The effects of volatility & correlation on CTA strategies

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KTH Industrial Engineering
and Management

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av

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Godkänt	Examinator	Handledare
2012-02-09	Tomas Sörensson	Tomas Sörensson
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	RPM	Per Ivarsson

Sammanfattning

Detta examensarbete analyserar effekterna av volatilitet och korrelation på trading strategier brukade av Commodity Trading Advisors (CTA´s). Denna studie bygger på en kvantitativ analys av data som insamlats från Barclay Hedge database. Studien har genomförts i samarbete med RPM Risk & Portfoliomanagement i Stockholm, Sverige. Traditionellt sett, när globala marknader visar på högre volatilitet än genomsnittet, har detta identifierats som ett tecken på en björnmarknad med negativ avkastning på aktier. Förhållandet mellan volatilitet och negativ avkastning på aktier var initialt uppmärksammat av Black år 1976. Förhållandet mellan volatilitet och korrelation mellan marknaderna har analyserats i denna uppsats och resultaten tyder på att högre nivåer av volatilitet för även med sig högre nivåer av korrelation. Den uppmäta korrelationen mellan volatilitet och korrelation var så hög som 0,7. CTA´s handlar så kallade Managed Futures, framtida kontrakt på råvaror, där varje kontrakt har en lång och kort position vilket gör det möjligt att nå en positiv avkastning även under hög volatilitet. De tre mest använda strategierna för CTA´s, short term trading (kortsiktig handel), fundamental handel och Trendföljande handel, presenteras i denna studie och deras möjlighet att bära positiv avkastning i en mycket volatil marknad härleds. Resultaten tyder på att en hög volatilitetsregim med hög korrelation gynnar den kortsiktiga handelsstrategin mer än fundamental och trendföljande handel.

Nyckelord

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Abstract

This master thesis analyses the impacts of volatility and correlation on common strategies for Commodity Trading Advisors (CTAs). It is based on a quantitative analysis of data gathered from the Barclay Hedge database. The study was done in cooperation with RPM Risk and Portfolio Management based in Stockholm, Sweden. Traditionally, when global markets see higher levels of volatility this has been identified as a sign of a bear market with negative returns on equities. The relationship between volatility and negative returns on equities was first acknowledged by Black in 1976. The relationship between volatility and correlation between markets has been analyzed in this thesis and the findings suggest that higher levels of volatility brings with it higher levels of correlation. The correlation between volatility and correlation is as high as 0.7. CTAs trade future contracts where every contract has a long and short position which is making it possible to reach positive returns even under extreme volatility. The three most popular strategies for CTAs, Short Term trading, Fundamental trading and Trend Following, are presented in this study and their possibility to have positive returns in highly volatile environments is derived from the analysis. The findings suggest that in a high volatility regime with high correlation Short Term trading strategy has been the most profitable.

Key-words: CTAs, Volatility, Correlation, Trend Following, Short Term, Fundamental, Managed Futures

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Any views or opinions expressed in this study are solely those of the author and not necessarily those of RPM or any of RPM's affiliates.

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1. Introduction

The global financial crises and the collapse of the investment bank Lehman Brothers in September of 2008 saw the VIX-index, also known as the fear index reach never before recorded levels (Szado 2009). The volatility spread quickly all over the financial globe and could be measured in a number of different markets spanning from equities to commodities to futures and so on. Ever since 1976 when Black published his paper on the inverse relationship between stock prices and volatility investor have fled markets when volatility spikes. Studying the effects of volatility on Managed Futures trading strategies this study has discovered that a Short Term trading strategy is to be preferred in a high volatility market and that positive returns are possible. The study also confirms that correlations between markets are on a higher level when volatility spikes.

Numerous studies (Both et al. 1997, Wen-Ling, Engle & Ito 1994, Campbell, Koedijk & Kofman 2002) have shown that when volatility spikes in one market it is very likely that other markets will see higher volatility levels as well. When these high levels of volatility spread over several markets it can be seen as a correlation risk for investors and hedge funds (Buraschi, Kosowski, & Trojani 2011). Wen-Ling, Engle & Ito (1994) argue that economic fundamentals of one country will have implications for another country due to the links of investments. Further they suggest that volatility can be seen as contagious between markets and that the behavior of investors in one market quickly transitions from a national to a global level. Solnik, Boucrelle & Le Fur (1996) found in their studies that a high level of volatility in financial markets, first of all, seems contagious between markets and, secondly, that the correlation between markets increase under such circumstances. Ang & Bekaert (2002) establish in their study that high volatility and high correlation coincides with bear markets and negative returns on equities. Black (1976) attributed this to the effects of leverage. However, more recent papers such as Figlewski & Wang (2000) found that the inverse relationship is accurate but attributed it to a 'down market effect' instead of a leveraged effect. Furthermore, Lo & Hasanhodzic (2010) argue that the inverse relationship is more likely driven by time-varying risk premia or cognitive mechanisms of risk perception. The inverse relationship between stock prices and volatility gives way for alternative investments. In the past Managed Futures have had a positive return in high volatility markets which means that futures can be used as somewhat of a safe haven for investors during bear markets. This theory is presented by Kaminsky (2010) and named Crisis Alpha.

Commodity Trading Advisors (CTAs) that trade futures have in this study been grouped into three different categories depending on their underlying trading strategy. The three strategies mainly used by CTAs are Fundamental trading, Short Term trading and Trend Following trading. The effects of high volatility and correlation on these three trading strategies for Managed Futures are analyzed and then the CTAs possibility to work as a Crisis Alpha generators for investors is derived from the analysis.

1.2 Objectives

The main objective of this master's thesis is to investigate how high / low volatility markets with a high / low correlation influence three separate strategies for trading Managed Futures. The rate of change of volatility and correlation is also an interesting variable which is taken into account in the final result. This idea for a thesis subject was originally suggested by RPM Risk and Portfolio Management (RPM). When high volatility occurs in the market the hypothesis at RPM was that a Short Term strategy would be the most beneficial. Consequently a portfolio containing all three strategies should have different proliferations to each strategy depending on the current volatility regime. If volatility is more or less the same over all markets (i.e. ripple effect) and we see higher correlation levels when volatility is high, then the desired diversification of a portfolio will shrink.

Another part of the objective is to test the validity of RPM's internal volatility index. This is done to validate the further use of this index in the paper when comparing volatility levels to different Rate of Returns (RoR) of the CTAs. Additionally, to test if there is a relationship between volatility and correlation might prove to be important when in the next stage the comparison between volatility and RoR is made. If there is a relationship between volatility and correlation this will have an effect on the results when taking both volatility and correlation regimes into account when comparing it to the RoR of the CTAs.

1.2.2 Purpose

The purpose is to analyze the effects of correlation and volatility on CTAs practicing Short Term trading strategy, Fundamental trading strategy and Trend Following strategy. If put as a research question the purpose of this thesis would be to answer the question:

Which of the underlying strategies for CTAs has been more profitable during high, or low, volatility and correlation?

1.2.3 Purpose decomposition

This thesis is meant to contribute to recent research on the subjects and internal research at RPM as well as to find indicators to predict the future profitability of fund managers. This research area is rather wide and could be analyzed using several different approaches. By decomposing the research question I hope to create a higher level of validity as well as creating a deeper understanding for the reader by going through the thesis question step by step. The decomposition can be found below.

> 1, To test the validity of RPM's internal volatility index by comparing and analyzing it against the VIX index from the Chicago Board of Trade (CBOT).
>
> 2, Determine if volatility affects correlation.
>
> 3, Evaluate the effects of volatility as well as the rate of change of volatility (the derivative of volatility) on the three strategies, Fundamental trading, Short Term trading and Trend Following trading.

1.2.4 Delimitation

This study has exclusively used data from CTAs who have profiled themselves to use one of the underlying strategies that are investigated. Therefore CTAs with multi strategy have been excluded from these tests. This report will neither try to explain in depth how or why a certain CTA or strategy actually performs superior than other CTAs during a given period. It should be noted that these results will never be more accurate than the actual data analyzed which means that if the data suffer from systematic disturbances, which are common in financial data, the result may also be affected.

1.3 Hypothesis

This report will analyze the volatility and correlation effects on the return of different CTAs strategy. The hypothesis presented was established by RPM and is based on their perception of past returns. The main purpose of the thesis is therefore to test if the hypotheses held are valid.

H_1; Volatility affects correlation

H_2; In a high volatility regime Short Term trading strategy is the most profitable.

- In a high volatility regime Short Term traders are fast on reversing their perception of the market and can therefore reverse their positions.

H_3; In a high volatility regime Trend Following strategies suffer losses among other factors due to swift reversals in the market.

- Having a longer investment horizon than Short Term traders it takes time to adjust to new trends and that could be why Trend Followers suffer losses in high volatility regimes.

H_4; Fundamental trading and Trend Followers seem to profit from the same conditions in the market.

1.4 Disposition

In Chapter 2 a background on the futures market and RPM is given as an introduction to enhance the understanding of this work.

Chapter 3 will focus on the theoretical framework used for the analysis such as correlation measurements and volatility. The chapter is concluded with a litterateur study to illustrate where the current research stands on these issues.

In Chapter 4 and 5 the data and the methodology are presented which is followed in chapter 6 by the analysis and results. In chapter 7 a discussion and application of the results are presented and chapter 8 contains the conclusions of the thesis.

2. Background

In order to understand the CTA market an overview of this section of the financial sphere is required. A short introduction to RPM as a company and what they do is also included to add to the understanding of the paper and the importance of it. A brief overview of each of the trading strategies will also be presented in depth in this chapter.

2.1 Managed Futures

A future contract can be defined as a contract between a seller and a buyer designed to deliver an asset or the cash value of the asset on a specified delivery date for a premeditated price. These contracts are standardized and exchange traded. The current futures price is the price today for delivery of the underlying asset at a pre-set date in the future (Kaminsky 2010). The buyer of the contract holds the so called long position and the seller, obtains the short position, will commit to deliver the product on an agreed future date. The person in the long position will therefore benefit from a price increase meaning that future contracts are sometimes held by people who have no interest in the underlying asset but have taken the position to profit from price increase or decrease. If a trader goes long at time 0 and then closes or reverses the position at time *t* the profit is derived from the simple equation:

$$F_t - F_0 \tag{1}$$

And the short trader earns:

$$F_0 - F_t \tag{2}$$

To acquire a position in a futures contract an investor must post collateral for the position in form of margin and maintain their margin account with a clearinghouse broker. Due to daily marking to market the margin required is around 5 – 15 % of the value. The markets for futures are known as highly liquid, efficient, transparent and credit protected (Gregoriou et al. 2004). Both hedgers and speculators engage in the trade of futures in the market. The underlying asset of a future ranges from metals, minerals, agricultural commodities, currencies and index futures. The underlying asset's value and the price change of the future are highly correlated. It is this correlation which enables future contracts to be well fitted to a directional trading strategy. Managed Futures is a pool of futures where CTAs take positions in regards to their underlying strategy to profit from the movements in the future contracts. The Managed Future industry has grown immensely during the last 10 years and is today approaching USD 300 billion. The sector is a part of the financial sphere known as alternative investments and in this category Managed Futures and CTAs is currently representing the largest sub category within alternative investments (Gregoriou et al. 2004). The figure below shows an overview of the market.

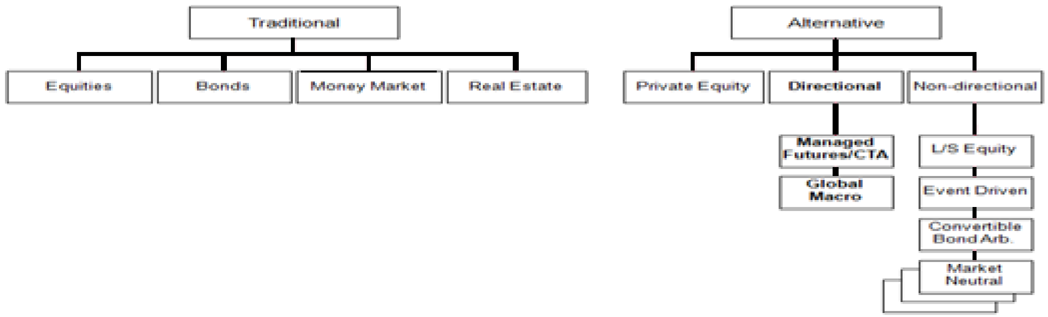

Exhibit 1 - Traditional and alternative investment tree
Overview of traditional and alternative investments commonly invested in.

Managed Futures are most often used as a diversification devise to lessen the risk in a portfolio by investors. This is represented in the graph below showing that a portfolio containing Managed Futures, in relation to private equities and fixed income will have less volatility and higher returns. One can follow the efficient frontier line in the graph.

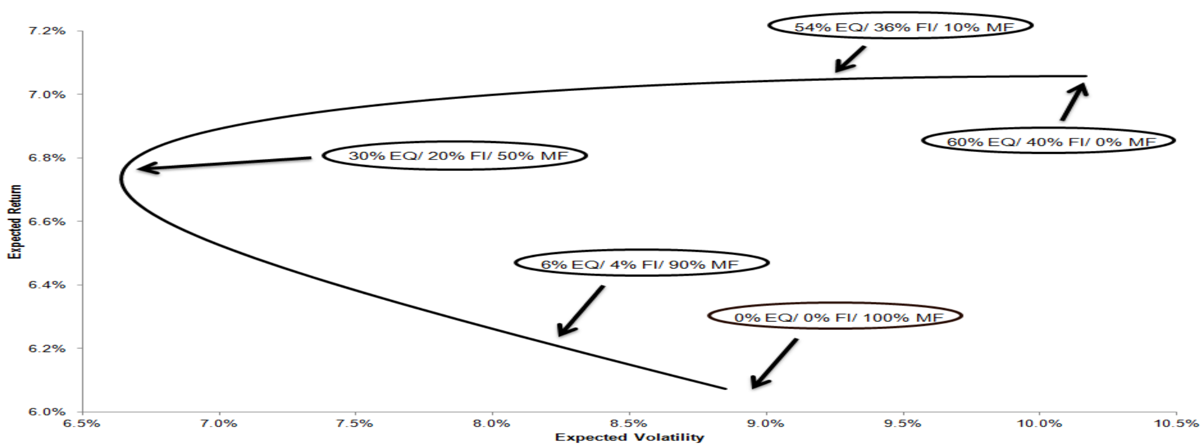

Exhibit 2 – Diversification benefits
Graph plotting different portfolios containing various parts of Managed Futures, Fixed income and Equities. The top line is a known as the efficient frontier. Data from JP Morgan Global Gvt. Bond, MSCI World total return gross and Barclay CTA index

The diversification received with Managed Futures in a portfolio containing the three asset classes' above is evident. The correlations between the assets are shown in a table below.

	Equities	Managed Futures	Fixed income
Equities	1.00	-0.07	0.21
Managed Futures	-0.07	1.00	0.21
Fixed income	0.21	0.21	1.00

Exhibit 3 - Correlation table
Correlation between asset classes, monthly data 1989-2011, Data from: JP Morgan Global Gvt. Bond, MSCI World total return gross and Barclay CTA index

2.2 RPM

RPM was founded in 1993 in Stockholm, Sweden. With a focus on directional investment strategies the clients of RPM are banks, pension funds and other financial institutions in Europe, Asia and the US. These clients usually search for further diversification in their portfolio then that of the equity and bond markets. The different portfolios under management by RPM include directional trading in currencies, energy, fixed income, equity indices, metals and other commodities as well as futures on single stocks. RPM falls within the financial sphere in the hedge fund section of alternative investments. RPM acts as an investment manager to a number of multi-manager funds that allocate and reallocate their assets among different trading managers in the Managed Futures and Global Macro sector to trade and invest.

RPM has several different CTAs which entail different underlying strategies for the Managed Futures market. RPM also allocates money between the managers depending on the company's own outlook of the economy, not just investing on past performance. This outlook is created through external and internal analysis by the investment team at RPM.

A directional investment strategy can basically be described as going short (sell) future contracts where it is predicted that the price of the contract and/or underlying security will decrease vice versa by going long (buy) future contracts where it is predicted that the price will increase. Whether this price movement occurs from a black swan event, fiscal decisions by governments or monetary decisions by central banks etc. the strategy aims to take a profitable position in the market. The position is taken from the trading analysis which is based on Fundamental strategy, Trend Following strategy or Short Term trading strategy or a combination of all three.

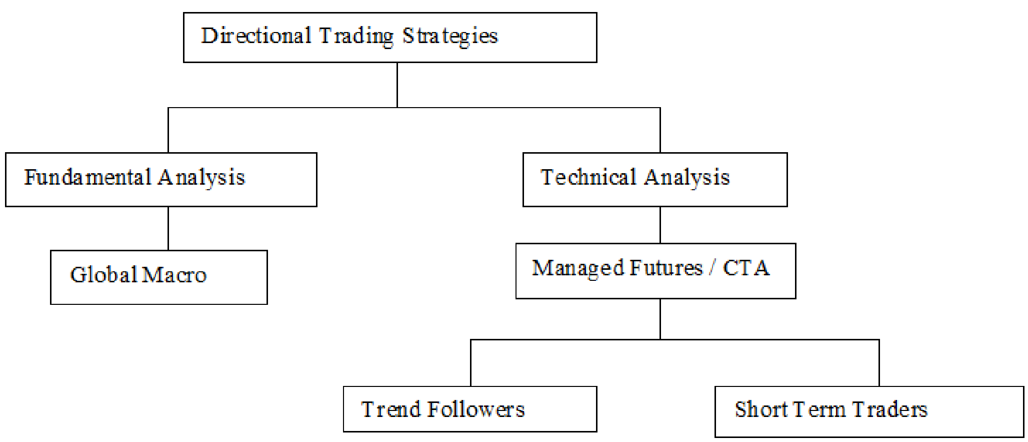

Exhibit 4 - Classification of managers
A tree graph presenting RPM's classification of managers. (Authors own illustration)

2.3 Trading strategies

A brief overview of each of the underlying strategies is presented using the findings of Kaminsky (2010) and Gregoriou et al. (2004).

2.3.1 Short Term traders

A Short Term strategy generally refers to any given strategy with a very narrow time horizon. This time horizon can range from intraday to a couple of weeks and the trader seeks to exploit short term price inefficiencies in the market. Most often the trader will use technical analysis and will be searching for patterns, short term trends, gaps and trading ranges to profit from. In recent years algorithmic trading has been widely adopted by the Short Term traders but there are still some discretionary Short Term traders at present.

2.3.2 Trend Followers

Trend Followers often attempt to take advantage of large movements or trends in prices and therefore are often classified as “long volatility” (Gregoriou et al. 2004). A wide range of technical analysis such as channel breakouts is typically done to determine when trends occur. The time frames for Trend Followers vary a great deal from short too long. Within all of the mentioned time frames the trader will remain in the position until they believe the trend has reversed. A Trend Follower does not try to forecast or predict future price levels but simply try to identify and follow the trend. Trend Following is the most popular form of strategies amongst CTAs (Vuille & Crisan 2004). A major thing that separates this strategy from others is the total lack of analysis of supply and demand factors which is significantly evident in the next strategy presented.

2.3.3 Fundamental trading

Fundamental traders take positions based on macro level data with less focus on physiological behavior amongst investors. This approach tries to predict the future and to identify opportunities where the price does not reflect the fundamental value of the investment. The search for mispriced assets which is believed to eventually obtain the “correct” price is executed by the use of relative valuation models and macroeconomic analysis among various set of methods. Qualitative and quantitative factors are both analyzed to shed light on mispriced assets.

3. Theoretical framework

In this part of the thesis a literature study is conducted with the purpose of finding out the effects of volatility and correlation on the market and the relationship between variables. Part of the literature study will focus on the ability to forecast volatility and correlation along with enhancing the understanding of the problems with forward looking models.

3.1 Volatility

Volatility is a measurement of how much the price of an asset changes over time or in other words the risk of probability distribution. Volatility is not directly observable and must therefore be calculated. There are two main methods commonly used to calculate volatility. The most common one used is historic volatility where historic movements of the assets return are used to determine the volatility. This is presented in the following steps:

$$\bar{R} = \frac{1}{T}(R_1 + R_2 + \cdots + R_T) = \frac{1}{T}\sum_{t=1}^{T} R_t \quad (3)$$

$$Var\,(R) = \frac{1}{T-1}\sum_{t=1}^{T}(R_t - \bar{R})^2 \quad (4)$$

where:

t = year or number of continues returns
R_t = realized / continues return
$\bar{R}$ = average annual return / mean price change

Then volatility or Standard Deviation (SD) is the square root of the Variance:

$$SD\,(R) = \sqrt{R} \quad (5)$$

When calculating volatility using daily data it is coherent to transform the data from daily to annualized data which is done by taking the square root of the number of trading days (Sweden: 250 days) and multiplying it with the Standard Deviation. Volatility has a propensity to be persistent and therefore historic volatility is used as a reasonable forecast for near future volatility. The other method is known as 'implied volatility' where one 'backs out' the volatility from the Black-Scholes model (Bodie, Kane & Marcus 2005). When backing out the volatility the following question is answered: "What standard deviation would be necessary for the option price that I observe to be consistent with the Black-Scholes formula?" This means the volatility level for the underlying asset that the option price implies. In other words, implied volatility is an estimate of the future volatility using the underlying assets option price. It is mathematically derived from the following equations.

$$C = f(\sigma, \cdot) \tag{6}$$

Where *C* is the theoretical value of an option and *f* is a pricing model that depends on σ (implied volatility) as well as other inputs that most often are directly observable. This can be seen in the Black-Scholes formula below which presents the value of a call option for a non-dividend paying underlying stock (Bodie, Kane & Marcus 2005).

$$C(S,t) = N(d_1)S - N(d_2)Ke^{-r(T-t)} \tag{7}$$

where $d_{1,2}$ is derived from the following equations:

$$d_1 = \frac{\ln(S/PV(K))}{\sigma\sqrt{T}} + \frac{\sigma\sqrt{T}}{2} \tag{8}$$

$$d_2 = d_1 - \sigma\sqrt{T} \tag{9}$$

where:

PV(K) = present value
N(.) = a cumulative distribution function of the standard normal distribution
T-t = time to maturity
S = spot price
K = strike price
R = risk free rate
σ = implied volatility

These formulas are presented here to create an understanding of how the implied volatility can be derived. *S, K, T* & *R* are directly observable variables and only σ is not directly observable according to Berk & DeMarzo (2011), Bodie, Kane & Marcus (2005). Another useful area for implied volatility is when calculating a delta neutral position. A delta neutral position is when an investor establishes a position in equities and in options to hedge against price fluctuations in the underlying asset. Simply put, it means that a portfolio's value does not increase or decrease in value when the equity price fluctuates. However, a delta neutral position can still be subject to volatility risk. Volatility risk is incurred from changes in volatility that is unpredictable (Bodie, Kane & Marcus 2005).

3.2 Correlation

Correlation is a statistical measurement derived from covariance and is scaled from -1 to 1. Linear correlation or Pearson's correlation is what most often is referred to when using correlation in finance (Bodie, Kane & Marcus 2005). A value of 0 would indicate that the variables move independent of each other whereas a positive value in correlation means that the variables move in tandem and a negative value that they move inversely, relative each other. To calculate the correlation it is first required to calculate the covariance. Covariance describes the degree of which two or more assets move in tandem or in other words the expected product of the deviations of two returns from their means.

$$Cov\left(R_i\,, R_j\right) = \frac{1}{T-1}\sum_t (R_{i,t} - R_i)(R_{j,t} - R_j) \tag{10}$$

$$Corr\left(R_i\,, R_j\right) = \frac{Cov\left(R_i\,, R_j\right)}{SD(R_i)SD(R_j)} \tag{11}$$

where:

$R_i\,, R_j$ = return for one asset

Correlation is an important concept for investors when they are attempting to diversify their assets. In order to do this, an investor needs to spread their portfolio holdings over many different investments to avoid exposure to any one source of risk. This risk is known as idiosyncratic risk and its opposite is known as systematic risk or market risk. This theory in finance was founded by Markowitz in 1952 (Markowitz 1952).

3.3 Granger-causality

To test if one variable is useful in forecasting another variable a valid method often used among researchers is the Granger causality test (Toda & Phillips 1994, Granger 1969). When using the Granger test a researcher is searching for a result such as X Granger-causes Y but not the opposite. However, it is not uncommon to find that neither variable Granger-causes the other or that the variables causes each other. Moreover, Granger-causality might not be sufficient in implying true causality. An underlying third factor that significantly affects both the variables can exist. These factors are referred to as Event Factors (Toda & Yamamoto 1994). The following equations are used.

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_m y_{t-m} + residual_t \tag{12}$$

where:

a = coefficients

y = stationary time series
m = greatest lag length

From this we retain y_{t-j} if it has a significant t-statistic (or F-statistic) and m is the greatest lag length for which the lagged dependent variable is significant. Then we use the auto regression by incorporating lagged values of x.

$$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_m y_{t-m} + b_p x_{t-p} + \cdots + b_q x_{t-q} + residual_t \quad (13)$$

where:

p = shortest lag length for which the lagged value of x is significant
q = longest lag length for which the lagged value of x is significant

From this equation we can verify the null hypothesis that Y does not Granger-cause X and if we turn the equations around we can verify the opposite. It is here important to notice that it is a null hypothesis and as such it can never be proven. The result can only reject it or fail to reject it. When the results from two sets of data do not reveal any statistical difference, it is not to be assumed there is no difference at all. It only means that one fails to reject the null hypotheses or, in other words, there is not enough evidence to reject it (Toda & Phillips 1994). The analysis outcome will be shown as two values, F and c_v, where:

F = the value of the F- statistic
c_v = the critical value from the F-distribution

Then, if F > c_v we can reject the null hypothesis that *y* does not Granger-cause *x.*

When performing the Granger analysis using Mathlab the lag length is chosen by using the Bayesian Information Criterion (BIC) (McQuarrie & Tsai 1998). This is a criterion for model selection among a finite set of models and it is based on the likelihood function. The BIC resolves an over fitting problem which comes from the increase of likelihood when fitting models by adding parameters. It is rendered form the following equation:

$$-2 * \ln p\,(x|k) \approx BIC = -2 * L + k \ln(n) \quad (14)$$

where:

x = observed data
n = the number of observations or sample size
k = the number of free parameters
$p(x|k)$ = the probability of the observed data given the numbers of parameters
L = the maximized value of the likelihood function for the estimated model

3.4 Literature study

Several authors (Both et al. (1997), Lin, Engle & Ito (1994), Campbell, Koedijk & Kofman (2002), Solnik, Boucrelle & Le Fur (1996)) have found that when volatility spikes in one market despite the cause it will spread over the worlds markets making it increasingly risky for investors Rate of Return (RoR). This notion of risk and volatility being feared by investors is due to the negative correlation between volatility and return on equities (Black 1976). Increasing uncertainty and in turn, high volatility, is a trademark for a bear market according to Ang & Beckert (2002). In general terms investors will lose money on equities in bear markets. Lin, Engle & Ito (1994) found that this phenomenon of volatility that spreads is very evident in a high volatility environment and significantly less evident in a low volatile environment confirming the hypothesis held by other authors. Stock markets around the globe are related through trades and investments which mean that the economic fundamentals of one country will have implications on another country. In its essence this means that volatility, particularly high levels spreads quickly over the financial globe.

There are scholars who imply that the relationship in trades and investments are not enough to fully explain the rapid spread of volatility. It is argued that volatility can be seen as contagious and that the mood of investors spreads fast beyond what can be explained through economic fundamentals. An example of this is brought forward by Lin, Engle & Ito (1994) studying the market crash in October of 1987. The crash is supposed to have started on the New York Stock Exchange (NYSE). When NYSE closed for the day the mood of the investors spread to a global level and traders on the Tokyo exchange followed the behavior brought from NYSE disregarding economic fundamentals in Japan. A behavioral finance term known as herd instinct or herding would in all likelihood provide a deeper explanation to the cause of contagions. The behavior of herding is even more evident when taking into account that the NYSE and the Tokyo stock exchange have no overlapping trading hours. There are however skeptics to the theory of contagious volatility. Forbes & Rigobon (2002) found that when analyzing volatility a bias exists and that there is no such thing as a contagion effect between markets even in a downturn. The authors only found interdependence between international markets.

In a recent paper by Kahled, Abderrahim & Tsafack (2009) the authors found that volatility seems to have an impact on correlation especially during downturn periods. This means that when we have a high volatility regime the correlation between markets are higher than average levels (i.e. market correlation). This is confirmed by Longin & Solnik (2001), who in turn studied the correlation between returns and volatility. However, Longin & Solnik (2001) theorizes that correlation is not actually related to volatility but more to a general market move or, in other words, volatility per se does not affect correlation. The authors do find that higher correlation values do appear in market downturns (i.e. bear markets) but not in bull markets. This increased correlation in bear markets is argued by Campbell, Koedijk & Kofman (2002) to limit the use of diversification methods that have been a part of modern portfolio theory created by Markowitz in 1952 (Berk & DeMarzo 2011). On the other hand, this can be argued to be seen as a systematic risk and not idiosyncratic.

The area of financial volatility has been fiercely debated in finance literature among academics. Figlewsky (1997) and Cumby, Figlewski & Hasbrouck (1993) is arguing that the simpler the model the more accurate the result. Figlewsky (1997) contend the work of other academics such as Andersen & Bollerslev (1997) and theorizes that forward looking models are not usable in the process of describing market behavior. The models built are to complex and the results from the models have expectations that are too high on the actual accuracy (Figlewsky 1997). Furthermore, he argues that a model based on implied volatility has never proven its accuracy and explains that this might be due to the difference between the mathematical model and the psychological behaviors of investors which a model cannot pick up on. Andersen & Bollerslev (1997), on the contrary, argues that the models are accurate and that this has been proven. They argue that the implementation of the models is where other authors fail and that they do not know how to properly use the model. This debate has been going on for years and both sides prove their models very credibly in academic papers that are regularly published. Poon & Granger (2003) have gone through 93 working papers on forecasting volatility and they state that volatility is clearly able to be forecasted. The most popular methods used are Generalized Autoregressive Conditional Heteroskedasticity (GARCH) which was designed by Bollerslev in 1986 and the Exponentially Weighted Moving Average (EWMA) model. In addition, Poon & Granger (2003) argues that it is only a question on how far ahead a model works. In their research the authors do not find the more complex models, like GARCH, better than the simpler ones such as historical average models. On the other hand, all authors seem to be in agreement that volatility is and will be an important way of measuring risk in the market.

4. Methodology

To validate a research it is crucial to go through the field of research methodology and understand its concepts. Unfortunately this is not an easy task and the different methods should be weighed against each other from the research questions perspective. What method would be most beneficial to use when answering the research question? Sometimes the questions in itself provide the answer of the best method. This chapter presents some of the methods that have been weighed against each other when producing this paper.

4.1 Deductive & Inductive

For academic research the concept of deductive and inductive approaches are central (Alvesson & Sköldberg 1994:42). These theories explain how to address the relationship between theory and empirics. Induction is based on the researcher drawing conclusions on the basis of empirics and claiming these to be valid for other entities. On the other hand, deduction means that a hypothesis based on theory is tested against empirics to confirm its validity. Such authors as Chalmers (1999) have argued that these two methods are extreme and that most research conducted are somewhere in the middle. Both of the theories carry with them inherent problems such as the inability to derive new theory (deduction) or generalization of a complex reality (induction).

4.2 Qualitative & Quantitative

Quantitative and qualitative research is a distinction on how to conduct the actual research. A qualitative research is conducted using measurements other then numerical. The aim is to gather in-depth understanding of human behavior and the reason for such behavior. The questions *why* and *how* are generally explained by qualitative research. On the other hand, quantitative research uses numerical measurements to answer research questions and hypothesis testing. It is said to answer questions more like *what*, *where* and *when*. In an analysis conducted by Hunter & Leahey (2008) they found that around 66 % of all research papers are conducted with a quantitative method.

4.3 Statistics

The statistics field can be somewhat simplified in two sub-fields, the first one being descriptive statistics and the second one analytical statistics. Descriptive statistics is as the name suggests describing data with parameters such as mean and average values which are measures of central tendency. Within descriptive statistics we also find distribution measurements such as Standard Deviation and quartile ranges. The second field is analytical statistics and is made up by two under categories, liaison analysis and comparing analysis. In a liaison analysis one is looking for liaison between variables. These can either be a covariance analysis or similarity analysis. In the covariance analysis section we find the regression analysis and the correlation analysis (Wallén 1996).

4.4 Validity and reliability

Validity in a research is a measurement on how valid the actual research data is in comparison to what is asked for. With reliability the actual method used when measuring something is intended. However, high reliability does not automatically mean high validity or vice versa. When performing a quantitative study one must take into account such things as face validity, (i.e. is the data gathering technique good/valid?), criterion validity, (i.e. the result is coherent with other studies on the same subject) and communicative validity (i.e. communicate ones path through the field of research)

4.5 Method

This papers main purpose is to test the hypotheses held by RPM about the effects of volatility on different CTAs underlying strategy. This will in its essence be a deduction work based on both literature studies and the results from the data. The theoretical part of the study is produced with the use of recent papers on the topic of econometrics and statistics as well as supplementary financial literature. The statistical model used will be both describing such as standard deviation as well as analytical. Therefore the analysis in the paper is based on quantitative methods and the results are as objective as possible. Even though the original idea was suggested by RPM which in itself holds implications for the integrity of the researcher the work conducted still followed common practice for research. My data was collected from both RPM's internal system, the Barclay hedge database and different stock exchanges websites which was used to calculate financial parameter such as correlation, volatility, standard deviation and rate of returns. The Barclay hedge database is one of the most comprehensive databases for CTAs. The data that was used is set to represent the financial sphere where RPM is present. Through statistical research and analysis of the data the hypotheses held by RPM is tested.

The first step of the process was to thoroughly evaluate the current literature and the findings in the area of econometrics as well as conducting an internal investigation on previous RPM research. This was conducted whilst a suitable method for the hypotheses testing was determined. This was done to build a theoretical framework for the paper to stand on. The theoretical framework gave indications about pitfalls in the data gathering which had to be taken into account when using Granger causality. The second step was to collect necessary data from the databases mentioned above. This was done by the use of Microsoft SQL server (see appendix) which is a standard for writing questions in a database. The work of actual acquiring the data ran smoothly however to check the data and rank it in categories was time consuming. The data from the CTAs were given as a list and was required to be put in a pivot-table. The list was revised down to meet the standards necessary for the research.

When the data was collected and checked the process of analyzing and testing the data against the hypothesis began. Excel and Matlab were the preferred tools used for analysis and hypothesis testing purposes and from this process the results presented in this paper were retained. To test the validity of the internal volatility index used by RPM the index was matched against the VIX index. In this study the volatility was first calculated to daily volatility and later transformed into annualized. This was done by multiplying the Standard Deviation with the square root of 260 which is the number of trading days used by RPM. The number of trading days varies internationally, the majority of markets most often use between 250 and 260 days when transforming daily volatility to annualized volatility. The correlation between the two indexes was calculated for different time periods to demonstrate if the internal index is representative. To test the relationship between volatility and correlation a Granger-causality test was used which is explained in the theory section.

The volatility and correlation of the index used in this paper has been divided into quartiles using the Excel function which works as follows:

$$y = (1\text{-}g)*x(j+1)+g*x(j+2) \quad (14)$$

where:

$$(n\text{-}1)*p = j + g \quad (15)$$

where:

p = p-th percentile (ex: p = 0.25, 0.5, 0.75)
y = percentile associated with p
n = number of observations
j = the integer part of n*p
g = the decimal part of n*p

Then the second and third quartiles are put together and called medium volatility or correlation. This means that the first and fourth quartiles are carrying the "extreme" numbers and are therefore identified as high - volatility / correlation or low - volatility / correlation. This was also used for correlation and volatility change but these are named high positive / medium / high negative - change in volatility and correlation. To view the actual levels of each category see appendix. This information is matched to each CTA rendered by the data collection. The four parameters: Correlation and correlation change, Volatility and volatility change is then compared to each CTA. Here it is determined how each of the CTAs has performed during periods of different volatility or correlation. When this was done an overview of each underlying strategy is created by captivating the average of each months RoR of the CTAs within the same strategy and comparing it to the other strategies as well as comparing it to the overall results of the groups put together.

4.5.3 Biases

A selection bias is also present in the data analyzed due to wide time spans as well as unobservable hedge funds are not taken into account. Another bias in the data is the survivorship bias. This means that only the hedge funds that have survived the 10 year span analyzed is in the actual analysis. The hedge funds that have been terminated during this time or newcomers who do not fit the ten year window have not been taken into account. Another bias is the multi period sampling bias which comes from the time period chosen for this paper.

5. Data

This chapter presents the data used to test the hypothesis held by RPM. The data was collected from RPM’s internal systems, the Barclay Hedge Database and the Chicago Board Of Trade’s (CBOT) website.

5.1 Hedge Funds / CTAs

The initial data yielded was comprised of over a 1000 different Hedge Funds and was revised down to meet the standards necessary.

- Commodity Trading Advisor
- Trading primarily future contracts (financial derivatives)
- At least 10 years monthly history
- No multi strategy
- Trading on different markets at the same time

Out of the initial 1000 hedge funds the filter yields 82 CTAs that matched the criteria above (See appendix 1).

64 CTAs with Trend Following strategies

10 CTAs with Short Term trading strategies

8 CTAs with Fundamental trading strategies

The data used here was collected from the Barclay Hedge Database using SQL (see appendix). Many of the hedge funds in the initial data of over a 1000 hedge funds do not adhere to a CTA strategy. The vast majority of hedge funds generated from Barclay hedge where long / short equity Hedge Funds. It can be argued that to construct a representative result for each category the number of CTAs for Short Term traders and Fundamental traders are too few. The limited number of CTAs yielded might be explained by the filter. In order to locate a CTA that has been successful enough to stay in business for 10 years with a specific strategy is hard. The data might therefore suffer from survivorship bias as well as multi period sampling bias. However, the actual CTAs contracted by RPM are fewer than the representatives of each strategy in this data series and would therefore suit this paper well as an overall measurement of each strategy. Furthermore I have tested the data with and without outliers to confirm that the actual data is representative for the strategy investigated.

5.2 Index

This part is dedicated to the indexes used to determine volatility and volatility change that is used. The comparison between the VIX index and RPM's internal volatility index is a part of validating the internal use of this index.

5.2.1 VIX

The initial volatility index used in this thesis is the VIX-index from the Chicago Board of Trade (CBOT). It is widely recognized as the fear index and measures implied volatility. It is important to understand the difference between VIX (implied volatility) and historical volatility. The VIX is forward looking which means that it is measuring the volatility investors expect to experience in the future whilst historical volatility measures the volatility in past time. It was through the use of Black-Scholes option pricing formula to derive implied volatility that the VIX-index was created in January 1990 (Berk & DeMarzo 2011). When the VIX index was introduced it was for two main reasons. First of all it was to provide a benchmark of expected short term market volatility. Second it was to provide an index where options and futures contracts could be written on volatility (Whaley 2008). VIX track thirty days implied volatility from options based on the S&P 500 index. It is quoted in percent per annum and has since become one of the most popular and cited indexes to measure volatility in the market, not just in the S&P 500. Through the rapid spread of volatility through markets many investors look at the VIX as a global index of investor uncertainty and it has therefore been named the fear index (Whaley 2008). Even though the index only measures implied volatility of the S&P 500, it is widely used in the financial world as an overall instrument or benchmark to measure market uncertainty and risk worldwide. The VIX index is known as a forward looking index since it displays future volatility in the market. In the exhibit below the VIX index is plotted.

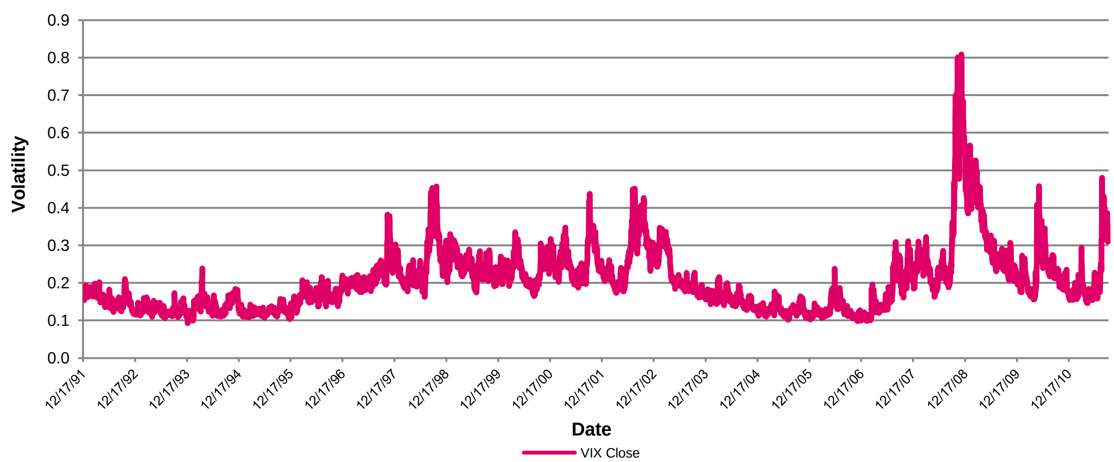

Exhibit 5 – VIX
Close levels of VIX from intraday data. Data from CBOT.

5.2.2 Continues contracts

RPM in turn uses its own index, named the continues index, when calculating volatility and correlation in the market. It is a backwards looking model and is put together by combining the data of 67 continues future contracts which is in close proximity to the sector distribution that the CTA managers contracted by RPM has (see appendix for complete list). These futures are highly liquid and have a high trading frequency. Through the sector distribution the continues contracts are seen as very representative for RPM's sphere of the financial world. The index is calculated by using an weighted average method where the settle price from the roll of both the expiring ticker and the new front month is used. As an example, if there are 30 days between the rolls, then on the first day, the generic is entirely skewed towards the front month. On the 10^{th} day is will be 2/3 front month and 1/3 second month and so on. This means that the in-house continues index uses realized volatility is not a so called forward looking model such as the VIX index. After each role date the averages are reset and this means that the date range should never matter as once the ticker rolls the percentages never get readjusted. This index has been analyzed and ran with the VIX index and the results can be seen in the analysis section. Because of internal use at RPM it is the primary index used in this study. The below exhibits presents the sector distribution and volatility levels of the continues contracts.

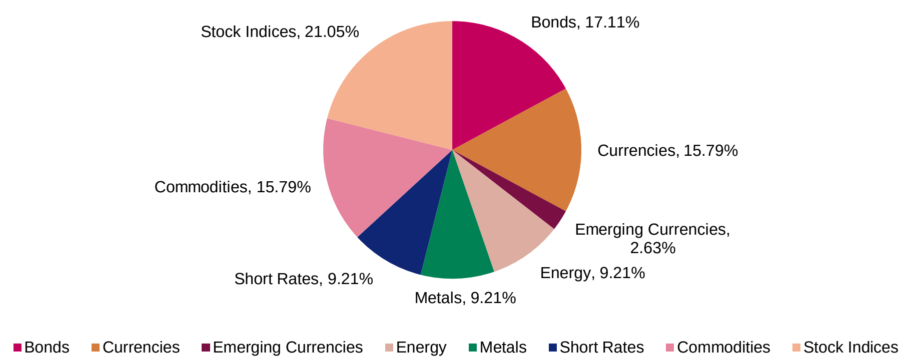

Exhibit 6 – Sector distribution
Sector distribution for the continues contracts used to calculate volatility and correlation at RPM.

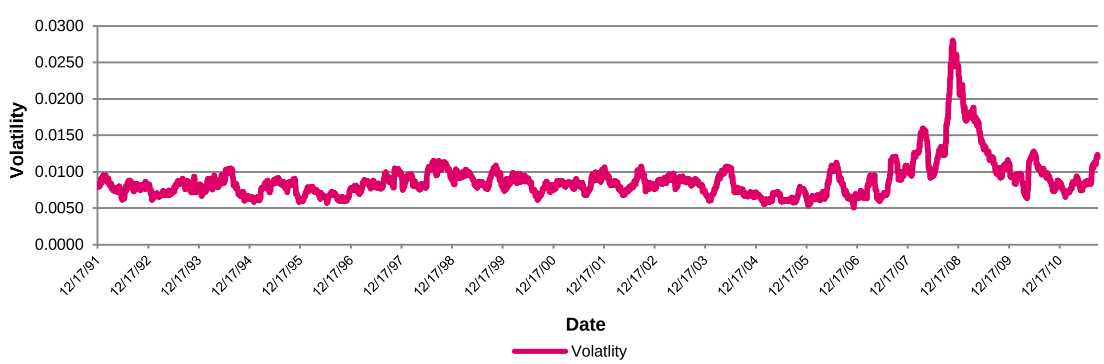

Exhibit 7 - Volatility levels for the continues contracts
Volatility levels for the in-house index based on the continues contracts.

6. Analysis and Result

In this section the result and analysis is presented in order of the purpose decomposition from chapter 1.2.

6.1 Volatility index

When analyzing the continues contracts volatility and the VIX index this paper found a high correlation of 0.7 between the variables for the period 1992 and 2011. When analyzing a shorter period, such as 2006-2011, the correlation is as high as 0.9 between the two indexes. The period 2006-2011 is interesting from a business cycle perspective. It contains “normal” years: 2007 and 2010, “difficult” years: 2008 and 2011 and “favorable” years: 2009. The graph below plots the VIX index together with the volatility for the continues contracts. It is here evident that volatility in one market such as the S&P 500, even though it is implied volatility, has spread through the markets. The continues contracts are collected from a number of different markets and could therefore be viewed as a truly global index. This makes the high correlation figures very interesting when determining if volatility is contagious. It is not possible to state where the spread started, only that at least this two indexes move in tandem and that the contagion of volatility is therefore evident. This means that from a finance perspective RPM’s in-house index for volatility seems to represent the financial world very well.

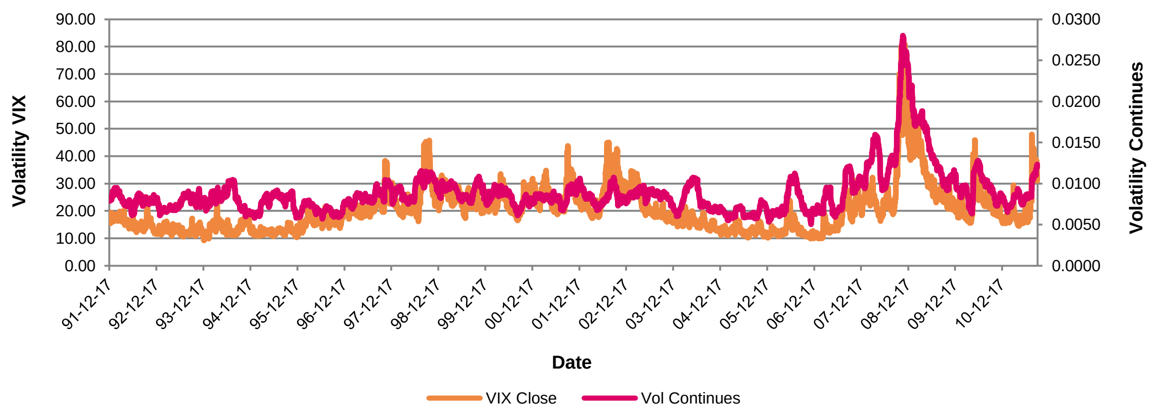

Exhibit 8 – VIX & Continues contracts volatility
Close levels of the VIX index together with RPM’s volatility index based on the continues contracts.

Since the VIX index is commonly used by market professionals to measure volatility worldwide and not just for the S&P 500 this correlation test between the VIX and the RPM in-house index indicates a high validity for the index. In other words, the in-house index portrays volatility levels very well. There are small differences/lags between the levels of the two indexes but this is customary since they do not have the same underlying base which the volatility is measured from. Another significant difference is, as explained in the data section, that VIX is a forward looking model and the continues index is realized (historic) volatility. What can be seen here is that over a 20 year period the models still seem to move in tandem even though the indexes are calculated differently.

6.2 Volatility and Correlation

In a correlation test between two data series of daily volatility and correlation of the continues contracts the result was 0.7 for three different periods (1991-2011, 2000-2011 & 2007-2011) which is a fairly high correlation figure. From this test one can argue that volatility and correlation for the continues contracts used by RPM move in tandem with each other. Below two of the periods are plotted in graphs.

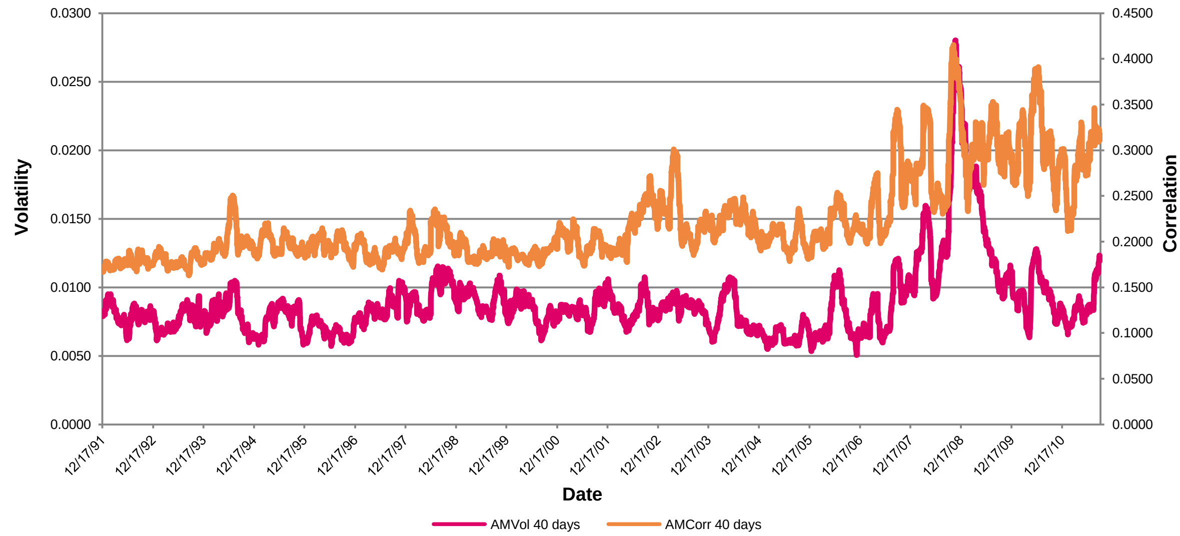

Exhibit 9 – Correlation & Volatility 20 years

Plotting correlation and volatility of the continues contracts for a 20 year time span.

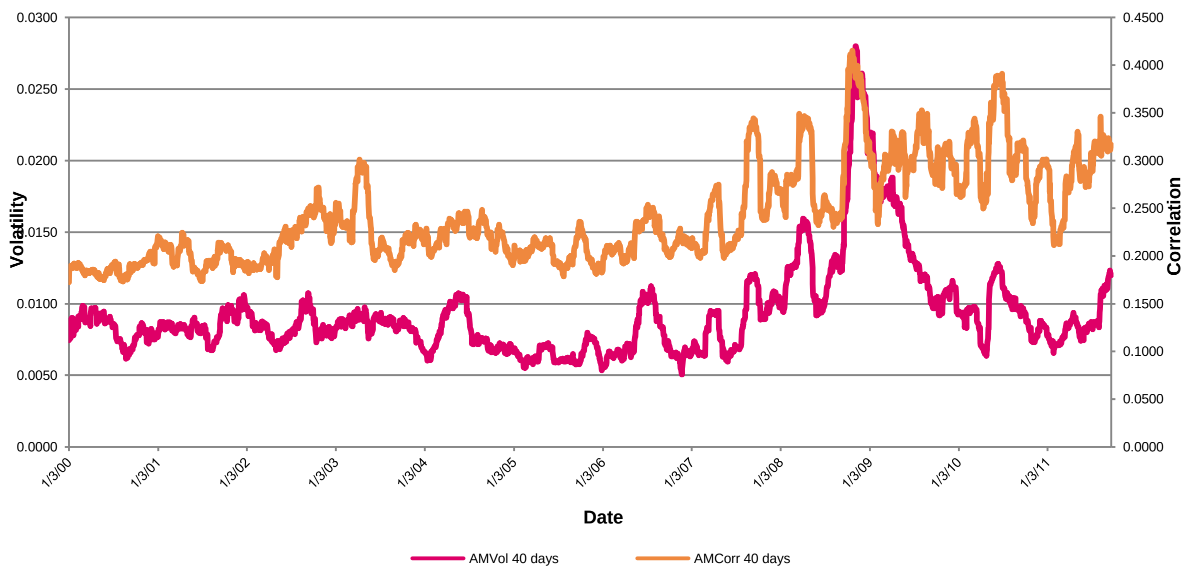

Exhibit 10 – Correlation & Volatility 11 years

Plotting correlation and volatility of the continues contracts for a 11 year time span.

To test if there is a true relationship between correlation and volatility and if volatility affects correlation, or the other way around, a Granger causation test was used. First test was to analyze if Y (volatility) granger cause X (correlation). The result can be found in Exhibit 11.

Alpha	Max lag	Result (F)	Result (c_v)
0.95	5	7	0.3
0.85	5	6.2	0.3
0.65	5	3	0.3
0.45	5	1.3	0.3
0.40	5	0.2	0.3

Exhibit 11 – Results of the first Granger causality test
Results of the granger causality test, Null hypothesis: Y (volatility) does not Granger cause X (correlation) can be rejected if F > c_v

If F > c_v we reject the null hypothesis that y does not Granger cause x. We can here see from the results that F > c_v and we can therefore reject the null hypothesis. We must go as low as alpha being 0.4 to receive the opposite that F < c_v. As explained in the theory section this does not mean that Y does Granger cause X. It merely means that we can reject the hypothesis that Y does not Granger causes X. The test was also used in the opposite way to see if Y (correlation) Granger causes X (volatility) and the results are presented in Exhibit 12.

Alpha	Max lag	Result (F)	Result (c_v)
0.95	5	7	0.3
0.85	5	5.8	0.3
0.65	5	2	0.3
0.45	5	0.86	0.3
0.40	5	0.1	0.3

Exhibit 12 – Results of the second Granger causality test
Results of the granger causality test, Null hypothesis: Y (correlation) does not Granger cause X (volatility) can be rejected if F > c_v

What we can see in Exhibit 12 is almost the same results as when Y was volatility and X was correlation. We can therefore reject the null hypothesis that Y (correlation) does not Granger cause X (volatility). In this test alpha must be as low as 0.4 to not reject the null hypothesis.

We can here see that first of all the correlation between volatility and correlation is very high which would indicate that volatility and correlation move almost in tandem. The results confirm that when volatility is high in the market we can expect correlation to be high as well. The opposite, that when volatility is low, correlation will be low we can also confirm. We can also reject the null hypothesis that volatility does not Granger cause correlation and vice versa. This means that there is a possibility that the two variables affect each other. However, no conclusion can be drawn of which of the variables affect the other one or to what extent and we can neither declare that the results are conclusive. There are always other factors that can be underlying to the effects on both correlation and volatility. The high correlation figures are still important when further analyzing the effects of volatility and correlation on the trading strategies for CTAs.

6.3 Volatility and the effect on trading strategies

The first test of volatility and volatility change comprise all the strategies together for an overall outcome. In the right column of the following exhibits the average performance is shown. This has been calculated as an average Rate of Return from monthly data over a 10 year period and is displayed to function as a comparison to the other results in the exhibits. The other results, which are dependent on the variables volatility and volatility change, are calculated as an average of monthly data from a 10 year period. The results for the three strategies equally weighed in one portfolio are presented in Exhibit 13:

		Volatility			
		High	Medium	Low	Average performance
Volatility change	High positive	0.49%	0.45%	0.94%	0.95 %
	Medium	-0.28%	1.08%	0.36%	
	High negative	1.45%	2.25%	0.31%	

Exhibit 13 – Volatility and volatility change
Volatility and volatility change table. Results of the three strategies equally weighed in one portfolio. Average performance is calculated as an average of the Rate of Return for a 10 year period.

What we can see in Exhibit 13 is that a low volatility with a high negative change is most profitable and high volatility with a medium change the least profitable. When the markets have low volatility levels and this volatility is rapidly decreasing the three strategies put as one will be most profitable.

6.3.1 Short Term strategy

In Exhibit 14 below the result form the Short Term trader's performance is presented.

		Volatility			
		High	Medium	Low	Average performance
Volatility change	High positive	1.87%	0.59%	1.44%	0.52 %
	Medium	0.05%	0.56%	0.03%	
	High negative	0.40%	-0.29%	0.09%	

Exhibit 14 – Volatility and volatility change for Short Term strategy
Volatility and volatility change table. Result for a portfolio containing Short Term trading strategy only. Average performance is calculated as an average of the Rate of Return for a 10 year period.

For Short Term strategies a high volatility environment with a high positive change is to be preferred. Due to the characteristics of the Short Term traders with a very narrow time frame for trading this makes sense. When the market volatility is raising rapidly this creates opportunities for profiting on contracts that move rapidly up or down in price. A Short Term trading strategy also means that a trader can quickly reverse their position when it is not profitable any more. The most difficult time for a Short Term trading strategy to profit is with medium volatility and a high negative change. This means that when the market volatility is rapidly decreasing down from high to medium and then to low the strategy has it more difficult to take advantage of the narrow time space for trading. It its essence this means that a rapidly rising volatility is to be preferred for a Short Term strategy to profit.

6.3.2 Fundamental strategy

In Exhibit 15 the result form the Fundamental strategy performance is presented.

		Volatility			
		High	Medium	Low	Average performance
Volatility change	High positive	-0.42%	0.24%	1.23%	0.71 %
	Medium	-0.16%	0.89%	0.63%	
	High negative	1.12%	2.37%	0.71%	

Exhibit 15 – Volatility and volatility change for Fundamental strategy
Volatility and volatility change table. Result for a portfolio containing Fundamental trading strategy only. Average performance is calculated as an average of the Rate of Return for a 10 year period.

Fundamental strategy prefers a market with medium volatility and a high negative change of volatility. This is suitable for fundamental strategies due to the characteristics of the trading model. Fundamental economic data when analyzed provides the strategy with an investing pattern. When high volatility occurs and contagion effects are evident then the rapid price movements of the securities and futures will move on other factors and variables then fundamental ones. For instance a fundamental economic variable could be a countries interest rate set by the central bank of that country. This can give a Fundamental strategy a hint on where the price is moving in the near future. When high volatility occurs the market is more so driven by instinct and fear among the investors creating a hazardous environment for the Fundamental strategy.

6.3.3 Trend Following strategy

In Exhibit 16 the result form the Trend Following strategy performance is presented.

		Volatility			
		High	Medium	Low	Average performance
	High positive	0.81%	0.40%	0.09%	1.05 %
Volatility change	Medium	-0.26%	1.06%	0.52%	
	High negative	2.22%	0.51%	2.68%	

Exhibit 16 – Volatility and volatility change for Trend Following strategy
Volatility and volatility change table. Result for a portfolio containing Trend Following trading strategy only. Average performance is calculated as an average of the Rate of Return for a 10 year period.

A Trend Following strategy profits from a low volatility environment with a high negative change. The strategy aims to ride out trends in the market which are pronominal and easier to follow in a low volatile environment. In a very volatile environment the trends shift more rapidly and are therefore harder to detect. It is also harder for Trend Following strategies to reverse or close their positions in this environment. The change is high negative which means that the levels of volatility are rapidly decreasing making these trends longer and more obvious for the trader.

6.4 Correlation and the effect on trading strategies

The first test of correlation and correlation change comprise all the strategies jointly for an overall outcome. The results are presented in Exhibit 17:

		Correlation			
		High	Medium	Low	Average performance
	High positive	-0.97%	0.69%	1.99%	0.95 %
Correlation change	Medium	-0.09%	0.46%	0.74%	
	High negative	0.29%	1.58%	0.50%	

Exhibit 17 – Correlation and correlation change
Correlation and correlation change table. Results of the three strategies equally weighed in one portfolio. Average performance is calculated as an average of the Rate of Return for a 10 year period.

The results presented in the table show that a low correlation with a high correlation change is to prefer when combining the three strategies together. The least profitable environment for the strategies positioned together is the high correlation with high positive change. This shows that a lower correlation between markets will favor the strategies when jointly operating as one. This would most likely occur under a high volatile environment if the results from the correlation test between volatility and correlation are accurate (see the discussion in chapter 7).

6.4.1 Short Term strategy

In Exhibit 18 the results from the Short Term strategy performance is presented.

		Correlation			
		High	Medium	Low	Average performance
Correlation change	High positive	0.87%	0.79%	-0.23%	0.52 %
	Medium	0.59%	0.39%	0.69%	
	High negative	-0.26%	0.13%	0.27%	

Exhibit 18 – Correlation and correlation change for Short Term strategy
Correlation and correlation change table. Result for a portfolio containing Short Term trading strategy only. Average performance is calculated as an average of the Rate of Return for a 10 year period.

The most profitable environment for a Short Term trading strategy is a high correlation environment with high positive change. This means that the markets move more in tandem with each other and as said before occurring most often in a highly volatile environment. When the correlation is high and the change is high positive a Short Term trading strategy will profit from the rapid moves in the market. When the correlation is high then all the markets will have the same volatility levels and the strategy has therefore more options in markets to invest in.

6.4.2 Fundamental strategy

In Exhibit 19 the results from the Fundamental strategy performance is presented.

		Correlation			
		High	Medium	Low	Average performance
Correlation change	High positive	0.12%	0.63%	0.45%	0.71 %
	Medium	-0.38%	0.32%	1.96%	
	High negative	0.28%	1.24%	1.04%	

Exhibit 19 – Correlation and correlation change for Fundamental strategy
Correlation and correlation change table. Result for a portfolio containing Fundamental trading strategy only. Average performance is calculated as an average of the Rate of Return for a 10 year period.

The Fundamental strategy profits from a low correlation in the market which would imply low volatility levels as well. This strengthens the result that when in a low correlation environment as well as low volatility the fundamentals of economics are more observable for fundamental strategy then in a high correlation market. When a low correlation exists between markets the fundamentals of one market, for instance equities, does not affect other markets, such as commodities. In a high correlation market the mood of investors more easily transitions from one market to another making it increasingly risky. This means that economic fundamentals that only should have implications on a specific part of the market transitions over and has an impact on more than just the market intended.

6.4.3 Trend Following strategy

In Exhibit 20 the results from the Trend Following strategy performance is presented.

		Correlation			
		High	Medium	Low	Average performance
Correlation change	High positive	-2.72%	0.65%	0.88%	1.05 %
	Medium	0.02%	0.34%	0.91%	
	High negative	0.52%	2.26%	2.73%	

Exhibit 20 – Correlation and correlation change for Trend Following strategy
Correlation and correlation change table. Result for a portfolio containing Trend Following trading strategy only. Average performance is calculated as an average of the Rate of Return for a 10 year period.

Just as for fundamental strategy the Trend Following strategy profits from low correlation between markets however for a different reason. Just as in a low volatility regime the Trend Following strategy can more easily pick up and ride on the trends which are more evident when the correlation levels are low. When high correlations occur the trends are harder to spot and the trends are weaker when spotted then in a low correlation environment. A high correlation environment will provide a very limited amount of trends and most of these trends will point in the same direction meaning that when they reverse which often happens in a high volatility environment the Trend Following strategy will incur large losses. The trends will most often reverse at the same time which is significant for a high correlation environment further adding to the losses incurred.

7. Discussion and Application

The volatility index used by RPM follows the VIX index levels very closely. The two indexes have a significantly high correlation figure between them proving that volatility spreads quickly both from markets to markets and from nation to nation. Since the VIX index is accepted amongst both scholars and professionals as a global index for volatility in any market the internal index at RPM must be granted as efficient in measuring volatility. To continue to use the internal index is therefore recommended by this paper. Academics who have studied the VIX index and the contagious behavior of volatility have concluded that it moves in tandem with many other indexes, especially when higher levels are recorded (Whaley 2008). This confirms the first step in the decomposition in this paper that the in house index is valid and a representable index for volatility. This means that even though the VIX index is a forward looking model and the in-house index uses realized annual data volatility evidently spreads between markets and the methods of calculating volatility signifies only small differences between the models. These tests of validity of the in house index could have been made using several different methods and indexes but since the use of the VIX index is accepted as a global measurement of volatility the results are considered valid.

The volatility and correlation levels of the continues contracts also move in tandem. When above average levels of volatility is recorded the same can be observed in correlation levels. When analyzing the composition of the in house index at RPM the index covers a vast range of markets making it a global measurement of volatility and correlation. The connection between volatility and correlation is of interest when trying to prove that volatility is contagious. If higher than average levels of volatility in one market transitions from a national to a global level without any regards to economic fundamentals this transition can be confirmed when analyzing the higher levels of correlation. This means that when investors believe one market to be risky which is shown in higher recorded volatility levels this mood can spread far beyond what economic fundamentals can explain. This is shown in the higher correlation levels recorded when volatility rises. A market in distress can therefore affect other markets which do not share the same economic fundamentals to react in an unforeseen manner creating momentum and cause herding behavior amongst investors. This paper did however, not find any evidence that volatility effects correlation or vice versa neither did it find the opposite that the variables do not affect each other. The analysis exhibit a high correlation relationship between the two variables but going further and finding dependencies between the variables have not been successful. To find a dependency between variables is difficult because of underlying factors that may affect the results are not taken into account either because these variables are unheard of or that these variables in turn are dependent on other variables.

When analyzing the effects of volatility on CTA strategy it is clear that volatility levels separate the trading strategies from each other. Short Term traders profit from high volatility levels where it is possible to make superior returns on rapid price movements. Fundamental strategy, on the other hand, suffers losses from these high volatility levels. This is possibly due to the actual panic that comes with volatility. A high level of volatility is a ratification of investor’s uncertainty and when investors are uncertain they no longer trust economic fundamentals on which Fundamental strategies are based. The Trend Following strategy does not perform well under these conditions either. The trends in a market with high volatility are either weak or rapidly changing which is making it hard to follow and profit from them. On the other hand a low volatility environment proves it hard for Short Term strategy to work. It seems that what makes the strategy profitable the opposite will strip the strategy of its benefits. When analyzing the rate of change of volatility the impacts on the strategies are almost identical to those of the volatility levels. The Short Term strategy perform best under a rapid positive change of the levels whereas the Fundamental and Trend Following strategies performs best under rapid negative change. What is evident is that the Trend Following and Fundamental strategy performs best under the same conditions but for different reasons. This would be an interesting topic to further analyze. The medium levels of both volatility and the change of volatility seem to make all of the strategies perform below the average level which is interesting. This is a factor to take into consideration when allocating funds to different trading strategies. The implications of the effects of volatility and the change of volatility would be to closely watch the levels for future allocations.

The correlation follows the results of the volatility closely. This was somewhat expected due to the high correlation figure between volatility and correlation. As a confirmation of the previous results with volatility it is noticeable that Short Term trading strategy benefits from a high correlation environment and that the opposite, low correlation, is beneficial for Trend Following and Fundamental strategies. However, high correlation between markets means that different markets move in tandem. If the markets move rapidly (i.e. high volatility) then there will be many different markets where the Short Term trading strategy could do exceedingly well in creating high RoR. Therefore it is arguable that the Short Terms strategy would prefer a high volatility environment with high correlation between markets and that the opposite would be to prefer for Trend Following and Fundamental strategies.

This study has found that the continues use of the in-house index for volatility and correlation would be recommended to RPM since the indexes are proven valid. When the in-house index exhibit higher levels of volatility in the markets then through the characteristics of each of the trading strategies it is evident that Short Term traders will perform better than average. However, if one seeks a well diversified portfolio within the CTA sphere then it is apparent that all three strategies would be a part of such a portfolio. From the results it is noticeable that the Fundamental and Trend Following strategies profit from the same conditions. However, when studying the results closely it is apparent that the strategies complement each other well under other conditions then the extremes of volatility and correlation.

Through this study the questions have been answered in order of the decomposition of the research question. This thesis has given me a lot of insights in the financial world which I truly value. I do believe that the knowledge gained during the production of this thesis will come to use in my professional life ahead.

8. Conclusion

Having explored the area of volatility and correlations in the market and the effects on trading strategies it must be said that is has been hard to prove relationships between the different variables. My analysis has been empirical in nature and has been leaning on already existing theory. The reason for this is the complexity of how a market functions and the large amount of factors that affect it. However, I do argue that the assumptions made in the study are reasonable and I think that I have gained valuable insights through my approach.

8.1 Reliability and validity

As mentioned in the methodology section validity is a measurement on how valid the research data is in comparison to what is asked for. I do believe that the data collected for this thesis holds a high validity for the research question. The validity could have been improved by taking more factors into account which is a common problem for research papers. It is arguable that the few CTAs yielded from the data search representing Short Term trading and Fundamental trading strategies would create problems for the analysis and that the results would be deemed vague. This implies a lower level of face validity for the study. However, I do believe that the research have a high communicative validity as well as high criterion validity. As mentioned in the methodology section the reliability of a study is the method of *how* something is measured. This thesis have measured volatility and correlation in a conventional approach commonly used amongst both scholars and professionals.

8.2 Answer to original question

Which of the underlying strategies for CTAs is more profitable during high, or low, volatility and correlation?

With a high volatility regime a Short Term trading strategy is to prefer and this is also true in a high correlation environment. With low volatility levels in the market a Trend Following strategy is to prefer which is also true for a low correlation market.

The validity and reliability of the in house index used at RPM has been tested and deemed very useful due to its high correlation figure with the VIX index. This thesis has been able to reject the null hypothesis that volatility does not affect correlation and vice versa.

8.3 Hypothesis validation

In the introduction section four different hypotheses were presented and here the validation of each hypothesis is presented. The hypotheses have been answered throughout the text but are here summarized more explicitly.

H_1; Volatility affects correlation.

As mentioned in the analysis section the results demonstrate that we can reject the null hypothesis in the Granger correlation test. I have also established that a high correlation figure is noticeable between the two variables. However, nothing can be concluded on the actual relationship between the variables and the hypothesis H_1 is not validated.

H_2; In a high volatility regime Short Term trading strategy is the most profitable.

The analysis render in the result that Short Term trading is the most profitable in a high volatility regime and therefore hypothesis H_2 can be validated.

H_3; In a high volatility regime Trend Following strategies suffer losses among other factors due to swift reversals in the market.

The results signify that higher volatility levels makes it increasingly hard for Trend Followers to profit in therefore the hypothesis H_3 can be validated.

H_4; Fundamental trading and Trend Followers seem to profit from the same conditions in the market.

The results show that a market with low volatility and correlation is to be preferred by both Fundamental and Trend Following strategies and therefore hypothesis H_4 can be validated.

8.4 Further research

During the time I have written this thesis it has been inevitable to come across other research topics that would be interesting to conduct further research on. This thesis also had to exclude some areas in order to be finalized and these areas are of high interest as well.

The relationship between correlation and volatility and how volatility spreads would be interesting topics to carry out further research on. The area is of interest for anyone who studies Markowitz and the creation of diversification benefits. As this thesis has dealt with trading strategies for CTAs a deeper investigation into each strategy to see what contracts and position they held under any given condition would be of interest. This would further add to the explanation why they profit from any given condition and add understanding to the question on when to invest in each strategy. That would be more of a qualitative research and would complement this quantitative research well.

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Appendix

Appendix 1 – CTAs

CTA:	Strategy:
A. S. Peskin and Company, Inc.	Syst Fundamental
Bridgewater Associates, Inc.	Syst Fundamental
Cipher Investment Management Company	Syst Fundamental
First Quadrant L.P.	Syst Fundamental
FX Concepts, LLC	Syst Fundamental
Newton Capital Partners	Syst Fundamental
QFS Asset Management	Syst Fundamental
Quality Capital Management, Ltd.	Syst Fundamental
Ashley Capital Management, Inc.	Syst Short term
Boronia Capital	Syst Short term
Conquest Capital Group LLC	Syst Short term
Coral Rock Investments, Inc.	Syst Short term
Hansen Capital Management, Inc.	Syst Short term
Kaiser Trading Group Pty. Ltd.	Syst Short term
Mapleridge Capital Corporation	Syst Short term
R. G. Niederhoffer Capital Management	Syst Short term
RAM Management Group, Ltd.	Syst Short term
Trafalgar Group	Syst Short term
Abraham Trading Company	Syst Trend
Aspect Capital Limited	Syst Trend
Atlas Futures Fund, LP	Syst Trend
Campbell & Co., Inc.	Syst Trend
Chesapeake Capital Corporation	Syst Trend
Clarke Capital Management, Inc.	Syst Trend
Clarke Capital Management, Inc.	Syst Trend
Commodity Futures Services	Syst Trend
Covenant Capital Management	Syst Trend
Derivative Systems Management Company	Syst Trend
Dexia AM	Syst Trend
Dreiss Research Corporation	Syst Trend
Drury Capital, Inc.	Syst Trend
DUNN Capital Management, LLC	Syst Trend
DUNN Capital Management, LLC	Syst Trend
Eagle Trading Systems Inc.	Syst Trend
Eckhardt Trading Company	Syst Trend
EMC Capital Management, Inc.	Syst Trend
Empyreal Investments Group	Syst Trend
Estlander & Partners	Syst Trend
Estlander & Partners	Syst Trend
EuroCapital Management LLC	Syst Trend
Fort Orange Capital Mgmt., Inc.	Syst Trend

FTC Capital GmbH	Syst Trend
GIC, LLC	Syst Trend
Graham Capital Mgmt., L.P.	Syst Trend
Graham Capital Mgmt., L.P.	Syst Trend
Hamer Trading, Inc.	Syst Trend
Hawksbill Capital Management	Syst Trend
Hyman Beck & Company, Inc.	Syst Trend
Integrated Managed Futures Corp.	Syst Trend
International Trading Advisors, B.V.B.A.	Syst Trend
International Trading Advisors, B.V.B.A.	Syst Trend
John W. Henry & Company, Inc.	Syst Trend
JPD Enterprises, Inc.	Syst Trend
Kinkopf Capital Management, LLC	Syst Trend
Lyxor Asset Management	Syst Trend
M.S. Capital Management Limited	Syst Trend
Man Investments	Syst Trend
Man Investments Ltd	Syst Trend
Mangin Capital Management	Syst Trend
Marathon Capital Growth Ptnrs., LLC	Syst Trend
Merit Alternative Investments GmbH	Syst Trend
Millburn Ridgefield Corporation	Syst Trend
Mulvaney Capital Mgmt., Ltd.	Syst Trend
Northfield Trading, L.P.	Syst Trend
Orix Investment Corporation	Syst Trend
Quest Partners, LLC	Syst Trend
Quicksilver Trading, Inc.	Syst Trend
Rabar Market Research	Syst Trend
Rotella Capital Management, Inc.	Syst Trend
Saxon Investment Corporation	Syst Trend
Scully Capital Management, LLC	Syst Trend
Silicon Valley Quantitative Advisors	Syst Trend
SMN Diversified Futures Fund	Syst Trend
Spackenkill Trading Corporation	Syst Trend
SSARIS Advisors, LLC	Syst Trend
Sunrise Capital Partners	Syst Trend
TradeLink Capital LLC	Syst Trend
Transtrend, B.V.	Syst Trend
Vail Trading and Research	Syst Trend
Willowbridge Associates, Inc.	Syst Trend
Winton Capital Management, Ltd.	Syst Trend

Appendix 2 – Continues contracts

3-MTH EURO$	
JPANESE YEN	
BRIT POUND	
EURO FX	
US 10YR NTE	
EURIBOR 3M	
LONG GILT	
100 OZ GOLD	
BUND FUT 6%	
LIGHT CRUDE	
NATURAL GAS	
EURO/YEN	
10YR JGB	
CANADIAN DL	
E-MINI S&P	
BRENT CRUDE	
3M 24HR ALUMIN.	
EURO STXX50	
NIKKEI 225	
SHORT STG	
FTSE INDEX	
10Y MINI JG	
HANG SENG	
GAS OIL	
SWISS FRANC	
US 5YR NTES	
MEXICAN PESO	
AUSTRLN DLR	
DAX INDEX	
10 YR BOND	
US T BONDS	
3M 24HR ZINC	
SPI 200	
NYM RBOB GAS	
NO 2 HT OIL	
SCHATZ 6%	
3M 24HR COPPER	
3M 24HR NICKEL	
CORN	
3MTH CDN BK	
BOBL FUT 6%	
TOPIX	
BP-JY FUTS	
SILVER 5000	

IBEX35 MI	
3 EURO-YEN	
NASD E-MINI	
SOYBEANS	
S&P 500 IDX	
BANK BILLS	
EURO/FRC	
CAC 40	
NEW ZEA DLR	
NASD 100	
FSMI INDEX	
10YR TB	
S&P/CDA 60	
OMXS30	
US 2YR NTES	
COTTON NO 2	
SUGAR 11	
3M 24HR LEAD	
SOY MEAL	
COFFEE C	
EURO/BP	
SO AFR RAND	
3YR TB	
WHEAT	
COCOA	
SOYBEAN OIL	
LIVE CATTLE	
LEAN HOGS	
US DLR IDX	
GLD SAC NDX	
FRZEN BELLY	
EURO YEN	
TCE RUBBER	
3M 24HR TIN	
TOKYO RAW SUGAR	

Appendix 3 – Volatility and correlation quartiles

Volatility and correlation quartiles
Quartile 0 = Min. value
Quartile 4 = Max. value

	Volatility	**Volatility change**		**Correlation**	**Correlation change**
Quartile 0	11.62%	-22.36%		17.69%	-21.63%
Quartile 1	14.13%	-8.28%		20.35%	-5.13%
Quartile 2	15.07%	-0.11%		22.41%	0.91%
Quartile 3	17.69%	8.06%		27.65%	5.78%
Quartile 4	44.08%	58.08%		39.50%	41.20%

Appendix 4 – Matlab code

```
% [F,c_v] = granger_cause(x,y,alpha,max_lag)

% Granger Causality test

% Does Y Granger Cause X?

% User-Specified Inputs:

%   x -- A column vector of data

%   y -- A column vector of data

%   alpha -- the significance level specified by the user

%   max_lag -- the maximum number of lags to be considered

% User-requested Output:

%   F -- The value of the F-statistic

%   c_v -- The critical value from the F-distribution

% The lag length selection is chosen using the Bayesian information

% Criterion

% Note that if F > c_v we reject the null hypothesis that y does not

% Granger Cause x

%Make sure x & y are the same length

if (length(x) ~= length(y))

error('x and y must be the same length');

end

%Make sure x is a column vector

[a,b] = size(x);

if (b>a)

%x is a row vector -- fix this
```

```
x = x';
end
%Make sure y is a column vector
[a,b] = size(y);
if (b>a)
%y is a row vector -- fix this
y = y';
end
%Make sure max_lag is >= 1
if max_lag < 1
error('max_lag must be greater than or equal to one');
end
%Proper model specification using the Bayesian Information
%Criterion for the number of lags of x
T = length(x);
BIC = zeros(max_lag,1);
%Specify a matrix for the restricted RSS
RSS_R = zeros(max_lag,1);
i = 1;
while i <= max_lag
ystar = x(i+1:T,:);
xstar = [ones(T-i,1) zeros(T-i,i)];
%Populate the xstar matrix with the corresponding vectors of lags
j = 1;
```

```
while j <= i

xstar(:,j+1) = x(i+1-j:T-j);

j = j+1;

end

%Apply the regress function. b = betahat, bint corresponds to the 95%

%confidence intervals for the regression coefficients and r = residuals

[b,bint,r] = regress(ystar,xstar);

%Find the bayesian information criterion

BIC(i,:) = T*log(r'*r/T) + (i+1)*log(T);

%Put the restricted residual sum of squares in the RSS_R vector

RSS_R(i,:) = r'*r;

i = i+1;

end

x_lag = find(min(BIC));

%First find the proper model specification using the Bayesian Information

%Criterion for the number of lags of y

BIC = zeros(max_lag,1);

%Specify a matrix for the unrestricted RSS

RSS_U = zeros(max_lag,1);

i = 1;

while i <= max_lag

ystar = x(i+x_lag+1:T,:);

xstar = [ones(T-(i+x_lag),1) zeros(T-(i+x_lag),x_lag+i)];

%Populate the xstar matrix with the corresponding vectors of lags of x
```

```
j = 1;

while j <= x_lag

xstar(:,j+1) = x(i+x_lag+1-j:T-j,:);

j = j+1;

end

%Populate the xstar matrix with the corresponding vectors of lags of y

j = 1;

while j <= i

xstar(:,x_lag+j+1) = y(i+x_lag+1-j:T-j,:);

j = j+1;

end

%Apply the regress function. b = betahat, bint corresponds to the 95%

%confidence intervals for the regression coefficients and r = residuals

[b,bint,r] = regress(ystar,xstar);

%Find the bayesian information criterion

BIC(i,:) = T*log(r'*r/T) + (i+1)*log(T);

RSS_U(i,:) = r'*r;

i = i+1;

end

y_lag = find(min(BIC));

%The numerator of the F-statistic

F_num = ((RSS_R(x_lag,:) - RSS_U(y_lag,:))/y_lag);

%The denominator of the F-statistic

F_den = RSS_U(y_lag,:)/(T-(x_lag+y_lag+1));
```

```
%The F-Statistic

F = F_num/F_den;

c_v = finv(1-alpha,y_lag,(T-(x_lag+y_lag+1)));

granger_cause(x,y,alpha,max_lag)

run('c:\Users\Kristoffer\granger_cause.m')
```

Appendix 5 – SQL Code

```
SELECT  BP.prog_id ,
        name ,
        MIN(date) AS mindate ,
        MAX(date) AS maxdate,
        MPS.Code
FROM    dbo.BarclayProgram BP
        INNER JOIN dbo.BarclayRor br ON br.prog_id = bp.prog_id
        INNER JOIN argus.dbo.ManagerProgram MP ON MP.ProgramId=bp.prog_id
        INNER JOIN Argus.dbo.ManagerProgramStrategy MPS ON MPS.id=MP.StrategyId
        WHERE BP.prog_id>90000000
       AND mp.FlagshipProgram=1
       GROUP BY BP.prog_id, name, Code
```

```
SELECT  BP.prog_id,date,ror,fum,  bp.denominat,bp.denominat_mum  FROM  dbo.BarclayRor
BR INNER JOIN dbo.BarclayProgram BP ON BP.prog_id= BR.prog_id
WHERE bp.prog_id IN
```