meaning the average mean of all returns summed up divided by the standard deviation of the return summed up. The drawdown is the maximum drawdown measured in one year for the strategy and the total return is the aggregated return for the strategy. The result is divided into three different portfolio strategies, one is the common portfolio where all assets are seen as one portfolio. The two other ones are the class portfolios of asset classes and geographical classes. For each strategy, all three lookbacks are evaluated.

4.1 Common portfolio

The common portfolio is the portfolio where the signals are the normalized product of delta and the weight. For this portfolio, different rebalancing points were tested: every day, once a week with different days of the week, once a month, and once a year.

4.1.1 Risk parity weights

The difference in lookback did not change a lot when it comes to the total return, only a couple of percent differed between the three for all rebalancing points. For a portfolio rebalanced each week, there were some differences in performance depending on what day the rebalancing was performed. Tuesdays, Wednesdays and Thursdays resulted in a better-performing portfolio in terms of all measurements compared to the weekdays the closest to the weekend. A portfolio rebalanced every day did not improve performance but lowered the Sharpe ratio slightly, same for the portfolio rebalanced each month. The portfolio rebalanced once a year gave a poor performance in terms of total return but the short signal generated a high Sharpe ratio. For the same strategy, the difference in Sharpe ratio between the three lookback periods was much higher than for the rest of the strategies.

Table 4.1: Performance of portfolios with different days of rebalancing - risk parity

Day of rebalancing	**Sharpe ratio**	**Maximum drawdown**	**Total return**
Monday			
Short	1.5718	-0.0394	0.2475
Medium	1.7341	-0.0438	0.2446
Long	1.9754	-0.0470	0.2625
Tuesday			
Short	1.8443	-0.0341	0.3293
Medium	1.779	-0.0410	0.3134
Long	1.9136	-0.0351	0.3014
Wednesday			
Short	1.9386	-0.0365	0.3324
Medium	1.8337	-0.0423	0.3272
Long	1.9210	-0.0382	0.3122
Thursday			
Short	2.0376	-0.0308	0.3371
Medium	1.9764	-0.0394	0.3087
Long	2.0263	-0.0367	0.2958
Friday			
Short	1.9786	-0.0457	0.2505
Medium	1.8053	-0.0501	0.2483
Long	2.0426	-0.0487	0.2651
Every day			
Short	1.6522	-0.0467	0.2563
Medium	1.5423	-0.0516	0.2451
Long	1.6648	-0.0469	0.2542
Last day of month			
Short	1.7566	-0.0359	0.3020
Medium	1.6335	-0.0392	0.3037
Long	1.8232	-0.0359	0.2887
Last day of year			
Short	3.0866	-0.0651	0.2184
Medium	2.5563	-0.0613	0.2211
Long	2.0759	-0.0692	0.1924

Figure 4.1: Risk parity return for Thursday rebalancing

Strongest signals

A minimum absolute delta value was tested for the strategy where the minimum delta ranged between 0 and 0.9. The table below shows the results when the rebalancing was set to every Thursday.

Table 4.2: Performance of portfolios with different cutoffs on delta - risk parity weights

Min absolute delta	Sharpe ratio	Maximum drawdown	Total return
No cutoff			
Short	2.0376	-0.0308	0.3371
Medium	1.9764	-0.0394	0.3087
Long	2.0263	-0.0367	0.2958
0.1			
Short	2.0334	-0.0318	0.3395
Medium	2.0007	-0.0396	0.3117
Long	2.0289	-0.0370	0.2980
0.2			
Short	2.0458	-0.0319	0.3516
Medium	2.0261	-0.0431	0.3151
Long	2.0372	-0.0394	0.3091
0.3			
Short	2.1381	-0.0357	0.37703

Table 4.2: Performance of portfolios with different cutoffs on delta - risk parity weights

Min absolute delta	Sharpe ratio	Maximum drawdown	Total return
Medium	1.9991	-0.0437	0.3338
Long	2.0435	-0.0390	0.3168
0.4			
Short	2.2715	-0.0379	0.3671
Medium	2.0392	-0.0407	0.3749
Long	2.0150	-0.0405	0.3482
0.5			
Short	2.5534	-0.1168	0.2723
Medium	1.9780	-0.0393	0.3971
Long	2.0214	-0.0430	0.3749
0.6			
Short	2.7167	-0.0600	0.4935
Medium	1.7016	-0.0500	0.3360
Long	2.1201	-0.0550	0.4768
0.7			
Short	1.7747	-0.1350	0.2895
Medium	2.0026	-0.0900	0.4983
Long	1.7002	-0.0500	0.5961
0.8			
Short	-0.2171	-0.1100	0.2361
Medium	0.6797	-0.1500	0.3801
Long	1.2520	-0.1200	0.3355
0.9			
Short	0.5343	-0.1500	0.3264
Medium	-1.2027	-0.1700	0.0052
Long	1.4261	-0.0700	0.2268

The optimal cutoff for both Sharpe ratio and total return is around 0.6. The drawdown for the same cutoff is around double the one without cutoff. If the purpose is to maximize the return, the cutoff can be used. On the other hand, if the strategy should work as a hedging strategy, drawdown is minimized with a 0-0.2 cutoff.

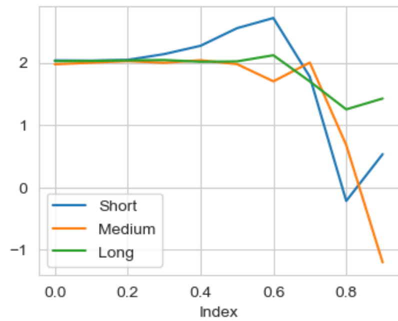

Figure 4.2: Sharpe ratio for different cutoffs - risk parity weights

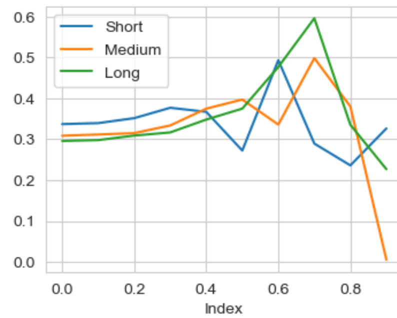

Figure 4.3: Return for different cutoffs - risk parity weights

4.1.2 Markowiz weights

Markowitz weights were examined to compare with risk parity weights. The strategies with these weights resulted in a portfolio with stronger performance in terms of total return and Sharpe ratio but with a higher drawdown. The portfolio rebalanced each day performed worse than the one rebalanced each week - here with rebalancing on Thursdays. The rebalancing each week lead to a more unstable strategy with a large decrease in aggregated return when there was no trend on the market, which lead to a substantially higher drawdown compared to the portfolio rebalanced each week. The aggregated return for the portfolio rebalanced each Thursday had a relatively flat curve when there was only a little trend but performed well during volatile times.

Table 4.3: Performance of portfolios with different days of rebalancing - Markowitz weight

Rebalancing	**Sharpe ratio**	**Maximum drawdown**	**Total return**
Once a week			
Short	2.0702	-0.0962	0.4280
Medium	2.2159	-0.0934	0.5098
Long	2.575	-0.1245	0.5061
Every day			
Short	1.6921	-0.1070	0.1718
Medium	2.040	-0.1136	0.3232
Long	2.5606	-0.1394	0.3847

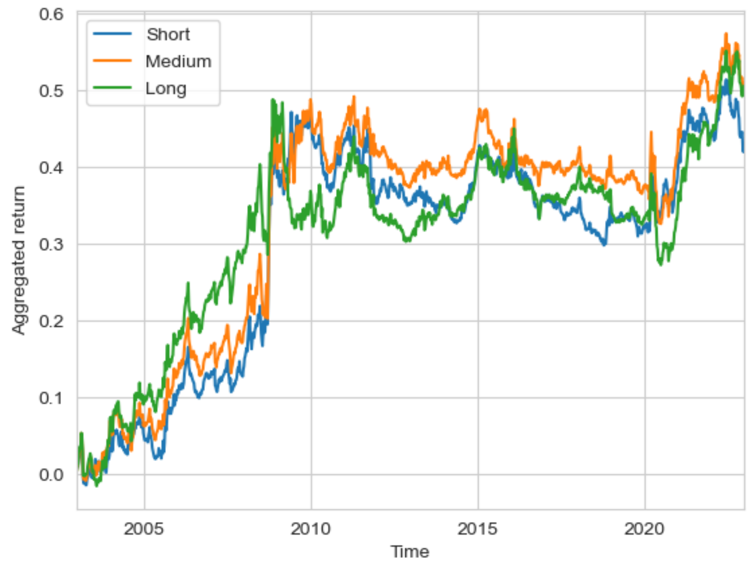

Figure 4.4: Markowitz weights return for Thursday rebalancing

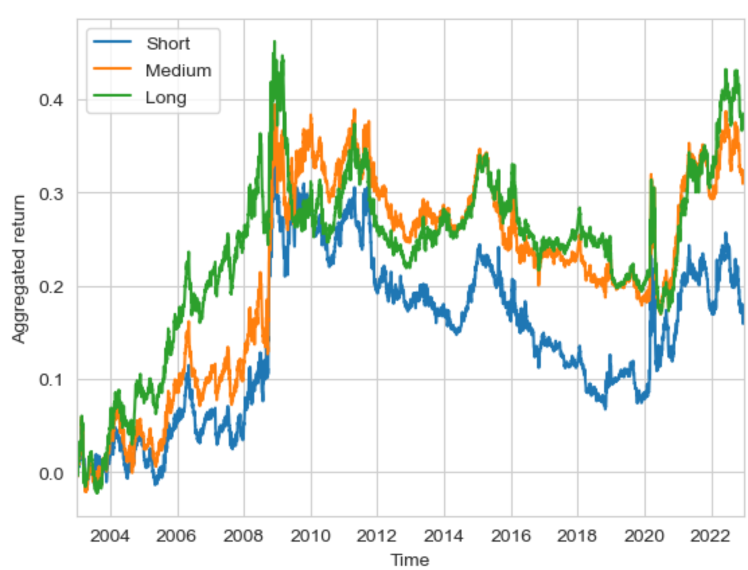

Figure 4.5: Markowitz weights return for daily rebalancing

4.1.3 Equal weight

Overall the total return of the equally weighted portfolio was higher than for the risk parity portfolio. The Sharpe ratio was a little higher as well but the drawdown is much more significant. Compared to risk parity weights, equal weights often benefited from longer lookbacks, all strategies except for the rebalancing each year had a higher return and Sharpe ratio for the long lookback compared to the short one. A rebalancing each day was not good at all for the equal weight, neither was a rebalancing each Monday, and they generated the worst performances. The Monday performance can be caused by a more volatile Monday market because of the two days of a closed market before. Comparing the best day of rebalancing, Wednesday, with rebalancing each month, the outcomes look very much alike. A slightly better Sharpe ratio for Wednesdays but the drawdown and total return were outperformed marginally by the portfolio rebalanced each month.

Table 4.4: Performance of portfolios with different days of rebalancing - equal weight

Day of rebalancing	**Sharpe ratio**	**Maximum drawdown**	**Total return**
Monday			
Short	1.4980	-0.0930	0.2287
Medium	2.0047	-0.1157	0.3626
Long	2.5656	-0.1321	0.4166
Tuesday			
Short	1.8911	-0.0751	0.4156
Medium	2.0855	-0.0871	0.4981
Long	2.4978	-0.1123	0.5048
Wednesday			
Short	2.1839	-0.0871	0.4752
Medium	2.2230	-0.1004	0.5605
Long	2.5532	-0.1137	0.5277
Thursday			
Short	2.1151	-0.0757	0.4191
Medium	2.2348	-0.0874	0.4862
Long	2.5292	-0.1043	0.4859
Friday			
Short	1.8563	-0.0793	0.3060
Medium	2.0848	-0.1032	0.4157
Long	2.5115	-0.1177	0.4560
Every day			
Short	1.6515	-0.0996	0.2563
Medium	1.9586	-0.1194	0.2451

Table 4.4: Performance of portfolios with different days of rebalancing - equal weight

Day of rebalancing	**Sharpe ratio**	**Maximum drawdown**	**Total return**
Long	2.4948	-0.1298	0.3542
Last day of month			
Short	1.9206	-0.0855	0.5124
Medium	2.0542	-0.0830	0.6277
Long	2.3296	-0.1006	0.5655
Last day of year			
Short	3.2159	-0.0920	0.4224
Medium	2.6501	-0.1546	0.2983
Long	2.1194	-0.2105	0.2741

Figure 4.6: Equal weight return for Thursday rebalancing

Compared to each other, the difference between risk parity weights and equal weights gets more clear. The equal weight benefits from higher returns while the risk parity weights sometimes scale the assets with high return. This is not only negative since the drawdown gets lower. Overall the equal weights can be seen as a more risky investment but they still generate a high Sharpe ratio because of their high return. When there is no trend, the equally weighted portfolio tends to lose a lot of its aggregated return and the risk parity portfolio stays more flat.

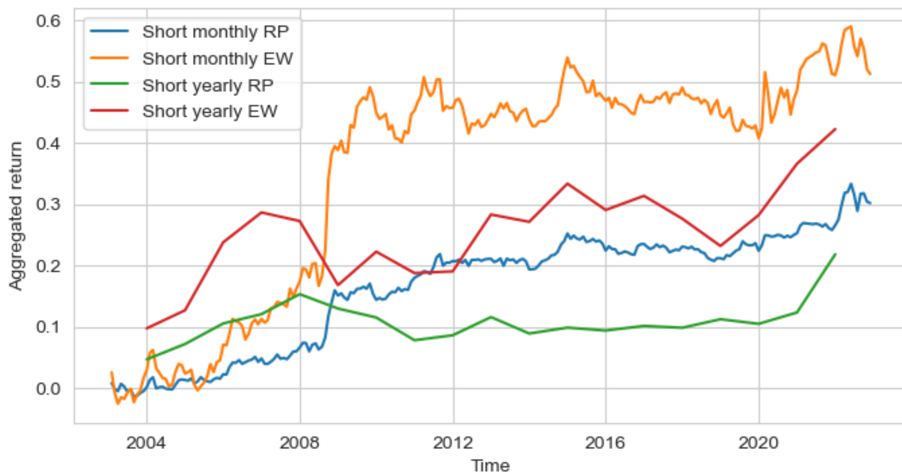

Figure 4.7: Yearly and monthly rebalancing, equal weight and risk parity weights

The yearly rebalancing provides a high Sharpe ratio but one can observe the slow movements of the aggregated return compared to the strategy rebalanced once a month. The low volatility explains the high Sharpe ratio since it is only a measure of the ratio between the return and the volatility. The equally weighted portfolio has a higher return but can still be considered to have a low risk, while the risk parity-weighted portfolio has an overall flat curve. Even though the risk parity strategy has a flat curve, its drawdown is higher than the strategy rebalanced each week or each month. A strategy rebalanced once a year is not preferred.

Strongest signals

All strategies with rebalancing on Thursdays.

Table 4.5: Performance of portfolios with different cutoffs on delta - equal weights

Min absolute delta	Sharpe ratio	Maximum drawdown	Total return
No cutoff			
Short	2.1151	-0.0757	0.4191
Medium	2.2348	-0.0874	0.4862
Long	2.5292	-0.1043	0.4859
0.1			
Short	2.1213	-0.0731	0.4289
Medium	2.2477	-0.0875	0.4930
Long	2.5192	-0.1059	0.4813

Table 4.5: Performance of portfolios with different cutoffs on delta - equal weights

Min absolute delta	Sharpe ratio	Maximum drawdown	Total return
0.2			
Short	2.1304	-0.0732	0.4622
Medium	2.2451	-0.0898	0.5013
Long	2.4597	-0.1121	0.5014
0.3			
Short	2.1559	-0.0700	0.5415
Medium	2.2644	-0.0894	0.5153
Long	2.4174	-0.1072	0.5380
0.4			
Short	2.1890	-0.0823	0.5106
Medium	2.2661	-0.0899	0.5449
Long	2.3987	-0.1031	0.5596
0.5			
Short	2.4642	-0.1242	0.4567
Medium	2.1605	-0.0983	0.5646
Long	2.2122	-0.1188	0.5405
0.6			
Short	2.2787	-0.0750	0.6253
Medium	2.0798	-0.0925	0.5973
Long	2.0923	-0.1275	0.5547
0.7			
Short	1.6241	-0.1300	0.5258
Medium	2.3515	-0.1600	0.5964
Long	2.0316	-0.1300	0.7077
0.8			
Short	0.5376	-0.1700	0.4444
Medium	1.1989	-0.200	0.4117
Long	1.8674	-0.1300	0.2976
0.9			
Short	-0.1923	-0.2169	0.0974
Medium	-1.081	-0.2665	0.008
Long	0.4550	-0.2376	0.0128

A higher cutoff increases return but does not increase the Sharpe ratio. Drawdown is minimal around 0-0.3 cutoff. The equal weight is more risky and that can explain why Sharpe does not increase with a higher cutoff. Since the strategy is riskier, the optimal cutoff is a low one, for example around 0.2.

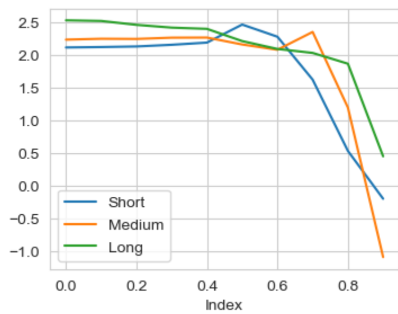

Figure 4.8: Sharpe ratio for different cutoffs - equal weights

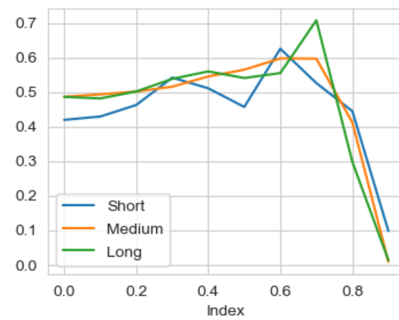

Figure 4.9: Return for different cutoffs - equal weights

4.2 Asset class portfolio

The assets were divided into 6 asset classes: equities, credits, rates, swaps, commodities, and currencies. Figure 4.10 shows the individual performances of the different classes. Only rebalancing once a week, on Thursdays, was considered and the purpose was to understand the difference between the asset class portfolio and the common portfolios with all assets in one portfolio. Therefore one rebalancing point was sufficient.

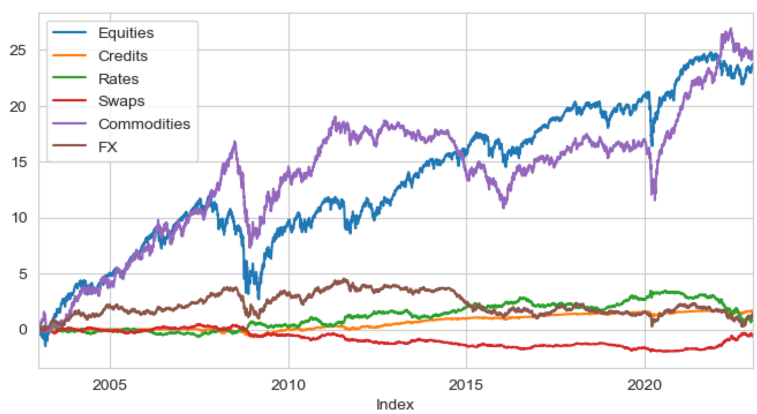

Figure 4.10: Aggregated return for each asset class

The equity and commodity portfolios both have a high return, which makes sense in the way that they both represent claims on actual assets and not future cash flows like fixed-income instruments are. They are also more volatile and have a high correlation to each other. The other instruments are therefore also needed to create a diversified CTA, especially since all the classes have different correlations to each other, some are very high and positive while some are negative to other classes.

4.2.1 Risk parity weights

The return of the asset class portfolio was significantly lower than for the portfolio of all the assets. For the short lookback, the drawdown was the highest which can be explained by the fact that the portfolio can be seen as riskier than the common portfolio. Each class of assets has a high correlation and the portfolios are not diversified themselves. The asset class portfolio performed better when the lookback was longer. The Sharpe ratio for all lookbacks was adequate but lower than for the common portfolio.

Some spikes of the aggregated return of the short lookback were observed, they were a product of spikes in aggregated return in the equity class where the trend signal entirely missed the return of the assets. The longer lookback was less volatile and performed the best of all lookbacks for Sharpe ratio, drawdown, and total return.

Table 4.6: Performance of asset class portfolio - risk parity weights

Rebalancing once a week	Sharpe ratio	Maximum drawdown	Total return
Short	1.3765	-0.2125	0.1758
Medium	1.418	-0.0949	0.1888
Long	1.4644	-0.0903	0.1934

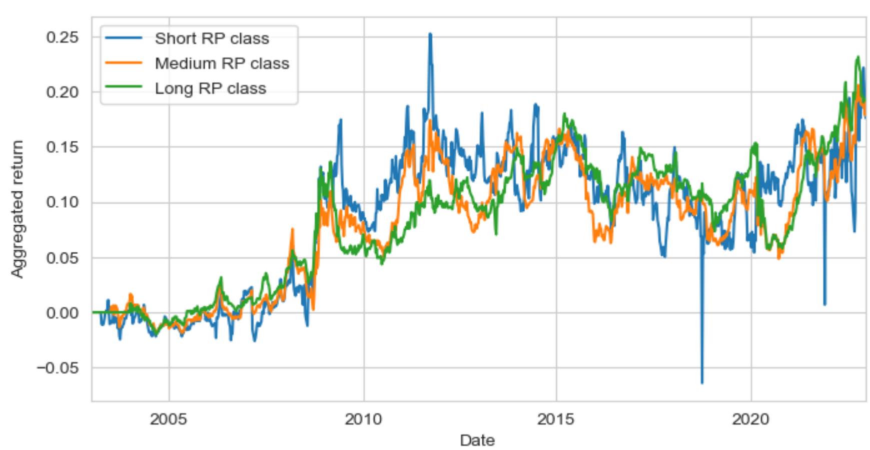

Figure 4.11: Aggregated return for asset class strategy with risk parity weights

4.2.2 Equal weight

Overall the equally weighted asset class portfolio was more volatile than the asset class portfolio weighted with risk parity weights. The Sharpe ratio was lower for all lookbacks except for the longer one. One can also observe that here, just like for the risk parity weights, the longer lookback is the strategy that performed the best. Generally, it has a higher drawdown but the aggregated return increases more when the trend on the market is strong compared to the risk parity-weighted asset class portfolio.

Table 4.7: Performance of asset class portfolio - equal weight

Rebalancing once a week	Sharpe ratio	Maximum drawdown	Total return
Short	1.2449	-0.1762	0.1098
Medium	1.5053	-0.1870	0.1380
Long	2.2648	-0.1523	0.2002

Figure 4.12: Aggregated return for asset class strategy with equal weights

4.3 Geographical portfolio

The assets were divided into four asset classes: Europe, South and North America, Asia and Oceania, and a global class. Figure 4.13 shows the individual performances of the different classes. Only rebalancing once a week, on Thursdays, was considered with the same purpose as the asset class portfolio; to understand the difference between the common portfolio and the geographical class portfolio.

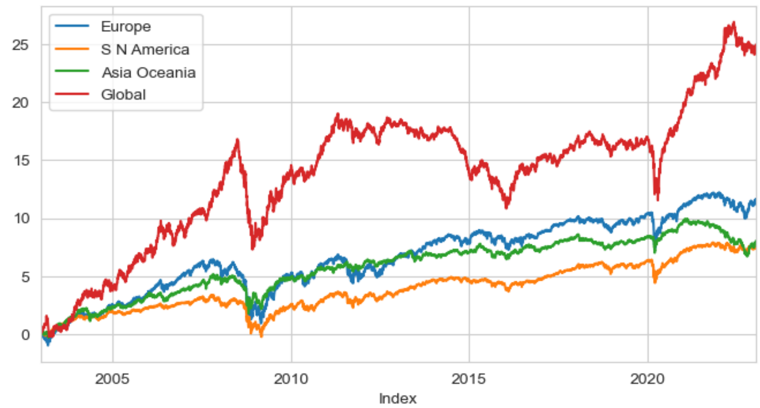

Figure 4.13: Aggregated return for each geographical class

All geographical portfolios are more diversified than the asset class portfolios and they have a higher correlation to each other. This applied to all geographical portfolios except the global portfolio, which only consists of commodities that are not bound to a certain geography.

4.3.1 Risk parity weights

The performance of the risk parity-weighted geographical portfolio was remarkably better than the same weights for the asset class portfolio but lower than for the common portfolio. One can note that here, just like for the asset class portfolios, the longer lookback generated the best strategy in terms of Sharpe ratio and total return. The drawdown, on the other hand, was higher than for both the common portfolio and the asset class portfolio. The geographical portfolios are more diversified on their own and that had the effect that the strategies perform more like the common portfolio that also consist of one portfolio with all asset and can be seen as diversified. The geographical strategies are more risky but can generate a better return and Sharpe ratio than the asset class portfolio. This strengthens the claim that CTAs should consist of diversified assets and not assets from, for example, the same asset class.

Table 4.8: Performance of asset geographical portfolio - risk parity weights

Rebalancing once a week	Sharpe ratio	Maximum drawdown	Total return
Short	1.4951	-0.1941	0.1940
Medium	1.8042	-0.1332	0.2578
Long	2.4401	-0.1701	0.3344

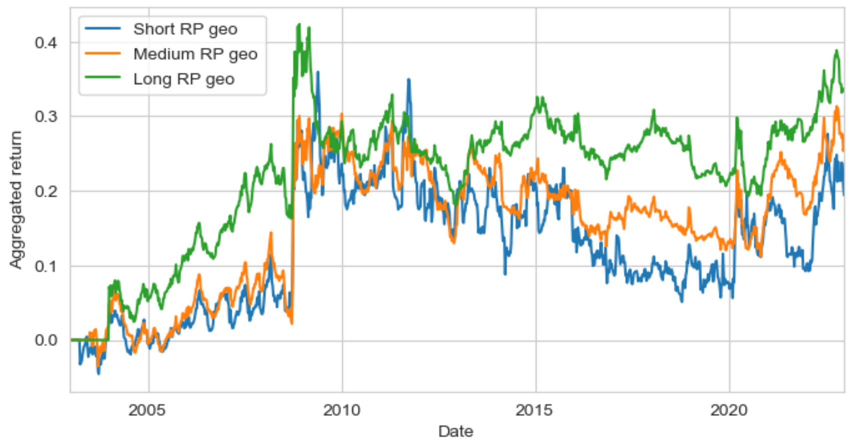

Figure 4.14: Aggregated return for geographical class strategy with risk parity weights

4.3.2 Equal weight

The equally weighted portfolio performed better than the equally weighted asset class portfolio for almost all measurements and lookbacks. Overall, the return of the equally weighted asset class portfolio was very low compared to the common portfolio and the geographical portfolio had returns closer to the common portfolio. Even though the drawdown is almost equally as bad for the geographical portfolio as for the asset class portfolio, the return and Sharpe ratio increased significantly. This can be explained by the more diversified sub-portfolios. Long lookback was the superior strategy of all three geographical class strategies with a high Sharpe ratio and total return. This was the case for both class-divided portfolios with equal weight. An explanation is that equal weight does not take the risk of the individual classes into account and the longer lookback is less sensitive to short trend.

Table 4.9: Performance of asset geographical portfolio - equal weight

Rebalancing once a week	Sharpe ratio	Maximum drawdown	Total return
Short	1.5941	-0.1606	0.2835
Medium	1.8154	-0.1699	0.3025
Long	2.4983	-0.1645	0.3796

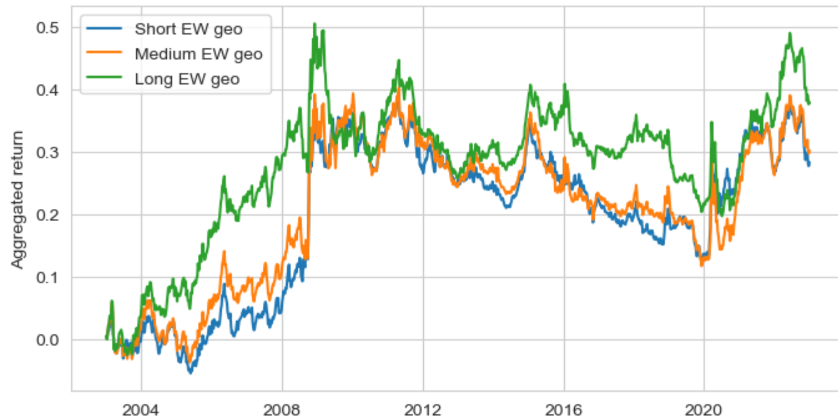

Figure 4.15: Aggregated return for geographical class strategy with equal weights

Chapter 5

Discussion

5.1 Method

The method of the CTA strategy invested is in theory very simple - almost too simple. Many more factors play in when designing a good CTA and for different times of the market, some things about the design need to change. This framework worked as a basis for research on how a CTA with a general signal works. Some variables were changed in the result to see if some improvement could be done but the method stayed almost the same for all portfolios researched.

For example, it can be a good idea to examine if a short signal should be used when the market volatility is high and a long signal when it is low. That level of switch could also be something to train the algorithm on. Another aspect of reflection is whether only strong signals should be used. The thesis covered a portfolio of only strong signals over a specific threshold but it would be an idea to try what would happen if only the N strongest signals were considered for each rebalancing point. When the strategy only considered signals over a certain threshold as a cutoff, the results improved for all strategies until one point where all measurements got worse. If this would be considered in a real-world implementation, signal cutoff should not be higher than an absolute delta of 0.5 to maintain a low drawdown.

The investment strategy is in this thesis seen as a simple index, no transaction cost or level of liquidity of the assets are considered at all. A realistic result would differ from what was seen here. One example is that the return of the strategies with frequent rebalancing would be even lower since the transaction cost would be higher, problems with liquidity would also be more likely since some of the instruments are not very liquid and can have a large spread between ask and bid.

5.2 Result

In times of high volatility, the CTA performed well, most significantly this was seen around 2008 and 2022. These periods were some of the worst years for holding long-only positions in some assets but it was shown that the persistent trend benefited the

CTA strategy. During periods of little trend in the market, we can see that the CTA strategy is not performing very well. For equally weighted portfolios the low volatility was specifically negative for the return and this led to a higher drawdown than for the risk parity-weighted portfolios. It is not enough to use CTAs as a sole investment strategy but it can be very beneficial to include it in a long-only strategy. The CTA can be seen as a hedging strategy because of the low or even negative correlation with for example equity indices. For the examined portfolio, all assets were used at all times, further work could explore if some assets are better suited or if some assets should be given a higher weight during some periods of markets.

5.2.1 Lookback

The lookback was simplified in the sense that a short lookback was the result of a strategy with a short weight lookback as well as a short lookback for delta. Overall, the shorter signals picked up trends quicker and could react to market movements in a way that the longer signals were not able to. This has its positive and negative aspects, for example, that it can generate returns quicker but it can also pick up things in the signal that might be seen as trend but is, in fact, random nose that makes the return lower than for the longer signal. The longer signal is more stable and slow. Generally, the long signal generated a higher Sharpe ratio because its risk is lower than for short signals. The return was often higher, especially for the equally weighted portfolios. The drawdown was a bit higher for the longer signals due to its late response to change.

5.2.2 Weight

Equal weight generates significantly higher peaks than risk parity weights. The return during the chosen time period might not seem to be too high because of the large drawdowns, a side effect of the more risky strategy when setting weights. With risk parity weight, the drawdown was around 4% for weekly rebalanced strategies while it for an equally weighted portfolio with same conditions was around 10% .

5.2.3 Class portfolios

Asset classes

Asset class portfolio was used to examine how the result would differ if the asset classes themselves would be seen as portfolios and the total portfolio would be the sum of each asset class portfolio times its own risk parity (or equal) weights. The delta was normalized within the classes such that the total investment of the portfolio would be invested at each rebalancing point. The delta times the risk parity weight was not normalized. The total return significantly decreased with this portfolio, as well as the Sharpe ratio. One possible reason could be that a portfolio of assets of the same asset class can no longer be seen as diversified itself, the diversification completely relied on the risk parity weights. The weights had to be regulated since some weights took over the portfolio due to the asset class' low and stable return. For this reason, the maximum risk parity weight was the double equal weight. The risk parity weight made the asset class portfolio more stable than the equally weighted portfolio but the result was overall not great. The drawdown was generally lower for the risk parity portfolio than the equally weighted, with the exception for the short signal that was heavily affected by some shorter trends in the equity class inter alia.

Geographical classes

The longer signals had a quite high Sharpe ratio and higher returns than the diversified, standard portfolio even though the drawdown was significantly higher ranging between 16 and 19% for both equally weighted and risk parity portfolios. The shorter signals were worse performing than the longer ones, the Sharpe ratio was also significantly higher for the long signals.

For both the asset class portfolio and the geographical class portfolio, the risk parity weight did not contribute to the benefits it did for the total portfolio. One explanation is that there are too few assets (if we denote the lower-level portfolios) to be diversified. The correlation matrix was also an arbitrary attempt of trying to capture the return and the delta of the assets and could be done differently.

5.3 Conclusion

In the thesis, a simple CTA strategy was investigated as an investment strategy. The method used for the CTA strategy provided a basis for research, but it was acknowledged that additional factors need to be considered for designing an effective CTA strategy, especially during different market conditions. Suggestions were made to explore the use of short signals during high market volatility and long signals during low volatility, as well as considering the use of only strong signals. The presented investment strategy is a simplified investment strategy and a realistic implementation of the strategy would yield different results, with higher transaction costs and potential liquidity issues impacting returns. Further analysis could be conducted to determine if certain assets are better suited or should be given higher weights during specific market conditions. The lookback period was found to impact the strategy's performance, short lookbacks react quicker to market movements but also potentially generate lower returns due to wrong signals as input. Longer lookbacks provided more stability but had a delayed response to market changes. Depending on the purpose of the CTA strategy, an investor should reflect on what weight suits their profile. Comparing risk parity and equal weight strategies showed that equal weight generated higher peaks but also larger drawdowns compared to risk parity. The return during the chosen time period may not appear high due to the significant drawdowns associated with the riskier equal-weight strategy. If the CTA is used only as a hedging strategy and to lower risk of a portfolio, risk parity weight might be preferred.

Overall we could see that CTAs benefits from a persisting and strong trend, no matter the direction of it. The worst periods for the strategy were the periods where the market oscillated and gave the trend signal false signals. The strategy performed well during periods of high volatility but struggled during market conditions with little trend. One important conclusion is that a CTA strategy should be used as a hedging strategy by allocating some weight of a total portfolio to it, it should never be used as a sole investment strategy. In conclusion, this thesis contributes to understanding the performance and limitations of a simple CTA strategy. It highlights the need for further research and consideration of additional factors for designing effective CTAs, such as market conditions, asset selection, and diversification strategies. Implementing the CTA strategy in a realistic setting would require accounting for transaction costs and liquidity. Overall, the CTA strategy can be a valuable component of a diversified long-only strategy, providing hedging benefits and potentially higher returns during volatile market periods.

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