NTNU – Trondheim
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A quantitative approach to asset allocation and trading

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A quantitative approach to asset allocation and trading	
Oppgavetekst/Problembeskrivelse	
The thesis will review and discuss technical trading methods within a commodity pool framework. An allocation key will be formulated and assessed according to it's value added. The procedure and the results will be thoroughly examined with the intention of gaining valuable insights on the behalf of the commodity trading fund, Holden Capital AS.	
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Bedrift/ekstern virksomhet: Eidsiva Marked AS og Holden Capital AS

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Sammendrag

Denne avhandlingen evaluerer og kontrollerer tekniske handelsstrategier og risikostyringsverktøy på vegne av Holden Capital AS. Strategiene er kvantitativt formulert ved å konstruere en komplett handelsmodell. Avhandlingen evaluerer videre om bruk av dynamisk allokering, styrt av trendgjenkjenningmetoder, kan tilføre handelsmodellen merverdi. Handelsmodellens resultater med statisk allokering er konsekvente og lønnsomme i out-of-sample periodene over ti år. Med en sammensatt årlig vekstrate på 19 % er modellen verifisert til å kunne utnytte trender i aktivapriser. Handelsmodellen utkonkurrerer referanseindekser konsekvent over risikojusterte prestasjonsmål. En betydelig forskjell i lønnsomhet for de ulike aktivaene indikerer at modellens rammeverk er bedre egnet for enkelte distribusjonskarakteristika enn andre.

En trendgjenkjennings- og allokeringsmodell er bygget for å vurdere om daglig dynamisk allokering av risikokapital forbedrer lønnsomheten til handelsmodellen. Av de syv trendgjenkjenningsmetodeme evaluert, evner ikke majoriteten å skille ut trendende aktiva, og allokerer nesten like bredt som ved statisk allokering. Tre metoder gjør det bedre enn statisk allokerings månedlige avkastning, samt oppnår en høyere Information Ratio i forhold til referanseindeksen. Ved bruk av risikojusterte prestasjonmålinger hvor avkastningen vurderes i forhold til volatiliteten, presterer samtlige trendgjenkjenningmetoder dårligere enn statisk allokering. Ved at færre aktiva får allokert kapital, reduseres diversifiseringseffekten og volatiliteten øker utover verdien av meravkastningen.

På grunn av avhandlingens sensitive karakter, er den underlagt restriksjoner som begrenser publisitet for en periode på fem år. En avtale om konfidensialitet har blitt signert av forfatterne, Marked Eidsiva AS, Holden Capital AS og NTNU.

A quantitative approach to asset allocation and trading

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Abstract

This thesis evaluates and verifies technical trading strategies and risk management tools on the behalf of Holden Capital AS. The strategies are quantitatively formulated by constructing a complete base trading model. The thesis further evaluates if the use of dynamic allocation, governed by trend recognition methods, could add value to the base model. The base trading model yield consistently profitable out-of-sample results when assessed over a ten year time period with static allocation. Yielding a compound annual growth rate of 19%, the model is verified as capable of exploiting trends in asset prices. The model consistently outperforms benchmark indices across risk adjusted performance measures. However, profitability differs significantly for the distinct assets, indicating the model framework is better suited for some distribution characteristics than others.

A trend recognition and allocation model is built to assess whether daily dynamic allocation of risk capital enhances the profitability of the base trading model. Out of the seven trend recognition methods evaluated, most fail to single out trending assets, allocating almost as wide as static allocation. Three methods outperform static allocation's monthly returns as well as obtaining higher information ratio statistics when compared to a benchmark index. When evaluated on risk adjusted performance measures considering return relative to volatility, all trend recognition methods are outperformed by static allocation. The loss of diversification when only allocating to certain assets increases volatility beyond the value of excess return.

Due to the sensitive nature of this work, the thesis is subject to restrictions limiting publicity for a time period of five years. A confidentiality agreement has been signed by the authors, Eidsiva Marked AS, Holden Capital AS and NTNU.

Preface

This master thesis was written at the Norwegian University of Science and Technology (NTNU), Department of Industrial Economics and Technology Management within the field of Financial Engineering. The motivation for the problem formulation, the models and the report comes from the commodity trading advisor Holden Capital AS, that needed an assessment of potential trading strategies, allocation procedures and risk handling methods.

The thesis is subject to restrictions limiting publicity for a time period of five years. A confidentiality agreement has been signed by the authors, Eidsiva Marked AS and Holden Capital AS. This is done to ensure that sensitive information regarding trading strategies and results remain confidential.

The report has been prepared in LaTeX, while numerical analysis, simulations and optimizations have been performed in Microsoft Excel 2010, Visual Basic and using Frontline Risk Platform Solver 2010, respectively. Statistical analyses have been performed in R. The data foundation for the thesis is mainly obtained from Pi Trading and Reuters EcoWin Pro.

We would like to thank our supervisor Associate Professor Sjur Westgaard with the Department of Industrial Economics and Technology Management for excellent guidance throughout the semester.

We would also like to thank our external supervisor Torstein Wibye Thinn with Eidsiva Marked AS and Holden Capital AS for hours of conversations and discussions around the clock, weekends as well as holidays. Without your exceptional guidance and feedback this thesis would never have come through. We would also like to extend gratitude to Associate Professor Lars Magnus Hvattum (NTNU) for helpful guidance in the formulation of optimization problems.

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John Bjørnsen — Håkon Heir — Amund Høsøien

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List of Abbreviations

ADX	Average Directional Index
ATR	Average True Range
BTM	Base Trading Model
CAGR	Compound Annual Growth Rate
CBOT	Chicago Board of Trade
CME	Chicago Mercantile Exchange
COMEX	Commodity Exchange
CRB	Thomson Reuters/Jefferies CRB Index
CSCE	Coffee, Sugar and Cocoa Exchange
CTA	Commodity Trading Advisor
CVaR	Conditional Value-at-Risk
dVaR	Daily Value-at-Risk
EMA	Exponential Moving Average
EMD	Empirical Mode Decomposition
EMH	Efficient Market Hypothesis
ETC	Exchange Traded Commodity
FDI	Fractal Dimension Indicator
ICE	Intercontinental Exchange
IMM	International Monetary Market
IR	Information Ratio
LPM	Lower Partial Movement
M/E	Margin-to-Equity
MA	Moving Average

MAR	Minimum Acceptable Return
MIFID	Markets in Financial Instruments Directive
MSCI WI	Morgan Stanley Capital International World Index
NEIXCTA	Newedge Index CTA
NEIXTRND	Newedge Index CTA Trend
NYMEX	New York Mercantile Exchange
OTC	Over-The-Counter
RAPM	Risk Adjusted Performance Measures
RSI	Relative Strength Index
S&P GSCI	Standard & Poor Goldman Sachs Commodity Index
SMA	Simple Moving Average
TIPS	Treasury Inflation-Protected Securities
TR	True Range
TRAM	Trend Recognition and Allocation Model
VaR	Value-at-Risk
VHF	Vertical Horizontal Filter
WDD	Worst Draw Down

1 Introduction

Commodity futures and forwards have been around for decades and are subject to trading in high volumes by both industrial and financial institutions. Apart from their intrinsic value, commodities can serve as an inflation hedge as well as a good diversifier to both bonds and equities. These characteristics have led to a large influx of investors to the commodity market during the last two decades. Assets under management for managed futures, managed by professional commodity trading advisors (CTAs), has in the 2000-2012 period grown from accounting for less than USD 40bn to over USD 325bn.

The profitability of trading managed futures based on technically trend analysis has however received an unjustified small amount of empirical research, despite the extensive use by market practitioners. Trend filtering techniques have become a widely used tool in technical analysis and are fundamental to most momentum strategies developed in asset management and the hedge fund sector. As of Q1 2012, managed futures assets under management traded by systematic traders accounts for USD 260bn, 80% of the managed futures total.

Holden Capital AS is a newly founded CTA, aiming to begin operations in Q3 2012. This thesis examines and explains the trading strategies and risk management methods considered by the Fund. The purpose of the work is twofold. Firstly the trading strategies are quantitatively formulated by constructing a complete base trading model (BTM), serving as test model and simulation platform. The generic framework is based on well-known technical trading methods combined in a complex model for asset trading and risk management. The methods seek to profit from trends in asset prices, setting positions relative to measured market risk and the capital allocated to each asset. Certain model parameters are recalibrated on a monthly basis, to adapt the model's configurations to each asset time series considered. The asset specific parameters are utilized as the model yields trading results over a one month out-of-sample period. The assessment of the model is conducted using historical prices of 24 continuous future and forward contracts over a ten year time period. When evaluated on certain risk adjusted performance measures and compared to relevant benchmark indices, the model exhibits outperforming results. Yielding a compound annual growth rate (CAGR) of 19%, the model is clearly verified as capable of exploiting trends in asset prices. The out-of-sample returns exhibit consistency, proving the model is able to capture and follow trends in all sample asset prices. The profitability varies across assets, indicating the model framework is better suited for some distribution characteristics than others. However, low volatility in the portfolio's return series proves the valuable diversification effect inherent in commodities as an asset class.

The second purpose of the thesis is to examine whether generalized trend recognition methods can enhance trading profitability. The methods seek to identify which assets prices are trending, and which are not. A trend recognition and allocation model (TRAM) is built to assess whether daily dynamic allocation of risk capital only to trending assets adds value to the base trading model. Seven distinct methods are utilized in the model, intended to calculate the allocation of risk capital on a daily basis. The risk capital allocated defines the Value-at-Risk limits for each asset. The trend recognition and allocation model is recalibrated on a monthly basis, where the parameters are generalized for all assets to capture overall asset pool dynamics. The results of dynamic allocation decided by the methods are evaluated in comparison to static allocation. The assessment using historical asset prices yields mixed results, as some methods outperform static allocation in terms of monthly returns, while other does not. Most methods fail in being able to single out trending assets, and allocate almost as wide as static allocation. The ADX, Aroon and EMD filters achieve higher monthly returns on average, as well as higher information ratio statistics when compared to a buy-and-hold index. When using risk adjusted performance measures considering return relative to volatility, all trend recognition methods fail to add value to the base trading model. The loss of diversification when only allocating to certain assets increases volatility beyond the value of excess return.

2 Background

Holden Capital AS, hereby referred to as “the Fund”, is a newly founded managed futures CTA, aiming to begin operations in Q3 2012. The Fund plans to raise a capital base of NOK 500 million, intended to be invested primarily in commodity futures and forwards, with a small portion available for investments in currencies and fixed income. The trading will mostly be controlled by automatic algorithms, based on the technical trading principle of trend following. Most of the trading rules creating the basis of their strategy have already been decided. Risk management principles are also set, such as the amount of risk capital relative to capital base. The daily risk management system controlling exposure is given using a daily Value-at-Risk approach.

Before initiating trading operations, the Fund wanted a third party assessment of their trading and risk management strategies. As a result, this thesis is conducted in close cooperation with the Fund.

2.1 Technical analysis and trend following

The use of technical analysis methods can be traced back to Munehisa Homna, a rice merchant trading at the Dōjima Rice Exchange, who developed the use of candlestick charts in the early 18th century (Nison, 1991). The first known written articles on technical analysis are a series of articles published by Charles H. Dow in the Wall Street Journal in the 1900-1902 period (Chen, 2010). The series was later referred to as the Dow theory and is the foundation of most technical analysis as the theory aims to identify long term trends in the stock market. Dow never used the term Dow theory, but the theory became known by several follower and associates who later collected and expanded his work, such as Hamilton (1922), Rhea (1932), Schaefer (1960) and Russell (1961).

Technical analysts believe that the market’s causality derives from unchanging aspects of human behavior and rely on technical indicators and models, such as price trend, cycles and volume patterns to forecast and identify low-risk/high-reward trading opportunities (Chen, 2010). Other methods such as momentum readings, sentiment indicators, Elliott Waves, Edwards and Magee patterns and Dow theory have also gained popularity among practitioners. Weissman (2005) divides technical analysis into two distinct sub-categories; subjective technical analysis and objective technical analysis. Whereas subjective technical analysis attempts to capitalize on visual chart analysis, which is subject to interpretation, objective technical analysis is based on mathematical and algorithmic rules.

Technical trend following strategies are methods of which the essence is to benefit from trends in asset prices, while accepting that returns will not be generated when markets are ranging (Bruder and Gaussel, 2011). Usually, the strategies' probability of losing is higher than gaining due to many small losses in ranging markets, but the average gain is much higher than the average loss. Modern trend filtering techniques used on price time series can be dated back to Muth (1960), who showed that the exponentially weighted moving average can be interpreted as the expected value of the time series. Trend filtering techniques have been extensively studied since the late seventies by, among others, Wilder (1978), Beveridge and Nelson (1981), Hodrick and Prescott (1997) and Ehlers and Way (2010). Trend filtering has as of date become a widely used tool in technical analysis and is fundamental to most momentum strategies developed in asset management and the hedge fund sector (Bruder et al., 2011).

There has been conducted an extensive amount of empirical research on the profitability of technical analysis, but the results have been ambiguous about whether or not technical analysis do add value. Among 92 modern studies, 58 studies found positive results regarding technical trading strategies, while 24 studies obtained negative results (Park and Irwin, 2004). There has however been a lack of empirical research on technically traded futures, even though the technique is extensively used by practitioners (Kidd and Brorsen, 2004). As of Q1 2012 asset under management of systematic CTAs, in which technical analysis plays a considerable part, accounting for more than 80% of all managed futures programs with a dollar value of USD 260bn (BarclayHedge, 2012).

2.2 Commodity forwards and futures

The birth of the modern futures market can be traced to 1848 when the Chicago Board of Trade (CBOT) begun to facilitate the trading of grain between producers and consumers (Morgan Stanley, 2007). Through time the market place has evolved to include more commodities and a larger variety of participants has entered the market. Although most commodities have realized a higher traded volume, they are still ultimately restricted by supply. However, with the introduction of new products, such as cash settled futures, the potential of volume growth has greatly increased. Over the past decade the market infrastructure has changed significantly. Exchanges tend to go from open-outcry to electronic trading in addition to a consolidation of derivatives exchanges (Hull, 2012; Shell, 2007). In appendix A an overview of the largest exchanges is provided.

2.2.1 Futures and forward fundamentals

Futures and forward contracts are both an agreement to buy or sell a given amount of an asset at a predetermined price and date. The contracts underlying asset consist usually of stocks, indices, currencies or commodities, but more exotic underlyings, such as weather are also commonly traded. While there are several differences between futures and forwards, an important difference is how they are settled. A forward contract is settled at the end of the contract, while a future contract is settled daily (Hull, 2012). If the interest rate development is known, the contracts will be priced the same, but as this is normally not the case, the price will be different. For example, if an asset is positively correlated with the interest rate, an increase in the interest rate is likely followed by an increase in the asset price. As the future contract is settled daily, one can then invest the gain with a higher return. Forward and futures contracts can be settled either for physical delivery of the asset or settled in cash (Lipscomb, 2005). *Cash settlement* is simply the difference between the spot price and the futures price.

As futures and forward contracts are leveraged positions, they are subject to credit risk. The most apparent being that one or more counterparties fail to honor their settlement obligation (CME Group, 2011). To ensure that this will not happen, a *clearing house*, a well capitalized financial institution, acts as a counterparty guaranteeing for all cleared transactions. By pooling together trades they can reduce the settlement risk by netting offsetting transactions. A clearing house is responsible for settling trading accounts, clearing trades and managing collateral. Each futures exchange has its own clearing house, in which each member of that exchange is required to clear their trades. Exchange traded forward contracts are also cleared, while for over-the-counter (OTC) forward contracts this is not a global requirement (Hull, 2012; LCH.Clearnet, 2011).

Future and forward properties are commonly described using a set of industry terms (Hull, 2012):

- *Initial Margin:* The initial deposit required to enter a future contract
- *Maintenance Margin:* The amount required to be in ones account to hold a future contract

- *Tick Size:* The minimum increment the future's price can change. Also known as the minimum fluctuation
- *Quoted Units:* The number of units for which the future price is quoted
- *Traded Units:* The number of units traded in a future contract. This number is always a multiple of the number of quoted units.

When initiating a futures trade, it is required to deposit an initial margin into a margin account. This deposit is used to debit any day-to-day market fluctuations as futures contracts are marked to market each day. When the position is liquidated, the remaining margin amount, adjusted for any losses/gains during the time span invested, are refunded (Hull, 2012). As the initial margin is the minimum required deposit to enter a futures contract, the maintenance margin is the minimum amount in the margin account before one is required to post additional collateral. When the margin account drops below the maintenance margin, brokers make a *margin call*, requiring that the margin is brought back up to the initial amount. The same dynamics apply for cleared forward contracts (LCH.Clearnet, 2011).

Primarily, futures and forward contracts are traded either to hedge risk, to exploit an arbitrage opportunity, or to speculate on the future price development (Hull, 2012). *Hedgers* include commodity producers and consumers seeking to reduce the risk from future price fluctuations. A buyer can seek to avoid the risk of rising prices of products or commodities used as raw material, while a seller may wish to lock in a price for their product. *Arbitrageurs* take offsetting positions in two or more products to lock in a profit while *speculators* bet on the markets future direction. Many traders often do not wish to take physical delivery of the underlying product. This can be done by either offsetting their position prior to expiry, i.e. a long position can be offset by selling the equal amount short, or by trading futures contracts with settlement in cash. If the trader is interested in keeping his position, he can *roll* the contract by first offsetting the contract that are close to expiration, and then take the same position in the next contract nearest to expiration, called the front contract.

2.2.2 Commodities as an asset class

Today, commodities play an important role in many portfolios. Apart from their intrinsic value, commodities can serve as an inflation hedge and as a good diversifier in many market conditions (Morgan Stanley, 2007). As shown in figure 1, on a five year rolling basis compared to equities, bonds and Treasury Inflation-Protected Securities (TIPS), commodities have been the premiere inflation hedge (Morgan Stanley, 2010). The relationship has generally held through both rising and falling inflation, in addition to when other markets failed as a hedge. Figure 2 shows that the S&P GSCI, formerly known as the Goldman Sachs Commodity Index, exhibits a strong positive correlation across all yield environments (Morgan Stanley, 2010).

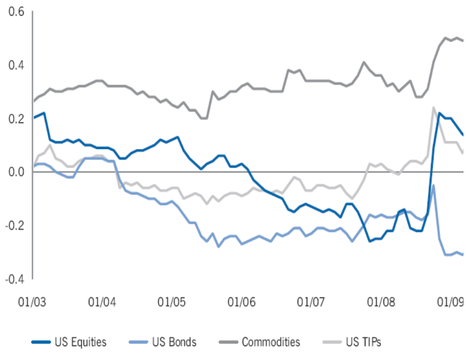


Figure 1: Rolling five-year correlations with change in inflation

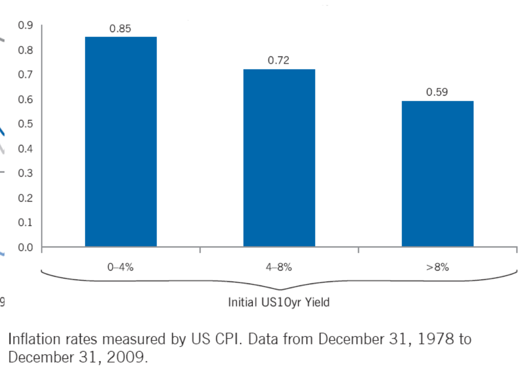


Figure 2: Correlation between S&P GSCI and inflation rate y/y change

Commodities have shown low correlation with equities, other asset classes and, in general, with other commodities (Gjolberg and Steen, 2012; Morgan Stanley, 2007). In addition commodities have historically shown more resilience to geopolitical and macro-economic shocks. It can be argued that the effects of geopolitical instability, with uncertainty regarding the supply and demand relationship, are biased to a tighter supply, resulting in higher prices. However commodities have not been a good diversifier in market downturns (Morgan Stanley, 2010). Downturns are often associated with declining inflation, which may account for some of the correlation between equity-bond portfolios.

Although the commodity market has been around for centuries, it was not until last decade that the market gained the average investor's interest. New rules for bank capital requirements in 2004 led to a large influx of hedge funds, pension funds, investment banks, index trackers and, increasingly, individual investors (Gjolberg and Steen, 2012; Morgan Stanley, 2007). As a result, a surge of commodity-linked products have been created, such as exchange traded commodities (ETCs), in addition to an increase in volumes traded on commodity futures (Kat, 2006; The City UK, 2011). From 2005 to 2010, commodities went from accounting less than 3% of the value of global exchange-traded derivatives, to 9%.

Another industry fueling the demand for commodities is *managed futures*, an industry comprised of commodity trading advisors (CTAs), professional money managers who invest discretionary into futures (CME Group, 2011). With the ability of going long and short, managed futures have the potential to profit in both declining and increasing markets. As seen in figure 3, managed futures has become increasingly popular over the past two decades (BarclayHedge, 2012). Prior to year 2000, such funds were nearly non-existent, proving an enormous growth over the last ten years.

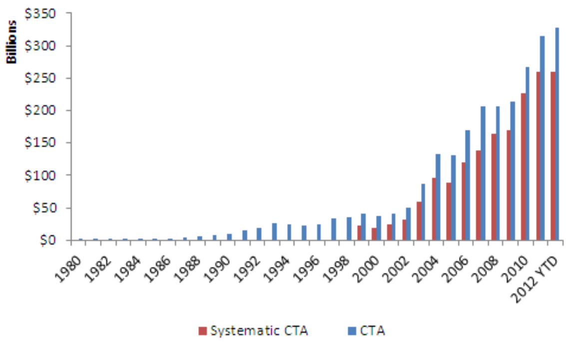


Figure 3: Historical growth of assets under management in managed futures

Over the long term, commodities have displayed returns of similar magnitude to equities. Figure 4 shows the development of the two commodity indices S&P GSCI and Thomson Reuters/Jefferies CRB Index (CRB), and the equity index Morgan Stanley Capital International World Index (MSCI WI). S&P GSCI is calculated primarily on a world production-weighted basis to reflect the relative significance of each of the constituent commodities, while the CRB is weighted according to represent broad trends in overall commodity prices (Jefferies & Company, 2011; Standard & Poors, 2012). The MSCI WI is a free float-adjusted market capitalization weighted index designed to measure the equity market performance of developed countries.

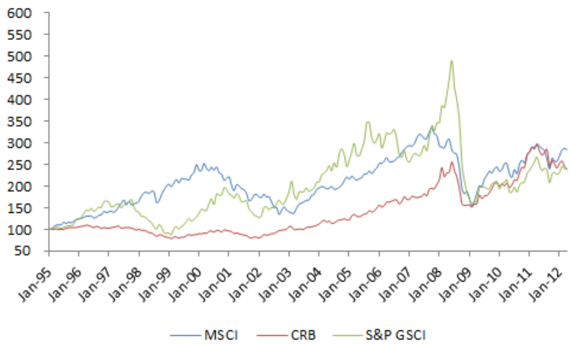


Figure 4: Commodity and equity price development.

For the past years, insatiable demand from emerging markets', as well as an under invested supply side, has kept pressures on commodity prices (Kat, 2006). However, the performance seen under the financial crisis suggests that commodities are sensitive to demand changes.

3 Data and descriptive statistics

3.1 Adjustment of discontinuous series

As described in section 2.2, futures and forward markets comprise of a set of individual contracts, each with a predetermined expiration date. As one contract expires, another is listed and thus the markets evolve. Hence there exists no tradable continuous series for these contracts. The limited history of each contract makes back testing challenging. One way to assess the long term history is to merge contracts together, the simplest being always quoting the front contract. However as contracts have different prices, primarily due to contango and backwardation effects, the series will display discontinuities. The figure below illustrates jumps that will occur when quoting the front contract.

Figure 5: Rolling front contract

Masteika et al. (2012) present several methods to remove discontinuities where the methods of point adjusting and proportional adjusting the series are the most relevant. These methods can be used to both forward and back adjust series, where the back adjusted series is considered best practice for trading activities (Masteika et al., 2012). Back adjusted series are also best suited for time series analysis such as moving average filtering, therefore this method is used for the data applied in the assessment. Point adjustment eliminates the discontinuities by adding or subtracting the price gap to all relevant data, whereas proportional adjustment adds or subtracts the proportional value of the price gap to all relevant data. Point adjustment is subject to the possibility of negative prices. The two methods can be exemplified with a roll gap represented with a front contract noted at 69.950 and the next contract noted at 62.525. The back adjustment will be 7.425 and 11.9% for point and proportional adjustment, respectively.

3.2 Asset pool description

24 assets are selected to be used for assessing the trading models. The assets are selected based on data availability, trading volume, liquidity, and diversification to match the Fund's expected exposure and risk profile. 19 out of the 24 assets are commodities while the remaining 5 are financial products. The data is quoted on a daily basis beginning in January 1998 and ending in February 2012. The time series are proportionally backwards adjusted, and are contributed by Pi Trading (2012), NASDAQ OMX, and Reuters. An overview of the assets is given in table 1. Test statistics and extensive data descriptions are provided in appendix C.

The original length of the return series contain 3452 data points. As the price time series originate from different markets and exchanges there exist days with missing prices. The days that are not consistent over all assets are either replaced with the average of the preceding and succeeding days' quote, or the entire date is deleted. However, as the assets stems from a handful of exchanges with normally the same trading days, the problem is not extensive. The fact that assets originate from markets across different time zones and opening hours are ignored when evaluating the correlations. To simplify the model, series that are not USD denominated are converted to USD, which applies for power on Nord Pool originally quoted in EUR. The close price of the currency cross is used for conversion.

Table 1: Asset pool overview

	Main Exchange	*Ticker*	*Mean*	*SD*
Commodity				
Light Crude Oil	NYMEX	CL	0.013%	1.32%
Heating Oil	NYMEX	HO	0.019%	1.35%
Natural Gas Oil	NYMEX	NG	-0.063%	1.43%
Power	NASDAQ OMX	ENOQ	-0.006%	2.37%
Corn	CBOT	C	-0.010%	1.15%
Rough Rice	CBOT	RR	-0.021%	0.93%
Soybeans	CBOT	S	0.026%	2.13%
Wheat	CBOT	W	-0.021%	1.16%
Cocoa	ICE (CSCE)	CC	-0.006%	1.53%
Coffee	ICE (CSCE)	KC	-0.012%	1.26%
Lumber	CME	LB	-0.036%	0.93%
Sugar	ICE (CSCE)	SB	0.024%	2.83%
Gold	COMEX	GC	0.036%	1.01%
Copper	COMEX	HG	0.046%	1.81%
Platinum	NYMEX	PL	0.045%	1.47%
Silver	COMEX	SI	0.036%	1.80%
Feeder Cattle	CME	FC	0.012%	0.70%
Live Cattle	CME	LC	0.001%	0.64%
Lean Hog	CME	LH	-0.013%	0.86%
Average			0.004%	1.40%
Financial product				
2 Year T-Note	CBOT	TU	0.007%	0.13%
10 Year T-Note	CBOT	TY	0.024%	0.57%
Eurodollar	CME (IMM)	ED	0.003%	0.05%
Japanese Yen	CME (IMM)	JY	0.005%	0.63%
Norwegian Kroner		NOK	0.007%	0.81%
Average			0.009%	0.44%

3.3 Descriptive statistics and subset analysis

The data are divided into two distinct subsets: One subset consist of the 19 commodities, and the other subset consists of the 5 financial products. Each subset is further divided into three equal length subseries in order to evaluate possible changes in each asset's dynamics.

The average mean of the commodities' daily return series is 0.0037% and ranges from -0.0626% to 0.0457%. The means are small compared to the standard deviation, which indicates that the returns are volatile. According to Taylor (2005), typical standard deviation for stocks and stock indices varies between 0.7% and 2%. The commodities average standard deviation is 1.40%, which may indicate that commodities are comparable to US large cap stocks as proposed by Kat (2006). However, the standard deviation seem to have gradually increased over the series duration with an average standard deviation of 0.96%, 1.19% and 1.84% for the first, second and third quantile respectively. For the financial products, the average mean and standard deviation is 0.0092% and 0.44%.

All commodities exhibit leptokurtic distributions with the lowest kurtosis of 5.00, for lumber, and the maximum of 16.78, for gold. The existence of fat tails is supported by extreme values of the series being on average approximately 8 standard deviations from the mean. Kat and Oomen (2006) states that the existence of fat tails, or leptokurtic distributions, is in part generated by time-varying volatility, but that overall the level of kurtosis and volatility persistence is comparable to that found in US large cap stocks. None of the commodity series exhibit particular skewness. Silver exhibits the largest absolute skewness of -0.80. The financial products show the same characteristics as the commodities. With the exception of the Eurodollar, the kurtosis and skewness are within the range provided by the commodities. The Eurodollar has values well above the other assets with kurtosis of 29.88 and a skewness of 1.21.

Under the null hypothesis of normality, the Jarque-Bera test refutes the null hypothesis at a lower than 1% level. However, for lumber in the first quantile and lean hog in the second quantile, the null is rejected at a 45% level. This is strongly biased, due to the selection of subseries. The augmented Dickey Fuller test rejects the null hypothesis of a present unit root for all series and subseries.

The Ljung-Box test for autocorrelation is preformed both on the return series and on the squared return series with three different lags; 5, 10 and 20. For all lags, squared returns have autocorrelation present at a high significance level. This autocorrelation is consistent with empirical studies as the effect of volatility clustering (Taylor, 2005). However, at a subseries level, some of the commodities exhibit no autocorrelation for squared returns. For the return series, 5, 10 and 20 lags have correspondingly 12, 14 and 20 assets that refute the null of no autocorrelation present at a 5% level.

4 Trading methods and indicators

4.1 Technical trading base methods

The foundation of the BTM consists of a few technical trading methods that are combined in a complex framework of trading rules. The methods are based on smoothed series of different underlyings, as well as measures of intraday fluctuations in price series.

4.1.1 Moving Average

A moving average (MA), also called a rolling average or running average, is a filter used to analyze data points by creating a series of averages of different subsets of the full data set (Farlex Inc, 2012). MA techniques form building blocks for many technical indicators and underlays, and might be one of the most commonly used tools by technical traders. MA filters can be used with time series to smooth out short-term fluctuations and highlight longer-term trends.

In financial applications, MA filters can be used on time series of prices, returns, standard deviations and such. There exist several types of MA filters which differ in how they weigh the observations included in the calculation of the average. Two of the most widely used MA filters are the simple moving average (SMA) and the exponential moving average (EMA). The filters are given on computational form in equation (4.1) and (4.2).

$$SMA_{n,t}(p^c) = \frac{1}{n}\sum_{i=0}^{n} p^c_{t-i} \tag{4.1}$$

$$EMA_{n,t}(p^c) = \begin{cases} p^c_t & \text{for } t = 1 \\ (p^c_t - p^c_{t-1})\frac{2}{n+1} + EMA_{n,t-1}(p^c) & \text{for } t \geq 1 \end{cases} \tag{4.2}$$

The filters are illustrated using the close price, p^c_t, of a time period t. The SMA filter is a unweighted mean of the previous n data points, while the EMA filter applies weighting factors which decrease exponentially. When implementing an MA filter there is a trade-off between the amount of smoothness required and amount of lag that can be tolerated when choosing the length n. Massive research has been conducted on finding filtering methods with lower lags giving the same amount of smoothness, resulting in methods such as Kaufman's

Adaptive MA, Jurik MA and John Ehler's Adaptive MA (Kaufman, 1998; Jurik Research, 2007; Ehlers, 2010). MA filters can be used separately or together to measure the trend or the momentum of a time series, as well as define areas of possible *support* and *resistance* in price series to support decision making regarding trades and risk.

4.1.2 Average True Range

Average True Range (ATR) is a price-volatility indicator that was introduced by Wilder (1978). The true range (TR) is calculated as the maximum range that the price moved from yesterday's close to the extreme point reached intraday. Hence the TR is absolute, not relative to the price level as opposed to the standard deviation. This feature has made the indicator widely used in conjunction to futures and forwards trading as it handles back adjustments of the contracts (Siegel, 2000). The calculations are given by equations (4.3), where p_t^h is the high price, p_t^l is the low price, and p_t^c is the close price of a time period t.

$$\begin{aligned} TR_t &= max(p_t^h, p_{t-1}^c) - min(p_t^l, p_{t-1}^c) \\ ATR_{n,t} &= EMA_{n,t}(TR) \end{aligned} \tag{4.3}$$

To measure volatility over more than one time step, the TR is averaged using an EMA over a certain number of periods, giving the ATR. Used as a volatility indicator, the ATR will react fast or slow depending on the number of periods used to obtain the average daily true range. ATR has been used as a component of numerous other indicators and trading systems since it was introduced, such as the ADX and the Vortex Indicator in section 4.2.1 and 4.2.7 respectively.

4.1.3 Relative Strength Index

The Relative Strength Index (RSI) was, like the ATR, introduced by Wilder (1978). The index is based on the concept of a momentum oscillator, measuring the velocity of directional price movements. The RSI is based on the amount of upwards and downwards movement over a certain period and gives a value between 0 and 100. High values indicate a positive trend, low values a negative trend and a value around 50 indicates neither. Extreme RSI levels can indicate an overbought or oversold market and signal the time for a correction in the asset price, indicating a trending price to reverse (Wilder, 1978). For technical traders seeking to exploit trends through long or short position, the index can be used to notify when to reduce or neutralize a trade.

The RSI concept has been further developed into several similar and popular methods, such as the AIQ-RSI (AIQ Systems, 2001). The base trading model utilize a modified version which is calculated using equation (4.5), where n denotes the number of periods used in the EMA, and U_t and D_t denotes the logarithmic return being positive or negative respectively, given in equation (4.4).

$$\begin{aligned} U_t &= \begin{cases} (r_t^o + r_t^c)/2 & \text{for } (r_t^o + r_t^c) > 0 \\ 0 & \text{for } (r_t^o + r_t^c) < 0 \end{cases} \\ D_t &= \begin{cases} 0 & \text{for } (r_t^o + r_t^c) > 0 \\ (r_t^o + r_t^c)/2 & \text{for } (r_t^o + r_t^c) < 0 \end{cases} \end{aligned} \tag{4.4}$$

$$\begin{aligned} RS_{n,t} &= \frac{EMA_{n,t}(U)}{EMA_{n,t}(D)} \\ RSI_{n,t} &= 100 - \frac{100}{1 + RS_t} \end{aligned} \tag{4.5}$$

In difference from the original RSI, the calculations are based on logarithmic returns instead of up and down price averages. Unlike most approaches, the calculation also considers the average between open and close prices instead of just the close price, and smooths the returns using an EMA instead of a SMA.

4.2 Technical trend recognition methods

The TRAM consists of seven distinct trend recognition methods, each intended to single out trending assets. None of the technical methods used for trend recognition have a clear definition of threshold value indicating a trending or ranging property of the underlying time series. The values are relative to each asset and must be interpreted accordingly. Trigger levels must be set according to the trader's preferred trading style and risk aversion, or in combination with an optimization process using historical data.

4.2.1 Average Directional Index

The Average Directional Index (ADX) was introduced together with the ATR and RSI by Wilder (1978), as an attempt to quantify trend strength. The index has since its launch become a widely used tool among technical traders to determine whether a market is trending or non-trending (Weissman, 2005).

The ADX can be interpreted as an EMA of the rating of directional movements. The directional movements, DM_t^+ and DM_t^-, are two components giving the portion of the price bar that is either above the high of the previous bar or below the low of the previous bar, given in equation (4.6). The directional indices, DI_t^+ and DI_t^-, are then calculated in equation (4.7) as an EMA of the directional movements as a percentage of the ATR over the same period n. Hence the directional indices are adjusted for both the price level, and the volatility of the time period. These form the basis for the ADX, given in equation (4.8) and (4.9). The ADX is the EMA of the absolute value of the difference between DI_t^+ and DI_t^-, divided by their sum.

$$\begin{aligned} DM_t^+ &= \begin{cases} p_t^h - p_{t-1}^h & \text{for } p_t^h > p_{t-1}^h \wedge p_t^h - p_{t-1}^h > p_{t-1}^l - p_t^l \\ 0 & \text{Otherwise} \end{cases} \\ DM_t^- &= \begin{cases} p_{t-1}^l - p_t^l & \text{for } p_t^l < p_{t-1}^l \wedge p_t^h - p_{t-1}^h < p_{t-1}^l - p_t^l \\ 0 & \text{Otherwise} \end{cases} \end{aligned} \tag{4.6}$$

$$\begin{aligned} DI_t^+ &= \frac{EMA_{n,t}(DM^+)}{ATR_{n,t}} \times 100 \\ DI_t^- &= \frac{EMA_{n,t}(DM^-)}{ATR_{n,t}} \times 100 \end{aligned} \tag{4.7}$$

$$DX_t = \frac{|DI_t^+ - DI_t^-|}{DI_t^+ + DI_t^-} \times 100 \tag{4.8}$$

$$ADX_{n,t} = EMA_{n,t}(DX) \tag{4.9}$$

The index ranges between 0 and 100, and higher value indicates a stronger trend. The more directional movement of an asset, the greater the difference between DI_t^+ and DI_t^- relative to their sum. Although the ADX value itself does not indicate the direction of the trend, the DI_t^+ and DI_t^- can be interpreted separately to illustrate if the price is trending upwards or downwards, giving higher values for DI_t^+ or DI_t^-, respectively.

4.2.2 Aroon Indicator

The Aroon Indicator was developed by Chande (1995) and is similar to the directional movement index, the foundation of the ADX. The main assumption behind the Aroon indicator is that the asset price will close at higher highs in an uptrend, and lower lows in a downtrend. The indicator is based on two ratios, A_t^+ and A_t^-, measuring the strength of uptrend and downtrend respectively. The indicator A_t^+ measures the time passed since the highest price relative to the total time period n, and A_t^- measures the time passed since the lowest price. The values are given in percentage, with higher levels indicating stronger trend in underlying prices, and values close to zero indicating ranging prices. The calculation given in equation (4.10), where T_n is the set of the preceding time periods n.

$$\begin{aligned} A_t^+ &= \left(1 - \frac{t - \sup_{t'}\{p_{t'}^h : t' \in T_n\}}{n}\right) \times 100 \\ A_t^- &= \left(1 - \frac{t - \inf_{t'}\{p_{t'}^l : t' \in T_n\}}{n}\right) \times 100 \end{aligned} \tag{4.10}$$

As an example, if a 20 period time frame is used and it has been 5 days since the highest price in the last 20 days, the A_t^+ value would be 75. If it has been 16 days since the lowest price, the A_t^- would be 20. The difference between the A_t^+ and the A_t^- is called the Aroon Oscillator, AO, and gives a number between -100 and 100, given in equation (4.11).

$$AO_t = A_t^+ - A_t^- \tag{4.11}$$

High positive and negative values of AO_t are indicating an uptrend and downtrend respectively, while values around zero indicate a ranging time series.

4.2.3 Autocorrelation

Autocorrelation is the degree of similarity between a given time series and a lagged version of itself over successive time intervals (Brooks, 2008). It is often used in signal processing for analyzing functions or time series, and can be used to identify repeating patterns such as a series of positive returns representing a trend. The given value lies in the interval $[1, -1]$, and indicates whether the two time series are positively correlated, not correlated or negatively correlated. A price sample autocorrelation, $\hat{\rho}_k(t)$, in price time series, p_t, with lag, k, is given in equation (4.12), with $\bar{p}$ representing the sample mean, and s the sample standard deviation.

$$\hat{\rho}_k(t) = \frac{\mathbb{E}[(p_t - \bar{p}_t)(p_{t-k} - \bar{p}_{t-k})]}{s_t s_{t-k}} \tag{4.12}$$

To identify whether or not there is significant autocorrelation in the time series, the Ljung-Box test is one of many autocorrelation tests that can be performed (Brooks, 2008). The zero hypothesis of the corresponding test is that the data is independently distributed, meaning autocorrelations in all lags are 0, and the alternative hypothesis is that one or more are not 0 and the data is not independently distributed. The test statistic, Q_{LB} is computed and compared to the chi-square distribution and rejected if greater value at the appropriate significance level, α.

$$\begin{aligned} Q_{LB} =& n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k} \\ Q_{LB} \sim& \chi^2_{1-\alpha,h} \end{aligned} \tag{4.13}$$

In equation (4.13), n represents the sample size and h the number of lags being tested. Positive autocorrelation in returns with significance at a proper level, such as $\alpha = 10\%$, indicates a trend in the price time series. As the value does not indicate the direction of the trend, the trader can combine the autocorrelation value with other methods to trade in the underlying asset.

4.2.4 Empirical Mode Decomposition

The use of Empirical Mode Decomposition (EMD) for recognizing trends of financial asset prices was introduced by Ehlers and Way (2010). The method is based on basic signal filter theory with the assumption that a time series have a trend component and a cycle component, making it possible to identify whether the time series is in trend mode or cycle mode.

The cycle component is extracted by bandpass filtering the data. This means filtering out the unwanted components, both low frequency trends and the high frequency noise, and retain only a range of frequencies over the desired swing period. The trend component is extracted by finding the average of the filtered data over the two most recent periods. This averaging recovers the mean offset of the cycle, representing a scaled and smoothed version of the trend.

The method uses the average of high and low as the price of a period: $p_t = (p_t^h + p_t^l)/2$. The input parameter, n, is the length of the assumed natural cycle of the specific time series, Δ is the approximate half bandwidth given as a part of n while Θ is the factor adjusting the threshold levels of trend indication to the time series. With a relatively more certain cycle, one can tighten the bandwidth, and vice versa, and adjust the fraction to adapt to ones preferred trading style. In equation (4.14), before calculating the bandpass, BP_t, the a, b and c are calculated separately to simplify the expression.

$$\begin{aligned}
a =& \cos\left(\frac{2\pi}{n}\right) \\
b =& \cos^{-1}\left(\frac{4\pi \times \Delta}{n}\right) \\
c =& b - \sqrt{b^2 - 1} \\
BP_t =& \frac{1}{2} \times (1 - c) \times (p_t - p_{t-2}) + a \times (1 + c) \times BP_{t-1} \\
& - c \times BP_{t-2}
\end{aligned} \tag{4.14}$$

To determine if the asset price is in trend mode, the approach is to compare the peak swings of the cycle mode to the amplitude of the trend mode. The comparison is done by capturing local highs and lows in the BP_t time series, represented by P_t and V_t respectively, given in equation (4.15).

$$\begin{aligned}
P_t &= \begin{cases} BP_{t-1} & \text{for } BP_{t-1} > BP_t \wedge BP_{t-1} > BP_{t-2} \\ P_{t-1} & \text{Otherwise} \end{cases} \\
V_t &= \begin{cases} BP_{t-1} & \text{for } BP_{t-1} < BP_t \wedge BP_{t-1} < BP_{t-2} \\ V_{t-1} & \text{Otherwise} \end{cases}
\end{aligned} \tag{4.15}$$

The time series of BP_t, P_t and V_t are then smoothed using an EMA, creating a trend line and a scaled upper and lower threshold, respectively. The trend indication rules are given in equation (4.16).

$$\begin{aligned} &EMA_{2n,t}(BP_t) > EMA_{2.5n,t}(P_t) \times \Theta &\rightarrow \text{Positive trend} \\ &EMA_{2n,t}(BP_t) < EMA_{2.5n,t}(V_t) \times \Theta &\rightarrow \text{Negative trend} \end{aligned} \tag{4.16}$$

If the trend line is above the trigger levels set by the upper threshold, the asset price time series is likely to be in a positive trend. Similarly, if the trend line is below the lower threshold, the asset price time series is likely to be in a negative trend. If the trend line is between the threshold levels, the time series is said to be in cycle mode.

4.2.5 Fractal Dimension Indicator

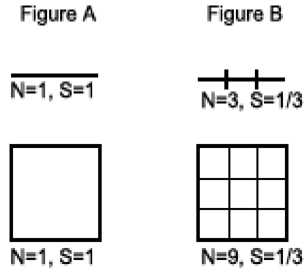
The Fractal Dimension Indicator (FDI) was introduced by Ehlers (2005). The technical indicator is based on the theory of fractals, which can be interpreted as self-similar patters; having the same or nearly the same form at every scale. A fractal is a mathematical set that has a fractal dimension, also known as Hausdorff dimension, that usually exceeds its topological dimension (Mandelbrot, 2004). Determining the fractal dimension, D, is done using equation (4.17), with N representing the number of self-similar objects, and S representing the length of the line defining each object.

$$\frac{N_b}{N_a} = \left(\frac{S_a}{S_b}\right)^D, \quad D = \frac{log(N_b/N_a)}{log(S_a/S_b)} \tag{4.17}$$

For sets describing ordinary geometric shapes the fractal dimension equals the set's familiar topological dimension; 0 for points, 1 for lines, 2 for surfaces and 3 for volumes. The simplest illustrations of determining the fractal dimension is using a line and a square, as in figure 6.

However, the fractal dimension can take non-integer values for fractal geometry, as exemplified with Sierpinski's triangle in figure 7. When decreasing S_b to $1/2$ of S_a, the number of self-similar objects, N_b, increases to 3.

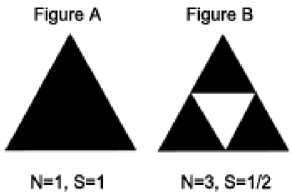
As with Brownian Motion, charts of asset prices can be interpreted as fractals as they look similar regardless of time frame (Ehlers, 2005). The fractal dimension of a time series is calculated by measuring how jagged or serrated it is. Accounting for that price samples are uniformly spaced, the object count is given by equation (4.18), which by definition is approximately the average slope of the price curve.



$$\frac{3}{1} = \left(\frac{1}{1/3}\right)^D, \quad D = 1$$

$$\frac{9}{1} = \left(\frac{1}{1/3}\right)^D, \quad D = 2$$

Figure 6: Illustration of Fractal Dimensions



$$\frac{3}{1} = \left(\frac{1}{1/2}\right)^D, \quad D = \frac{log(3)}{log(2)} \approx 1.585$$

Figure 7: Non-Integer Fractal Dimensions

$$N_{i,t} = \frac{\sup\{p_{t'}^h : t' \in T_n\} - \inf\{p_{t'}^l : t' \in T_n\}}{n} \tag{4.18}$$

The fractal dimension is calculated by computing N_i over two consecutive equal intervals and over the total interval, such that N_1 covers $[0, n]$, N_2 covers $(n, 2n]$, and N_3 covers the interval $[0, 2n]$. The fractal dimension is then defined as in equation (4.19) (Ehlers, 2005):

$$D_t = \frac{\log(N_{1,t} + N_{2,t}) - \log(N_{3,t})}{\log(2)} \tag{4.19}$$

In a two dimensional plane, as for price charts, the fractal dimension varies from $D = 1$ for prices trending in a straight line, to $D = 2$ for prices ranging up and down over the observation period. Hence a technical trader can use the FDI to identify when time series of asset prices are trending, and when they are not. As the FDI does not indicate the direction of the trend, a trader can combine the indicator with other methods to identify whether a long or short position should be initiated. The fractal dimension $D = 1.5$ represent a Gaussian random walk which sets the boundary between trending and ranging market, however the boundary must not be interpreted as a clean cut, but rather as an indication (Ehlers, 2005).

4.2.6 Vertical Horizontal Filter

The Vertical Horizontal Filter (VHF) was first introduced by Adam White (1991) as a simple method to help identifying if a market was trending or non-trending (Gopalakrishnan, 2000). The VHF is calculated by the difference between the highest and lowest closing price of the n preceding trading days, divided by the absolute returns of the close price over the same period as given in equation (4.20). The VHF value indicates the maximum price movement over the period, relative to its variance.

$$VHF_t = \frac{|\sup\{p^c_{t'} : t' \in T_n\} - \inf\{p^c_{t'} : t' \in T_n\}|}{\sum_{i=0}^{n} |r^c_{t-i}|} \tag{4.20}$$

The VHF value itself does not reflect trend direction, only an indication of whether a trend is apparent, and the strength of the indication. The values of the VHF lies in the interval $[0, 1]$, where values approaching 1 indicates a trending time series, and 0 indicating a ranging series. The values given from a random set are not symmetrically distributed, lower values are more common, and the values must be interpreted as such.

4.2.7 Vortex Indicator

The Vortex Indicator was developed by Botes and Siepman (2009) as a new and improved version of the ADX of Wilder (1978). The indicator is based on the vertical movement from one time period to the next, and uses these values to indicate a positive trend, a negative trend, or neither. The values VM^+_t and VM^-_t, measure the distance from yesterday's low to today's high and yesterday's high to today's low respectively, as given in equation (4.21).

$$\begin{aligned} VM^+_t &= |p^h_t - p^l_{t-1}| \\ VM^-_t &= |p^l_t - p^h_{t-1}| \end{aligned} \tag{4.21}$$

The values form the basis for VI_t^+ and VI_t^-, which represent the indication of positive and negative trend respectively, and is calculated as a EMA of the movement divided by the ATR. Hence the Vortex Indicator levels are adjusted to the price level and the volatility of the time series of the current asset price, as given in equation (4.22).

$$\begin{aligned} VI_t^+ &= \frac{EMA_{t,n}(VM_t^+)}{ATR_{t,n}} \\ VI_t^- &= \frac{EMA_{t,n}(VM_t^-)}{ATR_{t,n}} \end{aligned} \tag{4.22}$$

A large VI_t^+ value indicates a strong upward trend, and a large VI_t^- value indicates a strong downward trend. For a more easily interpretation of the Vortex Indicator, a technical trader can use some value, Γ, representing the threshold for the difference between VI_t^+ and VI_t^-, as given by equation (4.23).

$$\begin{aligned} VI_t^+ &> VI_t^- \times (1+\Gamma) \rightarrow \text{ Positive trend} \\ VI_t^- &> VI_t^+ \times (1+\Gamma) \rightarrow \text{ Negative trend} \end{aligned} \tag{4.23}$$

If the difference between the two indicators is greater than the threshold set by the trader, the Vortex Indicator signals that the underlying time series is trending.

4.3 Risk assessment methods

The risk assessment methodology is set by the Fund's risk management strategy, and includes both a Value-at-Risk model and a Conditional Value-at-Risk model, in addition to ATR based position scaling. The methods are used to assess position risk as well as measures during parameter calibration.

4.3.1 Value-at-Risk

Value-at-Risk (VaR) has during the last two decades become a widely used risk measure in financial risk management, and following the lead from both regulators and large international banks during the mid-1990s, almost all financial institutions now use some form of VaR as a risk metric (Alexander, 2008a). The function $VaR_{ht,\alpha}$ gives a single value at time t, such that for a given probability, (1-α), losses will not exceed this value over the next time interval, h, given that the portfolio is hold static. Using $h = 1$, the daily Value-at-Risk (dVaR) is obtained. As the risk measure is intuitively easy and widely used, the numerical value is easy to compare across portfolios.

Equation (4.24) defines the random variable X_t as the present value of the portfolio return over one period (Alexander, 2008a). The dVaR is then estimated as a percentage of the portfolio value by equation (4.25), where $x_{t,\alpha}$ represents the α quantile of the return distribution.

$$X_t = \frac{e^{-r_f} \times p_{t+1} - p_t}{p_t} \tag{4.24}$$

$$\begin{aligned} dVaR_{t,\alpha} &= -x_{t,\alpha} \\ P(X_t < x_{t,\alpha}) &= \alpha \end{aligned} \tag{4.25}$$

There are two major issues that are imperative to be aware of before utilizing VaR. The first issue is the calculation of the probability distribution. The second issue is that, conditional on the event that one has exceeded the threshold value, VaR says nothing about the severity of the movements or tail risks. Alexander (2008a) distinguish between three basic methods for estimating VaR, each handling the first issue in a separate way; normal linear VaR model, historical simulation model and Monte Carlo VaR model. Normal linear models assume that the asset returns are normally distributed, and that the portfolio returns are linear. Historical simulations models calculate the distributions out of a historical sample, whereas Monte Carlo VaR models can make a wide range of assumptions incorporating many different distributions.

The method used for controlling daily position risk in the base trading model is similar to the normal linear VaR model. The portfolio $dVaR_{t,\alpha}$, measured as percentage of portfolio value, is given by equation (4.26). It is calculated using the standard normal α quantile value of the portfolio return distribution, multiplied by the weighted returns' daily volatility given in equation (4.27) (Hull, 2012).

$$VaR_{t,\alpha} = \Phi^{-1}_{(1-\alpha)} s_t \tag{4.26}$$

$$s_t = \sqrt{(1-\Theta)\sum_{i=1}^{n}\Theta^{i-1}(r_{t-i}-\bar{r})^2 + \Theta^n s_{t-n}^2} \tag{4.27}$$

The degree of exponential decrease in the $EMA_{t,n}$ is given by Θ. For large n, the term $\Theta^n s_{t-n}^2$ converge to zero and can be ignored (Hull, 2012).

4.3.2 Conditional Value-at-Risk

While VaR says nothing about the severity of the incurred loss, given that one exceeds the VaR, Conditional Value-at-Risk (CVaR) does. CVaR provides the average expected tail loss defined by Alexander (2008a) in equation (4.28).

$$CVaR_{t,\alpha} = -\mathbb{E}[X_t | X_t < -VaR_{t,\alpha}] \tag{4.28}$$

The calculation of the CVaR used in the base trading model is given in equation (4.29). The function r_t^m represents the rolling monthly return at time t whereas $P_{10}(r^m)$ denotes the lowest 10th percentile of monthly returns in the lookback period T_n of length n.

$$CVaR_{t,\alpha} = \frac{1}{n}\sum_{t \in T_n} \left| r_t^m \times \mathbb{1}_{\{r_t^m < P_{10}(r^m)\}} \right| \tag{4.29}$$

As the normal linear VaR model is based on simplified assumptions regarding the risk factors and that the portfolio returns are linear, it is not a coherent risk measure, or in particular, VaR is not sub additive (Alexander, 2008a). Opposed to VaR, CVaR is always a coherent risk measure, meaning that portfolio CVaR is less than or equal to the sum of each asset's CVaR.

5 Risk adjusted performance measures

Risk adjusted performance measures (RAPMs) are used for performance evaluation and for decision on capital allocation within financial institutions (Alexander, 2008b). The RAPMs are supposed to bridge the gap between maximizing the investor's utility and optimally allocate risk capital. RAPMs make it possible for investors to rank investment opportunities, but only some RAPMs have a direct link to a utility function. The other RAPMs may still be used to rank investments but nothing can be deduced about investors' preferences from these rankings.

Traditional RAPMs such as Sharpe ratio and Information ratio were developed to compare long-only strategies and can be argued not to be suitable for dynamic trading strategies as they exhibit non-normal returns and non-linear exposure to risk factors (Alexander, 2008b). However, such methods are among the most widely used, even for dynamic trading strategies, and are therefore included. In the nineties, practitioners and academics developed alternative models such as Sortino, Kappa and Omega ratios which have become very popular for analyzing the performance of hedge funds and managed futures strategies.

All RAPMs should be interpreted in relation to a fund's Margin-to-Equity (M/E) ratio. The M/E ratio describes the sum of margin required to hold a portfolio of futures and forwards, relative to total capital base (Melin, 2010). The calculation of historical M/E ratio is simplified by using present margins, and its percentage of the contract value, adjusted back in time. Due to asset correlation within the portfolio, the actual required margins will be significantly lower than the estimates. However, this is not accounted for due to complexity and time consuming calculations. Hence the simplification will provide a worst case estimate for assessment.

5.1 Sharpe ratio

The Sharpe ratio was introduced by Sharpe (1966) and has become one of the most referenced risk/return measures in finance (Alexander, 2008b). The ratio is defined by equation (5.1) and measures the risk premium relative to the risk incurred in achieving it. The ratio is expressed by the excess expected return on an asset over the risk free rate, $\mathbb{E}[R] - r_f$, divided by the standard deviation of the asset returns distribution.

$$Sharpe = \frac{\mathbb{E}[R] - r_f}{\sigma} \tag{5.1}$$

By using the Sharpe ratio to compare assets or portfolios, there is assumed that investors preferences can be represented by exponential utility and that returns are normally distributed (Alexander, 2008b). As such, the Sharpe ratio can be a good measure for large, diversified liquid investments. While for smaller hedge funds, the ratio should not be used exclusively as it does not accommodate fat tails, kurtosis and skewness. However, the major advantage of using the Sharpe ratio is its simplicity and the extensive use by practitioners, which yields a good base for comparison between funds and indices (Bruder and Gaussel, 2011).

5.2 Information ratio

The information ratio (IR) is a RAPM that seeks to evaluate an actively traded portfolio against a passive benchmark portfolio. It is built on the Markowitz mean-variance paradigm, which states that the mean and variance is sufficient to evaluate a portfolio's performance (Goodwin, 1998). The ratio is given in equation (5.2), and expresses the average excess return per unit volatility in the excess return distribution. R_p denotes the return on the portfolio while R_b denotes the return on the benchmark.

$$IR = \frac{\mathbb{E}[R_p - R_b]}{\sqrt{VAR[R_p - R_b]}} \tag{5.2}$$

If confined to the benchmark's asset universe, the active manager can only add value by underweighting or overweighting individual assets. The different weighting represent the active manager's skill or the special information the manager possess (Goodwin, 1998). When utilizing the IR it is important to be aware that it does not include information on correlations between asset classes and that it ignores the investor's risk preference. Another factor that can affect the IR significantly is the choice of benchmark, thus making it easy to manipulate if compared to an inappropriate index. The IR represents a different methodology compared to the other RAPMs mentioned, and thus gives a valuable diversity effect when evaluating the performance of trading strategies.

5.3 Omega statistic

The Omega statistic was introduced by Keating and Shadwick (2002), and express the probability weighted ratio of gains to losses, relative to the investor chosen threshold τ. The Omega statistic is defined by equation (5.3), and is calculated from the expected return over τ divided by the lower partial movement (LPM) of first order. The LPM is an asymmetric risk measure that calculates the probability-weighted deviations of those returns falling below the specified threshold, and is given in equation (5.4). The threshold, τ, is usually referred to as the minimum acceptable return (MAR), and should be set so that investors consider return above τ as gains, and below as losses.

$$\Omega(\tau) = \frac{\mathbb{E}[max(R - \tau, 0)]}{LPM_1(\tau)} \tag{5.3}$$

$$LPM_1(\tau) = \mathbb{E}[max(0, \tau - R)] \tag{5.4}$$

By introducing MAR and accounting only for the downside variability, the Omega statistic does not penalize returns that are above the threshold. However, there are several caveats to be aware of when calculating the downside deviation using the LPM. The most important are the annualization of the observed values, and time horizon of the sample (Kidd, 2012). The Omega statistic can be highly vulnerable to biased data sets if the ex-post estimation is based on a period of upwardly trading returns. The downside deviation underestimates the two sided risk if loss periods are not included, and vice versa.

The Omega statistic incorporates all the characteristics of a return distribution and does not need any assumptions about risk preference or utilities (Keating and Shadwick, 2002). At any given τ, a higher value of Omega statistic is preferred to a lower one. Hence it is easily computed and interpreted, and the common use among practitioners makes it a valuable RAPM (Alexander, 2008b).

5.4 Sortino ratio

The Sortino ratio is similar to the Sharpe ratio except that the standard deviation in the denominator is replaced by the square root of the LPM of second order (Sortino and Satchell, 2001). The ratio is given in equation (5.5), and is calculated as the expected excess return over the investor's chosen MAR, τ, divided by LPM_2, which is given in equation (5.6).

$$Sortino = \frac{\mathbb{E}[R] - \tau}{\sqrt{LPM_2(\tau)}} \tag{5.5}$$

$$LPM_2(\tau) = \mathbb{E}[max(0, \tau - R)^2] \tag{5.6}$$

Similar to the Omega statistic, the Sortino ratio does not penalize returns above the MAR. It can be argued that this ratio is a more realistic measure of risk-adjusted return than the Sharpe ratio as investors are generally not averse against high positive returns as indicated by the standard deviation (Alexander, 2008b). The Sortino ratio is by many considered an improvement of the Sharpe ratio, and has therefore gained popularity since its introduction, making it a good RAPM for comparisons.

5.5 Kappa indices

Kaplan and Knowles (2004) introduced a generalized downside RAPM with the Kappa indices. The formulation is given by equation (5.7), and shows that both the Sortino ratio and the Omega statistic are special cases of Kappa indices.

$$K_\alpha(\tau) = \frac{\mathbb{E}[R] - \tau}{LPM_\alpha(\tau)^{\frac{1}{\alpha}}} \tag{5.7}$$

The function K_α is defined for any value of α exceeding zero. The index of α=2 represents the Sortino ratio described in section 5.4. The Kappa index of first order is closely related to the Omega statistic as given in equation (5.9) and (5.8).

$$LPM_\alpha(\tau) = \mathbb{E}[max(0, \tau - R)^\alpha] \tag{5.8}$$

$$K_1(\tau) = \Omega(\tau) - 1 \tag{5.9}$$

Despite for its popularity, practitioners have not found an applicable rule for choosing the appropriate Kappa index and threshold value in order to rank different investment opportunities (Alexander, 2008b). This follows from that the indices cannot be linked to a standard utility function. At any given threshold, a higher value of the distinctive Kappa index is preferred to a lower one, but the ranking of a given investment alternative can change according to the Kappa index chosen. All Kappa indices are negative for $\tau > \mathbb{E}[R]$, zero for $\tau = \mathbb{E}[R]$, and positive for $\tau < \mathbb{E}[R]$. Higher order Kappa indices are more sensitive to skewness and excess kurtosis due to the fact that they are more sensitive to extreme returns. Risk adverse investors can therefore rank portfolios using higher order Kappa indices while investors less risk adverse could rank portfolios using lower order Kappa indices. Higher order LPMs are also more sensitive to the choice of the threshold value. Higher order Kappa indices supplement the lower order indices, such as Omega statistic and Sortino ratio, by bringing diversification into the performance evaluation.

6 Asset allocation and trading procedure

A complete base trading model (BTM) is constructed to be able to assess the Fund's technical trading strategies. The model manages trading positions and risk for each of the assets in the asset pool, based on the amount of risk capital allocated to each asset. The model is assessed using historical time series data over a 14 year period.

As the second purpose of the thesis is to assess whether dynamic allocation adds value to the trading model, a separate trend recognition and allocation model (TRAM) is constructed. The TRAM analyzes all asset time series with the purpose of only allocating risk capital to the assets which time series is believed to be trending. The model uses a set of technical trend recognition methods, which are assessed separately on the value added compared to a static capital allocation.

Both models use a set of parameters which are recalibrated on a monthly basis during the assessment period.

6.1 The Base Trading Model

The base trading model increases and decreases the long and short positions in each of the assets. The model operates on a daily basis, basing decisions on technical analysis of the assets' price time series. The model framework is primarily based on three fixed EMAs and a RSI rule, as introduced in section 4.1. A volatility based position scaling function and a dVaR limitation rule is implemented to control risk. The framework is kept unchanged, but certain trigger levels and time period lengths, given in table 2, are recalibrated on a monthly basis. The BTM is calibrated separately for each asset, to adapt its trading rules and trigger levels to each asset's time series dynamics.

To assess the profitability of the BTM framework, the model is evaluated over the time period from January 1998 to February 2012. The monthly recalibration is based on an optimization process, which is further discussed in section 6.3.3. The BTM uses the parameters yielded by the optimization in a set of trading rules, which determines the timing of trades and the risk exposure by setting long or short positions. The positions, P_t, are expressed in the interval $[-1, 1]$, but ultimately scaled to the actual number of futures that should be traded.

Table 2: Monthly recalibrated BTM parameters

Parameter categories	*Notation*
ATR_{20} band width	α
High/Low significance level	β
RSI: EMA length	γ
RSI: Extreme levels	δ
RSI: Duration of reduction	ϵ
MA10 RSI: look back period	ζ
MA10 RSI: Extreme levels	η

6.1.1 Defining direction and sizing a position - the EMA_{50} rule

A 50-day EMA of the one period lagged close price, EMA_{50}, creates the base of the model, defining the direction of any position as long or short. Basically the model is long in an asset if the price is above the EMA_{50}, and short if it drops below. To prevent noise from creating mistrades, a band of a given percentage, α, of a 20-day one period lagged ATR, ATR_{20}, is added to the EMA_{50} as given in equation (6.1).

$$\begin{aligned} EMA_{50}^{+} &= EMA_{50} + \alpha \times ATR_{20} \\ EMA_{50}^{-} &= EMA_{50} - \alpha \times ATR_{20} \end{aligned} \tag{6.1}$$

The highest high and the lowest low of prices since a change of position direction, is defined as p_t^{hh} and p_t^{ll} respectively. The definitions are given in equation (6.2). The set T_P comprises of the time periods elapsed since initiation of the current long or short position.

$$\begin{aligned} p_t^{hh} &= \sup\{p_{t'}^{h} : t' \in T_P\} \\ p_t^{ll} &= \inf\{p_{t'}^{l} : t' \in T_P\} \end{aligned} \tag{6.2}$$

The initiation of new position direction is described in equation (6.3), where P_t^{50} represents the size of the position set by the EMA_{50} rule.

$$P_t^{50} = \begin{cases} 1/3 & \text{for } p_t^c \geq EMA_{50,t}^{+} \wedge p_{t-1}^c < EMA_{50,t-1}^{+} \\ -1/3 & \text{for } p_t^c \leq EMA_{50,t}^{-} \wedge p_{t-1}^c > EMA_{50,t-1}^{-} \end{cases} \tag{6.3}$$

Given no change of position direction in the current time period, t, the increase of the current position is given in equation (6.4). The EMA_{50} rule increases the exposure with steps of ⅓ each time the price reaches a higher high when long, or a lower low when short. The stepwise increment is used to minimize exposure in ranging markets. The higher high and lower low is only registered if they are more than a certain percentage, β, higher and lower respectively, to ensure they are significant enough for increased exposure. This percentage is set to reduce excess trading and as an insurance of trend strength.

$$P_t^{50} = \begin{cases} min(P_{t-1}^{50} + {}^1\!/_3, 1) & \text{for } p_t^h > (1+\beta) \times p_{t-1}^{hh} \wedge P_{t-1}^{50} > 0 \\ max(P_{t-1}^{50} - {}^1\!/_3, -1) & \text{for } p_t^l < (1-\beta) \times p_{t-1}^{ll} \wedge P_{t-1}^{50} < 0 \end{cases} \tag{6.4}$$

An example of the EMA_{50} rule is illustrated over a few time periods in figure 8.

t	p^h	p^l	p^c	p^{hh}	50+	50-	p^{50}
1	1.9	1.6	1.9		2.2	1.9	-1.0
2	2.8	2.1	2.8	2.8	2.1	1.9	1/3
3	2.8	2.3	2.3	2.8	2.2	1.9	1/3
4	2.7	2.3	2.6	2.8	2.2	1.9	1/3
5	3.6	2.8	3.5	3.6	2.2	1.9	2/3
6	4.1	3.6	4.1	4.1	2.3	2.0	1.0
7	4.0	3.4	3.5	4.1	2.4	2.0	1.0
8	2.2	1.8	2.0		2.4	2.1	-1/3

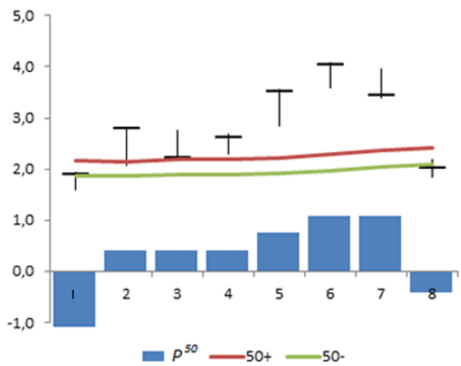


Figure 8: The EMA_{50} trading rule

As the price reaches above EMA_{50}^{+} in $t = 2$, a long position of ⅓ is initiated. The position is increased with steps of ⅓ on each significant new high, until full exposure. As the price drops below EMA_{50}^{-} in $t = 8$, the position is neutralized and a short position of ⅓ is initiated.

6.1.2 Reducing position as prices reverse - the EMA_{20} rule

As the BTM is increasing the exposure to assets based on the EMA_{50} rule, a 20-day EMA of the preceding close price, EMA_{20}, is used to decrease exposure when asset prices start to reverse their trending movement. As in equation (6.1), the EMA^{+}_{20} and $EMA^{-}_{20}$are given with the same percentage, α, of the ATR_{20} to reduce the impact of noise in time series. The EMA_{20} rule is given in equation (6.5), where P^{20}_t is the reduction of the P^{50}_t in absolute terms, assuming $P^{50}_t > 0$.

$$P^{20}_t = \begin{cases} 0 & \text{for } P^{50}_t \neq P^{50}_{t-1} \\ & \vee\, (p^c_t > (1+\beta) \times p^{hh}_{t-1} \wedge p^c_t > EMA^{+}_{20,t}) \\ 1/3 & \text{for } p^c_t < EMA^{-}_{20,t} \\ 1/6 & \text{for } (P^{20}_{t-1} > 0 \wedge p^c_t > EMA^{+}_{20,t}) \\ & \vee\, P^{20}_{t-1} = 1/6 \end{cases} \tag{6.5}$$

The conditions are ranked after cardinality. As the rule is symmetric for long and short positions, the contrary applies when $P^{50}_t < 0$. In figure 9 the EMA_{20} rule is illustrated with such an example.

t	p^h	p^l	p^c	p^{ll}	20+	20-	p^{20}
1	3.8	3.2	3.5	1.9	3.6	3.2	0
2	3.8	3.5	3.7	1.9	3.6	3.2	1/3
3	3.5	3.1	3.3	1.9	3.6	3.2	1/3
4	3.5	2.9	3.1	1.9	3.6	3.2	1/6
5	4.0	3.2	3.5	1.9	3.5	3.2	1/6
6	3.3	2.5	2.9	1.9	3.5	3.2	1/6
7	2.8	1.9	2.3	1.9	3.5	3.2	1/6
8	1.8	1.7	1.7	1.7	3.4	3.1	0

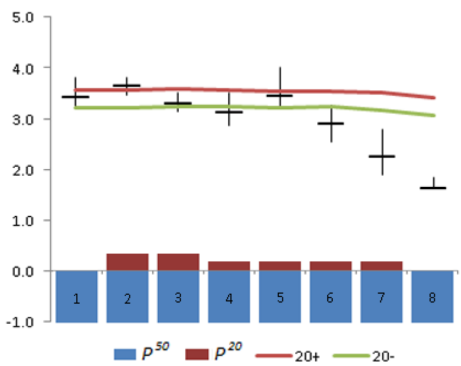


Figure 9: The EMA_{20} trading rule

While a short position is active, the price rises above the EMA^{+}_{20} in $t = 2$, and P^{20}_t is set to ⅓. The adjustment lasts until the price drops below the EMA^{-}_{20} in $t = 4$, as it changes to ⅙. The adjustment is completely removed as the price reaches a lower low in $t = 8$.

6.1.3 Reducing position due to extreme momentum - the RSI rule

To further control risk, the BTM uses an RSI rule to decrease the positions when an asset is believed to be overbought or oversold. The variable representing the length of the EMA of the RSI is denoted γ. The RSI value is defined as extreme when above the upper threshold, δ ,when $P_t^{50} > 0$, or below the lower threshold, $(100 - \delta)$, when $P_t^{50} < 0$. As the value reaches such levels, the position P_t^{50} is reduced in absolute terms. The reduction caused by the RSI rule is denoted P_t^{RSI}. The reduction is changed if prices see a significant higher high or lower low while the RSI value is no longer on extreme levels. The P_t^{RSI} is set to zero after a certain number of time periods, ϵ, after seeing extreme RSI values, or when P_t^{50} changes direction. The reduction, P_t^{RSI}, is given for $P^{50} > 0$ in absolute terms in equation (6.6).

$$P_t^{RSI} = \begin{cases} 0 & \text{for } P_t^{50} \neq P_{t-1}^{50} \\ & \vee\, t - \sup\{t' : t' \in (RSI_{t'} > \delta)\} > \epsilon \\ 1/3 & \text{for } RSI_t > \delta \\ & \vee\, (P_{t-1}^{RSI} > 0 \wedge p_t^c < (1+\beta) \times p_{t-1}^{hh}) \\ 1/6 & \text{for } P_{t-1}^{RSI} > 0 \wedge p_t^c > (1+\beta) \times p_{t-1}^{hh} \wedge RSI < \delta \end{cases} \tag{6.6}$$

The conditions are ranked after cardinality. As the rule is symmetric for long and short positions, the contrary applies when $P_t^{50} < 0$.

If the EMA_{20} rule has decreased a position to less than ⅓, the RSI rule will not create a position in the opposite direction of what is indicated by the EMA_{50} rule, but remain passive. In figure 10 the RSI rule is illustrated with an example.

While a short position is active, the RSI value drops below the trigger level $(100 - \delta)$ in $t = 2$, and P_t^{RSI} is set to ⅓. The adjustment changes to ⅙ as the RSI returns to normalized values and the price reaches a lower low in $t = 6$. The reduction is completely removed in $t = 8$ as the number of time periods since last extreme RSI value exceeds the example limit: $(t = 8) - (t = 3) > (\epsilon = 4)$.

6.1.4 Increasing sensitivity to extreme momentum - the EMA_{10} rule

A 10-day EMA of the preceding close price, EMA_{10}, is used to add sensitivity to oversold and overbought markets. The EMA_{10} rule is defined the exact same way as the EMA_{20} in equation (6.5), but conditional on observing one or more extreme RSI values in a last certain number of time periods, ζ. The RSI values

			δ = 85		ε = 4	
t	p^h	p^l	p^c	p^{ll}	RSI	p^{RSI}
1	4.6	3.9	4.0	3.9	17	0
2	2.9	2.3	2.5	2.3	13	1/3
3	2.7	2.3	2.7	2.3	14	1/3
4	3.4	2.5	2.9	2.3	18	1/3
5	3.2	2.9	2.9	2.3	17	1/3
6	2.6	1.7	1.9	1.7	16	1/6
7	2.1	1.9	2.1	1.7	17	1/6
8	2.9	1.9	2.5	1.7	19	0

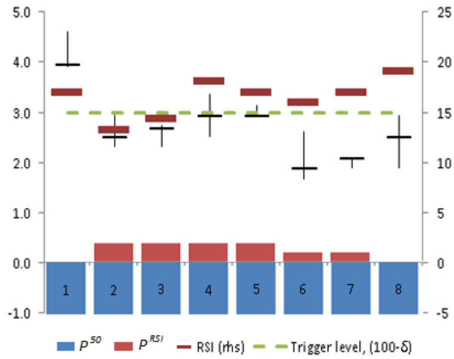


Figure 10: The RSI trading rule

are defined as extreme if they are above the upper threshold, η, when $P_t^{50} > 0$, or below the lower threshold, $(100 - \eta)$ when $P_t^{50} < 0$. The parameter η is not necessarily equal to δ. However if the EMA_{20} and RSI rules have decreased a position to less than ⅓, the EMA_{10} rule will not create a position in the opposite direction of what is indicated by the EMA_{50} rule, but remain passive. An illustration of the EMA_{10} rule is given in figure 11, where P_t^{10} represents the reduction due to the EMA_{10} rule.

			η = 70		ζ = 10			
t	p^h	p^l	p^c	p^{ll}	10+	10-	RSI	p^{10}
1	2.9	2.7	2.7	1.9	3.0	2.4	28	0
2	4.1	3.5	3.9	1.9	3.0	2.4	38	1/3
3	3.6	3.1	3.4	1.9	2.9	2.3	45	1/3
4	3.4	2.7	3.2	1.9	2.8	2.2	47	1/3
5	2.5	2.2	2.5	1.9	2.8	2.2	41	1/3
6	2.5	2.1	2.1	1.9	2.9	2.3	36	1/6
7	2.2	1.9	2.2	1.9	3.0	2.4	33	1/6
8	1.9	1.3	1.8	1.3	3.1	2.5	40	0

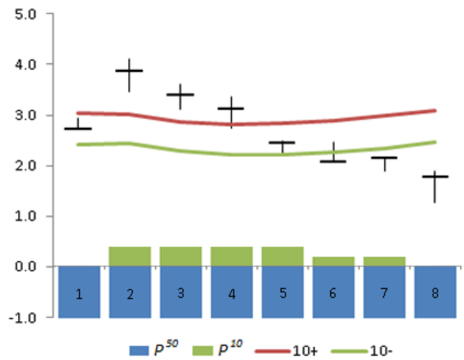


Figure 11: The EMA_{10} trading rule

While a short position is active, the price rises above the EMA_{10}^{+} in $t = 2$. P_t^{10} is set to ⅓ as a RSI value below $(100 - \eta)$ is observed in $t = 1$, which is less than $\zeta = 10$ periods ago. The adjustment lasts until the price drops below the EMA_{10}^{-} in $t = 6$, where it changes to ⅙. The adjustment is completely removed as the price reaches a lower low in $t = 8$.

6.1.5 Managing allocated risk capital - position scaling and the $dVaR$ rule

The position including all the introduced trading rules is denoted P_t^R, and is given in equation (6.7). The base position, P_t^{50}, initialized by the EMA_{50} rule, is adjusted by the EMA_{20}, RSI, and the EMA_{10} rules, giving P_t^R a value in the interval $[-1, 1]$.

$$P_t^R = P_t^{50} + P_t^{20} + P_t^{RSI} + P_t^{10} \tag{6.7}$$

To determine the actual number of future or forward contracts to be traded, SP, the positions are scaled such that the position dVaR at a time t, is adapted to the dVaR limit allocated to the asset. The scaling function S is converting the position value from $[-1, 1]$ to the actual number of contracts, and is given in equation (6.8). As the position is dependent on a 100-day ATR, the scaling function becomes an important risk control tool, adjusting to smaller positions when volatility increases in the underlying asset. As the ATR is calculated per quoted unit and the scaling function yields traded units, the function is divided by the ratio TU/QU.

$$S_t = \frac{dVaR_t^L}{ATR_{100,t} \times {}^{TU}/_{QU}} \times c \tag{6.8}$$

The factor c, called the scaling factor, is constant for all assets and all time periods. The factor is optimized to find a scaling function suitable for the Fund's preferred risk profile, a process described in section 6.3.2. The number of contracts are rounded down the nearest integer, as fractions of contracts are not traded.

As a final risk control tool, the $dVaR_t$ of a position at time t is limited by the $dVaR_t^L$. The total amount of $dVaR^L$ across all assets at a time t is determined by the Fund's risk and trading strategy, and accounts for 3% of the total capital base of the Fund.

If the volatility of an asset reaches high levels while BTM has fully accumulated a long or short position, the $dVaR_t$ might exceed the limit of allowed maximum risk. The dVaR is calculated with a 100-day weighted moving volatility measure. As given in equation (6.9), the final number of contracts, SP_t^A, is adjusted to the maximum position satisfying the risk limitation, SP_t^M. The position is readjusted if the difference between SP_{t-1}^A and SP_t^M exceeds 5% while the $dVaR_t > dVaR_t^L$.

$$SP_t^A = \begin{cases} P_t^R \times S_t & \text{for } dVaR_t < dVaR_t^L \\ SP_t^M & \text{for } dVaR_t > dVaR_t^L \wedge dVaR_{t-1} < dVaR_{t-1}^L \\ & \vee\, dVaR_t > dVaR_t^L \wedge \left|\frac{SP_t^M}{SP_{t-1}^A} - 1\right| > 5\% \\ SP_{t-1}^A & \text{for } dVaR_t > dVaR_t^L \wedge \left|\frac{SP_t^M}{SP_{t-1}^A} - 1\right| < 5\% \end{cases} \tag{6.9}$$

$$|SP_t^M| = min\left(\frac{dVaR_t^L}{p_t^c \times s_t \times \Phi_{5\%}^{-1} \times {}^{TU}/_{QU}}, S_t\right) \tag{6.10}$$

The maximum position satisfying the risk limitation, SP_t^M, is given in equation (6.10), as the inverse $dVaR_t$ function given in section 4.3.1. The trailing volatility is denoted s_t, and $\Phi_{5\%}^{-1}$ represents the inverse standard normal distribution at a 5% level. The scaling function and the $dVaR$ rule is illustrated with an example in figure 12.

In the example, the model reaches maximum exposure in $t = 3$. As the volatility increases faster than captured in S_t , the $dVaR_t$ exceeds the $dVaR_t^L$ in $t = 4$, and SP_t^A is set to SP_t^M. As SP_t^M moves more than 5% from where SP_{t-1}^A was adjusted, the SP_t^A is readjusted in times $t = 5$, 6 and 7. As the $dVaR_t$ drops below $dVaR_t^L$ in $t = 8$, SP_t^A is set to $P^R \times S_t$.

6.1.6 Profit, transaction costs and mistrades

As the model only interprets open, high, low and close prices of each trading day, some assumptions regarding intraday price moves are implemented. On days

$dVaR^L = 1000$

t	p^R	S_t	$dVaR$	SP^M	SP^A
1	1/3	210	300	70	70
2	2/3	210	650	140	140
3	1	205	950	205	205
4	1	203	1050	193	193
5	1	202	1070	181	181
6	1	201	1100	164	164
7	1	201	1040	191	191
8	1	202	900	202	202

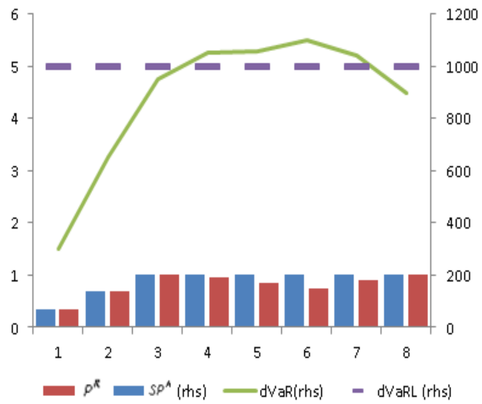


Figure 12: The $dVaR$ risk control

when a position is increased, decreased or fully reversed, the model assumes that the price move causing the decision only happen once during the day. Therefore, the monetary profit is calculated as the exposed amount of dollars multiplied by the change in close prices from one period to the next, and adjusted using the open, high and low prices. The adjustments, A, handles the difference between the close prices, and the trigger levels on where the trades are assumed to have been executed. The formula for calculating the monetary profit is given in equation (6.11), where M represents mistrades caused by the various trading rules, and TC denotes the transaction costs given in equation (6.12).

$$\begin{aligned} Profit_t^{USD} &= SP_{t-1}^A \times (p_t^c - p_{t-1}^c) \\ &+ A_t^{50} + A_t^{20} + A_t^{10} + M_t^{50} + M_t^{20} + M_t^{10} - TC_t \end{aligned} \tag{6.11}$$

$$TC_t = |SP_t^A - SP_{t-1}^A| \times (p_t^h - p_t^l) \times 5\% \tag{6.12}$$

As the Fund does not have access to the historical orderbook for an asset, the actual cost per transaction is impossible to determine. The transaction costs will vary from asset to asset, depending on general contract liquidity as well as time specific volatility. The transaction cost itself is only a small cost compared to the spread cost and liquidity cost, which are also incorporated in TC. As both spread and liquidity are somewhat dependent on volatility, the TC is formulated as a function of the intraday volatility, scaled by 5%, to best possibly estimate the total costs.

The profit adjustments, A, apply to all trades triggered by the close price crossing a certain level, such as the EMA_{50}, EMA_{20} and EMA_{10} rules. For the EMA_{50} rule, the adjustment of the profit is given in equation (6.13).

$$A_t^{50} = \begin{cases} [p_t^c - min(p_t^o, EMA_{50,t}^{-})] \times (P_t^{50} - P_{t-1}^{50}) \times S_t \\ \quad \text{for } P_t^{50} < 0 \wedge P_{t-1}^{50} > 0 \\ [p_t^c - max(p_t^o, EMA_{50,t}^{+})] \times (P_t^{50} - P_{t-1}^{50}) \times S_t \\ \quad \text{for } P_t^{50} > 0 \wedge P_{t-1}^{50} < 0 \\ [p_t^c - min(p_t^o, p_{t-1}^{ll})] \times 1/3 \times S_t \\ \quad \text{for } |P_t^{50}| > |P_{t-1}^{50}| \wedge P_{t-1}^{50} \neq 0 \wedge P_t^{50} < 0 \\ [p_t^c - max(p_t^o, p_{t-1}^{hh})] \times 1/3 \times S_t \\ \quad \text{for } |P_t^{50}| > |P_{t-1}^{50}| \wedge P_{t-1}^{50} \neq 0 \wedge P_t^{50} > 0 \\ 0 \;\; \text{Otherwise} \end{cases} \tag{6.13}$$

The corresponding adjustments made for the trades initiated by the EMA_{20} and EMA_{10} rules are found in Appendix D. Similarly, when prices cause intraday trades that are reversed the same day, i.e. mistrades, the model assumes these trades to only happen once during the day. Mistrades, M, happen as intraday prices, p_t^h and p_t^l, cross trigger levels and initiate trades, while the close price does not cross the same levels. The calculation of mistrades caused by the various rules are given in appendix D. The daily asset specific return, r_t^A, is then calculated as in equation (6.14), using the monetary profit and the allocated capital in the preceding time period.

$$r_t^A = \frac{Profit_t^{USD}}{100/3 \times dVaR_{t-1}^L} \tag{6.14}$$

As the Fund's dVaR limit is 3% of the capital base, the allocated capital is found by multiplying the $dVaR_t^L$ by $100/3$. The return of the entire portfolio is calculated relative to the total capital base, regardless of any non-allocated amount of capital.

6.2 The Trend Recognition and Allocation Model

The trend recognition and allocation model is built up of seven technical methods intended to recognize trends among assets' price time series. Each of the methods are described in section 4.2. Utilizing one of the seven methods at a time, the model gives a daily binary indication of whether an asset's price is trending or not. The TRAM allocates risk capital on a daily basis, in terms of dVaR limits to be invested in each of the trending assets. The TRAM is intended to to add value to the underlying trading operated by the BTM, by computing an enhanced dynamic capital allocation rather than allocating an equal amount of risk capital to all assets.

As the TRAM uses the results of the BTM assessment, each of the trend recognition methods is evaluated over the time period from February 2000 to 2012.

6.2.1 Trend recognition

Each of the seven trend indication methods used in the TRAM has a separate set of parameters, properties such as MA lengths and trigger levels, described in table 3 and explained in section 4.2. As each of the seven trend indication methods are utilized separately, each asset's time series is interpreted separately by each method. Unlike the BTM, the methods used in the TRAM evaluate all assets using the same configurations to consider each asset. Although the parameters may change from one time period to the next, they are equal for a time t regardless of which asset's time series is being analyzed, in line with the concept of a generalized configuration.

Similarly to the BTM, the TRAM is recalibrated each month through an optimization process of these parameters, which is further discussed in section 6.3.4. The optimization provides possibly unique values each month, and fits the methods to the current asset pool dynamics.

6.2.2 Allocation

The sum of trend signals among all assets is used to split the total risk capital among the trending assets on a daily basis. The risk capital is then exposed in long and short positions through the BTM in the next time period. If the TRAM changes an asset's allocated risk capital time t, the position is adjusted

Table 3: Monthly recalibrated TRAM parameters

Method	*Parameter*	*Notation*
Autocorrelation	Sample length	θ
	Significance level	ι
ADX	Time period length	κ
	Trend indication level	λ
	Trend indication limit	μ
Aroon Indicator	Time period length	ν
	Trend indication level	ξ
EMD	Total time period length	o
	Bandwidth factor	π
	Trend indication level	ρ
FDI	Total interval length	σ
	Trend indication level	τ
VHF	Time period length	υ
	Trend indication level	ϕ
	Trend indication limit	χ
Vortex	Time period length	ψ
	Trend indication level	ω

by the BTM in time $t + 1$.

The following allocation rules and constraints apply at all times to each of the trend recognition methods:

- dVaR limit of 3% of total capital base.
- Maximum of 20% capital allocation in financial instruments.
- Maximum of 20% capital allocation in one asset.

The constraint of maximum 20% capital allocated to financial instruments is due to the fact that the Fund wishes to define itself as a commodity fund. The constraint of maximum 20% allocation in each asset is set according to MiFID directives. The directives presently only apply to equity and fixed income funds, but are implemented to follow the intended risk diversification.

As there are different restrictions on commodities and financial futures, the allocation keys are slightly different. The allocation to a single trending commodity asset is described in equation (6.15). The factors N_t^C, N_t^F and N_t^T represents the number of assets indicated to be in a trend, among the commodity assets, financial products and all assets respectively. The factor D_t^T represents the total amount of risk capital available, equal to 3% of the Funds total capital base.

$$D_t^C = \begin{cases} D_t^T \times min\left(\frac{1}{N_t^T}, 20\%\right) & \text{for } \frac{N_t^F}{N_t^T} \leq 20\% \\ D_t^T \times min\left(\frac{(1-20\%)}{N_t^C}, 20\%\right) & \text{for } \frac{N_t^F}{N_t^T} > 20\% \end{cases} \tag{6.15}$$

The allocation to a single financial product indicated to have a trending time series at time t, is described in equation (6.16).

$$D_t^F = \begin{cases} D_t^T \times min\left(\frac{1}{N_t^T}, 20\%\right) & \text{for } \frac{N_t^F}{N_t^T} \leq 20\% \\ D_t^T \times min\left(\frac{20\%}{N_t^F}, 20\%\right) & \text{for } \frac{N_t^F}{N_t^T} > 20\% \end{cases} \tag{6.16}$$

As given from the equations, the sum of D_t^C and D_t^F will be less than D_t^T if few assets are indicated to trend. The total risk capital, D_t^T, is set constant through the entire time period during the historical assessment, assuming profits are used for dividends and that losses are replaced. This is done to be able to compare the results of the various trend indication methods to each other and to benchmark indices, creating an index from monthly returns.

6.3 Optimization

The recalibration during the historical assessment is performed separately for the BTM and the TRAM. A pre-stage optimization set to find the appropriate scaling function of the BTM is conducted prior to the historical assessment. For all optimizations, an evolutionary algorithm method is used, as described in section 6.3.1. The choice of method is due to the sensitive nature of the problems as well as the input of time changing data. Hence good stable solutions are preferred to globally optimal, but possibly less stable, solutions. In addition to using an evolutionary optimization algorithm, all variables are given a finite and appropriately small set of allowed solutions to further avoid the effect of overfitted variables, and to handle the optimization process within a manageable time limit.

The monthly optimization of the parameter recalibration for both the BTM and the TRAM uses a two year lookback period, and yield one month out-of-sample results. The BTM interprets data series starting on January 1998. The historical TRAM recalibration is dependent on the results of the BTM process, hence the TRAM lookback period starts in 2000, and yields results from 2002.

6.3.1 Evolutionary optimization method

The method of evolutionary optimization is used in optimizing parameters for the BTM and the TRAM. Unlike Simplex-methods and nonlinear methods such as Generalized Reduced Gradient, evolutionary optimization algorithms can handle both nonlinearity and non-smooth problems (FrontlineSolvers, 2010a). This allows the optimization problem to include discontinuous functions such IF-statements and LOOKUP-searches, which the models are widely dependent on.

An evolutionary optimization algorithm is a nondeterministic population-based algorithm, using mechanisms inspired by biological evolution such as inheritance, mutation, selection, and crossover. More specifically, the software used for the optimization, the Frontline Risk Platform Solver, combines methods from genetic algorithms with classical linear and nonlinear optimization methods. A genetic algorithm is a subset of evolutionary algorithms, a metaheuristic where a population encodes candidate solutions to an optimization problem, which evolves toward better solutions.

The evolution starts from a population of randomly generated individuals and happens in generations (Ashlock, 2010). In each generation, the fitness of every individual in the population is evaluated; multiple individuals are stochastically selected from the current population, and modified to form a new population. The new population is then used in the next iteration of the algorithm, described in table 4 as of Ashlock (2010).

A drawback of evolutionary algorithms is that the algorithm has no concept of optimality, or how to test whether a solution is optimal (FrontlineSolvers, 2010b). A solution is only compared to other possible presently known solutions. This also implicates that an evolutionary algorithm does not know for certain when to stop, and must run for a given length of time, number of iterations or to a satisfactory fitness level has been reached. A typical criterion for a final solution is a certain number of trials without improving the current

Table 4: Genetic optimization algorithm

Generate a population of structures
Loop
Test the structures for fitness
Select structures to reproduce
Produce new variations of selected structures
Replace old structures with new ones
Until satisfied

possible solution. If the algorithm terminates due to time or iteration limits, a satisfactory solution may or may not have been reached. Also, as the algorithm relies in part on random sampling, it may yield different solutions on different runs. However, an evolutionary algorithm is more likely to faster find stable solutions satisfying all constraints. Hence the method is very well suited for problems where good stable solutions with low sensitivity to variable change are preferred, rather than finding the global optimum.

6.3.2 Position scaling of the BTM

Before running the monthly parameter recalibration process of the BTM, a prestage optimization is conducted. This involves the optimization of the scaling function, which is performed in one single optimization over all assets over the entire time interval of data. The scaling function transforms the final position value given by the BTM, from the interval $[-1, 1]$ to the actual number of futures being traded. The scaling function, S_t, is repeated in equation (6.17).

$$S_t = \frac{dVaR_t^L}{ATR_t \times {}^{TU}/_{QU}} \times c \tag{6.17}$$

The factor c is optimized such that the BTM violates the dVaR limit a preferred number of times during a time period, i.e. the dVaR limit violation frequency. A certain violation frequency is preferred to make sure the model takes on the proper amount of risk. The optimization is performed with a set of base parameters for the BTM, given in table 5.

Table 5: Base parameters during scaling factor optimization

Parameter	*i*	*Base value*
ATR_{20} band width, α	1	15 %
High/Low significance level, β	2	6 %
RSI: EMA length, γ	3	25
RSI: Extreme levels, δ	4	15 & 85
RSI: Duration of reduction, ϵ	5	5
MA10 RSI: look back period, ζ	6	5
MA10 RSI: Extreme levels, η	7	30 & 70

The base parameters, as well as the $dVaR^L$, are constant for all time periods and assets. The goal function is set as the minimization of the absolute difference between the number of times the $dVaR$ of a position exceeds $dVaR^L$ and the ideal occurrence of violation. The optimization is run simultaneously over all assets, k, over all time periods, t. The optimization problem is formulated in table 6. The ideal occurrence of violation is set to 7.5 %, in accordance with the Fund's preferred risk profile.

The $dVaR_t$ is expressed as a function of the scaling factor, $\mathcal{F}_{kt}(c)$. The function is non smooth due to the extensive set of IF-statements and other non-smooth elements of the calculation. The scaling factor is chosen from a set of allowed values, $C = \{0.06, 0.12, ...1.20\}$, defined as a finite set of appropriate size to minimize the effect of overfitted variables.

The result of the optimization yields a scaling factor value of $c = 0.72$. This implies a goal function value of 1.18%, meaning the calculated dVaR of a position rises above the dVaR limit 6.32% on average for all assets through the time period. This represents an average number of 15.48 dVaR limit violations annually per asset. Although the scaling function is adapted to each time series using a 100-day ATR, the results vary slightly among the assets. A goal function value of 9.42%, equivalent of 41.71 violations annually, represents the most extreme result. However, the value is far within the acceptable range of risk taking according to the Fund. The rolling monthly limit violation is illustrated in figure 13.

Table 6: Scaling factor optimization problem

$$\underset{c \in C}{\text{minimize}} \quad A \quad = \quad \sum_{k \in K} \left| v - \sum_{t \in T} \mathbb{1}_{\{\mathcal{F}_{kt}(c) > dVaR^L\}} \right|$$

Sets
C : Set of allowed variable values
K : Set of assets
T : Set of time periods
Indices
k : Asset
t : Time period
Constants
v : Violation target
$dVaR^L$: Daily Value-at-Risk limit
Functions
$\mathcal{F}_{kt}()$: Calculated daily Value-at-Risk
Varibles
c : Scaling factor

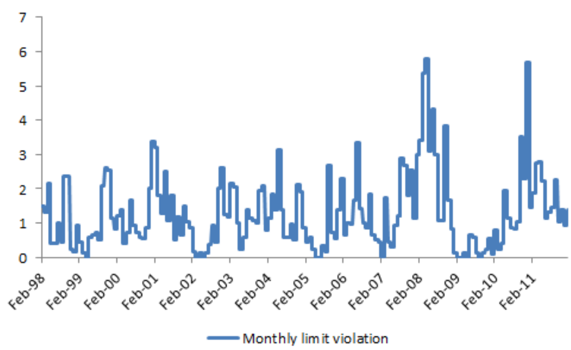


Figure 13: Occurrences of $dVaR$ exceeding allocated limit

The scaling factor is used over the same time period when running the historical parameter recalibration process of the BTM, as over which it was optimized. This might cause the pre-stage optimization to bias the results leading to better to risk control. However, the frequency of dVaR limit violation shows stability on an annual basis over the time period, justifying the use of a constant scaling factor.

6.3.3 BTM monthly parameter recalibration

Many of the parameters used in the BTM are set explicitly, decided according to the Fund's preferences of trading or risk strategy. The parameters that are recalibrated each month represent MA lengths, trigger levels and other factors adjusting the model to the dynamics of each time series for each month. The parameters used as variables in the optimization process are given in table 7 along with the finite sets, D_i, of allowed values for each variable category. The ranges of the sets are decided partly from the results of a short restriction free test run, which are then decreased to finite sets to limit the computational time of the entire process. Some ranges are also limited on purpose, for reasons such as decreasing the possibility of frequent intraday trading, which is unobservable due to daily data observations.

Table 7: Categories of optimization variables

Categories of variables	i	D_i
ATR_{20} band width, α	1	{5%, 10%, ...30%}
High/Low significance level, β	2	{2%, 4%, ...10%}
RSI: EMA length, γ	3	{15, 20, ...30}
RSI: Extreme levels, δ	4	{5 & 95, 10 & 90, ...25 & 75}
RSI: Duration of reduction, ϵ	5	{3, 5, 7}
MA10 RSI: look back period, ζ	6	{3, 4, ...6}
MA10 RSI: Extreme levels, η	7	{20 & 80, 25 & 45, ...40 & 60}

The optimization process is conducted separately for each asset on the last day of each month. The BTM optimization problem is formulated in table 8.

The goal function, R_{km} is expressed as the average of rolling monthly returns divided by the $CVaR_{10\%}$ function of the monthly returns. Both the numerator and the denominator assess the time period of the two years prior to each recalibration. Monthly rather than daily returns are used to avoid consecutive periods of negative values, as in compliance with an investor's evaluation of the

Table 8: BTM optimization problem

maximize R_{km}	$= \dfrac{1}{\lvert B_m \rvert} \dfrac{\sum_{t' \in B_m} \mathcal{G}_{kt'}(\mathbf{x}_{kt'})}{\lvert \mathcal{H}_{km}(\mathcal{G}_{kt} : t \in B_m) \rvert}$		$k \in K,\ m \in M$
subject to:			
	$\mathbf{x}_{kt}$	$= [x_{kt1}, x_{kt2} \ldots x_{ktn}]$	$k \in K$, t $\in T$
	x_{kti}	$\in D_i$	$k \in K$, t $\in T$, i $\in I$

Sets
K : Set of assets
T : Set of all time periods
$B_m \subset T$: Sets of past two years time periods
$M \subset T$: Set of the last time period of each month
I : Set of categories of variables
D_i : Set of allowed values for categories of variables
Indices
k : Asset
t : Daily time period
m : Monthly time period
i : Variable category
Constants
$n = |I|$: Number of variable categories
Functions
$\mathcal{G}_{kt}()$: Rolling monthly return
$\mathcal{H}_{km}()$: $CVaR_{m,10\%}$
Varibles
$\mathbf{x}_{kt}$: Vectors of trigger levels and lengths

Fund's performance. Also, rolling monthly returns show lower volatility than daily returns as they are smoothed, making the optimization favor stable returns rather than positive spikes. The CVaR risk measure encapsulates most of the undesired extreme downside returns, even during volatile periods. Hence the goal function is set to increase returns relative to downside risk.

The development of the the goal function values over the time period from 2000 to 2012 is illustrated in figure 14. The average of all the assets is rather stable over the total period, while the range varies significantly. Although there are large differences in the asset time series, a diversification effect stabilizes the average.

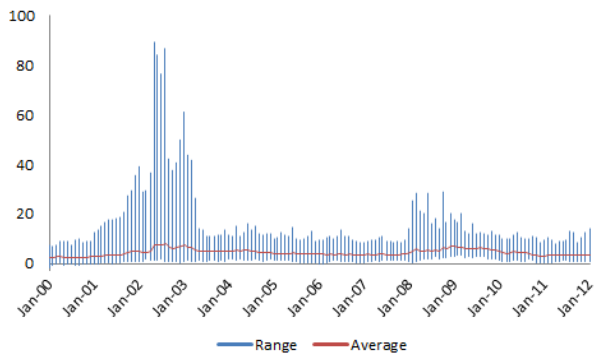


Figure 14: Development of the goal function

Table 9 summarizes the variable development of the optimization process. Each asset requires a computational time of 18 hours, making the total computational time 432 hours[1].

The variables given in one month are also optimal for the subsequent period in 27% to 60% over the time span. Except for β and ζ, the variables change less than one step on average each optimization. Conditioned on a change from one month to the next, the average steps of change were well below two for all variables. This could suggest that the selection of lookback period and recali-

[1]Using the Frontline Risk Platform Solver 2010 on a 64-bit Windows 7, 16GB RAM, 8 core 3.4GHz computer.

Table 9: Summary of parameter recalibrations

	Cont. variable	*Median*	*Mean*	*Mode*	*Avg. change*	*Avg. steps, given change*
α	60%	0.08	0.10	0.05	0.03	1.70
β	27%	0.06	0.06	0.04	0.03	1.68
γ	58%	19.58	19.57	20	2.65	1.26
δ	46%	79.38	80.99	75	4.17	1.57
ϵ	45%	5.00	5.08	5	1.31	1.19
ζ	28%	4.79	4.56	5	1.01	1.42
η	37%	65.21	65.65	65	4.63	1.48

bration frequency has mostly been fitting for the model at hand. Arguably the variable sample space can be too small and the resolution too low, thus forcing more stable variables than inherent in the return series.

For β, ϵ, and ζ, the distributions given in appendix E.1 imply that the sample range is fitting. For α and δ the most occurring variable is located at the lower bound of the range. The two distributions are heavily skewed to the left, suggesting that shifting the sample set lower or using a higher resolution around the lower bound could be beneficial. However, for α representing the ATR-band, the lower bound is set to avoid possible intraday trading. For δ the lower bound is set to limit the RSI impact, as mistrades due to high frequency of trading related to the RSI rule are unobservable using daily data. For γ and η the results are more dubious. The distributions suggest that the sample space is suitable thou shifted towards the lower end. However, for respectively ten and eight assets the most occurring variable is located on the lower bound, and the results could benefit from a sample space with additional lower values. The asset specific results are given in appendix E.1.

6.3.4 TRAM monthly parameter recalibration

Similar to the BTM, the parameters of the trend recognition methods used in the TRAM are recalibrated each month during the assessment of the model. The parameters that are decided through the optimization represent smoothing lengths, trigger levels and other factors adjusting the model to the dynamics of the asset pool for each month. The parameters are used as variables in the optimization process, and are given in table 10 along with the sets of allowed values for each variable category, E_{jl}.

Table 10: Categories of optimization variables

Method	*j*	*Variabel category*	*l*	E_{jl}
Autocorrelation	1	Sample length, θ	1	$\{5, 10, ...50\}$
		Significance level, ι	2	$\{0.05, 0.1, ...0.5\}$
ADX	2	Time period length, κ	1	$\{10, 15, ...30\}$
		Trend indication level, λ	2	$\{5, 10, ..., 30\}$
		Trend indication limit, μ	3	$\{30, 35, ..., 95\}$
Aroon Indicator	3	Time period length, ν	1	$\{10, 15, ...50\}$
		Trend indication level, ξ	2	$\{15, 20, ...95\}$
EMD	4	Total time period length, o	1	$\{30, 40, ...100\}$
		Bandwidth factor, π	2	$\{0.05, 0.1, ..., 0.5\}$
		Trend indication level, ρ	3	$\{0.01, 0.02, ...0.2\}$
FDI	5	Total interval length, σ	1	$\{4, 6, ...50\}$
		Trend indication level, τ	2	$\{1.4, 1.5, ...1.9\}$
VHF	6	Time period length, υ	1	$\{5, 10, ...30\}$
		Trend indication level, ϕ	2	$\{0.05, 0.1, ...1\}$
		Trend indication limit, χ	3	$\{0.55, 0.6 ...1\}$
Vortex	7	Time period length, ψ	1	$\{5, 10, ...30\}$
		Trend indication level, ω	2	$\{0.02, 0.04, ...0.4\}$

The optimization process is conducted separately for each trend recognition method on the last day of each month. The TRAM optimization problem is formulated in table 11.

The goal function, R_{jm} is exactly equal to the goal function of the BTM recalibration optimization found in table 8. However the optimization is performed for each trend recognition method, rather than for each asset. The optimization yield the enhanced variable values for each month, which are used as parameters when assessing the value added by the TRAM.

Figure 15 depicts the goal function development over the total time period. The methods exhibit a large variation in amplitude, while the form is more similar.

Table 11: TRAM optimization problem

maximize $R_{jm} \quad = \dfrac{1}{|B_m|} \dfrac{\sum_{t' \in B_m} \mathcal{G}_{jt'}(\mathbf{y}_{jt'})}{|\mathcal{H}_{jm}(\mathcal{G}_{jt} : t{\in}B_m)|} \qquad j \in J,\ m \in M$

subject to:

$\mathbf{y}_{jt} \quad = [y_{jt1}, y_{jt2} \dots y_{jtp_j}] \qquad j \in J,\ \mathrm{t} \in T$

$y_{jtl} \quad \in E_{jl} \qquad j \in J,\ \mathrm{t} \in T,\ l \in L_j$

Sets
T : Set of all time periods
$B_m \subset T$: Sets of past two years time periods
$M \subset T$: Set of the last time period of each month
J : Set of trend indication methods
L_j : Sets of categories of variables for each method
E_{jl} : Set of allowed values for categories of variables
Indices
t : Daily time period
m : Monthly time period
j : Trend indication method
l : Variable category
Constants
$p_j = |L_j|$: Number of variable categories for each method
Functions
$\mathcal{G}_{kt}()$: Rolling monthly return
$\mathcal{H}_{km}()$: $CVaR_{m,10\%}$
Varibles
$\mathbf{y}_{kt}$: Vectors of trigger levels and lengths

The goal function is highly sensitive to changes in the monthly returns. The returns affect both the nominator and the denominator, so periods with few large negative returns will reduce the CVaR as well as increase the sum of returns in the nominator. On average, and consistently over the percentiles, the optimization of the AC and Vortex filters yields the lowest goal function values, while the VHF filter yields the highest.

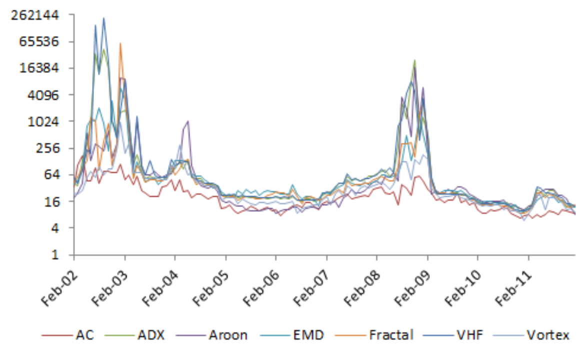


Figure 15: Development of the goal function

For the variables ι, κ, λ, τ and ω, the most occurring variable is a boundary value. As all variables are given a wide sample set of feasible solutions, this suggests that either the resolution is too low, or that the filter is ineffective where the boundary values allow the base model to allocate capital most widely. From table 12, for the ADX, VHF, Vortex, FDI and EMD filters, the latter is clearly the case where they on average indicate that well above 85% of the assets are trending over the time span.

The AC and Aroon filters indicate trending assets respectively 62% and 69% of the time, which accounts for the lowest values of the filters. However, 30% of the time, the AC variable ι is at its upper boundary of 50%. Obviously an autocorrelation with 50% significance level is not very reliable and should be discarded. The Aroon filter seems to better include the multivariate nature of the assets. The current sample set of ν and ξ appear to be well suited to encapsulate the underlying dynamics. The Aroon filter's continuous variable occurrences suggests that the variables are stable over the period.

Table 12: Summary of TRAM parameter recalibrations

	Cont. variable	*Median*	*Mean*	*Mode*	*Avg. change*	*Avg. steps, given change*
θ	45%	35.00	35.74	35	6.54	2.38
ι	27%	0.45	0.41	0.5	0.08	2.15
κ	52%	15.00	14.09	10	3.88	1.60
λ	40%	10.00	8.35	5	3.79	1.26
μ	26%	75.00	74.26	65	8.54	2.30
ν	48%	30.00	32.60	30	4.71	1.82
ξ	38%	25.00	26.57	20	7.79	2.53
o	33%	35.00	36.24	35	8.04	2.41
π	13%	0.35	0.34	0.3	0.10	2.32
ρ	18%	0.05	0.05	0.05	0.03	3.58
σ	38%	38.00	33.40	50	9.88	8.01
τ	80%	1.90	1.86	1.9	0.03	1.42
υ	42%	20.00	19.17	20	4.50	1.54
ϕ	37%	0.15	0.12	0.15	0.05	1.47
χ	30%	0.75	0.74	0.8	0.09	2.67
ψ	58%	10.00	9.59	10	3.96	1.90
ω	58%	0.02	0.04	0.02	0.03	3.28

7 Results

The assessment of the BTM profitability, and the value added by the TRAM methods, yield comparable results over a ten year period. The comparable return series consist of 2450 data points starting in March 2002 and ending in February 2012. For both models, the results are taken from the one month out-of-sample period following the lookback period for the recalibration process.

Although the BTM and TRAM utilize and considerate a constant capital base, monthly accumulated returns and indices are calculated to include interest effects, to better compare and benchmark results.

7.1 Base trading model assessment

Under constant risk capital allocation, the BTM performance index has a compound annual growth rate (CAGR) of 19.02%. The rolling monthly returns averages on 1.55% over all assets, as given in table 13. The largest monthly loss, i.e. the worst draw down (WDD) of the model during the period represents 3.10% of the total capital base.

For commodities, the BTM yield significantly better returns in addition to lower standard deviation than for financial products. The higher volatility among financial products reflects the diversification effect due to a higher number of commodity assets and lower intercorrelation. Although financial products show higher maximum daily and monthly returns, large losses result in a lower average as well as a lower CAGR. The financial products have a WDD of 5.90% compared to 2.50% for commodities.

All monthly return series exhibit leptokurtic distributions, indicating high peaks and fat tails. A positive skewness is present in all return series, yielding an overall value of 1.16. As the mode of the return distribution is positive, positive skewness indicates that large positive returns occur more often than large negative returns. All series refutes the null hypothesis of a normal return distribution. The complete return statistics for each asset are given in appendix F.1.

In both a daily settled and accumulative environment the most profitable assets were feeder cattle, copper, sugar and platinum and the least profitable where Japanese Yen, live cattle, Norwegian Kroner and gold, respectively. As-

Table 13: Profit and loss statistics for the BTM model

	All assets	*Commodities*	*Financial products*
Monthly accumulated statistics			
Average	1.6%	1.6%	1.4%
SD	1.5%	1.6%	2.9%
Min	-3.1%	-2.5%	-5.9%
Max	10.9%	11.7%	14.8%
Kurtosis	7.2	8.3	4.0
Skewness	1.2	1.4	0.6
Other statistics			
Index CAGR	19.0%	19.5%	16.7%
Min daily	-1.8%	-1.7%	-5.5%
Max daily	2.5%	2.1%	4.7%

set volatility and profitability are correlated with a coefficient of 0.37. The four most volatile assets are found among the top seven most profitable, inclining volatile assets yield more profitable returns using the BTM.

The development of the simplified portfolio Margin-to-Equity (M/E) ratio is illustrated in figure 16.

The ratio is higher for commodities then for financial products through the first half of the period, however a switch occurs in the period from 2006 to 2009. As the portfolio is weighted towards commodities, the ratio of the total follows tightly. The ratio ranges in the interval between 3% and 13% with an average of 8%. Compared to most funds, an average of 8% is considered relatively low, categorizing the BTM as conservative among CTAs (Melin, 2010).

7.2 Dynamic allocation assessment

The trend recognition methods utilized in the TRAM yield mixed return statistics compared to static allocation. As given in table 14, the ADX, Aroon and EMD enhance the average monthly returns to 1.56%, 1.69% and 1.56%, respectively. However, all methods yield a higher standard deviation and the majority

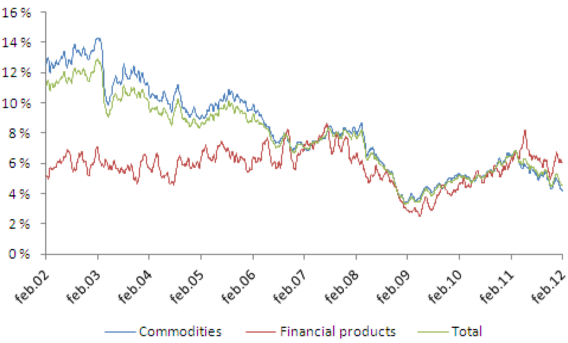


Figure 16: ME ratio development of the portfolio

exhibits larger extreme values. Most methods, except FDI, have higher WDD than static allocation, where the highest WDD of 4.48% is found among Aroon's returns. The cumulative return indices of the dynamic allocation methods are given in figure 17, illustrating their deviation from static allocation.

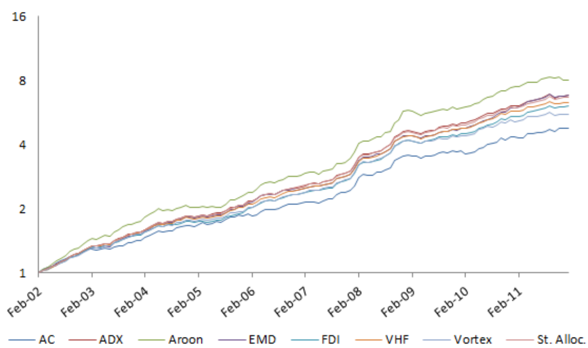


Figure 17: Cumulative return indices for static allocation and dynamic allocation methods

Similar to static allocation, most trend recognition methods, apart from AC, yield better returns for commodity assets than for financial products. For com-

Table 14: Accumulated monthly profit and loss

	AC	*ADX*	*Aroon*	*EMD*	*FDI*	*VHF*	*Vortex*	*Static alloc.*
All assets								
Avg.	1.27%	1.56%	1.69%	1.56%	1.47%	1.50%	1.40%	1.55%
SD	1.89%	1.57%	2.07%	1.64%	1.59%	1.55%	1.61%	1.54%
Min	-4.26%	-4.24%	-4.48%	-3.25%	-3.01%	-3.44%	-3.31%	-3.10%
Max	12.15%	11.04%	10.74%	10.99%	10.87%	11.04%	10.65%	10.92%
Kurt.	5.89	7.36	4.36	6.16	6.92	6.87	6.95	7.19
Skew.	0.92	1.09	0.63	1.03	1.12	1.07	1.14	1.16
Commodities								
Avg.	1.22%	1.60%	1.67%	1.54%	1.49%	1.50%	1.42%	1.58%
SD	1.96%	1.63%	2.08%	1.72%	1.67%	1.61%	1.68%	1.63%
Min	-4.14%	-2.59%	-5.03%	-2.64%	-2.44%	-2.56%	-2.81%	-2.50%
Max	12.16%	11.48%	11.28%	11.47%	11.33%	11.51%	11.65%	11.36%
Kurt.	6.51	8.47	4.36	7.27	7.92	7.74	8.29	8.25
Skew.	1.07	1.42	0.54	1.33	1.33	1.28	1.40	1.39
Financial products								
Avg.	1.42%	1.33%	1.57%	1.52%	1.30%	1.36%	1.18%	1.36%
SD	4.38%	3.24%	5.00%	3.56%	3.29%	3.12%	3.34%	2.88%
Min	-8.69%	-11.63%	-15.79%	-7.56%	-6.50%	-7.46%	-14.59%	-5.90%
Max	20.19%	16.07%	35.35%	16.94%	15.69%	16.26%	15.89%	14.79%
Kurt.	4.95	4.58	8.21	3.56	3.56	3.96	4.55	3.98
Skew.	1.00	0.28	1.29	0.59	0.59	0.58	0.25	0.63

modities, ADX and Aroon outperform static allocation with average monthly returns of 1.60% and 1.67% respectively. ADX's monthly returns also exhibit lower standard deviation. Most methods, except ADX and VHF, yield more extreme returns than static allocation.

Among financial products, AC, Aroon and EMD outperform the static allocation on average monthly return. However, the returns of all methods exhibit higher standard deviation. Aroon yields the most extreme returns, with a maximum monthly return of 35.35% and a WDD of 15.79%.

ADX is the only method exhibiting higher kurtosis than static allocation, while no method have higher skewness. All trend recognition methods show similar monthly return distributions as the static allocation. However, Aroon yields remarkably lower kurtosis and skewness. A complete overview of the return statistics for each method is given in appendix F.

As described in section 6.3.4, the optimization variables representing trend indication level take values located on the boundary for most methods, indicating they are not able to isolate a few assets in favor of allocating widely. The indication is verified in table 15, where the methods provide trend indication of a fairly high number of assets over the time period. AC and Aroon are the only two methods that manage to allocate to less than 85% of the total asset pool on average.

Table 15: Average number of indicated trending assets

	AC	*ADX*	*Aroon*	*EMD*	*FDI*	*VHF*	*Vortex*
All assets (24)	14.94	23.18	16.65	20.81	22.14	23.20	22.52
Commodities (19)	11.77	18.37	13.09	16.38	17.49	18.39	17.83
Financial products (5)	3.17	4.82	3.56	4.42	4.65	4.81	4.69

7.3 Benchmarking and performance evaluation

Benchmark indices are selected on the basis of data availability and relevance in terms of asset pool, size, and fund category. Both static and dynamic allocation methods are compared to the Thomson Reuters/Jefferies CBR Index

(CRB), the Newedge CTA Index (NEIXCTA) and the IASG CTA Trend Following Strategy Index (IASG). The CRB is a buy-and-hold index used due to the composition of commodities, which matches the asset pool used for the assessment of the model. The Newedge CTA Index tracks the 20 largest CTAs globally (Newedge, 2012). The IASG CTA Trend Following Strategy Index is an equally weighted index consisting of approximately 100 CTAs trading on a trend following strategy similar to the Fund (IASG, 2012). The composition of the indices are further described in appendix G.

The BTM's accumulated return index, under static allocation, is compared to the respective benchmark indices is figure 18. The BTM exhibits similar profit pattern as the other two CTA indices, but with a considerable larger magnitude and lower volatility. The BTM and the CTA indices do not experience CRB's draw down during 2008 as they are able to take short positions.

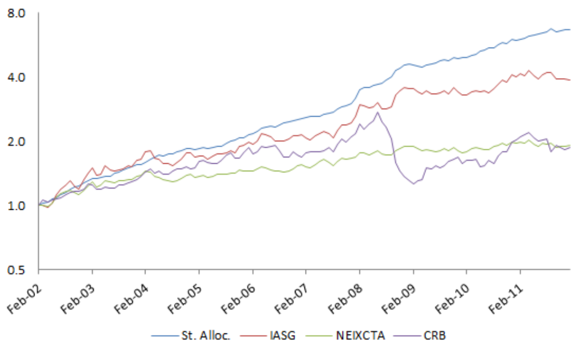


Figure 18: Static allocation compared to benchmark indices

The static allocation outperforms the benchmarks and the dynamic allocation when compared using RAPMs for most assets. The only exception is for IR, where ADX, Aroon and EMD score higher than the static allocation when evaluated against the CRB index. Table 16 shows that the top four performers on RAPMs for all assets are static allocation, ADX, EMD and VHF. ADX outperform static allocation on all RAPMs for commodities, but is only the fourth best performer for financial products. Even though Aroon exhibits considerable larger average return than static allocation and the other filters, the high volatility and WDD penalize the filter when assessed on the RAPMs.

Table 16: RAPM values[2]

	Sharpe	*Omega*	*Sortino*	*Kappa*$_3$	*IR (CRB)*
All assets					
AC	1.91	4.96	1.95	1.42	0.50
ADX	2.83	12.56	4.34	2.71	0.68
Aroon	2.32	8.92	3.60	2.54	0.78
EMD	2.69	10.98	4.27	2.93	0.69
FDI	2.65	10.23	3.85	2.68	0.63
VHF	2.75	10.99	4.13	2.76	0.64
Vortex	2.44	8.35	3.27	2.29	0.58
St. Alloc.	2.89	13.03	4.78	3.19	0.68
Commodities					
AC	1.66	4.01	1.57	1.17	0.46
ADX	2.76	12.16	4.96	3.46	0.71
Aroon	2.18	8.16	3.40	2.40	0.78
EMD	2.46	9.70	4.14	2.98	0.68
FDI	2.52	9.43	3.88	2.80	0.65
VHF	2.57	9.67	4.01	2.88	0.64
Vortex	2.33	7.85	3.24	2.35	0.60
St. Alloc.	2.74	11.92	4.88	3.42	0.70
Financial					
AC	1.05	3.26	1.21	0.91	0.47
ADX	1.23	3.47	1.22	0.80	0.46
Aroon	0.97	3.37	1.26	0.96	0.49
EMD	1.28	3.79	1.52	1.18	0.54
FDI	1.15	3.04	1.16	0.91	0.44
VHF	1.30	3.64	1.40	1.04	0.48
Vortex	0.99	2.57	0.79	0.55	0.37
St. Alloc.	1.40	3.92	1.58	1.20	0.49
Benchmarks					
IASG	0.72	1.90	0.51	0.39	
CTA	0.42	0.35	-0.40	-0.31	
CRB	0.18	0.60	-0.19	-0.12	

7.4 Discussion

The fact that monthly return series of the BTM exhibit leptokurtic distributions and positive skewness coincides with the trend following concept of the fund. The distributions can arguably be a good characteristic of a fund seeking to capture trends in asset prices. Large positive returns occur more often than large negative returns, indicating the model is able to follow trends on a monthly basis, while cutting losses in a ranging market. Considering that the BTM outperforms benchmark indices on total return and RAPM values with a conservative M/E ratio, the trend following framework is verified to perform as intended over the period assessed.

The simplified calculations of transaction costs and model mistrades reduce gross profits in the approximate range of 9-25% and 11-35% respectively. The averages of 16% and 23% is considered high enough to verify that the assumptions implemented in the models are not understating such costs.

Comparing the indices of the BTM's asset specific returns with the time series of each asset[3], the trend following ability of the model is further verified. The model is clearly able to follow trends, where especially short- to mid-term trends are profitable. This coincides with the use of 50 days EMA period. For long term trends, as in natural gas and gold, the model appears to be less profitable. The difference in returns between assets can be related to the difference in price series properties. Even though the model uses parameters fit to each asset time series, assets with higher volatility tend to be more profitable, indicating the model framework is better fit for some distribution characteristics than for others.

In assessment of the BTM's risk management efficiency, the main concern is washing losses. The model design is vulnerable to losses in ranging markets, so whether or not the ATR bands manage to minimize the degree of washing is a critical factor. When examining the WDD of monthly return series, it is apparent that in ranging markets, a sudden increase in volatility is punished hard. Eurodollar is accountable for the largest WDD of 23% of the asset specific allocation. Given the funds allocation limit of maximum 20% to a single

[2] The Sharpe ratio uses a risk free rate of 3%, while the Omega, Sortino and Kappa_3 uses an annual MAR of 9%. The parameters are set in accordance with industry practice (JP Morgan).

[3] Detailed information given in appendix F.1

asset, such a worst case loss is manageable.

The fact that most trend recognition methods fail to add significant value through dynamic allocation can be contributed to several factors. The majority of the methods fail to single out trending assets, and allocate almost as widely as static allocation, arguably due to the multivariate nature of the asset pool. Hence a generalized recalibration is insufficient for an enhanced allocation. Further, the optimization considers the same goal function as for the BTM. This causes the TRAM to optimize on already enhanced values adapted to each time series. The process may also be performed too seldom to adapt to changing asset price dynamics crucial for recognizing trends.

ADX, Aroon and EMD are the only filters that yield higher average returns, but the results from dynamic allocation yield higher standard deviation as the capital allocated is not equally distributed over the assets, thus reducing the diversification effect. The diversification effect is however exaggerated in our sample compared to the Fund, as the Fund's asset universe consist of a considerable higher number of assets.

Static allocation consistently outperforms the dynamic allocation methods for Sharpe, Omega, Sortino and Kappa measures. As the difference in profit is marginal compared to the volatility, the diversification effect becomes apparent. Across the board, the AC filter produces the worst scores, followed by Aroon and Vortex. As the AC and Aroon filter on average allocates to least assets, the volatility is correspondingly high, yielding low RAPMs. Although the volatility is lower for Vortex, it generates the lowest CAGR, which in turn produces unfavorable RAPMs. The ADX filter produces the highest scores of the methods, and even outperforms the static allocation for commodity assets. However, ADX fails to single out trending assets as it allocates to over 95% on average.

The profitability of both static and dynamic allocation is somewhat limited by the process of monthly recalibration. Unlimited parameter sample spaces or wider boundaries, as well as more parameters and more frequent optimization may increase returns, but also lead to over fitting and higher risk of unobservable intraday trading. The formulation of the goal function may also limit the intention of the optimization, in cases of positive CVaR being minimized in the expression.

8 Conclusion

The base trading concepts considered by the Fund are constructed as a complete trading model and simulation platform. The generic framework is based on moving average rules, as well as other well-known technical trading methods and risk management tools. For each asset, selected parameters are recalibrated on a monthly basis to adapt to changing asset price dynamics. Through an assessment using historical data of 24 different assets, the model is verified to outperform comparable benchmarks in terms of total return and risk adjusted performance measures. Over a ten year period, the model yields a CAGR of 19%, giving a monthly average return of 1.6%. The out-of-sample returns are consistent across all sample assets prices, proving the model's ability to capture and follow trends. However, profitability differs significantly for the distinct assets, with the most profitable represented by feeder cattle, copper, sugar and platinum, indicating the model framework is better suited for some distribution characteristics than others.

A trend recognition and allocation model is built to assess whether daily dynamic allocation of risk capital enhances the profitability of the base trading model, using general configurations for all assets. The trend recognition methods intend to improve trading performance, compared to a static allocation to each asset, by only allocating risk capital to assets with trending time series. The model is recalibrated each month, where the parameters are generalized for all assets to capture overall asset pool dynamics. The assessment yields mixed results, as most fail to single out trending assets; allocating almost as wide as static allocation. The ADX, Aroon and EMD filters outperform static allocation's monthly returns as well as obtaining a higher information ratio when compared to a buy-and-hold index. However, when evaluated on risk adjusted performance measures considering return relative to volatility, all trend recognition methods fail to add value to the base trading model. The loss of diversification when only allocating to certain assets increases volatility beyond the value of excess return.

9 Acknowledgments

The scope of this thesis is limited when compared to the full set of trading rules and risk management tool considered by the Fund. The thesis considers a pool of 24 assets where only the continuous contracts are examined. Hence a significant amount of tradable assets are excluded. Expanding the underlying commodity pool in addition to including more contracts for each commodity will enable greater flexibility and robustness in assessment of the trading models.

The approximation of transaction costs including spread costs and liquidity costs is fairly simple. The actual cost would depend on the market of the specific asset, its volatility and orderbook depth. The market effect of each trade, especially in less liquid assets, could prove considerable for large positions, but is impossible to calculate for past data without the historical orderbook.

The consequences of correlation among asset prices are an interesting subject of research, having high impact on allocation. Considering correlations and calculating VaR on groups or portfolio level, would give more accurate risk handling, as well as allowing larger allocations. Portfolio correlations will also lower margin requirements from clearing houses, decreasing the amount of required capital for the Fund's strategies.

The optimization process has several aspects of improvement. Optimization specific factors such as assigned time limit or accuracy requirements would improve the results, although be more computational demanding. With small parameter sets the parameters appear more stable than inherent. Setting more parameters as variables, and increasing the set of allowed values in addition to more frequent recalibration can enhance the model performance, although computational time increases drastically. A test of various goal function formulations before choosing an appropriate one, could also improve the recalibration process. For the TRAM, parameter calibration to each asset, or by asset group, could improve the adaptability of the trend recognition methods.

Creating an intraday framework would give a more realistic and accurate assessment, as well as simplify the model structure by removing mistrades and adjustment assumptions and calculations. However, an intraday assessment would require massive amounts of data, and increase computational demands considerably. Other framework adjustments of the base trading model could include the implementation of methods to better capture longer trends, such as a 200-day EMA based trading rule.

Verifying trading frameworks and strategies through backtesting does not guarantee future profit making, no matter the length of the time period or the diversification of the dataset. Thou it is more likely that a trading strategy that has consistently yielded a profit using an out-of-sample evaluation will continue to do so in the future. However, trading opportunities from well known filters could decrease due to their popularity. Further work could include newer and less common filters.

References

AIQ Systems. Technical indicators reference manual. http://aiqsystems.com/techmanual.htm, 2001. [Online; accessed 23-April-2012].

Carol Alexander. *Value-at-Risk Models*. John Wiley and Sons, Ltd, West Sussex, UK, 2008a. ISBN 9780470997888.

Carol Alexander. *Quantitative Methods in Finance*. John Wiley and Sons, Ltd, West Sussex, UK, 2008b. ISBN 9780470998007.

Daniel Ashlock. *Evolutionary Computation for Modeling and Optimization*. Springer, New York, USA, 2nd edition, 2010. ISBN 9781441919694.

BarclayHedge. Barclay CTA Index. http://www.barclayhedge.com/research/indices/cta/Money_Under_Management, 2012. [Online; accessed 07-May-2012].

Stephen Beveridge and Charles R Nelson. A new approach to decomposition of economic time series into permanent and transitory components with particular attention to measurement of the 'business cycle'. *The Journal of Monetary Economics*, 7:151–174, 1981.

Ethienne Botes and Douglas Siepman. Reliability is harder than it looks – the vortex indicator. *Technical Analysis of Stocks & Commodities*, December 2009.

Chris Brooks. *Introductory Econometrics For Finance*. Cambridge University Press, London, UK, 2nd edition, June 2008. ISBN 9780521694681.

Benjamin Bruder and Nicolas Gaussel. Risk-return analysis of dynamic investment strategies. *White Paper: Quant Research by Lyxor*, (7), June 2011.

Benjamin Bruder, Tung-Lam Dao, Jean-Charles Richard, and Thierry Roncalli. Trend filtering methods for momentum strategies. *White Paper: Quant Research by Lyxor*, (8), December 2011.

Tushar S. Chande. A time price oscillator. *Technical Analysis of Stocks & Commodities*, September 1995.

James Chen. *Essential of Technical Analysis for Financial Markets*. John Wiley & Sons, Inc., New Jersey, USA, 2010. ISBN 9780470625545.

CME Group. Managed futures: Portfolio diversification opportunities. *Technical Document*, May 2011.

John Ehlers. Frama - fractal adaptive moving average. *Technical Analysis of Stocks & Commodities*, October 2005.

John Ehlers. Mama - the mother of adaptive moving averages. *MESA Software Technical Papers*, 2010.

John Ehlers and Rick Way. Empirical mode decomposition. *Stocks and Commodities Magazine*, March 2010.

Farlex Inc. Farlex financial dictionary, moving average. `http://financial-dictionary.thefreedictionary.com/Rolling+average`, 2012. [Online; accessed 12-May-2012].

FrontlineSolvers. Excel 2010 solver offers more power for optimization. `http://www.solver.com/press201002.htm`, 2010a. [Online; accessed 10-May-2012].

FrontlineSolvers. Genetic algorithms and evolutionary algorithms. `http://www.solver.com/gabasics.htm`, 2010b. [Online; accessed 10-May-2012].

Ole Gjolberg and Marie Steen. Are commodity markets characterized by herd behaviour. 2012.

Thomas H. Goodwin. The information ratio. *Financial Analysts Journal*, 54 (4):34–43, 1998.

Jayanthi Gopalakrishnan. Vertical horizontal filter. *Technical Analysis of Stocks & Commodities*, 18:42–48, July 2000.

William P. Hamilton. *The Stock Market Barometer*. Harper and Brothers, New York, USA, 1st edition, 1922. ISBN 0471247383.

Robert J. Hodrick and Edward C. Prescott. Postwar U.S business cycles: An empirical investigation. *Journal of Money, Credit and Banking*, 29:1–16, February 1997.

John C. Hull. *Options, Futures, And Other Derivatives*. Pearson, Essex, UK, 8th edition, 2012. ISBN 9780273759072.

IASG. Iasg CTA Index. `http://www.iasg.com/cta-indexes/index/iasg-cta-index`, 2012. [Online; accessed 10-May-2012].

Jefferies & Company. Thomson reuters/jefferies crb index. `http://www.jefferies.com/cositemgr.pl/html/ProductsServices/SalesTrading/Commodities/ReutersJefferiesCRB/Details/Index.shtml`, 2011. [Online; accessed 11-May-2012].

JP Morgan. Industry standards.

Jurik Research. Jurik moving average. `http://jurikres.com/catalog/ms_ama.htm#top`, 2007. [Online; accessed 09-May-2012].

Paul D. Kaplan and James A. Knowles. Kappa: A generalized downside risk-adjusted performance measure. *Journal of Performance Measurement*, 8:42–54, 2004.

Harry M. Kat. Is the case for investing in commodities really that obvious? 2006.

Harry M. Kat and Roel C.A. Oomen. What every investor should know about commodities part i: Univariate return analysis. *Alternative investment Research centre working paper series*, 2006.

Perry J. Kaufman. *Trading Systems and Methods.* John Wiley & Sons, Inc., Canada, 3rd edition, November 1998. ISBN 9780471148791.

Con Keating and William F. Shadwick. A universal performance measure. *Journal of Performance Measurement*, 6:59–84, 2002.

Deborah Kidd. The sortino ratio: Is downside risk the only risk that matters? *CFA Institute*, 2012.

Willis V. Kidd and B. Wade Brorsen. Why have the returns to technical analysis decreased? *Journal of Economics and Business*, 56(3):159–176, 2004.

LCH.Clearnet. LCH.Clearnet Group. `http://www.lchclearnet.com`, 2011. [Online; accessed 18-May-2012].

Laura Lipscomb. An overview of non-deliverable foreign exchange forward markets. Technical report, Federal Reserve Bank of New York, May 2005.

Benoît Mandelbrot. *Fractals and Chaos.* Springer, Berlin, Germany, 2004. ISBN 9780387201580.

Saulius Masteika, Aleksandras V. Rutkauskas, and Janes Andrea Alexander. Continuous futures data series for back testing and technical analysis. *International Conference on Economics, Business and Marketing Management*, 2012.

Mark H. Melin. *High-Performance Managed Futures: The New Way to Diversify Your Portfolio.* John Wiley & Sons, Inc., New Jersey, USA, 2010. ISBN 978047088684.

Morgan Stanley. Commodities, an introduction for investors. *Morgan Stanley IQ*, 2007.

Morgan Stanley. Commodities: Friend or Foe? *Morgan Stanley, Investment focus*, February 2010.

John F. Muth. Optimal properties of exponentially weighted forecasts. *Journal of the American Statistical Association*, 55(290):229–306, June 1960.

Newedge. Newedge indices. `http://www.newedge.com/web/guest/brokerage_services/research/newedge_indices`, 2012. [Online; accessed 08-May-2012].

Steve Nison. *Japanese Candlestick Charting Techniques, A Contemporary Guide to the Ancient Investment Techniques of the Far East.* New York Institute of Finance, New York, USA, 1st edition, 1991. ISBN 0139316507.

Cheol-Ho Park and Scott H. Irwin. The profitability of technical trading rules in us futures markets: A data snooping free test. *AgMAS Research Report*, 2004.

Pi Trading. Commodity futures. `http://pitrading.com`, February 2012. [Online; downloaded 04-February-2012].

Thomson Reuters. Reuters ecowin pro. Database and time series analysis software. [Downloaded 04-February-2012].

Robert Rhea. *The Dow Theory.* Barron's, New York, USA, 1st edition, 1932. ISBN 9780870341106.

Richard Russell. *The Dow Theory Today.* Barron's, New York, USA, 1st edition, 1961.

Edward George Schaefer. *How I Helped More Than 10000 Investors to Profit in Stocks.* Prentice-Hall, New Jersey, USA, 1st edition, 1960. ISBN 9781558888081.

William F. Sharpe. Mutual fund performance. *The Journal of Business*, 39(1): 119–138, January 1966.

Adam Shell. Technology squeezes out real, live traders. `http://www.usatoday.com/money/markets/2007-07-11-nyse-traders_N.htm`, 2007. [Online; accessed 09-May-2012].

Joel G. Siegel. *International encyclopedia of technical analysis.* The Glenlake Publishing Company, Ltd., Chicago, USA, 2000. ISBN 1888998881.

Frank Sortino and Stephen Satchell. *Managing Downside Risk in Financial Markets.* Butterworth-Heinemann, Oxford, UK, 1st edition, 2001. ISBN 0750648635.

Standard & Poors. S&p gsci. `http://www.standardandpoors.com/indices/sp-gsci/en/us/?indexID=spgscirg--usd---sp-----`, 2012. [Online; accessed 11-May-2012].

Stephen J. Taylor. *Asset Price Dynamics, Volatility, and Prediction.* Princeton University Press, Princeton, USA, 1st edition, 2005. ISBN 9780691134796.

The City UK. Commodities trading. *Financial Market Series*, March 2011.

Richard L. Weissman. *Mechanical Trading Systems: Pairing Trader Psychology with Technical Analysis.* John Wiley & Sons, Inc, New Jersey, USA, 1st edition, 2005. ISBN 0471654353.

J. Welles Wilder. *New Concepts in Technical Trading Systems.* Hunter Publishing Company, Winston-Salem, USA, 1st edition, 1978.

A List of derivative exchanges

Major exchanges trading futures and options[75]

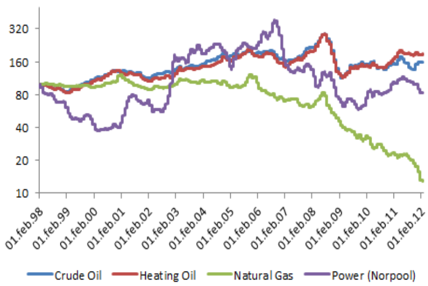
Australian Securities Exchange (ASX)	www.asx.com.au
BM&FBOVESPA (MBF)	www.bmfbovespa.com.br
Bombay Stock Exchange (BSE)	www.bseindia.com
Boston Option Exchange (BOX)	www.bostonoptions.com
Bursa Malaysia (BM)	www.bursammalaysia.com
Chicago Board Options Exchange (CBOE)	www.cboe.com
China Financial Futures Exchange (CFFEX)	www.cffex.com.cn
CME Group	www.cmegroup.com
Dalian Commodity Exchange (DCE)	www.dce.com.cn
Eurex	www.eurexchange.com
Hong Kong Futures Exchange (HKFE)	www.hkex.com.hk
IntercontinentalExchange (ICE)	www.theice.com
International Securities Exchange (ISE)	www.iseoptions.com
Kansas City Board of Trade (KCBT)	www.kcbt.com
London Metal Exchange (LME)	www.lme.co.uk
MEFF Renta Fija and Variable, Spain	www.meff.es
Mexican Derivatives Exchange (MEXDER)	www.mexder.com
Minneapolis Grain Exchange (MGE)	www.mgex.com
Montreal Exchange (ME)	www.m-x.ca
NASDAQ OMX	www.nasdaqomx.com
National Stock Exchange, Mumbai (NSE)	www.nseindia.com
NYSE Euronext	www.nyse.com
Osaka Securities Exchange (OSE)	www.ose.or.jp
Shanghai Futures Exchange (SHFE)	www.shfe.com.cn
Singapore Exchange (SGX)	www.sx.com
Tokyo Grain Exchange (TGE)	www.tge.or.jp
Tokyo Financial Exchange (TFX)	www.tfx.co.jp
Zengzhou Commodity Exchange (ZCE)	www.zce.cn

[75] (Hull, 2012)

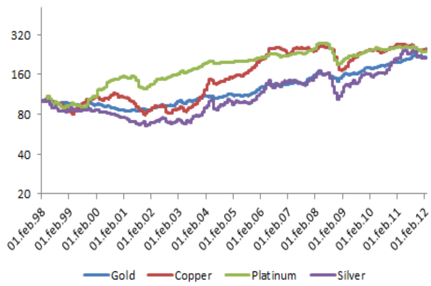
B Price and volume development of the asset pool

The figures below shows the price and volume development for the Fund's commodity universe. For power traded on Nord Pool, volume was not available. The asset based performance is more varied than what figure 4 in section 2.2.2 depicts. However, all figures plunge around the financial crisis which further verifies that commodities serve as a poor diversifier in market downturns. Another observation is that, between groups, commodities seem to have a low degree of correlation whereas the contrary appears to be true within the groups. This can be verified in appendix C where the correlations are given.

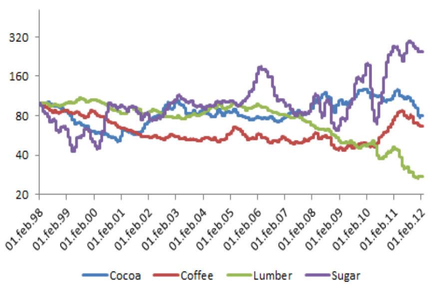
The figures also show that the volume traded has overall increased significantly the past 14 years. Some commodities appear to have large seasonal variations, which may be argued, is due to the cyclicality of the production process.



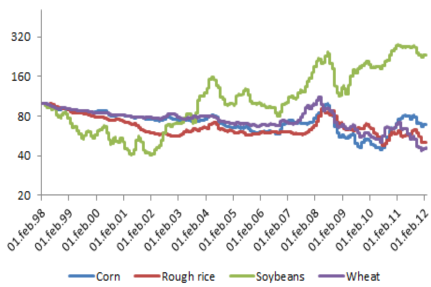
Price; energy futures



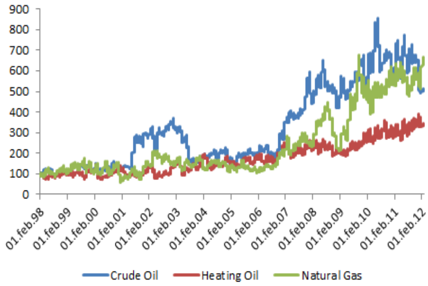
Price; metal futures



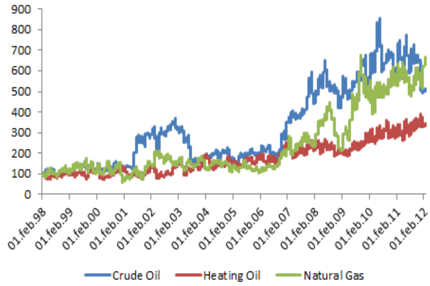
Price; softs futures



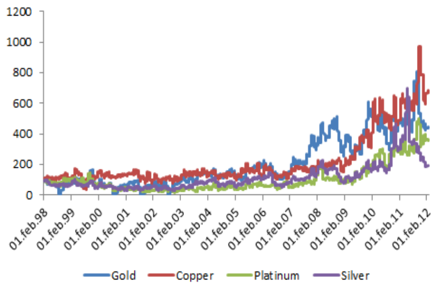
Price; grains futures



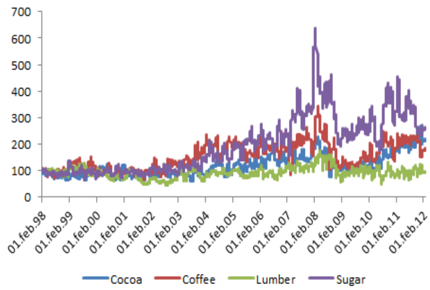
Price; meat futures



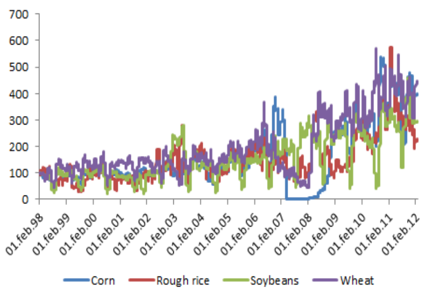
Volume; energy futures



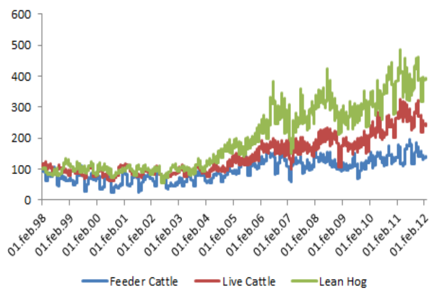
Volume; metal futures



Volume; softs futures



Volume; grain futures



Volume; meat futures

C Descriptive statistics

The table below summarize the time series included. The following tables describes, first, the entire time span thereafter describing the 1st, 2nd and 3rd Quantile, respectively. All statistics were calculated using R with the exception of the p-values where excel was used due to a higher accuracy.

Summary time series

Return series	Start date	End date	Data points
All	07-Jan-98	03-Feb-12	3452
1st Quantile	07-Jan-98	07-Oct-02	1150
2nd Quantile	08-Oct-02	28-Jun-07	1151
3rd Quantile	29-Jun-07	03-Feb-12	1151

Commodities, descriptive statistics[76]

	Light Crude Oil	*Heating Oil*	*Natural Gas*	*Power*	*Corn*
Min.	-8.859%	-8.519%	-8.057%	-15.660%	-6.454%
Median	0.034%	-0.004%	-0.024%	0.000%	0.000%
Mean	0.013%	0.019%	-0.063%	-0.006%	-0.010%
Max.	6.847%	7.016%	10.415%	24.090%	7.481%
SD	1.318%	1.375%	1.427%	2.368%	1.154%
Kurt	7.83	6.16	7.45	13.04	9.39
Skew	-0.47	-0.23	0.11	0.22	-0.09
ADF	-13.38 (0.0000***)	-14.25 (0.0000***)	-14.95 (0.0000***)	-13.6 (0.0000***)	-13.68 (0.0000***)
JB	3486.44 (0.0000***)	1465.12 (0.0000***)	2855.91 (0.0000***)	14539.97 (0.0000***)	5869.17 (0.0000***)
Q(5)	18.05 (0.0028***)	6.66 (0.2471)	17.75 (0.0032***)	35.1 (0.0000***)	13.55 (0.0186**)
Q(10)	23.08 (0.0104**)	10.94 (0.3615)	33.53 (0.0002***)	45.93 (0.0000***)	18.52 (0.0467**)
Q(20)	44.97 (0.0011***)	18.25 (0.5703)	56.1 (0.0000***)	79.8 (0.0000***)	65.77 (0.0000***)
$Q(5)^2$	715.4 (0.0000***)	443.5 (0.0000***)	677.77 (0.0000***)	1211.31 (0.0000***)	855.59 (0.0000***)
$Q(10)^2$	1352.92 (0.0000***)	875.47 (0.0000***)	1191.76 (0.0000***)	1475.59 (0.0000***)	1525.83 (0.0000***)
$Q(20)^2$	2533.27 (0.0000***)	1709.65 (0.0000***)	1723.09 (0.0000***)	2052.24 (0.0000***)	2658.1 (0.0000***)
	Rough Rice	*Soybeans*	*Wheat*	*Cocoa*	*Coffee*
Min.	-4.889%	-15.510%	-8.501%	-11.030%	-7.633%
Median	-0.030%	0.056%	-0.022%	0.000%	0.000%
Mean	-0.021%	0.026%	-0.021%	-0.006%	-0.012%
Max.	8.352%	10.831%	7.493%	8.289%	8.116%
SD	0.928%	2.126%	1.162%	1.526%	1.258%
Kurt	7.38	6.13	10.04	7.03	6.47
Skew	0.13	-0.36	-0.18	-0.34	-0.05
ADF	-14.38 (0.0000***)	-13.94 (0.0000***)	-14.32 (0.0000***)	-16.51 (0.0000***)	-15.42 (0.0000***)
JB	2768.99 (0.0000***)	1480.82 (0.0000***)	7146.73 (0.0000***)	2402.66 (0.0000***)	1732.32 (0.0000***)
Q(5)	48.14 (0.0000***)	8.93 (0.1117)	6.22 (0.2851)	5.13 (0.3997)	5.69 (0.337)
Q(10)	52.31 (0.0000***)	19.43 (0.0351**)	21.78 (0.0162**)	12.07 (0.2803)	12.05 (0.2817)
Q(20)	63.04 (0.0000***)	37.14 (0.0112**)	54.25 (0.0000***)	40.48 (0.0043***)	41.31 (0.0033***)
$Q(5)^2$	603.59 (0.0000***)	322.68 (0.0000***)	773.68 (0.0000***)	97.25 (0.0000***)	256.67 (0.0000***)
$Q(10)^2$	1104.77 (0.0000***)	597.59 (0.0000***)	1500.65 (0.0000***)	144.17 (0.0000***)	379.04 (0.0000***)
$Q(20)^2$	2087.24 (0.0000***)	981.47 (0.0000***)	2703.01 (0.0000***)	310.55 (0.0000***)	515.78 (0.0000***)

Q(5), Q(10), Q(20), $Q(5)^2$, $Q(10)^2$, $Q(20)^2$,denotes the Ljung Box test with 5, 10 and 20 lags for returns and squared returns respectively. *, ** and *** denotes a significance level of 10%, 5% and 1% respectively.

Commodities, descriptive statistics cont.

	Lumber	*Sugar*	*Gold*	*Copper*	*Platinum*
Min.	-4.310%	-16.123%	-6.289%	-12.127%	-13.877%
Median	-0.035%	0.000%	0.036%	0.051%	0.121%
Mean	-0.036%	0.024%	0.036%	0.046%	0.045%
Max.	4.112%	20.800%	13.350%	10.856%	9.948%
SD	0.932%	2.830%	1.005%	1.815%	1.467%
Kurt	5.00	7.15	16.66	6.53	9.42
Skew	0.10	-0.15	0.37	-0.22	-0.63
ADF	-14.33 (0.0000***)	-13.32 (0.0000***)	-14.73 (0.0000***)	-13.27 (0.0000***)	-13.12 (0.0000***)
JB	579.7 (0.0000***)	2496.11 (0.0000***)	26909.57 (0.0000***)	1818.39 (0.0000***)	6164.08 (0.0000***)
Q(5)	26.74 (0.0000***)	15.35 (0.0089***)	2.45 (0.7828)	30.09 (0.0000***)	26.65 (0.0000***)
Q(10)	34.14 (0.0001***)	17.39 (0.0661*)	14.57 (0.1483)	49.9 (0.0000***)	39.98 (0.0000***)
Q(20)	44.61 (0.0012***)	30.08 (0.0684*)	39.52 (0.0057***)	70.44 (0.0000***)	67.54 (0.0000***)
$Q(5)^2$	1638.95 (0.0000***)	438.77 (0.0000***)	202.43 (0.0000***)	614.26 (0.0000***)	523.12 (0.0000***)
$Q(10)^2$	2852.19 (0.0000***)	767.24 (0.0000***)	322.95 (0.0000***)	1001.94 (0.0000***)	782.56 (0.0000***)
$Q(20)^2$	5466.75 (0.0000***)	1363.78 (0.0000***)	561.02 (0.0000***)	1649.55 (0.0000***)	1249.94 (0.0000***)
	Silver	*Feeder Cattle*	*Live Cattle*	*Lean Hog*	
Min.	-19.432%	-7.246%	-5.553%	-3.644%	
Median	0.093%	0.019%	0.000%	0.000%	
Mean	0.036%	0.012%	0.001%	-0.013%	
Max.	17.973%	2.626%	2.684%	7.847%	
SD	1.795%	0.698%	0.641%	0.861%	
Kurt	15.34	7.44	6.20	6.34	
Skew	-0.80	-0.45	-0.30	0.20	
ADF	-14.88 (0.0000***)	-14.28 (0.0000***)	-14.72 (0.0000***)	-14.12 (0.0000***)	
JB	22261.35 (0.0000***)	2954.75 (0.0000***)	1528.65 (0.0000***)	1627.94 (0.0000***)	
Q(5)	1.57 (0.9047)	28.32 (0.0000***)	10.74 (0.0567*)	2.4 (0.7901)	
Q(10)	7.21 (0.7054)	46.83 (0.0000***)	31.51 (0.0004***)	12.66 (0.2428)	
Q(20)	13 (0.8771)	61.21 (0.0000***)	49.34 (0.0002***)	23.3 (0.2738)	
$Q(5)^2$	261.32 (0.0000***)	106.26 (0.0000***)	262.07 (0.0000***)	75.66 (0.0000***)	
$Q(10)^2$	405.85 (0.0000***)	186.57 (0.0000***)	369.12 (0.0000***)	156.04 (0.0000***)	
$Q(20)^2$	679.43 (0.0000***)	248.86 (0.0000***)	550.69 (0.0000***)	342.96 (0.0000***)	

Financial instruments, descriptive statistics

	2 Year T-Note	*10 Year T-Note*	*Eurodollar*	*Japanese Yen*	*Norwegian Kroner*
Min.	-0.981%	-2.675%	-0.507%	-3.934%	-4.712%
Median	0.000%	0.028%	0.000%	0.000%	0.027%
Mean	0.007%	0.024%	0.003%	0.005%	0.007%
Max.	0.905%	3.979%	0.644%	5.842%	5.612%
SD	0.126%	0.574%	0.046%	0.626%	0.807%
Kurt	7.87	5.11	29.88	9.51	5.81
Skew	0.02	-0.18	1.21	0.44	-0.10
ADF	-14.41 (0.0000***)	-14.32 (0.0000***)	-13.08 (0.0000***)	-15.38 (0.0000***)	-14.47 (0.0000***)
JB	3409.03 (0.0000***)	656.05 (0.0000***)	104803.67 (0.0000***)	6212.17 (0.0000***)	1140.7 (0.0000***)
Q(5)	14.21 (0.0142**)	7.28 (0.2004)	99 (0.0000***)	6.75 (0.2396)	6.85 (0.2314)
Q(10)	27.64 (0.002***)	12.12 (0.2766)	119.13 (0.0000***)	13.92 (0.1765)	16.27 (0.092*)
Q(20)	65.18 (0.0000***)	31.76 (0.0458**)	152.96 (0.0000***)	32.45 (0.0386**)	33.72 (0.028**)
Q(5)$\hat{2}$	473.43 (0.0000***)	198.5 (0.0000***)	448.95 (0.0000***)	99.42 (0.0000***)	786.57 (0.0000***)
Q(10)$\hat{2}$	801.13 (0.0000***)	364.52 (0.0000***)	594.77 (0.0000***)	136.96 (0.0000***)	1045.97 (0.0000***)
Q(20)$\hat{2}$	1026.8 (0.0000***)	634.87 (0.0000***)	752.61 (0.0000***)	240.1 (0.0000***)	1567.45 (0.0000***)

Correlations

	CL	HO	NG	ENOQ	C	RR	S	W	CC	KC	LB	SB
CL	1.00	0.86	0.28	0.13	0.33	0.20	0.28	0.29	0.20	0.23	0.11	0.23
HO	0.86	1.00	0.31	0.12	0.30	0.19	0.28	0.25	0.18	0.21	0.09	0.21
NG	0.28	0.31	1.00	0.05	0.14	0.11	0.13	0.12	0.09	0.11	0.02	0.11
ENOQ	0.13	0.12	0.05	1.00	0.05	0.03	0.04	0.03	0.07	0.06	0.04	0.03
C	0.33	0.30	0.14	0.05	1.00	0.29	0.54	0.65	0.17	0.25	0.11	0.27
RR	0.20	0.19	0.11	0.03	0.29	1.00	0.27	0.30	0.13	0.17	0.06	0.15
S	0.28	0.28	0.13	0.04	0.54	0.27	1.00	0.40	0.15	0.20	0.06	0.21
W	0.29	0.25	0.12	0.03	0.65	0.30	0.40	1.00	0.16	0.23	0.10	0.23
CC	0.20	0.18	0.09	0.07	0.17	0.13	0.15	0.16	1.00	0.23	0.05	0.17
KC	0.23	0.21	0.11	0.06	0.25	0.17	0.20	0.23	0.23	1.00	0.10	0.25
LB	0.11	0.09	0.02	0.04	0.11	0.06	0.06	0.10	0.05	0.10	1.00	0.06
SB	0.23	0.21	0.11	0.03	0.27	0.15	0.21	0.23	0.17	0.25	0.06	1.00
GC	0.29	0.26	0.10	0.06	0.20	0.15	0.19	0.18	0.19	0.16	0.03	0.14
HG	0.37	0.34	0.11	0.09	0.26	0.18	0.26	0.22	0.18	0.22	0.11	0.23
PL	0.29	0.27	0.11	0.08	0.22	0.19	0.21	0.19	0.18	0.20	0.05	0.17
SI	0.36	0.31	0.13	0.07	0.26	0.19	0.24	0.23	0.23	0.22	0.08	0.18
FC	0.12	0.09	0.05	0.04	-0.05	0.02	-0.02	-0.01	0.05	0.08	0.06	0.05
LC	0.17	0.14	0.07	0.04	0.17	0.07	0.13	0.15	0.09	0.13	0.06	0.11
LH	0.11	0.10	0.03	0.03	0.09	0.04	0.09	0.09	0.06	0.05	0.07	0.07
TU	-0.08	-0.06	-0.01	-0.02	-0.05	-0.02	-0.07	-0.05	-0.02	-0.05	-0.07	-0.03
TY	-0.14	-0.10	-0.02	-0.04	-0.08	-0.03	-0.09	-0.08	-0.06	-0.08	-0.09	-0.04
ED	0.00	0.01	-0.01	-0.01	0.02	-0.01	-0.01	-0.01	0.01	0.02	-0.04	0.02
JY	-0.07	-0.06	0.00	-0.05	-0.05	-0.02	-0.02	-0.02	0.01	-0.02	-0.03	-0.05
NOK	0.36	0.33	0.12	0.06	0.24	0.18	0.22	0.20	0.21	0.19	0.08	0.17

	GC	HG	PL	SI	FC	LC	LH	TU	TY	ED	JY	NOK
CL	0.29	0.37	0.29	0.36	0.12	0.17	0.11	-0.08	-0.14	0.00	-0.07	0.36
HO	0.26	0.34	0.27	0.31	0.09	0.14	0.10	-0.06	-0.10	0.01	-0.06	0.33
NG	0.10	0.11	0.11	0.13	0.05	0.07	0.03	-0.01	-0.02	-0.01	0.00	0.12
ENOQ	0.06	0.09	0.08	0.07	0.04	0.04	0.03	-0.02	-0.04	-0.01	-0.05	0.06
C	0.20	0.26	0.22	0.26	-0.05	0.17	0.09	-0.05	-0.08	0.02	-0.05	0.24
RR	0.15	0.18	0.19	0.19	0.02	0.07	0.04	-0.02	-0.03	-0.01	-0.02	0.18
S	0.19	0.26	0.21	0.24	-0.02	0.13	0.09	-0.07	-0.09	-0.01	-0.02	0.22
W	0.18	0.22	0.19	0.23	-0.01	0.15	0.09	-0.05	-0.08	-0.01	-0.02	0.20
CC	0.19	0.18	0.18	0.23	0.05	0.09	0.06	-0.02	-0.06	0.01	0.01	0.21
KC	0.16	0.22	0.20	0.22	0.08	0.13	0.05	-0.05	-0.08	0.02	-0.02	0.19
LB	0.03	0.11	0.05	0.08	0.06	0.06	0.07	-0.07	-0.09	-0.04	-0.03	0.08
SB	0.14	0.23	0.17	0.18	0.05	0.11	0.07	-0.03	-0.04	0.02	-0.05	0.17
GC	1.00	0.33	0.52	0.76	-0.02	0.04	0.03	0.12	0.07	0.03	0.18	0.34
HG	0.33	1.00	0.32	0.42	0.10	0.15	0.11	-0.11	-0.14	0.02	-0.04	0.29
PL	0.52	0.32	1.00	0.53	0.04	0.07	0.05	0.00	-0.05	0.03	0.06	0.27
SI	0.76	0.42	0.53	1.00	0.04	0.09	0.07	0.04	0.00	0.03	0.11	0.35
FC	-0.02	0.10	0.04	0.04	1.00	0.78	0.29	-0.09	-0.09	-0.02	-0.06	0.06
LC	0.04	0.15	0.07	0.09	0.78	1.00	0.34	-0.07	-0.07	-0.01	-0.06	0.08
LH	0.03	0.11	0.05	0.07	0.29	0.34	1.00	-0.04	-0.05	-0.02	-0.02	0.05
TU	0.12	-0.11	0.00	0.04	-0.09	-0.07	-0.04	1.00	0.84	0.58	0.28	0.08
TY	0.07	-0.14	-0.05	0.00	-0.09	-0.07	-0.05	0.84	1.00	0.47	0.25	0.02
ED	0.03	0.02	0.03	0.03	-0.02	-0.01	-0.02	0.58	0.47	1.00	0.16	0.12
JY	0.18	-0.04	0.06	0.11	-0.06	-0.06	-0.02	0.28	0.25	0.16	1.00	0.14
NOK	0.34	0.29	0.27	0.35	0.06	0.08	0.05	0.08	0.02	0.12	0.14	1.00

1st Quantile: Commodities, descriptive statistics

	Light Crude Oil	*Heating Oil*	*Natural Gas*	*Power*	*Corn*
Min.	-5.151%	-5.022%	-5.221%	-5.659%	-2.212%
Median	0.025%	-0.006%	0.005%	-0.011%	0.000%
Mean	0.023%	0.014%	-0.006%	-0.025%	-0.021%
Max.	3.317%	3.184%	4.071%	7.059%	1.610%
SD	0.784%	0.836%	0.647%	1.393%	0.402%
Kurt	5.49	5.02	16.07	5.86	5.36
Skew	-0.27	-0.23	-0.81	0.27	0.06
ADF	-10.85 (0.0000***)	-10.88 (0.0000***)	-8.87 (0.0000***)	-8.68 (0.0000***)	-11.45 (0.0000***)
JB	309.88 (0.0000***)	205.28 (0.0000***)	8306.48 (0.0000***)	406.48 (0.0000***)	266.81 (0.0000***)
Q(5)	10.71 (0.0572*)	3.2 (0.6683)	13.13 (0.0221**)	46.8 (0.0000***)	9.26 (0.0988*)
Q(10)	13.87 (0.1786)	4.39 (0.9278)	31.37 (0.0005***)	76.26 (0.0000***)	12.67 (0.2426)
Q(20)	33.13 (0.0326**)	22.4 (0.3189)	67.58 (0.0000***)	103.62 (0.0000***)	30.22 (0.0663*)
$Q(5)\hat{2}$	15.03 (0.0102**)	52.35 (0.0000***)	344.7 (0.0000***)	142.02 (0.0000***)	122.25 (0.0000***)
$Q(10)\hat{2}$	16.6 (0.0836*)	60.61 (0.0000***)	617.22 (0.0000***)	244.98 (0.0000***)	222.97 (0.0000***)
$Q(20)\hat{2}$	23.9 (0.2464)	84.99 (0.0000***)	1104.9 (0.0000***)	338.99 (0.0000***)	286.4 (0.0000***)
	Rough Rice	*Soybeans*	*Wheat*	*Cocoa*	*Coffee*
Min.	-2.539%	-12.579%	-1.500%	-7.054%	-5.282%
Median	-0.045%	-0.056%	-0.019%	-0.018%	-0.027%
Mean	-0.049%	-0.036%	-0.016%	0.003%	-0.050%
Max.	2.324%	10.831%	1.545%	5.005%	8.116%
SD	0.457%	2.122%	0.354%	1.138%	1.005%
Kurt	6.62	5.49	4.53	5.82	12.09
Skew	-0.25	-0.07	0.12	0.06	0.45
ADF	-10.25 (0.0000***)	-10.49 (0.0000***)	-11.22 (0.0000***)	-9.75 (0.0000***)	-11.98 (0.0000***)
JB	640.43 (0.0000***)	298.98 (0.0000***)	114.32 (0.0000***)	381.98 (0.0000***)	3998.02 (0.0000***)
Q(5)	18.8 (0.002***)	18.62 (0.0022***)	3.54 (0.6161)	6.1 (0.296)	10.45 (0.0634*)
Q(10)	29.77 (0.0009***)	24.6 (0.0061***)	5.38 (0.8639)	10.55 (0.3934)	28.85 (0.0013***)
Q(20)	46.06 (0.0007***)	33.01 (0.0335**)	13.27 (0.8654)	27.75 (0.1153)	41.08 (0.0036***)
$Q(5)\hat{2}$	272.85 (0.0000***)	95.81 (0.0000***)	98.18 (0.0000***)	38.93 (0.0000***)	257.38 (0.0000***)
$Q(10)\hat{2}$	312 (0.0000***)	178.51 (0.0000***)	181.56 (0.0000***)	65.47 (0.0000***)	278.8 (0.0000***)
$Q(20)\hat{2}$	314.27 (0.0000***)	302.56 (0.0000***)	229.09 (0.0000***)	109.66 (0.0000***)	295.51 (0.0000***)

1st Quantile: Commodities, descriptive statistics cont.

	Lumber	*Sugar*	*Gold*	*Copper*	*Platinum*
Min.	-2.332%	-11.610%	-2.839%	-5.752%	-7.797%
Median	-0.025%	0.000%	-0.022%	-0.061%	0.065%
Mean	-0.020%	-0.009%	-0.003%	-0.018%	0.053%
Max.	2.425%	20.800%	5.245%	6.566%	9.948%
SD	0.626%	2.531%	0.572%	1.285%	1.466%
Kurt	3.17	7.76	16.53	5.31	7.41
Skew	0.02	0.29	1.61	0.36	0.14
ADF	-9.39 (0.0000***)	-9.93 (0.0000***)	-11.43 (0.0000***)	-10.35 (0.0000***)	-11.24 (0.0000***)
JB	1.42 (0.4916)	1099.65 (0.0000***)	9265.69 (0.0000***)	281.92 (0.0000***)	935.18 (0.0000***)
Q(5)	8.45 (0.1329)	14.68 (0.0118**)	9.92 (0.0773*)	2.3 (0.8062)	15.49 (0.0084***)
Q(10)	14.45 (0.1534)	19.98 (0.0294**)	14.36 (0.1569)	11.91 (0.2908)	20.07 (0.0285**)
Q(20)	25.82 (0.1718)	33.32 (0.031**)	23.07 (0.2851)	28.76 (0.0925*)	32.69 (0.0364**)
Q(5)2̂	102.56 (0.0000***)	26.46 (0.0000***)	77.29 (0.0000***)	2.17 (0.8237)	41.36 (0.0000***)
Q(10)2̂	158.56 (0.0000***)	30.72 (0.0006***)	78.44 (0.0000***)	7.56 (0.6716)	75.24 (0.0000***)
Q(20)2̂	291.91 (0.0000***)	42.42 (0.0024***)	82.53 (0.0000***)	16.84 (0.6631)	101.96 (0.0000***)
	Silver	*Feeder Cattle*	*Live Cattle*	*Lean Hog*	
Min.	-3.320%	-1.722%	-1.411%	-2.374%	
Median	-0.017%	0.000%	-0.006%	0.000%	
Mean	-0.026%	-0.010%	-0.007%	-0.006%	
Max.	4.711%	2.061%	2.105%	7.847%	
SD	0.856%	0.614%	0.505%	0.730%	
Kurt	6.17	3.66	3.66	14.79	
Skew	0.07	0.08	0.24	1.10	
ADF	-10.84 (0.0000***)	-11.98 (0.0000***)	-12.36 (0.0000***)	-9.25 (0.0000***)	
JB	482.75 (0.0000***)	21.95 (0.0000***)	32.48 (0.0000***)	6893.84 (0.0000***)	
Q(5)	1.04 (0.9585)	8.41 (0.1347)	3.65 (0.6005)	8.16 (0.1474)	
Q(10)	10.04 (0.4364)	22.22 (0.0139**)	11.86 (0.2942)	20.96 (0.0213**)	
Q(20)	35.64 (0.0169**)	40.77 (0.0039***)	31.2 (0.0525*)	26.24 (0.1579)	
Q(5)2̂	155.42 (0.0000***)	103.33 (0.0000***)	53.45 (0.0000***)	0.34 (0.9968)	
Q(10)2̂	223.64 (0.0000***)	169.13 (0.0000***)	86.64 (0.0000***)	2.63 (0.9888)	
Q(20)2̂	377.54 (0.0000***)	305.54 (0.0000***)	182.96 (0.0000***)	5.55 (0.9993)	

1st Quantile: Financial instruments, descriptive statistics

	2 Year T-Note	*10 Year T-Note*	*Eurodollar*	*Japanese Yen*	*Norwegian Kroner*
Min.	-0.588%	-2.675%	-0.205%	-3.056%	-3.011%
Median	0.008%	0.050%	0.000%	0.000%	0.007%
Mean	0.010%	0.029%	0.005%	-0.011%	0.001%
Max.	0.733%	2.227%	0.644%	5.842%	4.527%
SD	0.141%	0.673%	0.048%	0.618%	0.659%
Kurt	5.47	3.90	35.50	11.73	5.61
Skew	0.18	-0.34	2.95	1.00	0.16
ADF	-9.92 (0.0000***)	-9.94 (0.0000***)	-9.28 (0.0000***)	-10.3 (0.0000***)	-10.9 (0.0000***)
JB	299.41 (0.0000***)	60.42 (0.0000***)	52265.49 (0.0000***)	3843.77 (0.0000***)	330.51 (0.0000***)
Q(5)	17.84 (0.0031***)	10.18 (0.0701*)	44.19 (0.0000***)	3.28 (0.6556)	3.8 (0.5777)
Q(10)	30.57 (0.0006***)	16.78 (0.0791*)	62.71 (0.0000***)	4.28 (0.9336)	5.49 (0.8554)
Q(20)	39.28 (0.0061***)	23.92 (0.2456)	71.32 (0.0000***)	10.64 (0.9549)	15.53 (0.7447)
Q(5)$\hat{2}$	107.52 (0.0000***)	68.33 (0.0000***)	30.06 (0.0000***)	13.38 (0.02**)	146.56 (0.0000***)
Q(10)$\hat{2}$	148.24 (0.0000***)	92.66 (0.0000***)	31.05 (0.0005***)	17.22 (0.0696*)	157.36 (0.0000***)
Q(20)$\hat{2}$	194.18 (0.0000***)	123.77 (0.0000***)	33.11 (0.0327**)	28.51 (0.0978*)	160.54 (0.0000***)

1st Quantile: Correlations

	CL	HO	NG	ENOQ	C	RR	S	W	CC	KC	LB	SB
CL	1.00	0.88	0.21	-0.03	0.06	0.06	0.00	0.06	0.00	0.00	0.04	0.04
HO	0.88	1.00	0.31	-0.05	0.07	0.06	0.01	0.06	0.00	-0.01	0.05	0.03
NG	0.21	0.31	1.00	-0.06	0.09	0.08	0.09	0.08	-0.04	0.01	0.01	0.02
ENOQ	-0.03	-0.05	-0.06	1.00	0.00	-0.04	-0.05	0.01	0.01	0.04	0.02	0.03
C	0.06	0.07	0.09	0.00	1.00	0.18	0.69	0.62	0.03	0.03	0.01	0.07
RR	0.06	0.06	0.08	-0.04	0.18	1.00	0.19	0.19	0.03	0.02	0.06	0.02
S	0.00	0.01	0.09	-0.05	0.69	0.19	1.00	0.50	0.05	0.04	-0.02	0.07
W	0.06	0.06	0.08	0.01	0.62	0.19	0.50	1.00	-0.01	0.06	0.03	0.05
CC	0.00	0.00	-0.04	0.01	0.03	0.03	0.05	-0.01	1.00	0.07	0.01	0.06
KC	0.00	-0.01	0.01	0.04	0.03	0.02	0.04	0.06	0.07	1.00	0.02	0.11
LB	0.04	0.05	0.01	0.02	0.01	0.06	-0.02	0.03	0.01	0.02	1.00	0.02
SB	0.04	0.03	0.02	0.03	0.07	0.02	0.07	0.05	0.06	0.11	0.02	1.00
GC	0.09	0.08	0.03	0.02	0.06	0.00	0.13	0.08	0.12	0.04	0.02	0.03
HG	0.07	0.08	0.03	-0.02	0.09	0.04	0.10	0.06	0.01	0.02	0.04	0.03
PL	0.11	0.09	0.03	0.03	0.07	0.01	0.10	0.04	0.04	0.09	0.00	0.04
SI	0.07	0.08	0.01	0.02	0.06	0.03	0.06	0.09	0.11	0.04	0.03	0.05
FC	0.01	-0.02	0.00	0.01	-0.20	0.00	-0.13	-0.07	-0.03	-0.01	0.06	-0.03
LC	0.02	0.01	0.02	0.02	0.04	0.02	0.04	0.04	-0.01	-0.03	0.01	-0.03
LH	0.05	0.05	0.03	-0.01	0.07	0.05	0.07	0.06	0.04	-0.04	0.04	0.03
TU	-0.07	-0.06	-0.03	0.02	-0.01	-0.03	-0.02	-0.02	0.02	-0.03	-0.12	0.00
TY	-0.08	-0.05	0.00	0.00	0.00	0.01	-0.02	-0.01	0.02	-0.03	-0.11	0.01
ED	-0.04	-0.05	-0.01	0.03	-0.03	-0.04	0.01	-0.04	0.05	-0.01	-0.14	0.00
JY	0.07	0.07	0.01	-0.04	0.08	0.02	0.12	0.06	0.06	0.05	0.02	0.02
NOK	0.05	0.03	0.04	0.00	0.02	0.01	0.06	0.03	0.09	-0.04	-0.02	0.04

	GC	HG	PL	SI	FC	LC	LH	TU	TY	ED	JY	NOK
CL	0.09	0.07	0.11	0.07	0.01	0.02	0.05	-0.07	-0.08	-0.04	0.07	0.05
HO	0.08	0.08	0.09	0.08	-0.02	0.01	0.05	-0.06	-0.05	-0.05	0.07	0.03
NG	0.03	0.03	0.03	0.01	0.00	0.02	0.03	-0.03	0.00	-0.01	0.01	0.04
ENOQ	0.02	-0.02	0.03	0.02	0.01	0.02	-0.01	0.02	0.00	0.03	-0.04	0.00
C	0.06	0.09	0.07	0.06	-0.20	0.04	0.07	-0.01	0.00	-0.03	0.08	0.02
RR	0.00	0.04	0.01	0.03	0.00	0.02	0.05	-0.03	0.01	-0.04	0.02	0.01
S	0.13	0.10	0.10	0.06	-0.13	0.04	0.07	-0.02	-0.02	0.01	0.12	0.06
W	0.08	0.06	0.04	0.09	-0.07	0.04	0.06	-0.02	-0.01	-0.04	0.06	0.03
CC	0.12	0.01	0.04	0.11	-0.03	-0.01	0.04	0.02	0.02	0.05	0.06	0.09
KC	0.04	0.02	0.09	0.04	-0.01	-0.03	-0.04	-0.03	-0.03	-0.01	0.05	-0.04
LB	0.02	0.04	0.00	0.03	0.06	0.01	0.04	-0.12	-0.11	-0.14	0.02	-0.02
SB	0.03	0.03	0.04	0.05	-0.03	-0.03	0.03	0.00	0.01	0.00	0.02	0.04
GC	1.00	0.12	0.31	0.54	-0.02	0.01	0.02	0.10	0.06	0.13	0.19	0.23
HG	0.12	1.00	0.08	0.22	0.00	0.01	0.02	-0.09	-0.09	-0.05	0.06	0.05
PL	0.31	0.08	1.00	0.29	-0.04	-0.05	0.02	-0.02	-0.04	0.03	0.15	0.07
SI	0.54	0.22	0.29	1.00	-0.02	0.03	0.07	0.04	0.01	0.05	0.19	0.19
FC	-0.02	0.00	-0.04	-0.02	1.00	0.78	0.30	-0.07	-0.05	-0.06	0.00	0.01
LC	0.01	0.01	-0.05	0.03	0.78	1.00	0.30	-0.02	0.00	-0.02	0.01	0.00
LH	0.02	0.02	0.02	0.07	0.30	0.30	1.00	-0.05	-0.07	-0.04	-0.01	0.01
TU	0.10	-0.09	-0.02	0.04	-0.07	-0.02	-0.05	1.00	0.84	0.72	0.01	0.15
TY	0.06	-0.09	-0.04	0.01	-0.05	0.00	-0.07	0.84	1.00	0.58	-0.04	0.09
ED	0.13	-0.05	0.03	0.05	-0.06	-0.02	-0.04	0.72	0.58	1.00	0.05	0.16
JY	0.19	0.06	0.15	0.19	0.00	0.01	-0.01	0.01	-0.04	0.05	1.00	0.23
NOK	0.23	0.05	0.07	0.19	0.01	0.00	0.01	0.15	0.09	0.16	0.23	1.00

2nd Quantile: Commodities, descriptive statistics

	Light Crude Oil	*Heating Oil*	*Natural Gas*	*Power*	*Corn*
Min.	-3.640%	-4.450%	-6.454%	-15.660%	-3.030%
Median	0.068%	-0.027%	-0.048%	0.000%	-0.037%
Mean	0.024%	0.031%	-0.029%	0.056%	-0.008%
Max.	3.310%	6.240%	10.400%	24.092%	4.010%
SD	0.914%	1.236%	1.273%	2.964%	0.695%
Kurt	3.33	3.89	10.81	12.94	7.05
Skew	-0.17	0.22	0.75	0.40	0.46
ADF	-10.62 (0.0000***)	-11.31 (0.0000***)	-9.68 (0.0000***)	-9.85 (0.0000***)	-10.63 (0.0000***)
JB	10.79 (0.0045***)	47.29 (0.0000***)	3036.81 (0.0000***)	4771.77 (0.0000***)	827.58 (0.0000***)
Q(5)	3.95 (0.5565)	5.25 (0.3858)	3.93 (0.559)	37.33 (0.0000***)	2.88 (0.7171)
Q(10)	7.72 (0.6554)	12.58 (0.2475)	11.12 (0.348)	56.54 (0.0000***)	7.25 (0.7012)
Q(20)	17.83 (0.5984)	24.06 (0.2395)	19.82 (0.469)	90.09 (0.0000***)	24.51 (0.2206)
Q(5)2̂	25 (0.0001***)	58.91 (0.0000***)	45.59 (0.0000***)	412.88 (0.0000***)	148.1 (0.0000***)
Q(10)2̂	53.28 (0.0000***)	94.44 (0.0000***)	59.48 (0.0000***)	473.64 (0.0000***)	199.42 (0.0000***)
Q(20)2̂	71.57 (0.0000***)	155.36 (0.0000***)	79.87 (0.0000***)	612.41 (0.0000***)	237.29 (0.0000***)
	Rough Rice	*Soybeans*	*Wheat*	*Cocoa*	*Coffee*
Min.	-2.890%	-8.256%	-2.430%	-7.510%	-4.620%
Median	0.000%	0.110%	-0.026%	-0.041%	-0.028%
Mean	0.005%	0.052%	-0.003%	-0.015%	-0.009%
Max.	4.250%	7.806%	2.940%	6.320%	5.810%
SD	0.712%	1.925%	0.676%	1.408%	1.044%
Kurt	5.60	4.42	4.93	6.14	4.95
Skew	0.31	-0.21	0.50	-0.44	0.16
ADF	-9.87 (0.0000***)	-9.12 (0.0000***)	-10.45 (0.0000***)	-11.41 (0.0000***)	-10.45 (0.0000***)
JB	341.56 (0.0000***)	104.71 (0.0000***)	225.77 (0.0000***)	509.84 (0.0000***)	187.51 (0.0000***)
Q(5)	9.09 (0.1052)	16.67 (0.0051***)	3.22 (0.666)	5.38 (0.3703)	4.84 (0.4354)
Q(10)	22.16 (0.0143**)	25.37 (0.0046***)	6.71 (0.7522)	16.82 (0.0782*)	7.75 (0.6528)
Q(20)	32.98 (0.0338**)	31.34 (0.0508*)	15.44 (0.7504)	27.96 (0.1101)	16.3 (0.6974)
Q(5)2̂	21.1 (0.0007***)	97.43 (0.0000***)	88.84 (0.0000***)	23.65 (0.0002***)	12.46 (0.0289**)
Q(10)2̂	29.52 (0.001***)	140.41 (0.0000***)	126.11 (0.0000***)	29.83 (0.0009***)	26.86 (0.0027***)
Q(20)2̂	40.32 (0.0045***)	207.6 (0.0000***)	178.7 (0.0000***)	37.34 (0.0106**)	50.01 (0.0002***)

2nd Quantile: Commodities, descriptive statistics cont.

	Lumber	*Sugar*	*Gold*	*Copper*	*Platinum*
Min.	-1.860%	-9.400%	-6.290%	-12.100%	-5.060%
Median	0.000%	0.059%	0.059%	0.195%	0.144%
Mean	0.001%	-0.015%	0.035%	0.151%	0.068%
Max.	2.740%	8.210%	3.760%	10.900%	5.148%
SD	0.703%	1.751%	0.867%	1.836%	1.089%
Kurt	2.79	5.88	7.49	7.42	5.19
Skew	0.19	-0.20	-0.85	-0.49	-0.40
ADF	-9.78 (0.0000***)	-11.29 (0.0000***)	-9.93 (0.0000***)	-9.58 (0.0000***)	-10.32 (0.0000***)
JB	8.6 (0.0135**)	405.38 (0.0000***)	1107.46 (0.0000***)	982.37 (0.0000***)	260.62 (0.0000***)
Q(5)	17.6 (0.0034***)	6.43 (0.2661)	4.46 (0.4841)	11.96 (0.0353**)	5.23 (0.3873)
Q(10)	22.74 (0.0117**)	15.1 (0.1282)	21.82 (0.016**)	37.34 (0.0000***)	16.07 (0.0973*)
Q(20)	30.71 (0.059*)	27.41 (0.124)	34.69 (0.0218**)	55.96 (0.0000***)	24.99 (0.2017)
Q(5)$\hat{2}$	15.81 (0.0074***)	121.14 (0.0000***)	80.02 (0.0000***)	27.91 (0.0000***)	74.31 (0.0000***)
Q(10)$\hat{2}$	45.84 (0.0000***)	199.96 (0.0000***)	127.5 (0.0000***)	40.14 (0.0000***)	95.82 (0.0000***)
Q(20)$\hat{2}$	87.33 (0.0000***)	397.53 (0.0000***)	457.71 (0.0000***)	85.49 (0.0000***)	161.63 (0.0000***)
	Silver	*Feeder Cattle*	*Live Cattle*	*Lean Hog*	
Min.	-12.700%	-7.250%	-5.550%	-1.610%	
Median	0.150%	0.055%	0.042%	0.035%	
Mean	0.057%	0.043%	0.024%	0.007%	
Max.	4.980%	2.630%	2.080%	2.760%	
SD	1.530%	0.744%	0.634%	0.662%	
Kurt	12.97	11.45	9.06	3.09	
Skew	-1.64	-0.89	-0.72	-0.06	
ADF	-10.05 (0.0000***)	-10.91 (0.0000***)	-11.77 (0.0000***)	-10.05 (0.0000***)	
JB	5288 (0.0000***)	3572.69 (0.0000***)	1863.24 (0.0000***)	0.99 (0.6095)	
Q(5)	0.46 (0.9934)	16.74 (0.005***)	14.41 (0.0131**)	4.49 (0.4799)	
Q(10)	8.01 (0.6274)	25.02 (0.0053***)	23.83 (0.008***)	19.15 (0.0383**)	
Q(20)	29.6 (0.0764*)	37.03 (0.0115**)	38.61 (0.0074***)	28.58 (0.0962*)	
Q(5)$\hat{2}$	50.06 (0.0000***)	35.19 (0.0000***)	131.9 (0.0000***)	13.09 (0.0224**)	
Q(10)$\hat{2}$	69.91 (0.0000***)	57.65 (0.0000***)	148.26 (0.0000***)	25.55 (0.0043***)	
Q(20)$\hat{2}$	186.95 (0.0000***)	65.82 (0.0000***)	163.97 (0.0000***)	66.37 (0.0000***)	

2nd Quantile: Financial instruments, descriptive statistics

	2 Year T-Note	*10 Year T-Note*	*Eurodollar*	*Japanese Yen*	*Norwegian Kroner*
Min.	-0.484%	-2.230%	-0.135%	-1.880%	-3.447%
Median	0.000%	0.000%	0.000%	-0.021%	0.034%
Mean	-0.001%	0.003%	-0.001%	-0.011%	0.020%
Max.	0.519%	1.890%	0.178%	1.920%	2.440%
SD	0.107%	0.480%	0.026%	0.478%	0.685%
Kurt	5.26	5.38	10.05	4.02	3.79
Skew	0.04	-0.23	0.39	0.17	-0.25
ADF	-11.36 (0.0000***)	-10.72 (0.0000***)	-10.96 (0.0000***)	-9.91 (0.0000***)	-10.91 (0.0000***)
JB	245.1 (0.0000***)	281.29 (0.0000***)	2412.56 (0.0000***)	55.66 (0.0000***)	41.81 (0.0000***)
Q(5)	4.99 (0.4166)	3.38 (0.6412)	21.3 (0.0007***)	1.06 (0.9569)	2.04 (0.8433)
Q(10)	6.97 (0.7277)	4.53 (0.9202)	31.46 (0.0004***)	6.85 (0.7386)	9.56 (0.4798)
Q(20)	21.68 (0.358)	17.03 (0.6506)	45.02 (0.001***)	19 (0.5214)	29.18 (0.0841*)
Q(5)$\hat{2}$	20.73 (0.0009***)	82.1 (0.0000***)	128.61 (0.0000***)	9.15 (0.1029)	7.11 (0.212)
Q(10)$\hat{2}$	37.74 (0.0000***)	137.29 (0.0000***)	146.36 (0.0000***)	21.42 (0.0183**)	31.08 (0.0005***)
Q(20)$\hat{2}$	102.97 (0.0000***)	338.77 (0.0000***)	162.51 (0.0000***)	39.73 (0.0053***)	41.71 (0.003***)

2nd Quantile: Correlations

	CL	HO	NG	ENOQ	C	RR	S	W	CC	KC	LB	SB
CL	1.00	0.84	0.42	0.11	0.14	0.00	0.14	0.13	0.05	0.10	-0.02	0.13
HO	0.84	1.00	0.46	0.11	0.14	0.00	0.14	0.14	0.05	0.11	0.01	0.14
NG	0.42	0.46	1.00	0.06	0.06	-0.01	0.10	0.03	0.02	0.01	-0.07	0.07
ENOQ	0.11	0.11	0.06	1.00	-0.01	0.01	0.03	-0.03	0.03	0.06	0.01	0.00
C	0.14	0.14	0.06	-0.01	1.00	0.18	0.56	0.59	0.01	0.11	0.06	0.09
RR	0.00	0.00	-0.01	0.01	0.18	1.00	0.22	0.15	0.00	0.00	-0.03	0.02
S	0.14	0.14	0.10	0.03	0.56	0.22	1.00	0.38	0.01	0.10	0.02	0.08
W	0.13	0.14	0.03	-0.03	0.59	0.15	0.38	1.00	0.00	0.08	0.04	0.12
CC	0.05	0.05	0.02	0.03	0.01	0.00	0.01	0.00	1.00	0.13	0.09	0.09
KC	0.10	0.11	0.01	0.06	0.11	0.00	0.10	0.08	0.13	1.00	0.09	0.12
LB	-0.02	0.01	-0.07	0.01	0.06	-0.03	0.02	0.04	0.09	0.09	1.00	0.01
SB	0.13	0.14	0.07	0.00	0.09	0.02	0.08	0.12	0.09	0.12	0.01	1.00
GC	0.26	0.25	0.12	0.05	0.18	0.10	0.13	0.14	0.11	0.11	0.02	0.11
HG	0.19	0.15	0.10	0.05	0.11	0.05	0.11	0.12	0.07	0.10	0.03	0.16
PL	0.14	0.14	0.08	0.03	0.09	0.07	0.07	0.10	0.08	0.10	0.01	0.10
SI	0.22	0.21	0.10	0.03	0.19	0.08	0.15	0.13	0.11	0.14	0.05	0.11
FC	-0.01	-0.04	0.03	0.02	-0.19	-0.03	-0.11	-0.11	0.02	0.02	0.02	-0.05
LC	0.02	0.00	0.04	-0.02	-0.02	-0.02	-0.01	-0.01	0.04	0.06	0.04	-0.01
LH	0.04	0.04	0.03	0.03	0.01	-0.07	0.04	0.01	0.00	0.05	0.03	-0.01
TU	0.07	0.08	0.02	-0.02	0.00	0.02	-0.04	-0.04	0.01	0.00	-0.04	0.01
TY	0.05	0.06	0.03	-0.02	-0.02	0.01	-0.04	-0.04	-0.01	0.00	-0.06	0.00
ED	0.08	0.12	0.03	-0.02	0.02	0.01	-0.03	-0.02	0.00	0.03	-0.02	0.03
JY	0.04	0.05	0.02	-0.04	0.00	0.03	0.03	0.03	0.05	0.04	-0.03	0.00
NOK	0.18	0.18	0.06	0.01	0.08	0.08	0.11	0.05	0.10	0.11	0.01	0.08

	GC	HG	PL	SI	FC	LC	LH	TU	TY	ED	JY	NOK
CL	0.26	0.19	0.14	0.22	-0.01	0.02	0.04	0.07	0.05	0.08	0.04	0.18
HO	0.25	0.15	0.14	0.21	-0.04	0.00	0.04	0.08	0.06	0.12	0.05	0.18
NG	0.12	0.10	0.08	0.10	0.03	0.04	0.03	0.02	0.03	0.03	0.02	0.06
ENOQ	0.05	0.05	0.03	0.03	0.02	-0.02	0.03	-0.02	-0.02	-0.02	-0.04	0.01
C	0.18	0.11	0.09	0.19	-0.19	-0.02	0.01	0.00	-0.02	0.02	0.00	0.08
RR	0.10	0.05	0.07	0.08	-0.03	-0.02	-0.07	0.02	0.01	0.01	0.03	0.08
S	0.13	0.11	0.07	0.15	-0.11	-0.01	0.04	-0.04	-0.04	-0.03	0.03	0.11
W	0.14	0.12	0.10	0.13	-0.11	-0.01	0.01	-0.04	-0.04	-0.02	0.03	0.05
CC	0.11	0.07	0.08	0.11	0.02	0.04	0.00	0.01	-0.01	0.00	0.05	0.10
KC	0.11	0.10	0.10	0.14	0.02	0.06	0.05	0.00	0.00	0.03	0.04	0.11
LB	0.02	0.03	0.01	0.05	0.02	0.04	0.03	-0.04	-0.06	-0.02	-0.03	0.01
SB	0.11	0.16	0.10	0.11	-0.05	-0.01	-0.01	0.01	0.00	0.03	0.00	0.08
GC	1.00	0.42	0.53	0.77	-0.01	0.03	0.03	0.15	0.13	0.16	0.29	0.43
HG	0.42	1.00	0.31	0.42	0.03	0.06	0.09	-0.01	-0.04	0.02	0.17	0.16
PL	0.53	0.31	1.00	0.49	0.03	0.06	0.00	0.10	0.05	0.11	0.15	0.22
SI	0.77	0.42	0.49	1.00	0.01	0.05	0.02	0.12	0.07	0.13	0.23	0.33
FC	-0.01	0.03	0.03	0.01	1.00	0.81	0.26	-0.07	-0.07	-0.08	0.00	-0.02
LC	0.03	0.06	0.06	0.05	0.81	1.00	0.29	-0.08	-0.08	-0.07	0.02	0.00
LH	0.03	0.09	0.00	0.02	0.26	0.29	1.00	-0.03	-0.03	-0.04	-0.01	0.01
TU	0.15	-0.01	0.10	0.12	-0.07	-0.08	-0.03	1.00	0.90	0.76	0.31	0.32
TY	0.13	-0.04	0.05	0.07	-0.07	-0.08	-0.03	0.90	1.00	0.64	0.27	0.28
ED	0.16	0.02	0.11	0.13	-0.08	-0.07	-0.04	0.76	0.64	1.00	0.33	0.26
JY	0.29	0.17	0.15	0.23	0.00	0.02	-0.01	0.31	0.27	0.33	1.00	0.42
NOK	0.43	0.16	0.22	0.33	-0.02	0.00	0.01	0.32	0.28	0.26	0.42	1.00

3rd Quantile: Commodities, descriptive statistics

	Light Crude Oil	*Heating Oil*	*Natural Gas*	*Power*	*Corn*
Min.	-8.859%	-8.519%	-8.057%	-12.316%	-6.454%
Median	0.020%	0.040%	-0.143%	0.010%	0.038%
Mean	-0.009%	0.012%	-0.154%	-0.050%	0.000%
Max.	6.847%	7.016%	7.360%	12.739%	7.481%
SD	1.940%	1.856%	2.015%	2.469%	1.830%
Kurt	4.68	4.58	3.72	5.58	4.29
Skew	-0.38	-0.32	0.06	-0.20	-0.11
ADF	-10.28 (0.0000***)	-10.19 (0.0000***)	-10.45 (0.0000***)	-10.13 (0.0000***)	-9.53 (0.0000***)
JB	164.03 (0.0000***)	140.22 (0.0000***)	25.57 (0.0000***)	326.95 (0.0000***)	82.46 (0.0000***)
Q(5)	10.36 (0.0656*)	5.43 (0.3655)	14.51 (0.0126**)	5.85 (0.3206)	6.28 (0.279)
Q(10)	12.17 (0.2737)	7.71 (0.6569)	19.7 (0.0321**)	9.84 (0.4543)	7.9 (0.6383)
Q(20)	25.01 (0.2008)	10.63 (0.955)	35.89 (0.0158**)	16.19 (0.7042)	30.92 (0.0561*)
Q(5)$\hat{2}$	85.49 (0.0000***)	58.21 (0.0000***)	134.27 (0.0000***)	209.86 (0.0000***)	56.16 (0.0000***)
Q(10)$\hat{2}$	151.83 (0.0000***)	117.48 (0.0000***)	224.5 (0.0000***)	308.09 (0.0000***)	84.62 (0.0000***)
Q(20)$\hat{2}$	272.18 (0.0000***)	231.44 (0.0000***)	253.45 (0.0000***)	550.39 (0.0000***)	119.54 (0.0000***)
	Rough Rice	*Soybeans*	*Wheat*	*Cocoa*	*Coffee*
Min.	-4.889%	-15.510%	-8.501%	-11.030%	-7.633%
Median	-0.025%	0.098%	-0.046%	0.089%	0.068%
Mean	-0.018%	0.061%	-0.045%	-0.005%	0.023%
Max.	8.352%	9.219%	7.493%	8.289%	5.630%
SD	1.367%	2.315%	1.862%	1.926%	1.626%
Kurt	4.21	7.14	4.47	5.85	4.37
Skew	0.08	-0.66	-0.12	-0.34	-0.26
ADF	-9.3 (0.0000***)	-10.15 (0.0000***)	-9.58 (0.0000***)	-9.6 (0.0000***)	-9.73 (0.0000***)
JB	71.8 (0.0000***)	907.4 (0.0000***)	106.48 (0.0000***)	411.83 (0.0000***)	103.05 (0.0000***)
Q(5)	25.45 (0.0001***)	1.25 (0.9393)	3.62 (0.6047)	2.48 (0.7787)	1.75 (0.8822)
Q(10)	27.25 (0.0023***)	5.61 (0.8464)	11.83 (0.2959)	7.44 (0.6824)	10.67 (0.3834)
Q(20)	33.54 (0.0293**)	22.76 (0.3002)	25.34 (0.1884)	26.82 (0.1402)	27.14 (0.1313)
Q(5)$\hat{2}$	47.74 (0.0000***)	110.21 (0.0000***)	47.06 (0.0000***)	10.61 (0.0596*)	11.42 (0.0435**)
Q(10)$\hat{2}$	77.99 (0.0000***)	231.66 (0.0000***)	86.95 (0.0000***)	12.76 (0.2372)	20.29 (0.0266**)
Q(20)$\hat{2}$	141.68 (0.0000***)	385.13 (0.0000***)	131.95 (0.0000***)	44.48 (0.0012***)	33.53 (0.0294**)

3rd Quantile: Commodities, descriptive statistics cont.

	Lumber	*Sugar*	*Gold*	*Copper*	*Platinum*
Min.	-4.310%	-16.123%	-5.997%	-10.290%	-13.877%
Median	-0.136%	0.093%	0.148%	0.026%	0.119%
Mean	-0.088%	0.098%	0.075%	0.004%	0.015%
Max.	4.112%	15.491%	13.350%	10.250%	6.907%
SD	1.311%	3.815%	1.397%	2.202%	1.768%
Kurt	3.45	4.76	11.80	4.89	9.11
Skew	0.17	-0.29	0.43	-0.17	-1.04
ADF	-9.9 (0.0000***)	-9.7 (0.0000***)	-11.06 (0.0000***)	-9.74 (0.0000***)	-9.11 (0.0000***)
JB	15.18 (0.0005***)	165.35 (0.0000***)	3753.45 (0.0000***)	175.66 (0.0000***)	1995.17 (0.0000***)
Q(5)	8.65 (0.1235)	8.52 (0.1296)	3.06 (0.6894)	24.64 (0.0001***)	13.48 (0.0192**)
Q(10)	13.84 (0.1802)	9.6 (0.4754)	20.57 (0.0242**)	28.19 (0.0016***)	28.35 (0.0015***)
Q(20)	24.95 (0.2033)	24.88 (0.2058)	37.88 (0.0091***)	48.7 (0.0003***)	50.13 (0.0002***)
Q(5)$\hat{2}$	302 (0.0000***)	91.74 (0.0000***)	39.09 (0.0000***)	392.45 (0.0000***)	218.32 (0.0000***)
Q(10)$\hat{2}$	479.14 (0.0000***)	155.62 (0.0000***)	59.5 (0.0000***)	633.74 (0.0000***)	308.9 (0.0000***)
Q(20)$\hat{2}$	894.22 (0.0000***)	257.72 (0.0000***)	92.29 (0.0000***)	957.6 (0.0000***)	495.13 (0.0000***)
	Silver	*Feeder Cattle*	*Live Cattle*	*Lean Hog*	
Min.	-19.432%	-4.355%	-3.658%	-3.644%	
Median	0.297%	0.018%	0.000%	-0.026%	
Mean	0.078%	0.002%	-0.013%	-0.039%	
Max.	17.973%	2.460%	2.684%	3.419%	
SD	2.568%	0.729%	0.759%	1.120%	
Kurt	9.33	4.71	4.39	3.61	
Skew	-0.53	-0.33	-0.18	0.03	
ADF	-10.37 (0.0000***)	-10.71 (0.0000***)	-11.52 (0.0000***)	-10.31 (0.0000***)	
JB	1977.17 (0.0000***)	160.95 (0.0000***)	98.9 (0.0000***)	17.78 (0.0001***)	
Q(5)	1.18 (0.9467)	17.68 (0.0033***)	6.23 (0.2837)	1.45 (0.918)	
Q(10)	8.75 (0.5558)	22.55 (0.0124**)	13.67 (0.1881)	5.08 (0.8856)	
Q(20)	15.3 (0.7585)	36.33 (0.014**)	26.01 (0.1654)	19.84 (0.4676)	
$Q(5)^2$	43.24 (0.0000***)	29.31 (0.0000***)	39.92 (0.0000***)	9.81 (0.0806*)	
$Q(10)^2$	59.43 (0.0000***)	57.64 (0.0000***)	80.53 (0.0000***)	23.35 (0.0095***)	
$Q(20)^2$	83 (0.0000***)	109.2 (0.0000***)	141.01 (0.0000***)	57.84 (0.0000***)	

3rd Quantile: Financial instruments, descriptive statistics

	2 Year T-Note	*10 Year T-Note*	*Eurodollar*	*Japanese Yen*	*Norwegian Kroner*
Min.	-0.981%	-2.527%	-0.507%	-3.934%	-4.712%
Median	0.007%	0.049%	0.000%	0.037%	0.046%
Mean	0.012%	0.039%	0.004%	0.035%	0.001%
Max.	0.905%	3.979%	0.475%	5.137%	5.612%
SD	0.128%	0.553%	0.058%	0.751%	1.024%
Kurt	11.69	6.21	18.56	7.76	4.99
Skew	-0.26	0.12	0.01	0.11	-0.10
ADF	-11.16 (0.0000***)	-9.88 (0.0000***)	-9.12 (0.0000***)	-10.97 (0.0000***)	-10.6 (0.0000***)
JB	3638.29 (0.0000***)	495.82 (0.0000***)	11613.16 (0.0000***)	1090.05 (0.0000***)	192.61 (0.0000***)
Q(5)	17.37 (0.0038***)	4.75 (0.4463)	71.19 (0.0000***)	8.21 (0.145)	5.51 (0.3567)
Q(10)	23.81 (0.0081***)	6.36 (0.7837)	80.21 (0.0000***)	15.19 (0.1249)	12.98 (0.2244)
Q(20)	63.48 (0.0000***)	22.09 (0.3352)	109.12 (0.0000***)	34.46 (0.0231**)	43.23 (0.0019***)
Q(5)$\hat{2}$	249.51 (0.0000***)	27.68 (0.0000***)	332.69 (0.0000***)	35.37 (0.0000***)	261.86 (0.0000***)
Q(10)$\hat{2}$	452.39 (0.0000***)	84.34 (0.0000***)	470.33 (0.0000***)	51.67 (0.0000***)	324.08 (0.0000***)
Q(20)$\hat{2}$	548.46 (0.0000***)	155.69 (0.0000***)	600.3 (0.0000***)	95.17 (0.0000***)	478.75 (0.0000***)

3rd Quantile: Correlations

	CL	HO	NG	ENOQ	C	RR	S	W	CC	KC	LB	SB
CL	1.00	0.87	0.25	0.20	0.40	0.27	0.47	0.34	0.31	0.33	0.16	0.31
HO	0.87	1.00	0.25	0.18	0.38	0.27	0.49	0.31	0.29	0.32	0.12	0.30
NG	0.25	0.25	1.00	0.06	0.17	0.15	0.18	0.14	0.15	0.17	0.04	0.15
ENOQ	0.20	0.18	0.06	1.00	0.10	0.05	0.10	0.06	0.12	0.08	0.06	0.05
C	0.40	0.38	0.17	0.10	1.00	0.32	0.62	0.66	0.24	0.33	0.13	0.35
RR	0.27	0.27	0.15	0.05	0.32	1.00	0.35	0.34	0.21	0.26	0.08	0.22
S	0.47	0.49	0.18	0.10	0.62	0.35	1.00	0.49	0.30	0.35	0.12	0.35
W	0.34	0.31	0.14	0.06	0.66	0.34	0.49	1.00	0.24	0.31	0.13	0.29
CC	0.31	0.29	0.15	0.12	0.24	0.21	0.30	0.24	1.00	0.33	0.05	0.25
KC	0.33	0.32	0.17	0.08	0.33	0.26	0.35	0.31	0.33	1.00	0.13	0.36
LB	0.16	0.12	0.04	0.06	0.13	0.08	0.12	0.13	0.05	0.13	1.00	0.08
SB	0.31	0.30	0.15	0.05	0.35	0.22	0.35	0.29	0.25	0.36	0.08	1.00
GC	0.33	0.30	0.10	0.08	0.23	0.19	0.27	0.21	0.24	0.20	0.03	0.18
HG	0.54	0.51	0.14	0.18	0.35	0.28	0.47	0.30	0.31	0.36	0.17	0.35
PL	0.42	0.41	0.15	0.16	0.31	0.29	0.37	0.26	0.31	0.29	0.09	0.26
SI	0.44	0.39	0.16	0.12	0.30	0.25	0.36	0.27	0.31	0.30	0.09	0.24
FC	0.24	0.22	0.08	0.08	0.02	0.05	0.14	0.03	0.11	0.16	0.08	0.15
LC	0.28	0.26	0.10	0.10	0.28	0.12	0.28	0.23	0.17	0.22	0.09	0.22
LH	0.15	0.14	0.03	0.05	0.12	0.08	0.13	0.12	0.09	0.09	0.09	0.11
TU	-0.16	-0.16	-0.02	-0.04	-0.09	-0.04	-0.13	-0.08	-0.07	-0.09	-0.06	-0.08
TY	-0.27	-0.25	-0.05	-0.09	-0.14	-0.07	-0.21	-0.14	-0.14	-0.16	-0.10	-0.10
ED	-0.01	0.00	-0.02	-0.02	0.03	-0.01	-0.02	-0.01	0.00	0.03	0.00	0.03
JY	-0.15	-0.16	-0.01	-0.07	-0.10	-0.05	-0.15	-0.05	-0.03	-0.08	-0.06	-0.11
NOK	0.51	0.49	0.16	0.13	0.34	0.25	0.39	0.28	0.32	0.31	0.14	0.26

	GC	HG	PL	SI	FC	LC	LH	TU	TY	ED	JY	NOK
CL	0.33	0.54	0.42	0.44	0.24	0.28	0.15	-0.16	-0.27	-0.01	-0.15	0.51
HO	0.30	0.51	0.41	0.39	0.22	0.26	0.14	-0.16	-0.25	0.00	-0.16	0.49
NG	0.10	0.14	0.15	0.16	0.08	0.10	0.03	-0.02	-0.05	-0.02	-0.01	0.16
ENOQ	0.08	0.18	0.16	0.12	0.08	0.10	0.05	-0.04	-0.09	-0.02	-0.07	0.13
C	0.23	0.35	0.31	0.30	0.02	0.28	0.12	-0.09	-0.14	0.03	-0.10	0.34
RR	0.19	0.28	0.29	0.25	0.05	0.12	0.08	-0.04	-0.07	-0.01	-0.05	0.25
S	0.27	0.47	0.37	0.36	0.14	0.28	0.13	-0.13	-0.21	-0.02	-0.15	0.39
W	0.21	0.30	0.26	0.27	0.03	0.23	0.12	-0.08	-0.14	-0.01	-0.05	0.28
CC	0.24	0.31	0.31	0.31	0.11	0.17	0.09	-0.07	-0.14	0.00	-0.03	0.32
KC	0.20	0.36	0.29	0.30	0.16	0.22	0.09	-0.09	-0.16	0.03	-0.08	0.31
LB	0.03	0.17	0.09	0.09	0.08	0.09	0.09	-0.06	-0.10	0.00	-0.06	0.14
SB	0.18	0.35	0.26	0.24	0.15	0.22	0.11	-0.08	-0.10	0.03	-0.11	0.26
GC	1.00	0.35	0.62	0.78	-0.02	0.05	0.04	0.12	0.06	-0.03	0.15	0.33
HG	0.35	1.00	0.45	0.48	0.22	0.26	0.15	-0.20	-0.27	0.05	-0.20	0.45
PL	0.62	0.45	1.00	0.67	0.10	0.15	0.08	-0.03	-0.10	0.01	-0.03	0.40
SI	0.78	0.48	0.67	1.00	0.08	0.14	0.09	0.02	-0.05	0.00	0.05	0.41
FC	-0.02	0.22	0.10	0.08	1.00	0.76	0.33	-0.12	-0.14	0.05	-0.15	0.14
LC	0.05	0.26	0.15	0.14	0.76	1.00	0.39	-0.11	-0.13	0.03	-0.15	0.17
LH	0.04	0.15	0.08	0.09	0.33	0.39	1.00	-0.03	-0.05	-0.01	-0.04	0.08
TU	0.12	-0.20	-0.03	0.02	-0.12	-0.11	-0.03	1.00	0.78	0.41	0.52	-0.09
TY	0.06	-0.27	-0.10	-0.05	-0.14	-0.13	-0.05	0.78	1.00	0.32	0.54	-0.19
ED	-0.03	0.05	0.01	0.00	0.05	0.03	-0.01	0.41	0.32	1.00	0.19	0.06
JY	0.15	-0.20	-0.03	0.05	-0.15	-0.15	-0.04	0.52	0.54	0.19	1.00	-0.03
NOK	0.33	0.45	0.40	0.41	0.14	0.17	0.08	-0.09	-0.19	0.06	-0.03	1.00

D Profit adjustments and mistrade calculations

$$A_t^{50} = \begin{cases} [p_t^c - min(p_t^o, EMA_{50,t}^-)] \times (P_t^{50} - P_{t-1}^{50}) \times S_t \\ \quad \text{for } P_t^{50} < 0 \wedge P_{t-1}^{50} > 0 \\ [p_t^c - max(p_t^o, EMA_{50,t}^+)] \times (P_t^{50} - P_{t-1}^{50}) \times S_t \\ \quad \text{for } P_t^{50} > 0 \wedge P_{t-1}^{50} < 0 \\ [p_t^c - min(p_t^o, p_{t-1}^{ll})] \times 1/3 \times S_t \\ \quad \text{for } |P_t^{50}| > |P_{t-1}^{50}| \wedge P_{t-1}^{50} \neq 0 \wedge P_t^{50} < 0 \\ [p_t^c - max(p_t^o, p_{t-1}^{hh})] \times 1/3 \times S_t \\ \quad \text{for } |P_t^{50}| > |P_{t-1}^{50}| \wedge P_{t-1}^{50} \neq 0 \wedge P_t^{50} > 0 \\ 0 \ \ \text{Otherwise} \end{cases} \tag{D.1}$$

$$A_t^{20} = \begin{cases} [min(p_t^o, EMA_{20,t}^-) - min(p_t^o, EMA_{50,t}^-)] \times 1/3 \times S_t \\ \quad \text{for } P_t^{50} < 0 \wedge P_{t-1}^{50} > 0 \\ [max(p_t^o, EMA_{20,t}^+) - max(p_t^o, EMA_{50,t}^+)] \times 1/3 \times S_t \\ \quad \text{for } P_t^{50} > 0 \wedge P_{t-1}^{50} < 0 \\ [min(p_t^o, EMA_{20,t}^-) - p_t^c] \times (P_{t-1}^{20} - P_t^{20}) \times S_t \\ \quad \text{for } P_t^{20} < P_{t-1}^{20} \wedge sign(P_t^{50}) = sign(P_{t-1}^{50}) \\ [p_t^c - max(p_t^o, EMA_{20,t}^+)] \times (P_t^{20} - P_{t-1}^{20}) \times S_t \\ \quad \text{for } P_t^{20} > P_{t-1}^{20} \wedge sign(P_t^{50}) = sign(P_{t-1}^{50}) \\ 0 \ \ \text{Otherwise} \end{cases} \tag{D.2}$$

$$A_t^{10} = \begin{cases} [min(p_t^o, EMA_{10,t}^-) - min(p_t^o, EMA_{50,t}^-)] \times 1/3 \times S_t \\ \quad \text{for } P_t^{50} < 0 \wedge P_{t-1}^{50} > 0 \\ [max(p_t^o, EMA_{10,t}^+) - max(p_t^o, EMA_{50,t}^+)] \times 1/3 \times S_t \\ \quad \text{for } P_t^{50} > 0 \wedge P_{t-1}^{50} < 0 \\ [min(p_t^o, EMA_{10,t}^-) - p_t^c] \times (P_{t-1}^{10} - P_t^{10}) \times S_t \\ \quad \text{for } P_t^{10} < P_{t-1}^{10} \wedge sign(P_t^{50}) = sign(P_{t-1}^{50}) \\ [p_t^c - max(p_t^o, EMA_{10,t}^+)] \times (P_t^{10} - P_{t-1}^{10}) \times S_t \\ \quad \text{for } P_t^{10} > P_{t-1}^{10} \wedge sign(P_t^{50}) = sign(P_{t-1}^{50}) \\ 0 \ \ \text{Otherwise} \end{cases} \tag{D.3}$$

$$M_t^{50} = \begin{cases} -2(p_t^h - p_t^l) \times (|P_t^{50}| + 1/3) \times S_t \times 5\% \\ \quad \text{for } sign(P_t^{50}) = sign(P_{t-1}^{50}) \wedge [(p_t^l < EMA_{50,t}^- \\ \quad \wedge p_t^c > EMA_{50,t}^- \wedge P_t^{50} > 0) \vee (p_t^h > EMA_{50,t}^+ \\ \quad \wedge p_t^c < EMA_{50,t}^+ \wedge P_t^{50} < 0) \vee (p_t^h > EMA_{50,t}^+ \\ \quad \wedge p_t^l < EMA_{50,t}^-)] \\ 0 \ \ \text{Otherwise} \end{cases} \tag{D.4}$$

$$M_t^{20} = \begin{cases} -2(p_t^h - p_t^l) \times max(|P_{t-1}^{20}|, {}^{1}\!/_{3} - |P_{t-1}^{20}|) \times S_t \times 5\% \\ \quad \text{for } P_t^{20} = P_{t-1}^{20} \wedge [(p_t^l < EMA_{20,t}^{-} \\ \quad \wedge p_{t-1}^c > EMA_{20,t-1}^{-} \wedge p_t^c > EMA_{20,t}^{-} \wedge P_t^{50} > 0) \\ \quad \vee(p_t^h > EMA_{20,t}^{+} \wedge p_t^c < EMA_{20,t}^{+} \\ \quad \wedge p_{t-1}^c < EMA_{20,t-1}^{+} \wedge P_t^{50} < 0) \\ \quad \vee(p_t^h > EMA_{20,t}^{+} \wedge p_t^l < EMA_{20,t}^{-})] \\ 0 \quad \text{Otherwise} \end{cases} \tag{D.5}$$

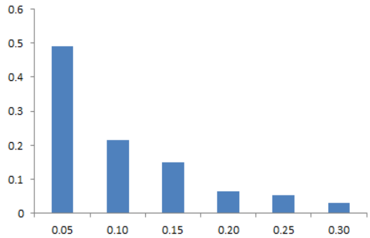
$$M_t^{10} = \begin{cases} -2(p_t^h - p_t^l) \times max(|P_{t-1}^{10}|, {}^{1}\!/_{3} - |P_{t-1}^{10}|) \times S_t \times 5\% \\ \quad \text{for } P_t^{10} = P_{t-1}^{10} \wedge [(p_t^l < EMA_{10,t}^{-} \\ \quad \wedge p_{t-1}^c > EMA_{10,t-1}^{-} \wedge p_t^c > EMA_{10,t}^{-} \wedge P_t^{50} > 0) \\ \quad \vee(p_t^h > EMA_{10,t}^{+} \wedge p_t^c < EMA_{20,t}^{+} \\ \quad \wedge p_{t-1}^c < EMA_{10,t-1}^{+} \wedge P_t^{50} < 0) \\ \quad \vee(p_t^h > EMA_{10,t}^{+} \wedge p_t^l < EMA_{10,t}^{-})] \\ \quad \wedge t - \sup\{t : t \in (RSI_t > \delta)\} > \epsilon \\ 0 \quad \text{Otherwise} \end{cases} \tag{D.6}$$

E Optimization variable distribution

E.1 BTM monthly recalibration

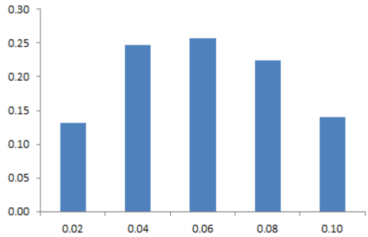
Summary of BTM parameter recalibrations

	Cont. variable occurency	*Median*	*Mean*	*Mode*	*Avg. change*	*Avg. steps changed cond. on change*
α	0.6036	0.0792	0.102783	0.05	0.0333	1.7001
β	0.2686	0.0596	0.059863	0.04	0.0245	1.6841
γ	0.5759	19.583	19.57477	20	2.6451	1.2568
δ	0.4595	79.375	80.99458	75	4.1724	1.5715
ϵ	0.4486	5	5.084475	5	1.3098	1.1913
ζ	0.2822	4.7917	4.559075	5	1.0098	1.4159
η	0.3653	65.208	65.65068	65	4.6293	1.4797



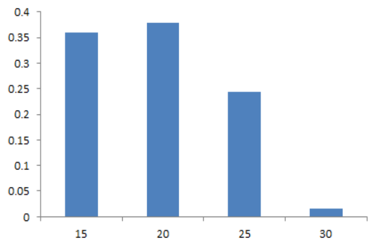
ATR_{20} band width, α

ATR_{20} band width, α	*CL*	*HO*	*NG*	*NP*	*C*	*RR*	*S*	*W*
Cont. variable occ.	63%	59%	75%	47%	49%	60%	58%	59%
Median	0.100	0.100	0.050	0.100	0.100	0.100	0.050	0.100
Mean	0.100	0.100	0.091	0.134	0.128	0.124	0.093	0.123
Mode	0.05	0.1	0.05	0.05	0.05	0.05	0.05	0.05
Avg. change	0.031	0.035	0.022	0.056	0.039	0.039	0.031	0.033
Avg. steps changed cond. on change	1.70	1.72	1.78	2.12	1.54	1.96	1.52	1.64
	CC	*KC*	*LB*	*SB*	*GC*	*HG*	*PL*	*SI*
Cont. variable occ.	62%	51%	51%	58%	68%	64%	65%	49%
Median	0.050	0.100	0.050	0.050	0.050	0.050	0.100	0.100
Mean	0.091	0.109	0.088	0.086	0.071	0.074	0.120	0.123
Mode	0.05	0.05	0.05	0.05	0.05	0.05	0.15	0.1
Avg. change	0.035	0.046	0.033	0.034	0.024	0.029	0.029	0.042
Avg. steps changed cond. on change	1.87	1.88	1.38	1.61	1.52	1.60	1.66	1.66
	FC	*LC*	*LH*	*TU*	*TY*	*ED*	*JY*	*USDNOK*
Cont. variable occ.	55%	64%	63%	60%	63%	66%	76%	62%
Median	0.100	0.050	0.050	0.100	0.050	0.100	0.050	0.150
Mean	0.114	0.071	0.076	0.110	0.088	0.109	0.078	0.166
Mode	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Avg. change	0.041	0.029	0.023	0.032	0.034	0.025	0.022	0.035
Avg. steps changed cond. on change	1.88	1.67	1.26	1.65	1.87	1.52	1.91	1.89



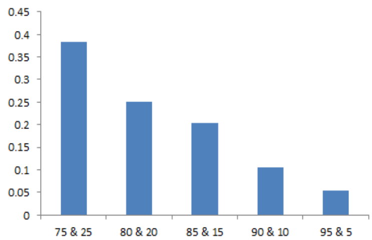
High/Low significance level, β

High/Low level, β	*CL*	*HO*	*NG*	*NP*	*C*	*RR*	*S*	*W*
Cont. variable occ.	23%	22%	28%	37%	30%	36%	27%	28%
Median	0.040	0.060	0.060	0.060	0.060	0.060	0.060	0.060
Mean	0.057	0.055	0.057	0.064	0.063	0.059	0.059	0.054
Mode	0.04	0.04	0.06	0.1	0.06	0.04	0.04	0.06
Avg. change	0.030	0.024	0.025	0.026	0.025	0.020	0.025	0.022
Avg. steps changed cond. on change	1.96	1.54	1.77	2.07	1.80	1.58	1.70	1.54
	CC	*KC*	*LB*	*SB*	*GC*	*HG*	*PL*	*SI*
Cont. variable occ.	29%	23%	35%	18%	21%	27%	17%	25%
Median	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060
Mean	0.060	0.058	0.060	0.061	0.059	0.058	0.062	0.063
Mode	0.06	0.04	0.06	0.08	0.04	0.04	0.06	0.06
Avg. change	0.025	0.023	0.023	0.030	0.027	0.024	0.027	0.024
Avg. steps changed cond. on change	1.74	1.52	1.76	1.85	1.69	1.66	1.66	1.60
	FC	*LC*	*LH*	*TU*	*TY*	*ED*	*JY*	*USDNOK*
Cont. variable occ.	23%	39%	32%	24%	28%	24%	25%	25%
Median	0.060	0.050	0.080	0.060	0.060	0.060	0.060	0.060
Mean	0.061	0.052	0.068	0.065	0.059	0.061	0.060	0.065
Mode	0.08	0.04	0.08	0.08	0.04	0.06	0.04	0.06
Avg. change	0.028	0.018	0.020	0.022	0.024	0.024	0.024	0.026
Avg. steps changed cond. on change	1.84	1.50	1.52	1.45	1.71	1.57	1.64	1.76



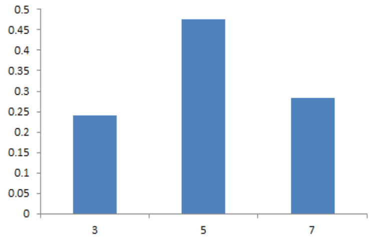
RSI: EMA length, γ

RSI: EMA length, γ	*CL*	*HO*	*NG*	*NP*	*C*	*RR*	*S*	*W*
Cont. variable occ.	58%	55%	47%	66%	68%	44%	60%	65%
Median	20	20	20	20	20	20	15	15
Mean	20.7	18.4	20.9	19.3	20.0	21.4	17.8	17.4
Mode	20	15	25	15	20	25	15	15
Avg. change	2.55	2.62	3.66	2.00	1.83	3.28	2.34	2.10
Avg. steps changed cond. on change	1.21	1.17	1.39	1.21	1.15	1.17	1.19	1.22
	CC	*KC*	*LB*	*SB*	*GC*	*HG*	*PL*	*SI*
Cont. variable occ.	52%	68%	56%	58%	47%	63%	60%	64%
Median	20	20	20	20	20	20	20	20
Mean	19.9	18.3	21.1	20.0	21.1	19.7	18.9	19.1
Mode	20	20	20	20	20	15	15	15
Avg. change	2.83	1.79	2.72	2.48	3.24	2.45	2.69	2.07
Avg. steps changed cond. on change	1.19	1.16	1.25	1.20	1.24	1.34	1.37	1.15
	FC	*LC*	*LH*	*TU*	*TY*	*ED*	*JY*	*USDNOK*
Cont. variable occ.	53%	58%	57%	64%	58%	56%	49%	56%
Median	15	20	20	20	20	20	20	25
Mean	18.0	19.6	19.2	19.1	19.8	18.9	19.0	22.3
Mode	15	20	20	20	15	15	20	25
Avg. change	3.10	2.52	2.52	2.28	3.03	2.83	3.31	3.24
Avg. steps changed cond. on change	1.34	1.20	1.18	1.27	1.46	1.30	1.30	1.50



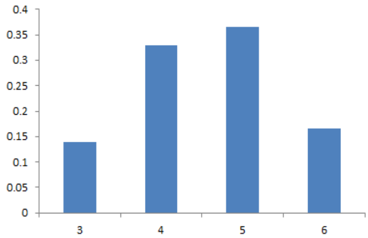
RSI: Extreme levels, δ

RSI: Extreme levels, δ	*CL*	*HO*	*NG*	*NP*	*C*	*RR*	*S*	*W*
Cont. variable occ.	44%	47%	28%	40%	57%	42%	52%	40%
Median	80.0	80.0	80.0	80.0	80.0	85.0	75.0	80.0
Mean	80.0	80.8	81.6	80.7	80.2	83.6	79.2	80.2
Mode	75	75	85	75	75	85	75	75
Avg. change	4.66	4.07	5.34	4.62	2.86	4.38	3.62	4.10
Avg. steps changed cond. on change	1.68	1.55	1.50	1.55	1.39	1.51	1.50	1.38
	CC	*KC*	*LB*	*SB*	*GC*	*HG*	*PL*	*SI*
Cont. variable occ.	56%	73%	48%	46%	44%	41%	44%	53%
Median	75.0	75.0	80.0	75.0	80.0	80.0	80.0	85.0
Mean	77.6	77.2	82.2	79.4	82.9	81.0	79.7	83.5
Mode	75	75	75	75	75	75	75	85
Avg. change	3.10	2.10	4.31	4.55	3.55	5.10	4.41	3.52
Avg. steps changed cond. on change	1.42	1.61	1.70	1.70	1.29	1.76	1.58	1.63
	FC	*LC*	*LH*	*TU*	*TY*	*ED*	*JY*	*USDNOK*
Cont. variable occ.	51%	53%	29%	47%	38%	47%	35%	47%
Median	80.0	75.0	80.0	80.0	80.0	80.0	80.0	80.0
Mean	79.8	80.4	82.5	81.9	82.4	81.7	82.5	83.2
Mode	75	75	80	80	75	80	80	80
Avg. change	4.21	4.41	4.86	4.45	5.21	3.90	5.07	3.72
Avg. steps changed cond. on change	1.74	1.92	1.39	1.71	1.74	1.48	1.58	1.44



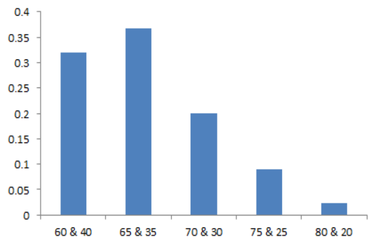
RSI: Duration of reduction, ϵ

RSI: Duration, ϵ	*CL*	*HO*	*NG*	*NP*	*C*	*RR*	*S*	*W*
Cont. variable occ.	52%	47%	43%	40%	44%	54%	42%	42%
Median	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Mean	5.2	5.2	5.4	5.0	5.3	5.2	5.0	5.0
Mode	5	5	5	5	5	5	5	5
Avg. change	1.12	1.17	1.42	1.45	1.48	1.14	1.41	1.21
Avg. steps changed cond. on change	1.17	1.12	1.26	1.21	1.32	1.26	1.23	1.05
	CC	*KC*	*LB*	*SB*	*GC*	*HG*	*PL*	*SI*
Cont. variable occ.	43%	47%	40%	60%	37%	33%	45%	57%
Median	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Mean	5.2	4.7	5.2	5.5	5.1	5.4	5.1	4.7
Mode	5	5	7	5	5	5	5	5
Avg. change	1.34	1.35	1.52	0.87	1.54	1.53	1.31	0.91
Avg. steps changed cond. on change	1.18	1.27	1.28	1.09	1.23	1.14	1.20	1.06
	FC	*LC*	*LH*	*TU*	*TY*	*ED*	*JY*	*USDNOK*
Cont. variable occ.	45%	38%	45%	52%	43%	42%	48%	38%
Median	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Mean	4.7	4.8	5.4	4.8	5.1	5.2	4.9	5.0
Mode	5	5	7	5	5	5	5	5
Avg. change	1.26	1.59	1.38	1.13	1.31	1.39	1.09	1.52
Avg. steps changed cond. on change	1.15	1.28	1.25	1.19	1.16	1.20	1.05	1.24



MA10 RSI: look back period, ζ

MA10 RSI: look back, ζ	*CL*	*HO*	*NG*	*NP*	*C*	*RR*	*S*	*W*
Cont. variable occ.	29%	27%	28%	31%	27%	29%	23%	34%
Median	4.0	4.0	5.0	5.0	4.0	5.0	5.0	5.0
Mean	4.5	4.4	4.5	4.6	4.5	4.5	4.6	4.6
Mode	4	5	4	5	4	4	5	5
Avg. change	0.97	1.07	0.97	1.07	1.10	0.96	1.10	0.83
Avg. steps changed cond. on change	1.36	1.46	1.35	1.56	1.50	1.35	1.47	1.26
	CC	*KC*	*LB*	*SB*	*GC*	*HG*	*PL*	*SI*
Cont. variable occ.	18%	31%	29%	31%	24%	31%	22%	25%
Median	5.0	5.0	5.0	5.0	5.0	5.0	4.5	5.0
Mean	4.6	4.5	4.7	4.5	4.5	4.7	4.5	4.6
Mode	5	4	4	5	5	5	4	5
Avg. change	1.11	1.01	0.98	0.99	1.08	0.98	1.14	1.08
Avg. steps changed cond. on change	1.36	1.48	1.40	1.43	1.43	1.42	1.46	1.43
	FC	*LC*	*LH*	*TU*	*TY*	*ED*	*JY*	*USDNOK*
Cont. variable occ.	27%	29%	31%	29%	34%	30%	31%	29%
Median	5.0	5.0	5.0	4.0	5.0	5.0	4.5	5.0
Mean	4.7	4.5	4.5	4.5	4.5	4.6	4.4	4.6
Mode	5	4	5	4	5	5	5	5
Avg. change	1.09	0.84	0.97	1.06	0.94	1.01	0.94	0.98
Avg. steps changed cond. on change	1.51	1.21	1.40	1.50	1.44	1.45	1.37	1.38



MA10 RSI: Extreme levels, η

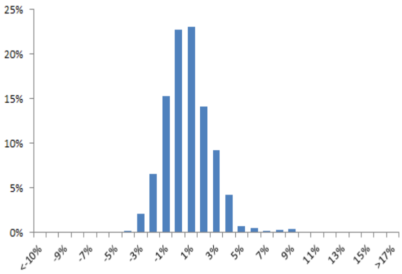
MA10 RSI: Levels, η	*CL*	*HO*	*NG*	*NP*	*C*	*RR*	*S*	*W*
Cont. variable occ.	33%	25%	38%	45%	38%	34%	34%	39%
Median	65.0	65.0	65.0	65.0	65.0	65.0	65.0	65.0
Mean	65.5	66.3	64.5	65.4	66.2	64.1	66.1	66.5
Mode	60	65	60	65	65	60	60	65
Avg. change	5.31	5.97	4.31	4.10	4.55	4.14	5.31	4.24
Avg. steps changed cond. on change	1.59	1.59	1.41	1.49	1.47	1.28	1.62	1.42
	CC	*KC*	*LB*	*SB*	*GC*	*HG*	*PL*	*SI*
Cont. variable occ.	30%	31%	34%	39%	34%	37%	42%	40%
Median	65.0	65.0	65.0	65.0	65.0	65.0	65.0	65.0
Mean	65.9	66.1	65.3	65.7	64.9	65.6	66.7	64.1
Mode	65	60	60	65	65	60	65	65
Avg. change	5.14	5.17	4.45	4.38	4.59	5.17	4.31	3.55
Avg. steps changed cond. on change	1.48	1.58	1.40	1.44	1.42	1.72	1.52	1.18
	FC	*LC*	*LH*	*TU*	*TY*	*ED*	*JY*	*USDNOK*
Cont. variable occ.	39%	45%	31%	48%	35%	32%	34%	42%
Median	65.0	65.0	65.0	65.0	65.0	65.0	65.0	70.0
Mean	65.8	65.0	66.3	64.2	66.2	65.9	65.2	68.2
Mode	60	65	65	60	65	65	65	70
Avg. change	4.24	3.62	6.17	3.17	4.52	5.55	5.07	4.07
Avg. steps changed cond. on change	1.40	1.37	1.85	1.24	1.43	1.65	1.55	1.41

E.2 TRAM monthly recalibration

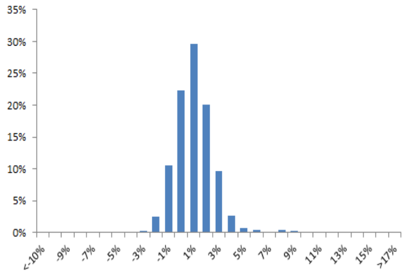
Summary of TRAM parameter recalibrations

	Cont. variable occurency	*Median*	*Mean*	*Mode*	*Avg. change*	*Avg. steps changed cond. on change*	*Variable on lower bound*	*Variable on upper bound*
θ	45%	35.00	35.74	35	6.54	2.38	0%	7%
ι	27%	0.45	0.41	0.5	0.08	2.15	1%	30%
κ	52%	15.00	14.09	10	3.88	1.60	50%	0%
λ	40%	10.00	8.35	5	3.79	1.26	50%	0%
μ	26%	75.00	74.26	65	8.54	2.30	0%	3%
ν	48%	30.00	32.60	30	4.71	1.82	0%	8%
ξ	38%	25.00	26.57	20	7.79	2.53	20%	0%
o	33%	35.00	36.24	35	8.04	2.41	2%	14%
π	13%	0.35	0.34	0.3	0.10	2.32	0%	8%
ρ	18%	0.05	0.05	0.05	0.03	3.58	17%	0%
σ	38%	38.00	33.40	50	9.88	8.01	9%	13%
τ	80%	1.90	1.86	1.9	0.03	1.42	0%	76%
υ	42%	20.00	19.17	20	4.50	1.54	0%	6%
ϕ	37%	0.15	0.12	0.15	0.05	1.47	18%	0%
χ	30%	0.75	0.74	0.8	0.09	2.67	4%	2%
ψ	58%	10.00	9.59	10	3.96	1.90	39%	2%
ω	58%	0.02	0.04	0.02	0.03	3.28	67%	0%

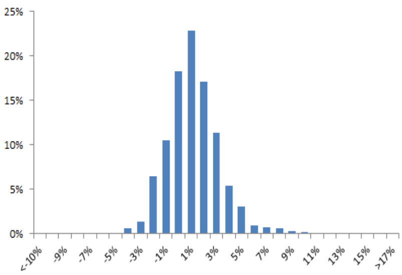
F Monthly return statistics



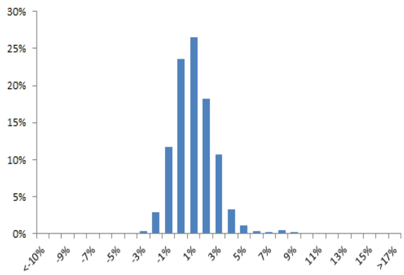
Return dist. AC



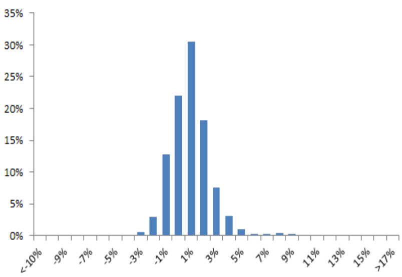
Return dist. ADX



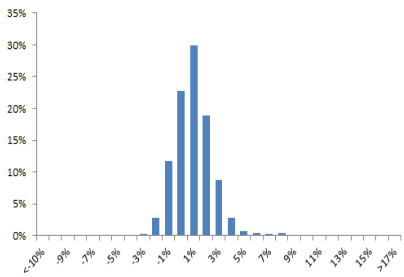
Return dist. Aroon



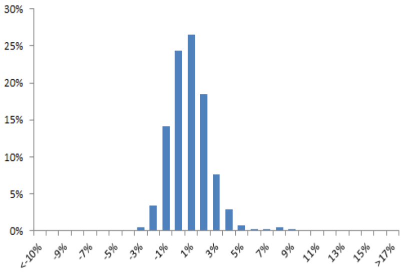
Return dist. EMD



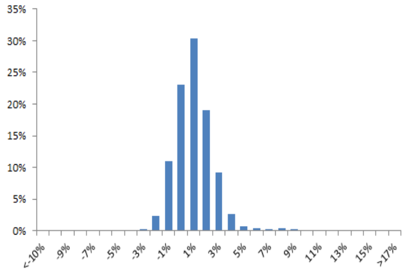
Return dist. FDI



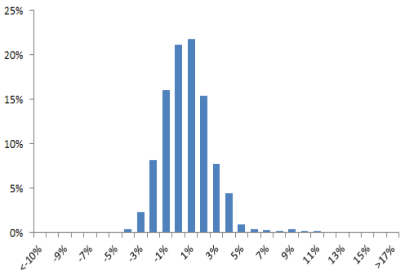
Return dist. VHF



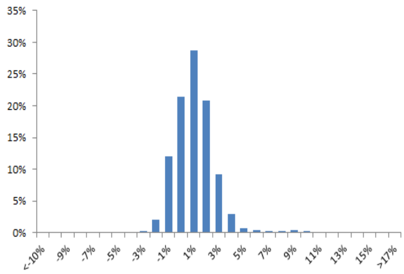
Return dist. Vortex



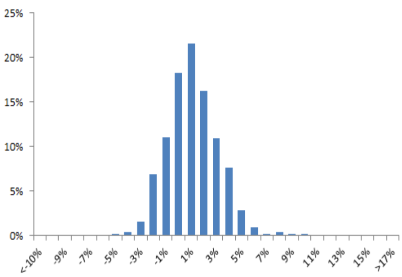
Return dist. static allocation



Return dist. AC, commodities



Return dist. ADX, commodities



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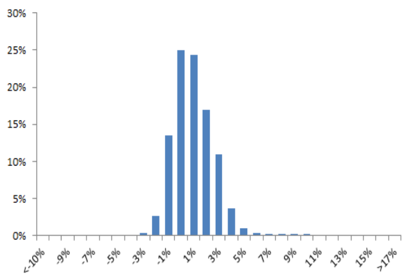
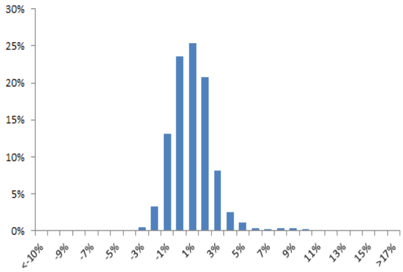
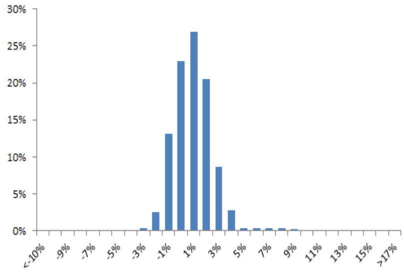


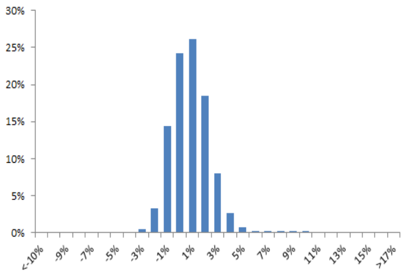
Return dist. EMD, commodities



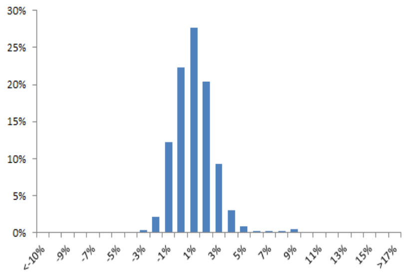
Return dist. FDI, commodities



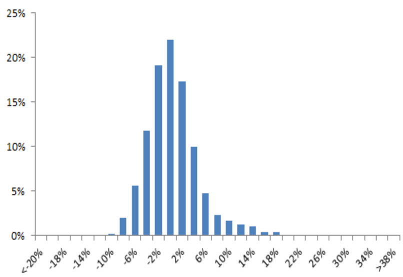
Return dist. VHF, commodities



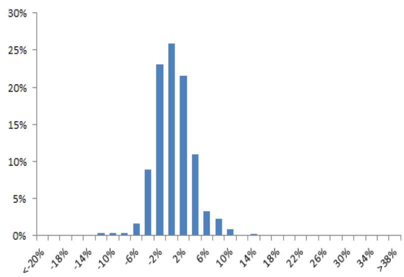
Return dist. Vortex, commodities



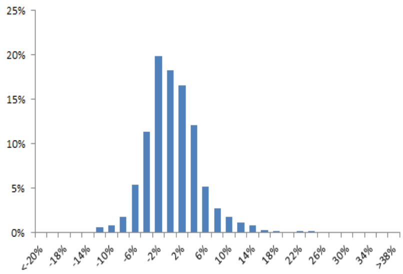
Return dist. static allocation, commodities



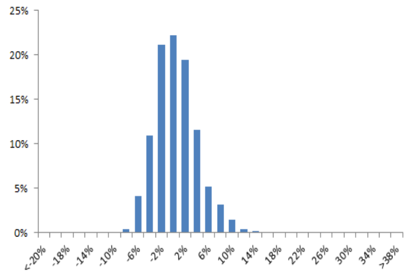
Return dist. Aroon, financial



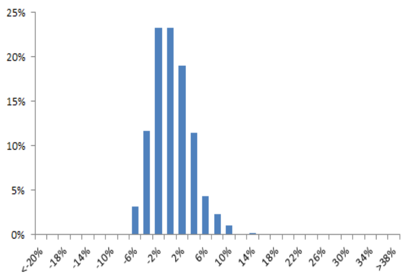
Return dist. ADX, financial



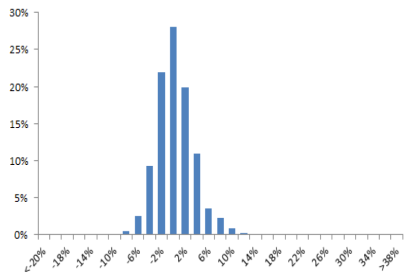
Return dist. Aroon, financial



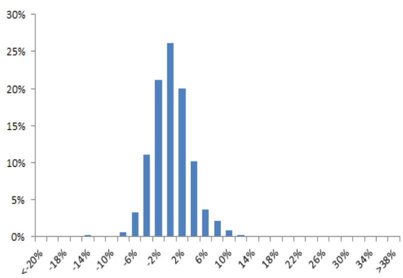
Return dist. EMD, financial



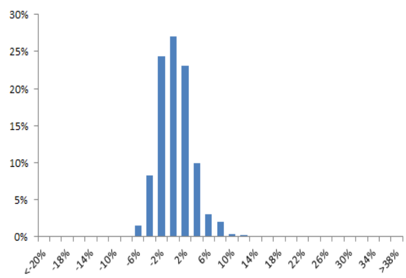
Return dist. FDI, financial



Return dist. VHF, financial

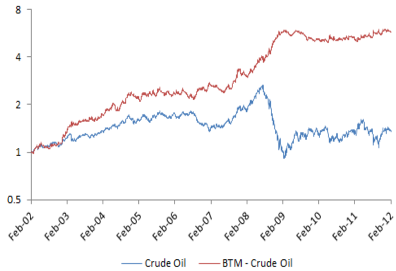


Return dist. Vortex, financial



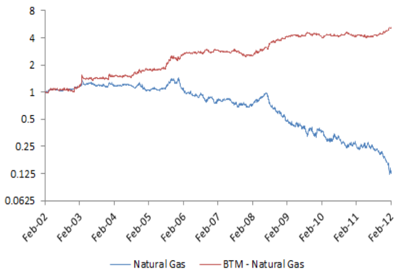
Return dist. static allocation, financial

F.1 Asset specific cumulative performance of the BTM

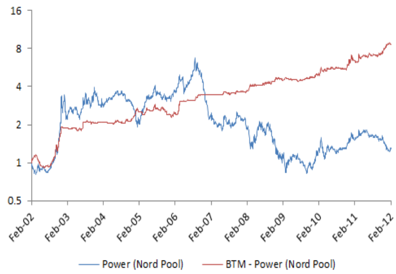


Crude Oil

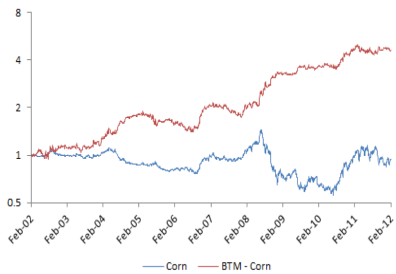
Heating Oil



Natural Gas



Power (Nord Pool)

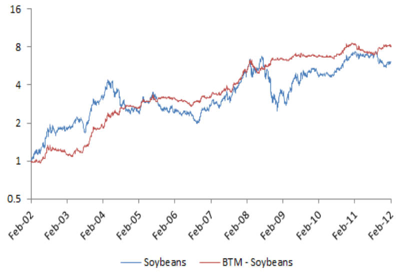


Corn

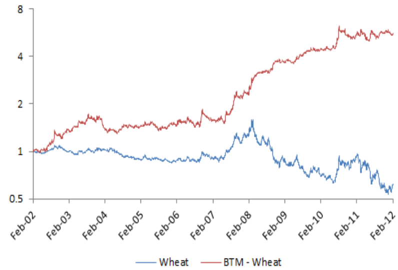
Rough Rice

Descriptive statistics of the trend recognition methods monthly return series

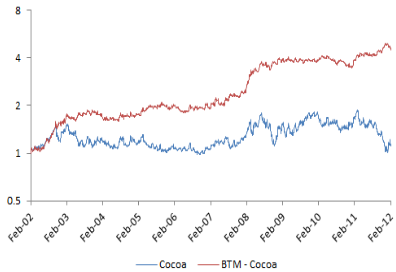
	Min.	*Median*	*Mean*	*Max.*	*SD*	*Kurt*	*Skew*	*ADF*	*JB*
All assets									
AC	-4.26%	1.13%	1.27%	12.15%	1.89%	5.89	0.92	-10.10	1,197
ADX	-4.24%	1.44%	1.56%	11.04%	1.57%	7.36	1.09	-8.36	2,420
Aroon	-4.48%	1.53%	1.69%	10.74%	2.07%	4.36	0.63	-7.59	353
EMD	-3.25%	1.39%	1.56%	10.99%	1.64%	6.16	1.03	-8.49	1,452
FDI	-3.01%	1.37%	1.47%	10.87%	1.59%	6.92	1.12	-8.05	2,079
VHF	-3.44%	1.38%	1.50%	11.04%	1.55%	6.87	1.07	-8.20	1,994
Vortex	-3.31%	1.28%	1.40%	10.65%	1.61%	6.95	1.14	-8.48	2,123
St. alloc.	-3.10%	1.41%	1.55%	10.92%	1.54%	7.19	1.16	-8.34	2,336
Commodities									
AC	-4.14%	1.10%	1.22%	12.16%	1.96%	6.51	1.07	-10.40	1,727
ADX	-2.59%	1.48%	1.60%	11.48%	1.63%	8.47	1.42	-8.73	3,874
Aroon	-5.03%	1.56%	1.67%	11.28%	2.08%	4.36	0.54	-8.53	311
EMD	-2.64%	1.32%	1.54%	11.47%	1.72%	7.27	1.33	-8.72	2,581
FDI	-2.44%	1.38%	1.49%	11.33%	1.67%	7.92	1.33	-8.27	3,197
VHF	-2.56%	1.40%	1.50%	11.51%	1.61%	7.74	1.28	-8.79	2,960
Vortex	-2.81%	1.28%	1.42%	11.65%	1.68%	8.29	1.40	-9.00	3,649
St. alloc.	-2.50%	1.45%	1.58%	11.36%	1.63%	8.25	1.39	-8.79	3,608
Financial									
AC	-8.69%	0.99%	1.42%	20.19%	4.38%	4.95	1.00	-8.67	795
ADX	-11.63%	1.09%	1.33%	16.07%	3.24%	4.58	0.28	-9.25	287
Aroon	-15.79%	1.01%	1.57%	35.35%	5.00%	8.21	1.29	-7.48	3,448
EMD	-7.56%	1.18%	1.52%	16.94%	3.56%	3.56	0.59	-8.39	174
FDI	-6.50%	0.95%	1.30%	15.69%	3.29%	3.56	0.59	-9.11	173
VHF	-7.46%	1.07%	1.36%	16.26%	3.12%	3.96	0.58	-8.64	232
Vortex	-14.59%	1.05%	1.18%	15.89%	3.34%	4.55	0.25	-9.00	271
St. alloc.	-5.90%	1.13%	1.36%	14.79%	2.88%	3.98	0.63	-8.69	262



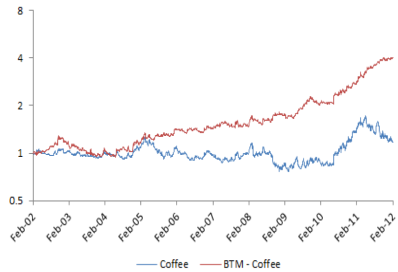
Soybeans



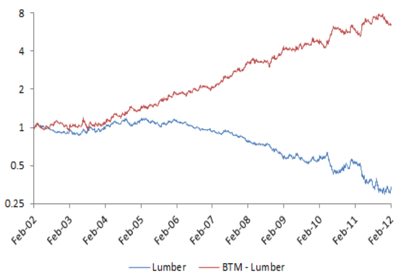
Wheat



Cocoa



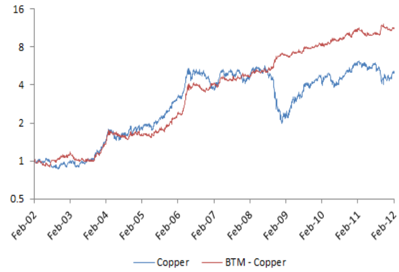
Coffee



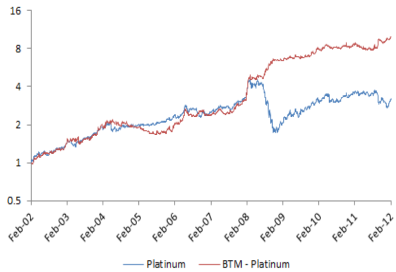
Lumber

Sugar

Gold

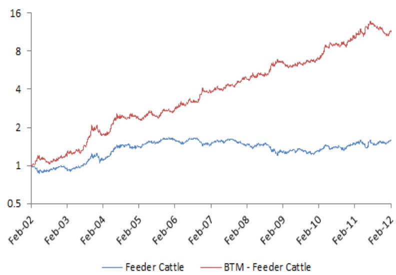


Copper

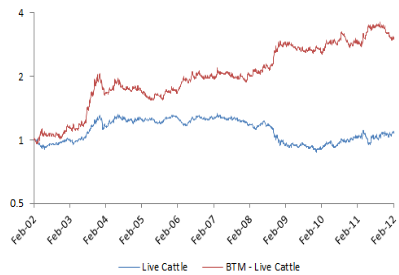


Platinum

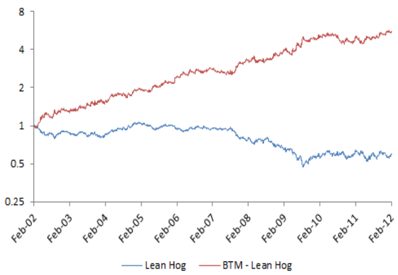
Silver



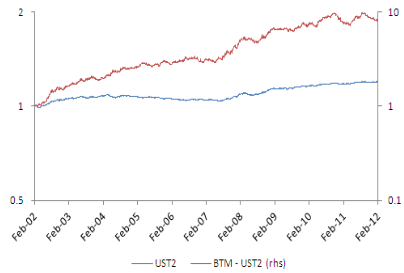
Feeder Cattle



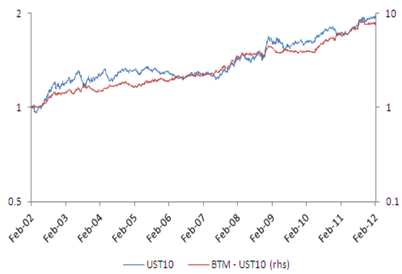
Live Cattle



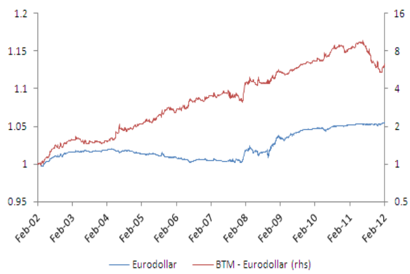
Lean Hog



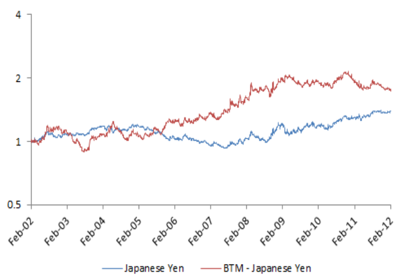
Two year US treasury note



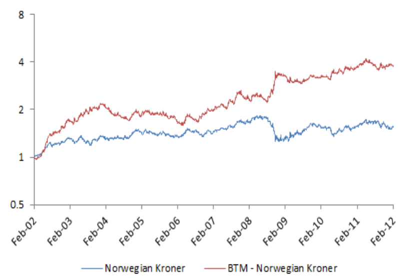
Ten year US treasury note



Eurodollar



Japanese Yen



Norwegian Kroner

Descriptive statistics of the BTM's monthly return series

	Min.	*Median*	*Mean*	*Max.*	*SD*	*Kurt*	*Skew*	*ADF*	*JB*
Total	-3.10%	1.41%	1.55%	10.92%	1.54%	7.19	1.16	-8.34	2,336
Commodities	-2.50%	1.45%	1.58%	11.36%	1.63%	8.25	1.39	-8.79	3,608
Financial	-5.90%	1.13%	1.36%	14.79%	2.88%	3.98	0.63	-8.69	262
CL	-10.36%	0.88%	1.44%	19.34%	4.49%	3.27	0.51	-9.84	113
HO	-11.36%	0.63%	1.22%	25.86%	4.61%	4.93	0.97	-8.92	763
NG	-10.16%	0.61%	1.34%	31.06%	4.28%	8.34	1.48	-8.54	3,806
ENOQ	-13.91%	0.50%	1.71%	34.93%	5.22%	10.25	1.93	-8.23	6,895
C	-11.36%	0.76%	1.26%	22.36%	4.70%	4.68	0.83	-9.15	572
RR	-18.81%	0.78%	1.44%	29.54%	5.85%	5.33	0.88	-9.14	872
S	-13.27%	0.72%	1.74%	24.49%	4.94%	4.10	0.84	-9.10	410
W	-15.58%	0.85%	1.38%	24.67%	5.07%	5.26	0.88	-9.85	841
CC	-9.79%	0.58%	1.23%	18.84%	4.32%	3.59	0.69	-9.59	232
KC	-8.87%	0.64%	1.12%	15.78%	3.96%	3.42	0.58	-10.54	155
LB	-16.29%	1.14%	1.52%	25.09%	5.27%	3.80	0.48	-10.44	158
SB	-12.08%	0.91%	1.89%	28.26%	5.65%	5.08	1.09	-9.26	923
GC	-20.71%	0.45%	1.00%	20.71%	4.66%	4.64	0.40	-9.83	341
HG	-10.63%	1.15%	1.99%	37.44%	5.51%	8.28	1.67	-8.91	3,976
PL	-11.03%	0.99%	1.85%	42.21%	5.31%	10.23	1.77	-9.32	6,615
SI	-19.39%	0.90%	1.63%	29.77%	4.90%	4.65	0.85	-9.29	574
FC	-15.13%	1.53%	1.97%	21.28%	5.07%	3.44	0.52	-8.50	131
LC	-17.50%	0.33%	0.91%	19.71%	4.54%	4.47	0.56	-8.59	347
LH	-11.10%	0.89%	1.41%	18.11%	4.33%	3.41	0.48	-11.21	111
TU	-13.68%	1.30%	1.71%	19.13%	4.88%	3.10	0.35	-8.98	51
TY	-12.26%	1.21%	1.68%	21.73%	4.79%	4.09	0.64	-10.01	290
ED	-23.60%	1.60%	1.46%	34.73%	5.41%	7.85	0.42	-9.48	2,472
JY	-11.58%	0.17%	0.46%	19.19%	3.91%	4.06	0.58	-9.47	251
USDNOK	-10.37%	0.56%	1.11%	31.78%	4.57%	5.27	0.88	-9.04	840

G Benchmark indices

G.1 Thomson Reuters/Jefferies CRB Index

The original CRB Index was created in 1957 and included 28 commodities. Over the past 50 years it has evolved in order to maintain the critical role of the Index, which is to remain a leading, transparent and widely available benchmark for the performance of commodities as an asset class.

The Thomson Reuters/Jefferies CRB Index (”TRJ/CRB”) reflects the tenth revision to the original CRB Index. In keeping with previous revisions, it is designed to provide a liquid and economically relevant benchmark that provides a timely and accurate representation of commodities as an asset class.

web: http:www.jefferies.com

CRB weighting as of December 30, 2010	
Group I – Incl. only petroleum products	
WTI Crude Oil	23%
Heating Oil	5%
RBOB Gasoline	5%
Group II – Highly liquid	
Natural Gas	6%
Corn	6%
Soybeans	6%
Live Cattle	6%
Gold	6%
Aluminum	6%
Copper	6%
Group III – Highly liquid, but lower weighted	
Sugar	5%
Cotton	5%
Coffee	5%
Cocoa	5%
Group IV – Meaningful diversification	
Nickel	1%
Wheat	1%
Lean Hogs	1%
Orange Juice	1%
Silver	1%

G.2 Newedge CTA Index

The Newedge CTA Index is equal-weighted and reconstituted annually and has become recognized as the key managed futures performance benchmark. The index calculates the net daily rate of return for a pool of CTAs selected from the largest managers open to new investment. Assets under management must be greater than one standard deviation above the mean (minimum of 20 managers; Cutoff for 2012 = USD1.57 bn)

Website: www.newedgegroup.com

Newedge CTA Index constituents, as of 2012
Winton Capital (Diversified)
Man Investments (AHL Diversified)
Transtrend (Enhanced Risk)
Aspect Capital (Diversified)
Brummer and Partners (Lynx)
Graham Capital (K4D-15V)
Quantitative Investment Mgmt. (Global)
FDO Partners (Emerging Markets Quant Currency)
Ortus Capital (Currency)
FX Concepts (Multi-Strategy)
Capital Fund Management (Discus)
PE Investments (FX Aggressive)
FX Concepts (GCP)
Campbell & Co. (FME Large)
IKOS Futures Fund
Skandinaviska Enskilda (SEB Asset Sel.)
Boronia Capital (Diversified)
Graham Capital Mgmt. (Discretionary - 6V)
Cantab Capital (Aristarchus)
Armajaro Commodities Fund

G.3 IASG CTA Trend Following Stretagy Index

IASG Indexes are generated daily based on CTA manager-supplied sector focus, investment strategy and performance. To participate in the IASG CTA index, a program must have a minimum track record of 3 year's performance. Other indexes require a minimum two year track record. Strategy-based indexes require the program's composition be more than 50% of the specific strategy.

Website: www.iasg.com