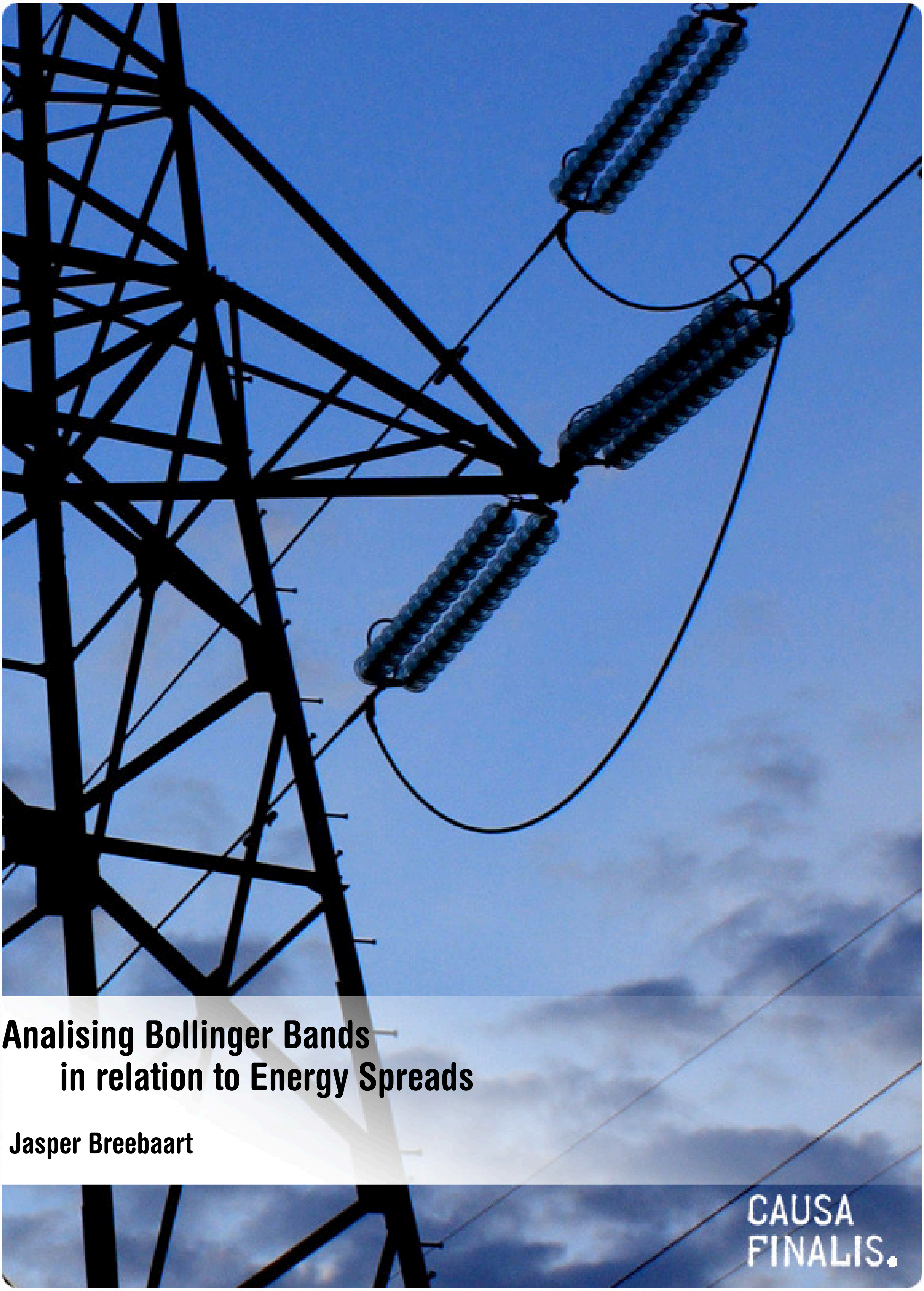

# Analising Bollinger Bands in relation to Energy Spreads

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# Analysing Bollinger Bands in Relation to Energy Spreads

Thesis submitted for the degree
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**Jasper Breebaart**

# Declaration

Herewith I, as a Masters in Finance & Banking candidate at the British University in Dubai, certify that:

a. This thesis is my own work
b. Except where due acknowledgement has been made, the work is that of the candidate alone;
c. The work has not been submitted previously, in whole or in part, to qualify for any other academic award;
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## Abstract

This thesis examines the signalling ability of Bollinger Bands when analysed with energy spreads. The study evaluates the profitability of preliminary trading systems over different spread constructions to identify the Bollinger Band signalling efficiency. The test is thus an analysis of the weak form Efficient Market Hypothesis as proposed by Fama (1970).

Earlier research has illustrated varied conclusions. The research into Bollinger Bands has illustrated that Bollinger Bands trading systems are unable to yield economic profits and perform worse than other Technical Analysis methods. The spread research, on the other hand, clearly identifies that there are inefficiencies and large potential for automated trading systems, also with Bollinger Bands or comparable methods.

This study has found that Bollinger Bands generate inefficient signals, are not a good predictor of spread movements. On average the performance between 1995 and 2009 has generated a loss. On this basis a “contra mean reversing” (trending) approach of the highest loss giving settings has been deeper analysed to find considerable signalling efficiency, thus potential trading profits.

The evaluation incorporates conventional energy spreads like the Crack and Frac spreads and created additional spreads. A created spread of the end products of the crack spread, heating oil and unleaded gasoline, generated the best results indicating the need for further research into this spread.

The profitability of the contra Bollinger Band system indicates that the Efficient Market Hypothesis should be rejected in the weak form.

# Acknowledgements

*Diogenes was one the famous Greek philosophers and schooled by Socrates. He was exiled from Athens and therefore moved to Corinth. He was exiled because, as a beggar, he turned extreme poverty into a virtue. He lived in a large tub instead of a house, and walked the streets with a lamp claiming to be searching for an honest man. When the Corinthians informed Diogenes that they too where planning to exile the thinker, he told them that he would prove that his lifestyle is a choice. In spring he visited the farmers surrounding the city and bought their summer's harvest. Due to a big drought in the summer Diogenes was able to sell the harvests with great profit, which he immediately distributed over the poor of the city, returning to his tube to enjoy the sun.*

Translated: Störig H. (2005) *Geschiedenis van de Filosofie* (History of philosophy)

The author would like to thank dr. John Anderson for the "intellectual fights" that provided more insight than any academic paper can. Although for academics life equals publish or perish, for knowledge there is no substitution for an argument.

The author is dyslectic. Sincere apologies for any mistakes that are not corrected thereby decreasing reading easiness.

Yours Sincerely,

Jasper Breebaart

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**ENCLOSED: CD-ROM WITH DISCUSSED ARTICLES**

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# 1.0 Introduction

## *1.1 Human environment manipulation*

The evolution of animals shows that our increased evolutionary fitness of the brain is accompanied by an increased ability for manipulating and using its surroundings. This is illustrated by the usage of tools observed with all kinds of animals, from birds to ants. It is self-evident that the Homo species, with Sapiens as the true masters, have taken this to full extremes. We try to harvest all the earth, our surroundings, have to offer. Our classification of history in ages is firstly separated by the dominant materials used and later by other names still representing times of other material usage. The industrial revolution was, in essence, kicked off with the implementation of coal. Coal was used for fires due to the scarcity of wood on the British isle resulting in knowledge of coal's properties. The steam engine turned out to work particularly well with very high temperatures, which coincidentally could only be obtained by burning coal.

With the industrial revolution, the importance of technological advancement installed a constant drive for more, other, and better ways to use our surrounding, though creating not only advances but also a direct dependency on these resources. The manipulation of fire by means of coal, gas and oil, accompanied with our ability to manipulate, store and use electricity resulted in a boom in resource usage, thus dependency. The explosion engine became the preferred method for powering transport (the model T-Ford) embedding a need for oil into the world. Adolf Hitler already identified the essential place oil has taken in our lives and adjusted the order of countries invaded according to the long-term effects on energy availability. These adaptations changed the primary energy-harvesting source from the living organism (man and animal power) to fossil fuel. One could coin the past century the Oil & Gas age both illustrating our dependency and the time of change to renewable energy sources.

The geophysicist Hubbert (1956) presented a paper[1] to the American Petroleum Association in 1956 illustrating a theory for the lifecycle of oil production, currently known a the "Peak Oil Theory". The theory puts forward the idea that total supply of oil is finite while our demand is infinite (ceteris paribus). Due to the means of exploration the production curve is similar to a bell curve putting forward the idea that the oil production will, at some point, be at its peak. Although the model is highly debatable, it does illustrate a problem with finite resources making the model expandable to numerous other resources. The first decade of the 21st century has illustrated that the peak oil theory has a catalyst from the demand site. As the non-western world develops, the demand for oil will rise accordingly pressing demand to a higher basis. Accompany this with a decrease in supply (or at the minimum a increase in production costs due to inhospitable locations) and a long-term prediction of increasing oil prices has a high probability. On the other hand, due to high prices, the motivation for energy innovation becomes increasingly profitable increasing the probability of an abundant alternative energy source. Imagine that someone, in this garage for instance (since this is usually the location of the most innovative laboratories), invents a means to win energy from seawater. When the world would be able to harvest all its energy from a sustainable source, the demand for oil would be limited to transportation and as a raw material for production (for the time being since in time transportation would also change) which would leave sufficient supply for at least a century.

What the above has illustrated is that the interdependency between the different types of energy sources and their various forms will increase substantially in the coming period. The manipulation of our surroundings has changed from its basic form into a manipulation in light of electricity. We need electricity to produce all elements the human society requires. Our future means of energy generation for transportation will decide whether or not we will move to complete electricity dependency. The sources from where this electricity is generated will become more and more interchangeable resulting in a co-dependency never seen before. A better understanding of the valuation-patterns behind these relationships would greatly increase our knowledge and understanding of future derivatives trading.

[1] Hubbert, M (1956) "Nuclear energy and the fossil fuels" Presented for the American Petroleum Institute, spring meeting

## 1.2 Research Overview

This study aims to identify whether Bollinger Bands (BB) hold any signalling power over energy markets when applied to energy spreads. The study tests different BB settings and variations. Where extreme profitability (losses) is identified, strategies will be subjected to an in-depth evaluation (the inverse strategy for losses).

Chapter 2 provides an overview of current academic literature on technical analysis, trading spreads, and energy futures. Although most research points towards identifying the value of theoretical (mostly individual) conversion, storage and usage costs, this research follows the more practical school that aims to identify the relationship and its range. Here, trading results are presented only when they add information to the paper as a whole.

Chapter 3 explains the method used for analysing the BB and energy spread relationship. Here that data is analysed and spread construction explained and analysed. Furthermore, the method of strategy analysis and its specific setting and variable are explained.

The results are presented in chapter 4 which are analysed overall and per variable, per setting, and per spread. The chapter is concluded by an in-depth evaluation of the performance of strategies that are most promising as a full trading mechanism.

Finally, in chapter 5 the conclusions are presented and the findings compared to the existing literature and suggestions for further research are presented.

# 2.0 Literature Review

## *2.1 Efficient Market Hypothesis*

In 1969 Eugene Fama presented a paper to the American Finance Association, Fama (1970), where he reviews the literature concerning market efficiency. The paper begins with the following paragraph (page 383):

> *“The primary role of the capital market is allocation of ownership of the economy’s capital stock. In general terms, the ideal is a market in which prices provide accurate signals for resource allocation: that is, a market in which firms can make production-investment decisions, and investors can choose among the securities that represent ownership of firms’ activities under the assumption that security prices at any time “fully reflect” all available information. A market in which prices always “fully reflect” available information is called “efficient”.”*

Fama (1970) afterwards illustrates that the final statement is to general for empirical testing, thus needs specification. The price formation process has to be defined as that it explains what the term “fully reflect” implies. This definition of full reflection of information was created by Fama (1970) and became the primary definition of the Efficient Market Hypothesis (EMH). In the following paragraph, Fama’s (1970) hypothesis is evaluated in the form of an analysis of the Efficient Market Hypothesis in its three forms. These forms are identified by Fama (1970) and categorised into the weak, the semi-strong, and the strong form. Firstly, Fama (1970) identifies that under the weak form all historical information (i.e. returns and prices) is reflected in the current price. The semi-strong form defines that all publicly available information is priced in. Specifically the speed that is required for new information to adjust the price. Finally, the strong form testes whether all information (also that available only to a certain group of people) is integrated in the present price. This form tests if “*any investor or groups (e.g. management of mutual funds) have monopolistic access to any information relevant for the formation of prices have recently appeared*”, according to Fama (1970), page 388. He further identifies that the full reflection is most fittingly stated in the two parameter Sharpe (1964) equilibrium prices model, due to which the best tests are based on expected returns. The expected return assumption leads to a "fair game" property of the price (and information) since the expected return of the price a t+1 with the same information set is zero. From this Fama (1970), page 385, concludes that "*they rule out the possibility of trading systems based only on (available) information … that have expected profits or returns in excess of equilibrium expected profits or returns*". The submartingale model is another possible specification of the EMH since the expected return is equal or greater than the zero, from which one can conclude that a trading system cannot have profits greater than a buy and hold strategy since there is a reward for the risk of holding an instrument. The EMH in its most strong form is often compared to the random walk model which states that successive price changes are independent. The analysis hereunder starts with an analysis of Fama (1970) presented followed by a both empirical and philosophical evaluation with some reference to empirical research (other than the ones discussed by Fama(1970)).

Testing for market efficiency requires an asset pricing and/or evaluation model. As stated above, Fama (1970) identifies that most research is based on the model of expected returns and since later research is mostly based on the CAPM model, which has a direct connection to the former, which is still the most dominant model for efficiency testing benchmarking. Fama (1970) analyses the EMH in its three forms to see where the hypothesis can be rejected. His survey illustrates that in the 1970's there is no good research contradicting the weak and semi-strong form but some evidence against the strong form hypothesis. Although the EMH is validated, the random walk specification is refuted by multiple studies since there is no independence but a random walk with drift at best. The empirical analysis presented by Fama (1970) can be both in the form of trading system results evaluation or in covariance of returns and correlation evaluation. Fama mathematically shows that both forms are equally relevant for testing the hypothesis.

The weak form EMH is firstly illustrated via empirical evidence published by Fama himself in 1965, Fama (1965). The paper analyses the correlation between returns of the 30 stocks of the Dow Jones Industrial Average and finds no or extremely small correlations. Alexander (1961) published a paper of a trading system where a stock is bought based on its volatility, as have Fama & Blume (1966) who tested the same system. Both tests show that this system yields limited profits, which are eroded by transaction costs validating the EMH. An element of the random walk theory is the need for independence, tested by studies of Osborne (1962), Niederhoffer & Osborne (1966), and Fama (1965) who illustrate that large daily price changes are followed by large daily changes. Due to fact that the direction of the sign is random, Fama (1970) remarks that this dependence only contradicts the random walk and not efficiency. However, it does illustrate a problem, not presented by Fama (1970), or at least require more research into this effect with the EMH since there is a potential trading system where one uses a certain method of sign prediction. In reference to Treasury bill markets, Roll (1968) illustrates weak form efficiency under the different pricing assumptions. Finally efficiency is tested under multiple stocks models which, according to Fama (1970), validate efficiency. A problem, not identified by Fama (1970), is that the paper shows that 50% of variance comes from a "market factor" and an additional 10% from industry factors. The EMH will only hold if this variation is fully (mostly) due to real profit influencing factors and not by spilling moves from other companies, which is at least not proven and probably not the case. It is, for example, very likely that change in information will result in a reaction with its competitor price though this change has no influence over the other companies results.

The semi-strong form EMH is vindicated by a study published by Fama, et al. (1969) who analyse the adjustment of stock prices to stock splits and find that the information assumed to be included in a split is adjusted for when published. The results potentially create a trading system where one shorts all stocks after stock split accompanied price increases which is not addressed by Fama (1970). Ball & Brown (1968) do a similar analysis on earnings announcements and find the market's expectations to be generally on track resulting in efficiency. The efficiency of discount rate changes is published by Waud (1970), as is Scholes' (1969) evaluation of the efficient nature of IPO's. These analyses have the problem that they all strongly rely on the CAPM model due to which one cannot unconditionally reject the non-efficiency hypothesis since the CAPM model relies on the idea of efficiency to work.

Fama (1970) rejects the strong form EMH in its full status. The above mentioned studies by Niederhoffer & Osborne (1966) and Scholes (1969) both lead to the rejection of the strong form due to the insider positions that the specialist with his order book and the adjustment of prices to the publication of company information, respectively. The fact that insider trading is illegal already disproves the strong form as do the exchange rules that quoted companies have to distribute their corporate information simultaneously. The specialist book mentioned by Fama (1970) in the 1970's is currently less clear of an advantage since the introduction of computerised trading reduced the bird-view over all trading positions (though a bank employee might still be able to find all info). The new trading methods have created new insiders potentially found with the high frequency trading algorithms operated by hedge funds and investment banks who use both the timing and quantity of information for profitable trading. Fama (1970) continues by analysing Jensen (1968) who looked at the profitability of investment funds relative to market performance. He finds that this is not the case, proving nothing however since an average result just illustrates that the market is on average efficient. Furthermore, the current relevance is debatable since the information availability that investment funds have in excess of other investors is very small or non-existent. The primary problem with the strong form is that theoretically it is impossible to prove since the nature of the information to be considered is undisclosed, hence cannot be used for testing at that moment. The following will behold an analysis of the problems with the EMH.

The first philosophical problem with the EMH is stated in the theoretical part of Fama (1970). It states (page 387): a market is efficient where "*all agree on the implications of current information for the current price and distributions of future prices of each security.*" Thus, the participants as a group need to agree on a subject. Conversely, other disciplines involving human behaviour base their theories on the idea that people do not agree. This furthermore implies that all the investors and speculators make their decisions equally, thus rational. The idea that within a large group of people there are no emotional decisions without rational reasoning seems unlikely. Interestingly, before the dominance of the EMH, economists already tested irrational behaviour as shown by Simon (1959) who illustrates that in binary choice experiments people use event matching, instead of playing the optimal strategy against a certain probability they mimic the probability.

These behavioural deviations are further illustrated by an immense body of psychological research that identified that decision-making is not (always) rational, Wegner's (2002) overview of psychology illustrated that a very large part of our behaviour, and decisions, are the result of automatic processes, generally called heuristics. These ideas formed the basis for the behavioural finance school which tries to change the rational model for a rational-emotional model. This concept is partly based on Kahneman & Tversky's (1979, 1986) prospect theory that allows for irrational behaviour based on psychology. The models function on concepts like loss aversion (the higher weighting of loss than profits), anchoring (the influence of expectations by unrelated recently learned data), or overconfidence (the overestimation of probabilities for a group of events). There is an abundance of finance research contradicting the EMH and validating the concept of behavioural finance. Since this is not the place for a full-scale analysis of behavioural finance, some research has been listed aiming to illustrate the diversity of the field. Examples are: De Bondt & Thaler (1985) who illustrate that stock prices tend to overreact to changes in earnings, Shleifer (1986) shows that stocks tend to jump when added to the S&P index for no rational reason, Fama & French (1988) point out that stock prices are mean reversing, Barberis, Shleifer & Vishny (1998) illustrate an underreaction to earining announcements and an overreaction to news, Henrich, et al. (2001) evaluated rational behaviour across 15 relatively small-scale societies and found extremely large variations in rational economic behaviour, and finally Olsen (2009) who matches investor (irrational) behaviour with animal foraging behaviour.

When evaluating investors' actions concerning distressed securities, for example, it is clear that a theoretical knowledge mismatch exists. The original owner of the security is willing to sell under the fair price since it requires in depth knowledge on bankruptcies, bankruptcy laws, and company specific (finance) information that this person does not have. The selling can be seen as a payment to another investor for this knowledge, contradiction EMH. A similar contradiction is illustrated by Huberman & Regev (2001) who show that the placement of old news in a major weekend edition of The Times (all information remained equal) led to a major rally in the company's stock price and even positively influenced its competitors price. This influence on other industry participants, very frequently observed in the financial markets, holds another potential refutation of the EMH since an increased outlook of company A could have no or a negative influence over company B (both operating in the same industry). The increased position of A might dilute B's competitive strength. It is clear that there are situations where growth of one company could have a positive influence over the whole industry, but the opposite is also possible. It would be interesting to see further research into a trading system where one trades the "irrational" dual price moves of the uninfluenced competitors.

The EMH "proof" as presented by Fama (1970) also holds the epistemological problem that the structure of the hypothesis firmly relies on proof by rejection. The EMH is illustrated by rejecting the other possibilities. The problem is that this only proofs that under the available set of knowledge there is no contradictory proof for EMH, but that any time other trading systems not earlier considered can lead to the rejection of EMH. When one takes the semi-strong form, for example, it is clear that all other publicly available information can never be fully tested leading to the impossibility of the semi-strong EMH claim. The number of possible trading strategies are practically unlimited, hence can never be all tested and disproved.

The EMH operates in analogy with the Homo Economicus (the rational economic human) and is, along with the Homo Economicus, based on Utility theory. The problems found in this portrayal of mankind have been clear in both economics and finance for the past decades. This is consistent with the practical problem that, after more than 30 years of research the practitioner community is not even close to accepting the EMH but does accept its antithesis: technical analysis, as illustrated by Taylor & Allen (1992).

The early Behavioural Finance research focused on contradicting the EMH without a clear underlying market model. An alternative price forming model was proposed by Shiller (2000) in his book *Irrational Exuberance* and put into context in Shiller (2003). He put forward the Feedback theory, price-to-price feedback theory in academic terms, as a model for the price creation. The oldest published source of this model (as far as we know) is an anonymous account of the Dutch *Tulipmania* published in 1637 and has since been described often to explain economic crashes. The model illustrates that primary investor attention (success) is the source of additional investor attention due to i.e. word-of-mouth and media attention of the initial success. "*The talk attracts attention to "new era" theories and "popular models" that justify the price increases.",* according to Shiller (2003) page 91. This process will continue until a bubble is formed which is ultimately unsustainable leading to a crash which could again be exponentially fueled by the feedback theory but now in a negative spiral leading to a unsustainable bearish outlook. Intuitively, this price forming model fits better with human nature as with the reality observed in the financial markets.

The above illustrated the critical position this paper takes in relation to the Efficient Market Hypothesis. The historical information, current finance and economic research, and faulty assumption that decision-making is mostly rational leads to a rejection of the EMH. From this point it will be assumed that the EMH is rejected, however where necessary additional discussion will be provided. The rejection of EMH is mostly due to its contradiction of human behaviour, on the other hand, humans do have the tendency to over estimate our understanding of a certain concept and our influence over this, the illusion of knowledge as proposed by Bowman & Buchanan (1995)

## *2.2 Technical Analysis research*

The concept of Technical Analysis (T.A.) directly contradicts the efficient market theory. Since the latter was the dominant idea in 1970's and 1980's (as illustrated above), very little T.A. research had been published at that time. In course of the 1980's more and more research contradicting the EMH was presented. For example Fama & French (1988), ironically since it was the same Fama (1970), documented problems with the efficient market theory. As stated before, they found that in the long run stock prices reverse to their mean illustrating their predictability.

In the beginning of the 1990's the amount of empirical T.A. research really grew substantially with numerous studies being published. One of the primary research articles is Brock, Lakonishok & LeBaron (1992) who analysed two simple T.A. rules, namely moving average and Trading-range breaks, over the 1897-1986 period. They found the rules to be statistically profitable and better than the comparable bootstrap results (random walk with drift, AR(1), GARCH-M ,and EGARCH). The fact that the study spans an extremely long period is seen as de facto evidence that technical analysis can yield results.

Lo, Mamaysky & Wang (2000) published one of the first papers that directly analysed and compared the theoretical similarities and expressional differences between (scientific) statistics and (practitioner) technical analysis. They finalised the methodology of scientifically analysing pattern recognition on charts by means of using a nonparametric kernel regression over several hundred U.S. stock prices from the NYSE and NASDAQ (specific stocks are unspecified) spanning from 1962 to 1996. The comparison between conditional and unconditional distribution harvested evidence of the functionality of technical indicators. The basic nature of this analysis adds weight to other T.A. research since it illustrates that T.A. profits do not (fully) arise from equilibrium returns made by investors willing to bear the risk of holding financial products.

From this point, the floodgates of academic research in the field opened, arguably, due to two reasons. One, the increased computational processing power enabled people to do calculations that needed a super computer a decade ago on their laptops. Moore's law (after Dr. Moore, a former Intel executive) predicts that the increase in computing power increased exponentially, approximately doubling every two years. Finally, the increasing popularity of Behavioural Finance has provided a theoretical framework for T.A. since one cannot both prove T.A. and operate under the Efficient Market Hypothesis. Pioneering researchers like, Thaler, Shiller, Tversky & Kahneman paved the way for this alternative finance theory. Due to this large body of research the following will focus on Technical Analysis research that is comparable to the one conducted in this paper.

One of the first papers analysing BB was Leung & Chong (2003), who compare moving average envelopes with BB's. The study compares the profitability between both methods using the main stock market indices of the G7 countries and the 4 "Asian Tigers" from 1985 to 2000.[2] The research does not take transaction costs, dividend and risk free return into account but instead focuses on the relative result. It shows that BB do not consistently and significantly outperform Moving average envelopes. The Moving average envelopes are better measures for short-term horizon (10, 20 & 50 days) while BB performs better for long term periods (250 days).

[2] Dow Jones (USA), Toronto 300 (Canada), BCI Global (italy), FTSE 100 (UK), DAX (Germany), Nikkei 225 (Japan), CAC40, KOSPI (S. Korea), Straits Time (Singapore) Hang Seng (Hong Kong) & TWSE (Taiwan)

*Table 2.1 Average Annual Rate of Return - Leung & Chong (2003)*

| | MAE 3%/10 | MAE 5%/10 | BB 2/10 | MAE 3%/20 | MAE 5%/20 | BB 2/20 |
|---|---|---|---|---|---|---|
| Average return | 2.36 % | 3.27 % | 1.91 % | 3.18 % | 2.91 % | 2.91 % |
| | MAE 3%/50 | MAE 5%/50 | BB 2/50 | MAE 3%/250 | MAE 5%/250 | BB 2/250 |
| Average return | 3.82 % | 2.45 % | 1.36 % | 1.73 % | 1.00 % | 2.18 % |

The return presented in table 2.1 represents averaging of annual returns calculated over 250 trading days. Since the paper does not incorporate any risk free return rate, the return of non-investment periods is not taking into account with annual return calculation (the model assumes short trading is not allowed). Appendix A provides the complete return table.

Liu, Et. Al. (2006) use the concept of BB's in cooperation with the Black & Scholes model. The authors identified that more than 94% of prices (15 years of historical data of Dow Jones, S&P500 and NASDAQ) are within the BB, which to their surprise was similar for the Black & Scholes stock price model. Due to this finding the paper was created to present mathematical proof that the Black & Scholes model has characteristics that are comparable to the concept behind Bollinger Bands. Based on the theory behind the Black & Scholes model the paper furthermore tries to identify the best performing settings for BB based on the theoretical connection between both models. The paper finds that a 12 day Moving Average and 88% inclusion band (or 1.55 std. dev.) generates most theoretical profits, which has been included in the testing of BB's in relation to energy spreads.

Lento & Gradojevic (2007) tested numerous technical analysis methods in reference to the S&P, TSX 300, DJIA, NASDAQ, and Canada/USD spot exchange rate. They evaluated different types of Filters, Moving Averages, BB and Trading Range Break Out systems. The research compares each system to a buy and hold strategy and than tested for significance via a bootstrap method and robustness via sub period analysis, while considering transaction costs. The results are variable but clear in the fact that Bollinger Bands have least predictive power. Table 2.2 illustrates the difference in absolute returns of a 7/12 combined signal approach (7 out of 12 signals have to agree to generate a signal) where the second figure excludes BB. Refer to appendix A for the table with complete returns relative to a buy and hold strategy.

*Table 2.2 Return with including and excluding BB – Lento & Gradojevic (2007)*

| | TSX | DJIA | NASDAQ | CDN/US$ |
|---|---|---|---|---|
| Including BB | 10.4 % | 11.5 % | 17.4 % | - 0.9 % |
| Excluding BB | 13.4 % | 7.9 % | 21.6 % | 2.0 % |
| Difference | 3.4 % | 3.6 % | -4.2 % | -2.9 % |

The paper furthermore illustrates that profitability is greatly enhanced by using a combined signal method instead of a single model.

Lento, Gradojeciv & Wright (2007) presented a paper with results from the above displayed research (has the exact same dataset & time period) but provided extra attention to the BB performance. They test the profitability of Bollinger Bands using TSX, DJIA, NASDAQ, and Canada/USD spot exchange rate. The authors analyse two types of BB in the same way as above, again with keeping transaction costs into account. The study shows that a BB strategy is unable to yield any economical profits, though a contra-strategy approach improves profitability. Appendix A provides the results of both the BB and the contra-BB strategies.

## *2.3 Spread Literature*

Trading the spread between related products has been an economic activity for as long as we have written accounts. Around 400 b.c. traders in the Greek city of Athens already traded the spread between olives and olive oil as explained by Verbrugge (2008). City accounts show that the trading direction was both short and long depending on the mispricing in different Mediterranean countries. The research into spread trading on the other hand has seen a slow start. In the 1980's there was minimal research with academics like Jones (1981) and Rentzler (1986) publishing on the subject. Poitras, in 1985, conducted his PhD. research on the gold future spreads and published several papers on the subject which set of a stream of further spread research. In the following decade spread research into all different fields was conducted with Poitras publishing on numerous products. Since there is an abundance of spread literature, this paragraph focuses on research of energy or comparable topics.

A paper on the Soybean complex spread, Poitras & Rechner (1993), is theoretically comparable to oil spreads. Here a trading strategy is based on the gross processing margin of converting raw soybeans into oil and meal. The paper evaluated the profitability of the soy complex on both intraday and interday strategies in yearly sub-periods. The paper considers transaction costs, but varies these between the different strategies since intraday trading requires less capital and costs. Different filters were incorporated to evaluate the robustness of profits. The results illustrate that over the 1987 to 1991 period, the trading profits for the spread have been substantial, constant and economically viable. Appendix A provides the total performance.

One of the first pieces of published research into energy spreads (correlation) was Borenstein, et al. (1997) who tested the responsiveness of the gasoline price to changes in the price of crude oil over the 1986 to 1992 period by statistically analysing the pricing change movement and their lag. They observed an asymmetrically response where the upward pressure results in a quick adjustment while the downward pressure has a slow adjustment. Potential reasons for this irregularity can be inventory adjustments or market power by sellers. The paper evaluates both options by looking at different points in the production chain as on different locations. Borenstein, et al. (1997) conclude that both factors have an influence over the discrepancy.

Girma & Paulson (1999) analyse the oil crack spread between Crude oil, gasoline & heating oil. Firstly, the study finds cointegration and a long-term stationary spread by using the ADF test and Phillips-Perron Z test. It then continues by analysing profit opportunities from the different production crack spreads and, taking transactions costs into account, finds them to be profitable. A moving average with standard deviations is used as a trigger (relatively comparable to the Bollinger Bands as proposed in this paper), of which multiple days and standard deviations are tested resulting in the identification of the standard deviation between 2 and 2.5 to be most profitable from 1984 to 1994. The average percentage of profitable trades is 83.38% with a maximum of 100% and a minimum of 74.4% of trades. Appendix A provides the full results table.

Another analysis of energy spread was conducted by Emergy & Liu (2002) who analyse the Spark spread of natural gas and electricity futures between 1996 and 2000. The data is tested using the ADF test and weighted symmetric unit root test created by Pantula, Gonzalez, Farias & Fuller (1994). They find cointegration between the two instruments on both of the main electricity delivery locations. Although the production, natural gas usage, is different in both locations, the authors did not find a large deviation. The regression model (with a $R^2$ of 0.85) is the basis for a trading system that assumes that the spark spread will reverse back to its equilibrium. The model results in significant economically trading results and makes the assumption of total transaction costs of approximately $62 round trip. The out of sample trades where profitable 94% of long and 86% of short trades. When confined to only the Palo Verde contracts, 100% of trades where profitable both long and short (Due to limited relevance, please refer to the paper found on the accompanied cd-rom for the results).

In Poitras & Teoh (2003) a system of oil spread trading based on different estimated production conversion factors between crude oil and gasoline & heating oil, using the open and closing prices of 1996 to 1999, is tested. The system uses formulas to test for deviations in the opening prices and then day-trades between the open and close price in order to profit from the reverting of the production relationships. Poitras & Teoh (2003) illustrates that the oil complex crack spread can de economically profitably traded when transaction costs are incorporated. The 3:2:1 ratio is the most profitable both long and short. Table 2.3 illustrates the intraday 3:2:1 ratio profitability and appendix A provides the profitability of the 1:1:0 and 1:0:1 spreads.

*Table 2.3 Crack spread 3:2:1 profitability – Poitras & Teoh (2003)*

| *Filter Size* | 0 | 3 | 6 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|
| # profitable trades | 310 | 241 | 187 | 117 | 72 | 33 |
| % profitable trades | 43,54 | 45,73 | 49,08 | 54,17 | 60,00 | 67,35 |
| Mean % | -1,88 | -0,86 | 0,01 | 1,17 | 2,71 | 5,25 |
| Stan. Dev. % | 16,22 | 16,32 | 16,91 | 17,21 | 17,95 | 20,33 |
| *Filter Size* | -0 | -3 | -6 | -10 | -15 | -20 |
| # profitable trades | 333 | 262 | 192 | 125 | 80 | 53 |
| % profitable trades | 46,25 | 49,16 | 52,32 | 53,42 | 61,07 | 65,43 |
| Mean % | -1,17 | -0,54 | 0,62 | 1,06 | 3,55 | 4,93 |
| Stan. Dev. % | 19,19 | 18,73 | 19,64 | 20,85 | 22,22 | 26,26 |

Dunis, et al. (2005) analysed the 1995 to 2005 Gasoline oil crack spread and found a non-linear cointegration using a unit root test, namely A Dickey-Fuller test extended in Enders & Granger (1998). They found an asymmetrical variation with the movements away three times bigger on the downside. The paper, furthermore, tests trading systems based on a higher order neural network, recurrent neural network, and a multilayer perception network against a fair value non-linear cointgration model. The models are evaluated both in an out-of-sample and by means of results before transaction costs, unfiltered, by threshold filter, by correlation filter, and by asymmetric threshold. The results illustrate that the usage of a threshold filter (optimized in the sample data) is most profitable. The threshold is most comparable to a BB illustrating this research validity. Refer to appendix A for the trading simulation results.

The spread between Natural Gas and propane futures prices, the Frac spread, is tested by Mougoué (2007) and illustrated that there is cointegration in this spread by testing the future prices between 1993 to 2005 using the ADF. The paper continues with using this cointegrated quality to test for profitable trading opportunities via a moving average and standard deviation system (again relatively comparable with BB's). The research harvested an economic and risk adjusted profits but accounted for transaction costs of $35 per spread which is low considering one trade constitutes 5 propane and 2 natural gas contracts. The system produced a hypothetical average profit of $4,807.97 over 47 trades of which 31 are winning trades. The average return per trade is 19.25% of which long trades have a 25.04% profit while short trades 13.21%. Appendix A presents the results

## *2.4 Energy Literature*

The futures exchanges introduced oil futures since the end of 1970's, beginning of the 1980's. In 1983 Hirschfeld was the first to publish on the subject by writing an overview of energy futures. Chen, et al. (1987) followed by analysing the correlation between energy futures and spot oil prices. They researched the hedging effectiveness of heating oil, Gasoline, and Crude futures using regression analysis and find that there is a substantial correlation between future price movement and spot prices serving as prove for the effectiveness of futures for hedging.

Adrangi, et al. (2001) researched whether or not the three oil futures market have a chaotic structure or and/or non-linearity. This structure would indicate an increased effectiveness of (short term) technical analysis. The study uses a correlation dimension test by Grassberger & Procaccia (1983), a BDS statistic which is a combination of ARCH tests by Brock et al. (1987), and Kolmogorov entropy in accord with crude, heating and Gasoline future prices from 1983 to 1995. They find the data to be non-linear, not consistent with chaos, and mostly explained by ARCH type processes.

An analysis of the price spread between similar oil products, Brent and WTI, has been conducted by Milonas & Henker (2001) who look at the similarities and price differential between both with a specific look at the convenience yield differential. The authors firstly identify that WTI produces slightly more Gasoline than Brent, which is more valuable thus giving WTI a slight theoretical price advantage. By analysing data from 1991 to 1996 the authors calculate the daily convenience yield estimation as the price spread and use regression to identify that the spread is mean reversing and influenced by numerous factors like convenience yield, for example due to seasonality effects, local supply and demand disruptions, and most importantly cash market prices.

The potential predictive power of oil future prices in relationship to spot prices was analysed by Chinn, et al. (2005). They examine the future and spot relationship for multiple energy commodities, namely: crude oil, heating oil, gasoline, and natural gas by testing the 1999 to 2004 period with an OLS regression. The research looks into the futures prices ability to predict spot prices, and finds that futures market are unbiased but not accurate predictors of spot prices. Furthermore, they find that they do outperform time series and random walk models, illustrating the potential predictive power under a different more complex system.

Coppola (2008) created a study comparable to Chinn, et al. The study uses a vector error correction model to evaluate deviations from the long run relationship between the two oil prices. The model uses the spot and future t-1 prices over a 1986 to 2006 period to estimate a fair future price. A comparison to a random walk system illustrated that the vector model outperforms in both in and out of sample tests.

# 3.0 Methodology

## *3.1 Introduction*

This study has analysed the ability of Bollinger Bands to signal deviation from spreads. The theoretical rationale is that spreads have a certain average and accompanied mean reversing behaviour since they represent practical pricing relationship between the underlying products. Conversely, the markets are inefficient, thus price deviations could exist for longer periods. BB's can be seen as a "middle of the road" method where both mean reversing and irrationality are accounted for since the deviation from the average is tested but only of the average of a certain period. The following will illustrate how the testing has been structured and executed.

## *3.2 Energy futures*

Trading in forward delivery contracts (forwards) has most likely been a human activity since the shift from Hunter-gatherer to farmer. Athens, as mentioned before, already bought a lot of their imports forward taking advantage of price fluctuations at the harvest period, Verbrugge (2008).

This study uses daily prices of the following energy futures: Crude Sweet Light Oil delivery at Cushing (NYMEX), Heating Oil delivery at NY Harbour (NYMEX), Unleaded Gasoline delivery at NY Harbour (NYMEX), Natural Gas delivery at Henry Hub (NYMEX) & Propane delivery at Mont Belvieu (NYMEX). The Data is taken over the period starting the 1$^{st}$ of January 1995 (the 3$^{rd}$ is the first trading day) and ends on the 6$^{th}$ of July 2009. The futures data is a continuous time series using 2 months ahead future contract prices. The contracts are rolled into next the month approximately 10 working days ahead of next month's expiration, resulting in a rolling around the 10$^{th}$ of the new month.

These data series are sourced from tradingblox.com, an organisation that strives to create trading simulation platforms. Since the company's product is simulation software they provide free data to assist their products. The data contains: Date, Open, High, Low, Close, Volume, Open Interest, Delivery Month, and Unadjusted Close which is sufficient for this analysis. The data is supplied in .txt files, which can be directly loaded into Tradestation (to be explained below). This source does not supply any propane future prices which are taken from Energy Information Administration (the official energy statistics from the U.S. government www.eia.doe.gov). When the other data from this source is analysed (EIA also supplies crude, heating oil, gasoline) it is clear that the same data set and time series construction is used for both sources (most likely originating from NYMEX itself). The reason that EIA is not the source of all data is that EIA does not supply any Natural Gas prices as that it only provides close prices. From this analysis we can safely assume that the data is comparable.

Table 3.1 illustrates the statistical properties of the data series used. For all data series the standard deviation is extremely large. The average standard deviation over all futures is 61.68% and the difference between the maximum and minimum observations are on average 3.1 times the mean, illustrating the large variation along the time period.

*Table 3.1 Descriptive Statistics of Data*

| *Future Data* | *Crude* | *Heat.Oil* | *Un.Gasoline* | *Nat. Gas* | *Propane* |
|---|---|---|---|---|---|
| Mean | 39.44640 | 1.09860 | 1.11182 | 4.79263 | 0.64578 |
| Std Deviation | 25.96422 | 0.74535 | 0.66689 | 2.75052 | 0.37050 |
| Kurtosis | 2.10406 | 2.00490 | 1.18466 | 0.68737 | 1.01226 |
| Skewness | 1.51640 | 1.48948 | 1.31553 | 0.97618 | 1.24603 |
| Maximum | 145.78000 | 4.11160 | 3.57100 | 15.42700 | 1.99000 |
| Minimum | 11.02000 | 0.29520 | 0.32920 | 1.34300 | 0,20400 |
| Count | 3630 | 3630 | 3630 | 3630 | 3630 |

The commodity bubble of the past years (approximately 2003 to 2008) is obviously the most influential factor for this large variation in the data. Theoretically, the use of Bollinger Bands would be ideally suited for long term irrationality (move from average spread) which are very likely to occur with variations that large. Appendix B illustrates the price development in graph form, where the variations can be visually analysed.

## *3.3 Spread construction*

Traders have used inter-commodity spread trading for a long time. NYMEX treats the official Crack, Spark (not analysed in this paper due to lack of electricity data), and Frac spreads as a single position when determining the margin requirements illustrating the widespread use of these spread instruments. Furthermore, they offer spread options for the market participant who wants to insure the risk instead of hedging it away. The determination of the “normal” spreads has been the subject of multiple studies with variable results. Theoretically, a spread between two related products represents the margin a refiner has to transfer one into the other. This margin is not stable since the base products movements are not synchronised, and each factor potentially has different supply and/or demand factors influencing their price.

This paper takes the Crack spread 3:2:1, 1:1:0 and 1:0:1 as the Frac spread 5:2 and adds 0:1:1, 0:2:1 cracked spreads and 1:1 oil/propane Frac spread as variations on the original. The first four spreads are conventional spreads based on production relationships. The 3:2:1 Crack spread for example derives from using 3 barrels of oil as raw material and producing 2 barrels of heating oil and 1 barrel of unleaded gasoline. The 3:2:1, 1:1:0, and 1:0:1 cracks represent a crude oil : heating oil : unleaded gasoline ratio while the Frac spread 5:2 represents a propane 5 : natural gas 2 ratio. The other spreads are created for this analysis where the 0:1:1 and 0:2:1 are regular crack ratios and the 1:1 oil propane Frac stands for a 1 to 1 oil : propane ratio

The Crack spread is the spread between crude sweet light oil and heating oil and unleaded gasoline respectively. The term crack derives from the process of refining which “cracks” crude into its final products. Gasoline production is approximately twice the amount of distillate fuel oil, which is the cut of the crude that holds heating oil and diesel fuel (chemically identical). Due to this relationship the crack spread primary used is 3:2:1, however other spreads are known be used by, for example, refiners with a less efficient or unconventional production setting. Formula 3.1 illustrates the mathematical spread calculation used in this study.

*Formula 3.1 Crack Spread 3:2:1*

| | |
|---|---|
| $CSV(t,T) = \dfrac{\left(42\times\left(\mathrm{m}\times\mathrm{HU(t,T)}\right)+\mathrm{n}\times\mathrm{HO(t,T)}\right)-\left(\left(\mathrm{m}+\mathrm{n}\right)\times\mathrm{CL(t,T)}\right)}{\left(\mathrm{m}+\mathrm{n}\right)}$ | 3.1 |

To calculate the value of the crack spread (CSV) one takes unleaded gasoline (HU) and multiplies this by the crack ratio (m), as is the case with heating oil (HO) which is multiplied by its ratio (n). This product is then multiplied by 42 to account for the difference between the future contracts since crude is traded per 1,000 barrels while the end products are traded per 42,000 gallons. Since 42,000 gallons is equivalent to 1,000 barrels there is no need for any conversion between the products. This is then subtracted by the crack ratio (m+n) of crude times the price of crude (CL). The end product is then divided by the (one side) amount of futures contracts (m+n) to present the Crack Spread value over 1 contract combination.

Based on the same production relationship a 1:1:0 and 1:0:1 spread is analysed. The idea behind these ratio's is that one takes part of the conventional 3:2:1 relationship and hedges just this element. Formulas 3.2 and 3.3 illustrate the calculations behind these spreads. Due to the fact that these spreads are based on a 1 to 1 ratio the formula changes into a simple subtraction between the products. Here unleaded gasoline/heating oil is converted into a barrel figure and simply subtracted from the price of crude.

*Formula 3.2 Crack Spread 1:1:0*

$$CSV(t,T) = \frac{\left(42 \times \left(\mathrm{m} \times \mathrm{HU(t,T)}\right)\right) - \left(\mathrm{m} \times \mathrm{CL(t,T)}\right)}{\mathrm{m}} = \left(42 \times \mathrm{HU(t,T)}\ -\ \mathrm{CL(t,T)}\right) \tag{3.2}$$

*Formula 3.3 Crack Spread 1:0:1*

$$CSV(t,T) = \frac{\left(42 \times \left(\mathrm{n} \times \mathrm{HO(t,T)}\right)\right) - \left(\mathrm{n} \times \mathrm{CL(t,T)}\right)}{\mathrm{n}} = \left(42 \times \mathrm{HO(t,T)}\ -\ \mathrm{CL(t,T)}\right) \tag{3.3}$$

As stated before, the 3:2:1, 1:1:0, and 1:0:1 relationships are conventional production relationship and therefore frequently analysed in academic research presented in this paper. The 3:2:1 ratio is tested by Girma & Paulson (1999) and Poitras & Teoh (2003). While the 1:1:0 ration is tested by Poitras & Teoh (2003), and the 1:0:1 ratio is evaluated by Borentein, et al. (1997) and Poitras & Teoh (2003).

By evaluating the theoretical basis for the above presented crack spread one can reason that, due to the relationship between heating oil and unleaded gasoline as a moving pair against crude, it is very likely that there is a price movement relationship between these two products. Following this rationale, the paper created a spread between the two main crude end-products, coined "cracked spread". Two separate spreads are evaluated: the 2:1 cracked spread which is based on the conventional 3:2:1 crack, and the 1:1 cracked spread which is tested to test if the relationship between the two products is less complex than intuitively predicted. Formula 3.4 illustrates the logic behind the spread calculation. Since both products are trading in 42,000 gallons per contact, the calculation is simply the ratio multiplied by the price after which both results are subtracted. The 2:1 ratio implies that m = 0,5 and n = 1 while the 1:1 ratio holds both variables at 1.

*Formula 3.4 Cracked Spread 0:2:1 & 0:1:1*

$$C'dSV(t,T) = \mathrm{m} \times \mathrm{HU(t,T)} \ - \ \mathrm{N} \times \mathrm{HO(t,T)} \tag{3.4}$$

NYMEX indentifies the spread between propane and natural gas as the Frac spread. The rationale behind this spread is that Natural Gas processing is a primary raw material for propane production. The spread allows propane producers to hedge their production margin against unfavourable market movements. The two products trade in completely different measurements, propane in 42,000 gallons per contract while natural gas is traded in 10,000 million British thermal units (mmBtu), creating a conversion problem.

*Formula 3.5 Frac Spread 5:2*

$$FSV(t,T) = 0.0915 \times \mathrm{PN(t,T)} \ - \ \mathrm{NG(t,T)} \tag{3.5}$$

In Formula 3,5, which illustrates the spread calculation, a 0.0915 conversion factor is used. This factor is based in the concept that one gallon of propane (PN) generates approximately 91,500 Btus or 0.0915 mmBtus. The most common Frac ratio's are 5:2 and 3:1, here the 5:2 ratio is used since the heating value of propane relative to natural gas is (NG) on average 38.4%, according to Kinday & Parrish (2006), which is closer to this ratio. The converted price of propane per mmBtu is than subtracted by the price of natural gas to calculate the Frac spread value. Mougoué (2007) evaluated the same spread relationship.

The oil/propane Frac spread is a variation on the original Frac, based on the rationale that propane can also be produced from crude. Consequently, this theoretical relationship allows for a possible tradable spread in the future markets. Since the standard or average conversion relationship between both products cannot be obtained, the study uses a simple 1 to 1 ratio and an arbitrary conversion factor of 50 (since 50 creates a propane price that is relatively equal in size to the crude price). The Oil Frac spread value is estimated by subtraction of the propane prices adjusted by a factor of 50 from the price of crude.

*Formula 3.6 Oil Frac Spread 1:1*

$$OFSV(t,T) = \mathrm{CL(t,T)} - 50 \times \mathrm{PN(t,T)} \quad (3.6)$$

The spreads have been created as separate data sets to allow for statistical analysis. Tables 3.2 and 3.3 provide the descriptive statistics for the spread data.

*Table 3.2 Descriptive Statistics of Spreads*

| *Spread Data* | *Crack 3;2;1* | *Crack 1;1;0* | *Crack 1;0;1* | *Cracked 0;2;1* |
|---|---|---|---|---|
| Mean | 7,0649 | 7,2501 | 6,6947 | 0,5625 |
| Std Deviation | 4,2306 | 4,9316 | 5,8735 | 0,3098 |
| Kurtosis | 4,6166 | 6,7269 | 1,5344 | 0,4376 |
| Skewness | 1,9313 | 2,0034 | 1,3875 | 1,1471 |
| Maximum | 29,4816 | 36,7910 | 36,1148 | 1,5756 |
| Minimum | 0,9152 | -7,6060 | -0,1954 | 0,1638 |
| Count | 3630 | 3630 | 3630 | 3630 |

| *Spread Data* | *Cracked 0;1;1;* | *Frac *0.0915* | *Oil Frac *50* |
|---|---|---|---|
| Mean | 0,0132 | 2,2645 | 7,1504 |
| Std Deviation | 0,1582 | 2,1901 | 8,7579 |
| Kurtosis | 2,7934 | 2,7899 | 4,3673 |
| Skewness | -1,2173 | 1,6788 | 1,8645 |
| Maximum | 0,5457 | 11,5368 | 53,5650 |
| Minimum | -0,6795 | -3,4366 | -17,7800 |
| Count | 3630 | 3629 | 3629 |

The tables, presented above, illustrate that the differences between the spread data is very large. The standard deviation is large for all spreads (as was theoretically expected), however in the case the Cracked 1:1 and Oil Frac spread the standard deviation is bigger than the mean and for the conventional Frac spread standard deviation and mean are approximately equal indicating a large variation from positive to negative spread values. The difference between the highest and lowest observations furthermore indicate that both the 3:2:1 crack and 2:1 cracked spread never fall into negative territory which is surprising for spread calculations.

## *3.4 Technical Analysis Methodology Construction*

One of the reasons technical analysis became widely researched in the academic world is the increased processing power of computers. It is therefore essential that, when analysing technical analysis, one is able to create and evaluate automated trading systems. This analysis uses Tradestation 8.16 for this task, which is a software package (widely used in the financial industry) with a build-in code compiler to allow the user to create and evaluate tailor made trading strategies. The compiler uses a special purpose computer language called EasyLanguage (based on the Pascal Code) to transform strategies into computer code.

This paper analyses the effectiveness of Bollinger Bands as a signalling method for spread trading. BB's where invented in the 1980's by John Bollinger, a CNBC commentator, Bollinger (2002). The tool uses past X days of data to create a Moving Average. Over the same X days of data it calculates the standard deviation and uses this to create a moving trading band around the M.A. (using the M.A. as mean). The idea for this research is that a break out of the upper (lower) standard deviation band indicates an exception from the regular pattern signalling an opportunity to sell (buy) (short the end product and long the source product) since a return into the bands is expected. The BB therefore is a variation on a trading band with the advantage that the band's width varies along with the volatility of the underlying instrument. These deviations from the mean are magnified through the use of standard deviations which allows BB's to show volatility so clearly. Formula 3.7 illustrates the BB calculation where n is the time period used and Y the amount of times the standard deviation is taken to create the band (positive for upper band and negative for lower band).

*Formula 3.7 Bollinger Band Calculation*

$$MA(t,T) = \frac{\sum_{k=1}^{n} p(t...t-n)}{n} \qquad BB(t,T) = MA(t,T) + \sigma \times Y \tag{3.7}$$

*Illustration 3.1 Bollinger Band of Crude 2005-2009*


Illustration 3.1 provides a visual BB representation of crude oil prices over the 2005-2009 period. The green symbols represent the future prices while the red line is the lower band (BB-low), the blue line the upper band (BB-up), and the grey line the M.A.

The Bollinger Bands are coded[3] in the following way:

```
Bollingerband = Average (Price, Length) + NumDevs +
StandardDev (Price, Length, 1)
Cl2 = close of data2

BB-Average = Average (cl2, Length)
BB-up = Bollingerband (cl2, Length, Std. dev.)
BB-low = Bollingerband (cl2, Length, -Std. dev.)
```

[3] The coded and other Bollinger Band examples are all presented as buy on break out of upper band for clarity. One has to keep into account that spread positions has both a buy and a sell element simultaneously

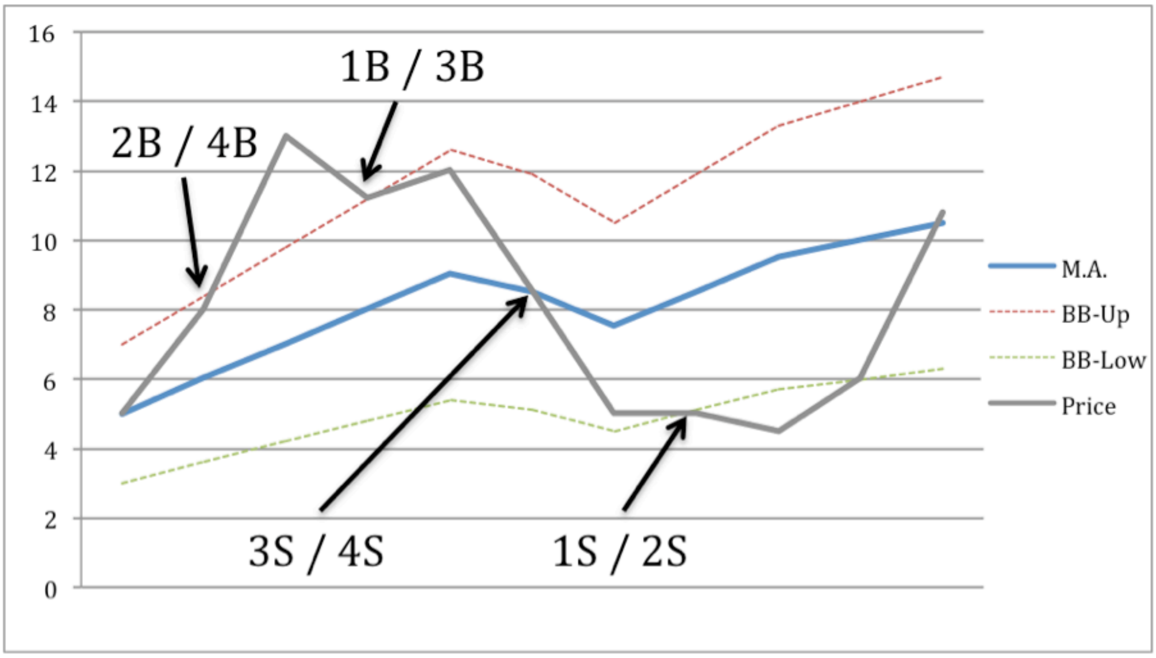
The BB model creates an indicator from which one can extrapolate trading signals. What trading signals and at what moment to trade is subject to debate. This analysis therefore takes four different signalling settings namely:

1. Buy when price moves back into band and sell when it moves out opposite band
2. Buy when price moves out of the band and sell when it moves out opposite band
3. Buy when price moves back into band and sell when it crosses the M.A.
4. Buy when price moves out of the band and sell when it crosses the M.A.

Bollinger bands are most commonly used as setting 2 as tested by Lento & Gardojevic (2007), Lento, Gardojevic & Wright (2007), and referring to the buy signal by Mougoué (2007) since here a sell order is automatically executed are a certain period. Setting 1 is tested by Leung & Chong (2003) and is tested here since it considers long-term irrationality. The selling on M.A. is a variation, often used in trading, on the original model which is takes the form of a profit/loss stop on the original sell setting.

The hypothetical graph presented in Illustration 3.2 visually shows the buy and sell moments for the different settings. The points are identified with for example 1B which respresents a buying signal of the first setting, or 3S which indicates a sell signal of the third setting. The graph does not present any short signals, however one can logically create this by using the long signals in an opposite situation. The short signals can also be identified from the examples of code, which are presented below the illustration.

*Illustration 3.2 Exemplary Bollinger Band for signals illustration*




The 1st setting (buy cross in sell cross out, abbreviated into: BCISCO ) is coded by[4]:

```
if Spread crosses under BB-up then buy next bar open;
if Spread crosses under BB-low then sell this bar close ;
if Spread crosses under BB-low then sellshort next bar open;
if Spread crosses under BB-up then buytocover this bar close;
```

The 2nd setting (buy cross out sell cross out, abbreviated into: BCOSCO) is coded by:

```
if Spread crosses over BB-up then buy next bar open;
if Spread crosses under BB-low then sell this bar close ;
if Spread crosses under BB-low then sellshort next bar open;
if Spread crosses over BB-up then buytocover this bar close;
```

The 3rd setting (buy cross in sell M.A., abbreviated into: BCISMA) is coded by:

```
if Spread crosses under BB-up then buy next bar open;
if Spread crosses under BB-Average then sell this bar close ;
if Spread crosses over BB-low then sellshort next bar open;
if Spread crosses over BB-Average then buytocover this bar
close;
```

[4] The definition and codes of BB-up, BB-Low and BB-Average are presented above, page 24 / 25

The 4th setting (buy cross out sell M.A., abbreviated into: BCOSMA) is coded by:

```
if Spread crosses over BB-up then buy next bar open;
if Spread crosses under BB-Average then sell this bar close ;
if Spread crosses under BB-low then sellshort next bar open;
if Spread crosses over BB-Average then buytocover this bar
close;
```

The second group of variations used is the variables within the Bollinger Band. When creating a BB, one has to choose a moving average time period and a standard deviation setting. This study test three settings: 20 day period and 2 standard deviations, 12 days and 1.555 standard deviations, and finally 50 days and 1.645 standard deviations.

Due to Bollinger (2002) the conventional variable is a 20 day period with 2 standard deviations bands. When one takes a trading program, website, or any other tool and implements a, pre-programmed, BB over the data a time period of 20 days with 2 standard deviation bands is used. Bollinger (2002) based this statement on the idea that this setting will allow a 1 month period (approximately 20 trading days) and allows for 88 to 89 percent of prices to be contained into the band, Bollinger (2002), which he argues yield most profits. This same setting is also evaluated by Leung & Chong (2003), Lento & Gardojevic (2007), and Lento, Gardojevic & Wright (2007).

The test of a 12 day period with 1.55 standard deviations is based on a paper, summarized above, from Lui, et al. (2006). They create a theoretical mathematical comparison between BB's and the Black & Scholes model. This comparison identifies that a 12 day moving average with bands including 88% standard deviations. (which is equal to a std. dev. z-score of 1.555) is the theoretical optimal setting to identify break out with mean reversing characteristics.

The final variable is a long-term system. Here the moving average is set to 50 days and the standard deviation to 90%, or 1.645. This choice is taken arbitrarily with the theoretical logic of 50 days being the maximum Bollinger (2002) presents and 1.645 representing 90% under a standard normal distribution.

The 20 day 2 standard deviation is coded in the following way:

```
BB-Average = Average (cl2, 20)
BB-up = Bollingerband (cl2, 20, 2)
BB-low = Bollingerband (cl2, 20, -2)
```

The 12 day 1.55 standard deviation is coded in the following way:

```
BB-Average = Average (cl2, 12)
BB-up = Bollingerband (cl2, 12, 1.555)
BB-low = Bollingerband (cl2, 12, -1.555)
```

The 50 day 1.645 standard deviation is coded in the following way:

```
BB-Average = Average (cl2, 50)
BB-up = Bollingerband (cl2, 50, 1.645)
BB-low = Bollingerband (cl2, 50, -1.645)
```

### *3.5 Trading & Return analysis*

Transaction costs are estimated to be $100 for a regular full trade. This incorporates items like bid-spread deviation, brokerage costs, etc. These costs are consistent with Poitras & Rechner (1993), Poitras & Teoh (2003), Girma & Paulson (1999), and Anderson (2002). Since the complexity of the spread position evaluated varies, transaction costs have been set to $20 round trip per contact to adjust for the different contract amounts between the different spread positions. This setting results in average transaction costs to be below the $100 mark, however since most strategies require only 2 contracts per trade, intuitively this appears to be a healthy estimation.

Example of a full coded strategy

```
Variable: Cl2(0), BB-up(0), BB-Average(0), BB-low(0)
Cl2 = close of data2

BB-Average = Average (cl2, 12)
BB-up = Bollingerband (cl2, 12, 1.555)
BB-low = Bollingerband (cl2, 12, -1.555)
```

```
if Spread crosses under BB-up then buy 1000 contracts next bar
open;
if Spread crosses under BB-Average then sell 1000 contracts
this bar close ;
if Spread crosses over BB-low then sellshort 1000 contracts
next bar open;
if Spread crosses over BB-Average then buytocover 1000
contracts this bar close;
```

The strategies determine the amount of products bought depending on the strategy applied. The strategies signal to buy the number of contracts times the number of products per contracts and term this as “contracts”. The number of products purchased represents the amount of products (barrels, gallons, mmbtu) the future contract stipulates times the spread ratio requirement, it therefore varies from 1000 for the 1 crude contract (1000 barrels times 1) to 210,000 for 5 propane contracts (42,000 gallons times 5 contracts). This workaround is created since it is easier to code this than to manually adjust the setting of every strategy for the required quantity of products per contract[5]. The strategies do not incorporate any other elements like stop-loss or fixed amount of days after purchase sale for the reason that this study does not analyse trading strategies but analyses the functionality of BB’s as a market movement signal in energy spreads.

The individual product and spread data is loaded into Tradestation over which the strategies are evaluated. The strategies use the spread data as the signalling source while trading on the product data. Due to a Tradestation limitation (it allows only trading with one product per workplace requiring multiple results per spread) the analysis was performed per product, and then exported into excel for combination and further, statistical, analysis. Due to this limitation the “contract quantity” workaround, explained above, produced additional testing efficiency. Here the, for example, the long heating oil and unleaded gasoline positions are combined with the short crude position to create the spread position.

[5] Tradestation requires a manual input to adjust the contract specific number of products in order to calculate the total value of one contract. Leaving this at 1 and making this adjustment in the coding saves a great amount of time however unfortunatley reduces clariy

The combination of the different trading data is organised via the use of gross profit positions per trade and then combined over the multiple product series. The transaction costs are taken into account to create per trade profit positions. This series is then used for descriptive and statistical analysis. The results are used to generate: the average position per trade, total profit, total generated profit, total generated loss, total number of trades, percentage profitable, total transaction costs, standard deviation, t-value (one-sample t-test where 1.645 represents a 95% and 2.576 a 99% probability that the result is statistically different from zero), kurtosis, skewness, maximum and minimum. The methodological explanation assumes that the reader is familiar with the statistical tools listed above (appendix C provides some more detailed information about the descriptive statistics used).

Final open position (the last opened position not yet closed: sold/boughttocover) is not taken into account in the result analysis, which however should not have any influence over the trading results since the testing period is big enough without this factor.

Though this analysis does not strive to search for profitable trading methods for future technical trading, the results indicate that some strategies appear to be exceptionally profitable. This can be both positive and negative results, since an extreme negative results indicates a inverse correlation between the spread movement and the product move. Therefore, the study evaluates most profitable settings and variables in-depth. The data divided over three periods (1995-2000, 2001-2005, 2006-2009), a break-even transaction costs figure is provided, and an equity curve is constructed. The results are presented and analysed to indicate whether or not these settings require more analysis for transformation into potentially successful trading strategies.

### *3.6 Conclusion*

The above has illustrated the thoroughness and depth of the analysis. Since the analysis is executed through coding, it is hard to visualize the process. The combination of the different spread constructions and the different BB settings and variables provide sufficient results to generate meaningful conclusions concerning the combination of both items as BB and energy spreads individually.

# 4.0 Empirical Results

## *4.1 Introduction*

The evaluation of BB in light of energy spreads is based on the quantity of tests with a focus on statistical analysis. The test results are presented in separate paragraphs starting with the average results along with the extreme individual results (appendix D lists the results for all tests). Afterwards, paragraph 4.3 provides the analysis of specific Bollinger Band settings which will be followed by the specific BB variables in paragraph 4.4. The results grouped by spreads are evaluated in paragraph 4.5 and finally an in-depth look into the most profitable trading strategies can be found in paragraph 4.6.

## *4.2 Individual Results*

Illustration 4.1 provides a buy and sell signal diagram to illustrate how the strategies are tested. Subsequently, table 4.1 illustrates the average total results whilst table 4.2 illustrates the profitable strategies followed by tables 4.3 and 4.4 which show the top 3 best and worst performing strategies. Afterwards, these results are evaluated to show and explain that BB's ability to signal energy spread movements is not significant. As stated above, all results are provided in appendix D

*Illustration 4.1 BB Buy & Sell signal diagram of Crack 3:2:1 - ma 20 sd 2*

*Table 4.1 Total average test results*[6]

| **Trades** | *Total avg. results* |
|---|---|
| Average Net Profit Per Trade | -$ 397,02 |
| Avg. Total Net Profit | -$ 75.778,76 |
| Avg. Total Generated Profit | $ 246.458,32 |
| Avg. Total Generated Loss | -$ 322.237,08 |
| Avg. Number of Trades | 135,2 |
| Avg. Percent Profitable | 34,76% |
| Avg. Total Transaction Costs *Per Trade* | $ 8.926,19 |
| Avg. Standard Deviation | $ 7.684,10 |
| Sum t-Value | -5,506 |
| Avg. Kurtosis | 9,316 |
| Avg. Skewness | 1,503 |
| Maximum | $ 148.100,00 |
| Minimum | -$ 79.840,00 |

The analysis illustrates that the Bollinger Band trading system is not a good predictor of energy spread market movement. Overall, the model produced mostly negative results. Exactly 25% of the strategies have positive results (table 4.2 provides an overview of all profitable strategies), while 64.3% results are not statistically significant (even though the number of trades are large enough to expect reliable t-test statistics) illustrating this point. The only strategies whose results are consistently statistically significant are the Crack spread 3:2:1 / 20-2, the Crack spread 1:0:1 / 20-2 and the Frac spread 5:2 / 12-1.55. An average total return of - $ 75,778.76, an average profit per trade of - $ 397.02, and the average profitable trade percentage of 34.76% furthermore imply the rejection of Bollinger Bands as a viable indicator which is finally elucidated by the t-value of 5.506 which represents a 99,99999998% significance.

*Table 4.2 Overview of profitable strategies*[7]

| **Profitable Trades** | | *Profit p. trade* | *Total profit* | *t-value* |
|---|---|---|---|---|
| 1. BCISCO | | | | |
| Cracked 0:1:1 | m.a. 50 std. 1.645 | $ 775,29 | $ 39.540,00 | 1,048 |
| Cracked 0:2:1 | m.a. 20 std. 2 | $ 3.679,22 | $ 253.866,00 | **1,882** |
| Frac 5:2 | m.a. 20 std. 2 | $ 450,28 | $ 31.970,00 | 0,138 |
| Frac 5:2 | m.a. 50 std. 1.645 | $ 3.514,20 | $ 175.710,00 | 0,862 |
| Oil Frac 1:1 | m.a. 12 std. 1.55 | $ 174,88 | $ 174,88 | 0,737 |
| 2. BCOSCO | | | | |
| Crack 1:1:0 | m.a. 50 std. 1.645 | $ 4,13 | $ 194,00 | 0,006 |
| Cracked 0:1:1 | m.a. 20 std. 2 | $ 197,08 | $ 14.978,00 | 0,309 |
| Cracked 0:1:1 | m.a. 12 std. 1.55 | $ 18,95 | $ 3.240,00 | 0,057 |

[6] t-value, max & min are specific calculations for this table and following "average tables"
[7] Sign. = statistically significant under 95% confidence level

| | | | | |
|---|---|---|---|---|
| Cracked 0:1:1 | m.a. 50 std. 1.645 | $ 710,12 | $ 35.506,00 | 0,841 |
| Cracked 0:2:1 | m.a. 20 std. 2 | $ 3.839,91 | $ 264.954,00 | **1,952** |
| Cracked 0:2:1 | m.a. 50 std. 1.645 | $ 2.613,18 | $ 133.272,00 | 1,226 |
| Frac 5:2 | m.a. 50 std. 1.645 | $ 1.837,00 | $ 91.850,00 | 0,490 |
| Oil Frac 1:1 | m.a. 12 std. 1.55 | $ 114,07 | $ 20.076,00 | 0,499 |
| 3. BCISMA | | | | |
| Cracked 0:1:1 | m.a. 50 std. 1.645 | $ 702,69 | $ 58.323,40 | 1,440 |
| Cracked 0:2:1 | m.a. 12 std. 1.55 | $ 56,34 | $ 15.438,00 | 0,135 |
| Cracked 0:2:1 | m.a. 50 std. 1.645 | $ 157,88 | $ 12.630,00 | 0,107 |
| 4. BCOSMA | | | | |
| Crack 1:1:0 | m.a. 50 std. 1.645 | $ 34,28 | $ 2.914,00 | 0,076 |
| Cracked 0:1:1 | m.a. 20 std. 2 | $ 351,68 | $ 46.422,00 | 0,903 |
| Cracked 0:1:1 | m.a. 50 std. 1.645 | $ 383,07 | $ 31.412,00 | 0,673 |
| Cracked 0:2:1 | m.a. 20 std. 2 | $ 927,58 | $ 120.585,60 | 0,988 |
| Cracked 0:2:1 | m.a. 50 std. 1.645 | $ 2.327,54 | $ 181.548,00 | 1,520 |

The three most successful strategies based on total earnings are generated with the cracked Spread 0:2:1. Although one of them is not statistically significant (93,6%, just below the 95% confidence level) the other two are both profitable and significant but have a profitability percentage of 47,83% and 43,48% indicating potential problems as a structural trading methodology. This strategy will be further analysed for potential trading in paragraph 4.6. The three results with the highest percentage of profitable trading (53,33%, 50,00, and 48.19%) are not statistically significant, however the fact that they are approximately 50% profitable already contradicts to the concept of a working signal.

*Table 4.3 3 Best performing strategies*

| ***Cracked Spread 0;2;1*** | **BCISCO** | **BCOSCO** | **BCOSMA** |
|---|---|---|---|
| | *ma.20 sd.2* | *ma.20 sd.2* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | $ 3.679,22 | $ 3.839,91 | $ 2.327,54 |
| Total Net Profit | $ 253.866,00 | $ 264.954,00 | $ 181.548,00 |
| Total Generated Profit | $ 488.370,00 | $ 489.096,00 | $ 401.616,00 |
| Total Generated Loss | -$ 234.504,00 | -$ 224.142,00 | -$ 220.068,00 |
| Total Number of Trades | 69 | 69 | 78 |
| Percent Profitable | 47,83% | 43,48% | 41,03% |
| Total Transaction Costs | $ 4.140,00 | $ 4.140,00 | $ 4.680,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 16.239,70 | $ 16.339,22 | $ 13.521,88 |
| t-Value | 1,882 | 1,952 | 1,520 |
| Kurtosis | 5,306 | 5,707 | 9,148 |
| Skewness | 1,898 | 2,186 | 2,546 |
| Maximum | $ 69.786,00 | $ 71.046,00 | $ 71.046,00 |
| Minimum | -$ 25.638,00 | -$ 15.432,00 | -$ 19.422,00 |

Although most strategies have negative results, only 15% of the tests have a bigger minimum performance per trade than a bigger maximum performance. The primary reason for this is that almost all strategies generated large profitable results during the collapse of the resources markets in the 3rd and 4th quarter of 2008.

*Table 4.4 3 Worst performing strategies*

| ***Frac Spread 5;2*** | **BCOSCO** | **BCISMA** | **BCOSMA** |
|---|---|---|---|
| | *ma.12 sd.1.55* | *ma.12 sd.1.55* | *ma.12 sd.1.55* |
| Average Net Profit Per Trade | -$ 3.158,66 | -$ 2.163,49 | -$ 2.549,73 |
| Total Net Profit | -$ 634.890,00 | -$ 644.720,00 | -$ 757.270,00 |
| Total Generated Profit | $ 1.183.940,00 | $ 403.980,00 | $ 572.020,00 |
| Total Generated Loss | -$ 1.818.830,00 | -$ 1.048.700,00 | -$ 1.329.290,00 |
| Total Number of Trades | 201 | 298 | 297 |
| Percent Profitable | 33,33% | 22,48% | 19,53% |
| Total Transaction Costs | $ 28.140,00 | $ 41.720,00 | $ 41.580,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 24.654,01 | $ 7.459,60 | $ 10.400,49 |
| t-Value | -1,816 | -5,007 | -4,225 |
| Kurtosis | 12,428 | 12,360 | 12,578 |
| Skewness | 2,006 | 1,929 | 2,323 |
| Maximum | $ 148.100,00 | $ 44.490,00 | $ 60.190,00 |
| Minimum | -$ 79.840,00 | -$ 29.750,00 | -$ 35.960,00 |

A reverse Bollinger Band strategy, using a band cross as an indicator of further price moves in that direction, would transfer the losses into profits (the +/- signal does not simply change since transaction costs are also a loss). Table 4.4 illustrates that the strategy with most potential is the Frac spread 5:2 with 12 day and 1.55 standard deviation setting since this variable has the three highest total losses (The fourth biggest is the BCISMA setting of this strategy). The best setting is buy on cross out and sell on moving average where 19.53% of trades are profitable and overall profit, including transaction costs, is - $ 757,270 ($ 674,110 profit when adjusted for Transaction costs). The 5:2 Frac spread also generates the highest maximum profitable trade of $ 148,100, which is generated by the buy on cross out and sell cross out setting during the 2008 resources market collapse. Furthermore, the fact that the maximum return/loss of the sell on moving average setting are relatively small indicates that this setting has a relatively even return distribution. The above and the large t-value significance, well above the 99% for the sell on moving average and above 95% for the BCOSCO setting, illustrate an inverse trading potential which will be analysed in paragraph 4.5 in-depth.

## *4.3 Bollinger Band Settings Results*

The results specific to the different setting chosen for the BB's are presented in table 4.5. The tables illustrate that the buy on cross in sell on cross out and the buy on cross out sell on cross out are both not statistically significant (calculated over the average results). The setting where the sell signal comes from a moving average crossing has better results, indicating the requirement for different sell strategies.

*Table 4.5 Total Bollinger Band settings Results*

| **Trades** | Buy cross In | *Buy cross out* | B cr in SellMA | *B c.out SellMA* |
|---|---|---|---|---|
| Average Net Profit Per Trade | -$ 281,14 | -$ 220,93 | -$ 567,23 | -$ 508,26 |
| Avg. Total Net Profit | -$ 45.490,61 | -$ 53.244,91 | -$ 98.500,30 | -$ 103.343,73 |
| Avg. Total Generated Profit | $ 244.343,62 | $ 257.411,45 | $ 221.565,39 | $ 250.255,14 |
| Avg. Total Generated Loss | -$ 289.834,23 | -$ 310.656,36 | -$ 320.065,70 | -$ 353.598,88 |
| Avg. Number of Trades | 104,5 | 98,7 | 166,6 | 166,3 |
| Avg. Percent Profitable | 36,05% | 34,76% | 34,03% | 32,53% |
| Avg. Total Transaction Costs *Per Trade* | $ 6.914,29 | $ 6.523,64 | $ 10.944,76 | $ 11.011,43 |
| Avg. Standard Deviation | $ 9.128,71 | $ 8.879,07 | $ 6.034,66 | $ 6.271,13 |
| Sum t-Value | -1,443 | -1,160 | -5,560 | -4,789 |
| Avg. Kurtosis | 7,873 | 5,951 | 13,235 | 9,922 |
| Avg. Skewness | 1,284 | 1,444 | 1,411 | 1,805 |
| Maximum | $ 128.490,00 | $ 148.100,00 | $ 140.130,00 | $ 116.390,00 |
| Minimum | -$ 56.020,00 | -$ 79.840,00 | -$ 43.252,00 | -$ 35.960,00 |

The buy on cross out sell on moving average has worst performance hence is most suitable for reverse strategy applications. This result further strengthens the motivation for further analysis of this setting for the Frac spread (which was most potentially profitable).

## *4.4 Bollinger Band Variables Results*

Table 4.6 shows the average results per variable. The long term, 50 – 1.645, variable is not statistically significant (calculated over the average results) and is close to the 50% profitability percentage marker.

*Table 4.6 Total Bollinger Band variables Results*

| **Trades** | var 20 - 2 | *var 12 - 1.55* | var 50 - 1.64 |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 326,82 | -$ 688,33 | -$ 175,91 |
| Avg. Total Net Profit | -$ 42.561,26 | -$ 162.115,60 | -$ 22.659,41 |
| Avg. Total Generated Profit | $ 224.999,43 | $ 337.824,40 | $ 176.551,14 |
| Avg. Total Generated Loss | -$ 267.560,69 | -$ 499.940,00 | -$ 199.210,56 |
| Avg. Number of Trades | 105,2 | 229,3 | 71,1 |
| Avg. Percent Profitable | 34,03% | 34,45% | 35,79% |
| Avg. Total Transaction Costs *Per Trade* | $ 6.815,00 | $ 15.302,14 | $ 4.661,43 |
| Avg. Standard Deviation | $ 8.235,13 | $ 6.071,36 | $ 8.745,80 |
| Sum t-Value | -2,154 | -9,085 | -0,897 |
| Avg. Kurtosis | 9,252 | 10,434 | 8,263 |
| Avg. Skewness | 1,458 | 1,318 | 1,734 |
| Maximum | $ 139.080,00 | $ 148.100,00 | $ 140.130,00 |
| Minimum | -$ 49.620,00 | -$ 79.840,00 | -$ 44.538,00 |

When analysing the results from a reverse strategy viewpoint the 12 – 1.55 again appears to have the most potential. The statistical significance is very large, at 9.085, as is the generated loss.

## *4.5 Spread Results*

The average spread results, presented in Table 4.7 and 4.8, illustrate that only the cracked (0:2:1 & 0:1:1) are profitable on average. The profitability percentage of both spreads was below the 50% indicating potential problems, furthermore, this is illustrated by the fact that the cracked 0:1:1 spread is not statistically significant.

*Table 4.7 Total Spread specific Results 1*

| **Trades** | *Crack 3:2:1* | *Crack 1:0:1* | *Crack 1:1:0* | *Cracked 0:1:1* |
|---|---|---|---|---|
| Average Net Profit Per Trade | -$ 1.815,08 | -$ 473,10 | -$ 378,94 | $ 174,04 |
| Avg. Total Net Profit | -$ 211.089,23 | -$ 52.846,50 | -$ 54.533,58 | $ 6.977,39 |
| Avg. Total Generated Profit | $ 235.858,33 | $ 63.649,67 | $ 129.187,42 | $ 185.606,69 |
| Avg. Total Generated Loss | -$ 446.947,57 | -$ 116.496,17 | -$ 183.721,00 | -$ 178.629,30 |
| Avg. Number of Trades | 130,8 | 136,7 | 129,7 | 131,7 |
| Avg. Percent Profitable | 33,28% | 30,38% | 36,43% | 42,46% |
| Avg. Total Transaction Costs *Per Trade* | $ 13.075,00 | $ 5.466,67 | $ 5.186,67 | $ 5.266,67 |
| Avg. Standard Deviation | $ 8.212,90 | $ 2.035,76 | $ 3.954,09 | $ 4.601,62 |
| Sum t-Value | -8,754 | -9,411 | -3,780 | 1,503 |
| Avg. Kurtosis | 8,175 | 5,503 | 5,695 | 5,131 |
| Avg. Skewness | 0,718 | 0,840 | 0,291 | 1,219 |
| Maximum | $ 49.562,00 | $ 18.936,00 | $ 19.284,00 | $ 24.404,00 |
| Minimum | -$ 43.906,00 | -$ 19.200,00 | -$ 21.856,00 | -$ 19.444,00 |

*Table 4.8 Total Spread specific Results 2*

| **Trades** | *Cracked 0:2:1* | *Frac 5:2* | *Oil Frac 1:1* |
|---|---|---|---|
| Average Net Profit Per Trade | $ 919,94 | -$ 973,62 | -$ 232,39 |
| Avg. Total Net Profit | $ 53.863,30 | -$ 250.860,83 | -$ 21.961,83 |
| Avg. Total Generated Profit | $ 441.208,00 | $ 557.459,17 | $ 112.239,00 |
| Avg. Total Generated Loss | -$ 387.344,70 | -$ 808.320,00 | -$ 134.200,83 |
| Avg. Number of Trades | 130,3 | 141,8 | 145,6 |
| Avg. Percent Profitable | 39,46% | 28,28% | 33,00% |
| Avg. Total Transaction Costs *Per Trade* | $ 7.820,00 | $ 19.845,00 | $ 5.823,33 |
| Avg. Standard Deviation | $ 12.237,92 | $ 19.530,81 | $ 3.215,56 |
| Sum t-Value | 2,973 | -2,056 | -3,021 |
| Avg. Kurtosis | 12,202 | 18,271 | 10,238 |
| Avg. Skewness | 2,380 | 3,067 | 2,008 |
| Maximum | $ 73.314,00 | $ 148.100,00 | $ 25.730,00 |
| Minimum | -$ 44.538,00 | -$ 79.840,00 | -$ 14.504,00 |

Again, the reverse strategy analysis indicates that the frac spread 5:2 has most potential for further strategy performance. An average profitability percentage of 28.28% illustrates this potential. The fact that the 0:2:1 cracked spread remains relatively profitable on average indicates a further need for a more in-depth analysis of this spread with a 20 – 2 variable.

## *4.6 Best Results Trading Analysis*

This section divides the 15 year period into three half decades to see whether the results are distributed relatively even. This analysis will not determine whether or not the strategies are suitable for future trading rather provide an illustration of potential need for further analysis on items like for example drawdown, return analysis or order size fluctuation. The best performing strategy of the study is analysed which results are presented in table 4.9. Here the Cracked 0:2:1 with 20 day m.a. and 2 standard deviations is analysed over the buy on cross in sell on cross out and buy on cross out sell on cross out settings.

*Table 4.9 Cracked 0:2:1 20 -2 results per 5 years*

| *BCISCO Cracked 0;2;1 20-2* | *Total* | *1995 - 1999* | *2000-2004* | *2005-2009* |
|---|---|---|---|---|
| Avg. Trade Net Profit | $ 3.679,22 | $ 1.805,11 | $ 3.081,16 | $ 6.373,30 |
| Total Net Profit | $ 253.866,00 | $ 48.738,00 | $ 58.542,00 | $ 146.586,00 |
| Gross Profit | $ 488.370,00 | $ 119.592,00 | $ 92.952,00 | $ 275.826,00 |
| Gross Loss | -$ 234.504,00 | -$ 70.854,00 | -$ 34.410,00 | -$ 129.240,00 |
| Total Number of Trades | 69 | 27 | 19 | 23 |

| | | | | |
|---|---|---|---|---|
| Percent Profitable | 47,83% | 48,15% | 47,37% | 47,83% |
| *Per Trade* | | | | |
| Standard Deviation | $ 16.239,70 | $ 11.021,28 | $ 7.992,61 | $ 24.640,01 |
| t-Value | 1,882 | 0,851 | 1,680 | 1,240 |
| Kurtosis | 5,306 | 7,049 | -1,301 | 1,208 |
| Skewness | 1,898 | 1,614 | 0,515 | 1,305 |
| Maximum | $ 69.786,00 | $ 42.402,00 | $ 16.908,00 | $ 69.786,00 |
| Minimum | -$ 25.638,00 | -$ 23.370,00 | -$ 6.318,00 | -$ 25.638,00 |

| *BCOSCO Cracked 0;2;1 20-2* | *Total* | *1995 - 1999* | *2000-2004* | *2005-2009* |
|---|---|---|---|---|
| Avg. Trade Net Profit | $ 3.839,91 | $ 1.990,22 | $ 2.314,11 | $ 7.271,74 |
| Total Net Profit | $ 264.954,00 | $ 53.736,00 | $ 43.968,00 | $ 167.250,00 |
| Gross Profit | $ 489.096,00 | $ 123.576,00 | $ 88.962,00 | $ 276.558,00 |
| Gross Loss | -$ 224.142,00 | -$ 69.840,00 | -$ 44.994,00 | -$ 109.308,00 |
| Total Number of Trades | 69 | 27 | 19 | 23 |
| Percent Profitable | 43,48% | 40,74% | 47,37% | 43,48% |
| *Per Trade* | | | | |
| Standard Deviation | $ 16.339,22 | $ 13.712,38 | $ 8.549,96 | $ 22.904,81 |
| t-Value | 1,952 | 0,754 | 1,180 | 1,523 |
| Kurtosis | 5,707 | 15,368 | -1,043 | 1,285 |
| Skewness | 2,186 | 3,610 | 0,588 | 1,298 |
| Maximum | $ 71.046,00 | $ 62.604,00 | $ 19.470,00 | $ 71.046,00 |
| Minimum | -$ 15.432,00 | -$ 9.258,00 | -$ 7.956,00 | -$ 15.432,00 |

The tables illustrate that 5 of the 6 periods are statistically insignificant. The fact that only the buy on cross in of the period 2000-2004 is significant (with 95% confidence, but not 99%) illustrates that this strategy is not as strong as it seems. On the other hand, one has to keep into account that the small amount of trades has a big influence on the significance level. Of the profit harvested, approximately 60% is generated in the last 5 years for both strategies signalling a high dependability on high volatility, though the other periods still harvest a profit. All the profitability percentages are close to the 50% benchmark, further decaying the strategy's potential. The break-even point transaction costs[8] is $ 3739 for the buy on cross in sell on cross out and $ 3800 for the buy in cross out sell on cross out strategy which is relatively high. Due to the above and the fact that a total return of $ 253,866 and $ 264,954 respectively over a 15 year period is not very substantial, this paper advises not to continue with further research into this strategy combination. However, further analysis of the spread in combination with other trading methods looks potentially promising.

[8] Break even transaction costs: The level of transactions costs where the trading strategy's yield is approx. zero

*Table 4.10 Frac 5:2 12 -1.55 results per 5 years*

| *BCISCO Frac 5:2 12-1.55* | *Total* | *1995 - 1999* | *2000-2004* | *2005-2009* |
|---|---|---|---|---|
| Avg. Trade Net Profit | $ 2.036,81 | $ 488,14 | $ 2.244,03 | $ 3.310,93 |
| Total Net Profit | $ 421.620,00 | $ 34.170,00 | $ 139.130,00 | $ 248.320,00 |
| Gross Profit | $ 1.121.250,00 | $ 167.920,00 | $ 271.030,00 | $ 682.300,00 |
| Gross Loss | -$ 699.630,00 | -$ 133.750,00 | -$ 131.900,00 | -$ 433.980,00 |
| Total Number of Trades | 207 | 70 | 62 | 75 |
| Percent Profitable | 73,91% | 74,29% | 72,58% | 74,67% |
| *Per Trade* | | | | |
| Standard Deviation | $ 15.318,41 | $ 7.223,11 | $ 7.648,31 | $ 23.503,34 |
| t-Value | 1,913 | 0,565 | 2,310 | 1,220 |
| Kurtosis | 27,957 | 10,768 | 1,862 | 13,711 |
| Skewness | -3,482 | -2,719 | -1,263 | -2,773 |
| Maximum | $ 55.740,00 | $ 12.690,00 | $ 13.510,00 | $ 55.740,00 |
| Minimum | -$ 128.770,00 | -$ 33.950,00 | -$ 24.640,00 | -$ 128.770,00 |

| *BCOSCO Frac 5:2 12-1.55* | *Total* | *1995 - 1999* | *2000-2004* | *2005-2009* |
|---|---|---|---|---|
| Avg. Trade Net Profit | $ 2.822,24 | $ 1.072,88 | $ 3.903,83 | $ 3.496,40 |
| Total Net Profit | $ 567.270,00 | $ 70.810,00 | $ 234.230,00 | $ 262.230,00 |
| Gross Profit | $ 1.282.650,00 | $ 184.370,00 | $ 329.190,00 | $ 769.090,00 |
| Gross Loss | -$ 715.380,00 | -$ 113.560,00 | -$ 94.960,00 | -$ 506.860,00 |
| Total Number of Trades | 201 | 66 | 60 | 75 |
| Percent Profitable | 74,13% | 71,21% | 75,00% | 76,00% |
| *Per Trade* | | | | |
| Standard Deviation | $ 15.757,57 | $ 6.806,15 | $ 7.407,57 | $ 24.124,00 |
| t-Value | 2,539 | 1,281 | 4,082 | 1,255 |
| Kurtosis | 13,810 | 11,675 | 1,620 | 5,650 |
| Skewness | -1,993 | -2,327 | -1,015 | -1,537 |
| Maximum | $ 64.020,00 | $ 16.040,00 | $ 17.200,00 | $ 64.020,00 |
| Minimum | -$ 106.080,00 | -$ 34.890,00 | -$ 20.100,00 | -$ 106.080,00 |

| *BCISMA Frac 5:2 12-1.55* | *Total* | *1995 - 1999* | *2000-2004* | *2005-2009* |
|---|---|---|---|---|
| Avg. Trade Net Profit | $ 1.883,49 | $ 728,87 | $ 661,81 | $ 3.691,95 |
| Total Net Profit | $ 561.280,00 | $ 70.700,00 | $ 54.930,00 | $ 435.650,00 |
| Gross Profit | $ 985.540,00 | $ 163.110,00 | $ 189.130,00 | $ 633.300,00 |
| Gross Loss | -$ 424.260,00 | -$ 92.410,00 | -$ 134.200,00 | -$ 197.650,00 |
| Total Number of Trades | 298 | 97 | 83 | 118 |
| Percent Profitable | 72,82% | 63,92% | 68,67% | 83,05% |
| *Per Trade* | | | | |
| Standard Deviation | $ 7.459,60 | $ 5.021,96 | $ 5.786,31 | $ 9.572,51 |
| t-Value | 4,359 | 1,429 | 1,042 | 4,190 |
| Kurtosis | 12,360 | 34,319 | 13,858 | 8,553 |
| Skewness | -1,929 | -4,540 | -2,774 | -1,776 |
| Maximum | $ 29.470,00 | $ 12.690,00 | $ 10.880,00 | $ 29.470,00 |
| Minimum | -$ 44.770,00 | -$ 37.210,00 | -$ 33.260,00 | -$ 44.770,00 |

| BCOSMA Frac 5:2 12-1.55 | Total | 1995 - 1999 | 2000-2004 | 2005-2009 |
|---|---|---|---|---|
| Avg. Trade Net Profit | $ 2.277,87 | $ 1.202,53 | $ 2.261,88 | $ 3.197,83 |
| Total Net Profit | $ 674.250,00 | $ 114.240,00 | $ 192.260,00 | $ 367.750,00 |
| Gross Profit | $ 1.263.460,00 | $ 203.910,00 | $ 287.820,00 | $ 771.730,00 |
| Gross Loss | -$ 589.210,00 | -$ 89.670,00 | -$ 95.560,00 | -$ 403.980,00 |
| Total Number of Trades | 296 | 95 | 85 | 115 |
| Percent Profitable | 77,70% | 75,79% | 76,47% | 80,87% |
| *Per Trade* | | | | |
| Standard Deviation | $ 10.417,16 | $ 5.633,30 | $ 6.319,98 | $ 14.936,04 |
| t-Value | 3,762 | 2,081 | 3,300 | 2,296 |
| Kurtosis | 12,540 | 26,644 | 12,570 | 6,335 |
| Skewness | -2,322 | -3,315 | -1,991 | -1,964 |
| Maximum | $ 35.680,00 | $ 20.180,00 | $ 17.510,00 | $ 35.680,00 |
| Minimum | -$ 60.470,00 | -$ 38.150,00 | -$ 34.140,00 | -$ 60.470,00 |

Tables 4.10 illustrate that the reverse strategy of the Frac 5:2 with 12 day m.a. and 1.55 standard deviation is very profitable. These strategies have been created by doing the exact opposite as wound be theoretically required for spread trading, thus short (long) propane and long (short) natural gas. This way the BB method becomes a trending signal instead of a reverse to mean signal. The percentage profitability is relatively constant between 63.92% and 83.05%, which implies robustness. Total results are statistically significant on a 99% for all strategies with the exception of the first strategy which is only significant with 95% confidence. Only 6 out of the 12 periods tested is statistically significant with 95% confidence and only 2 periods are significant with a 99% confidence level. The 2000-2004 period is the only significant period (95%) for both the buy on cross in sell on cross out and the buy on cross out sell on cross out strategies. The buy on cross in sell on moving average strategy on the other hand only retains confidence in the 2005-2009 period although this is at a 99% level. Finally, the buy on cross out sell on moving average strategy is statistically significant in all periods with the 2000-2004 being 99%.

The maximum and minimum are both observed under the buy on cross in sell on M.A. which also experiences the most volatility in profits. The most stable and also highest grossing strategy is buy on cross out sell on moving average which has an 77.70% total profitability rate (and a very small variation on this figure) and as stated above is fully significant. This paper advices more research into the Frac spread especially in the field of short term movements. The successful result of this reverse spread trading leads the author to believe that in the propane / natural gas markets a move away from the relational mean is usually longer term and is likely to intensify.

The break-even transaction costs for these strategies are presented in table 4.11. The highest transaction costs are required for the buy on cross out sell on cross out strategy followed by the buy on cross out sell on moving average. The level off all transaction costs illustrate that the strategies are profitable. When taking all of the above into account the buy on cross out sell on moving average is clearly the strategy with most potential.

*Table 4.11 Break even transaction costs Frac 5:2 ma. 12 std.dev. 1.555*

| **Frac 5:2 12-1.55** | *T.Costs* |
|---|---|
| 1. BCISCO | $ 2177 |
| 2. BCOSCO | $ 2962 |
| 3. BCISMA | $ 2023 |
| 4. BCOSMA | $ 2418 |

Appendix E presents the equity curve for the above tested strategies. These illustrate that all the strategies that received special attention have developed on a positive and relatively even curve. Although some strategies have some negative equity in the first trading years, the scale, a maximum drawdown of $ 34,782 and $ 11,200 excluding the Cracked 2;1 BCOSCO, indicates that the initial trading capital should be sufficient to cover these drawdowns.

## *4.7 Conclusion*

The testing results presented above illustrate that the past energy prices contain information on future price developments. This is fully contradictory with all forms of the Efficient Market Hypothesis since, by definition, the weak form states that all information included in the past prices is fully reflected in the current price and therefore a profitable trading system based on this information does not exist. When the weak form hypothesis is rejected, automatically the other forms are rejected was well. These findings are consistent with the theoretical analysis of the EMH presented in chapter 2.

Although the trading system is not fully crystallised, the preliminary results of the 5:2 Frac spread with a 12-1.555 variable and a buy on cross out sell on moving average setting are robust and sufficient enough to conclude the rejection of the EMH.

Especially since the testing revealed that Bollinger Bands do not have much signalling power over energy spreads, from which one can conclude two things. Firstly, the likelihood of a better and more robust system based on some technical analysis method analogous to BB is large (and requires more research). Secondly, markets would be efficient if energy spread would be completely mean reverting but unable to generate trading profit with this fact. The results indicate that the most profitable trading system is a contra-mean reverting, thus trending, system illustrating both a practical and theoretical deviation from market efficiency.

# 5.0 Conclusion

## *5.1 Introduction*

This study evaluated the signalling ability of Bollinger Bands of energy spread movement and found there to be no strong ability. In the process there have been some new potential spreads constructed as specific Bollinger Band settings. The findings have been mostly coherent with the literature, as explained below. The potential behind the Bollinger Bans settings allows the rejection of the Efficient Market Hypothesis in its strong form since past price information has been used to predict future price movements.

## *5.2 Results in relation to literature*

Since the literature on Bolllinger Bands was strongly negative, the findings presented here are consistent with the results of Bollinger Band analysis. Leung & Chong (2003), Lento & Gradojeciv (2007), and Lento, Gradojevic & Wright (2007) all found that Bollinger Bands hold no to little predictive power. The fact that the most successful strategy is a reverse Bollinger Band illustrates the poor functionality of the model. The theoretical variables indentified by Lui, et. al. (2006) has proven to be most profitable, when used in opposite form both on average over all tests and since this is the variable of the most successful result. The fact that only the reverse has predictive power has no influence over the robustness of Lui, et al (2006) their findings. Lento, Gradojevic & Wright (2007) found that an inverse bb setting was more profitable, similar to this study's findings.

The literature on spread trading appears to be relatively profitable. The study assumes that the results would be substantially lower than presented in the literature for the reason that most papers are relatively old after which the market has been flooded by hedge funds trading on technical analysis algorithms and this industry's focus on the commodities market in the 2000's. The findings of Girma & Paulson (1999) are not reproduced by this study. Although one has to keep in mind that the comparability between both studies is limited, similarity of results would be expected if the inefficiency still existed. Crack spread results have moved to the expected average of 50% profitability as would be expected in a market with more speculative players, hence more efficiency. Poitras & Teoh (2003) found that, although analysing day trading, the bigger filter produced more profits which is intuitively expected. This study found that in relation to spread trading via Bollinger Bands this does not hold. On the contrary, the smallest filter generated the most accurate signals. Mougoué (2007) found that the Frac spread holds great opportunities for the trading. These results are analogous to its findings except for the fact that here a reverse system is employed. An in-depth study on the methodology of Mougoué (2007) does not supply any specific spread calculation specifics accept for the fact that they differ from this paper.

## *5.2 Further Research Recommendation*

This paper has identified that an inverse Bollinger Band over the Frac 5:2 spread holds robust indicating power. Therefore, further research into this signal is needed to identify whether or not this can be transformed into a viable complete trading system. The fact that NYMEX considers a Frac position as one and calculates margin requirements accordingly intensifies this potential.

The usage of Bollinger bands is most robust when selling on M.A. crosses. This allows for a search into an other and better sell timing mechanism, for example a fixed amount of days. The Cracked 0:2:1 spread also has potential for further in-depth research. The theoretical relationship between both crude final products appears to be a strongly under-evaluated element of energy spreads and its academic analysis. Finally, the successful signalling properties of inverse BB's over the Frac spread, a relatively new spread, indicate that an analysis of the Sparc (electricity and natural gas) has the potential to yield significant results.

Finally, a future research opportunity presented in the theoretical analysis of the EMH, above, is a study of the profitability of ungrounded price movements based on competitor specific news. A scan of the literature has not found any research on this idea, though intuitively one would expect a high level of irrationality when prices move based on the news that does not, or negatively, influence that companies profit expectations. The dual price movement of competitors would furthermore be a very clear and effective test of the Efficient Market Hypothesis.

## 5.3 Final Thoughts

The results found in this study often contradict intuitive and theoretical expectations. However, when using Technical Analysis, a trading method that operates on the assumption that markets are not efficient but controlled by greed and fear, as a basis for trading strategy it is not very strange to find irrationality. It would have been shocking if we did not find any since this would imply that the markets are efficient thereby eliminating our methodology for our strategies.

The history of scientific understanding of human behaviour has been marked by an increase in complexity. Currently, it is the dualism between rationality and emotions that are used as a basis for the two dominant schools in finance: Efficient Market Hypothesis and Behavioural Finance. Although Behavioural Finance is currently perceived to be more robust, there is a philosophical problem with this distinction. The sciences that research the development and process of human behaviour have rejected the distinction between rationality and emotions and replaced this with a distinction between biologically evolutionary and culturally evolutionary processes. It’s just a matter of time before the finance academics catch up, and when they do the thesis of Efficient markets and the antithesis of Behavioural finance will merge into a new synthesis where a trader has and uses both rationality and emotions, thus becoming human.

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# Appendix A – Research Overview Tables

*Table A.1 Average Annual Rate of Return - Leung & Chong (2003)*

| Index Names | MAE 3%/10 | MAE 5%/10 | BB 2/10 | MAE 3%/20 | MAE 5%/20 | BB 2/20 |
|---|---|---|---|---|---|---|
| Dow Jones | 6% (25) | 3% (5) | 11% (68) | 8% (31) | 6% (8) | 9% (49) |
| Toronto 300 | 2% (15) | 5% (4) | 1% (51) | 0% (26) | 5% (7) | 2% (34) |
| BCI Global | 4% (47) | -1% (13) | 3% (53) | 4% (47) | 1% (23) | 0% (44) |
| FTSE 100 | 2% (18) | 2% (3) | 2% (52) | 3% (28) | -1% (7) | 3% (41) |
| DAX | 4% (43) | 13% (11) | 7% (57) | 3% (41) | 9% (19) | 4% (44) |
| Nikkei 225 | 0% (44) | -1% (12) | -2% (54) | -2% (39) | -1% (21) | -1% (43) |
| CAC40 | 1% (46) | 6% (11) | 3% (47) | 3% (41) | 6% (18) | 20% (32) |
| KOSPI | 4% (73) | 4% (31) | -9% (38) | 1% (54) | -2% (31) | -7% (32) |
| Straits Time | 3% (49) | 3% (19) | 1% (60) | 0% (41) | -5% (21) | -1% (46) |
| Hang Seng | 4% (60) | 8% (23) | 10% (59) | 9% (50) | 4% (27) | 10% (44) |
| TWSE | -4% (80) | -6% (36) | -6% (49) | 6% (58) | 10% (35) | -7% (33) |
| Index Names | MAE 3%/10 | MAE 5%/10 | BB 2/10 | MAE 3%/20 | MAE 5%/20 | BB 2/20 |
| Dow Jones | 7% (26) | 4% (12) | 6% (25) | 2% (7) | 2% (4) | 3% (3) |
| Toronto 300 | 4% (23) | 2% (10) | 3% (21) | 2% (9) | 2% (6) | 4% (4) |
| BCI Global | 5% (32) | 3% (22) | 1% (19) | 3% (12) | 0% (6) | 0% (3) |
| FTSE 100 | 5% (22) | 4% (15) | 2% (18) | 5% (13) | 7% (9) | 5% (4) |
| DAX | 9% (29) | 9% (19) | 6% (19) | 2% (11) | 4% (8) | 7% (6) |
| Nikkei 225 | 1% (29) | -4% (16) | -3% (20) | -1% (7) | -2% (6) | -5% (4) |
| CAC40 | 0% (28) | 6% (20) | 3% (19) | 1% (10) | 2% (7) | 3% (3) |
| KOSPI | 2% (30) | -4% (21) | -4% (18) | -3% (9) | -7% (9) | -5% (4) |
| Straits Time | -3% (27) | 3% (21) | -1% (20) | 6% (14) | 2% (9) | 8% (7) |
| Hang Seng | 5% (32) | 4% (18) | 7% (19) | 3% (12) | 4% (9) | 8% (5) |
| TWSE | 7% (35) | 0% (24) | -5% (17) | -1% (12) | -3% (9) | -4% (4) |

*Table A.2 Combined Signal approach Returns - Lento & Gardojevic (2007)*

| | Annual Returns | | Buy and Hold | | Excess Returns | | No. of Trades | |
|---|---|---|---|---|---|---|---|---|
| **Markets** | (7/12) | (8/12) | (7/12) | (8/12) | (7/12) | (8/12) | (7/12) | (8/12) |
| **TSX** | | | | | | | | |
| All Trading Rules | 10,4 | 7,1 | 8,6 | 8,6 | 1,75 | -1,5 | 105 | 153 |
| No Bollinger Band | 13,4 | 10,4 | 8,6 | 8,6 | 4,8 | 1,8 | 99 | 105 |
| **DJI A** | | | | | | | | |
| All Trading Rules | 11,5 | 5,5 | 8,8 | 8,8 | 2,7 | -3,4 | 131 | 195 |
| No Bollinger Band | 7,9 | 8,8 | 8,8 | 8,8 | -0,9 | 0 | 139 | 147 |
| **NASDA Q** | | | | | | | | |
| All Trading Rules | 17,4 | 13 | 4,1 | 4,1 | 13,3 | 8,9 | 104 | 207 |
| No Bollinger Band | 21,6 | 15,5 | 4,1 | 4,1 | 17,5 | 11,4 | 112 | 157 |
| **CDN/US$** | | | | | | | | |
| All Trading Rules | -0,9 | -0,1 | -2,5 | -2,5 | 1,5 | 2,3 | 88 | 88 |
| No Bollinger Band | 2 | 1,3 | -2,5 | -2,5 | 4,4 | 3,8 | 48 | 22 |

*Table A.3 Bollinger Band rule Profitability - Lento, Gardojevic, & Wright (2007)*

| MA (days)/ s.d. | . 20 / 2 | . 20 / 1 | . 30 / 2 |
|---|---|---|---|
| **TSX** (N=2421) | | | |
| Annual return | -3,4 | -9,1 | -5,1 |
| p-value | 0,98 | 0,99 | 0,99 |
| Buy-and-hold return | 9,1 | 9,1 | 9,2 |
| Over/(under) performance | -12,5 | -18,1 | -14,3 |
| No. of trades | 68 | 92 | 48 |
| **Dow Jones** (N=2421) | | | |
| Annual return | 4,6 | 4,3 | 5,5 |
| p-value | 0,43 | 0,39 | 0,42 |
| Buy-and-hold return | 10,8 | 10,8 | 11,3 |
| Over/(under) performance | -6,2 | -6,5 | -5,8 |
| No. of trades | 84 | 144 | 70 |
| **NASDAQ** (N=2195) | | | |
| Annual return | -12,3 | -10,8 | -8,2 |
| p-value | 0,96 | 0,91 | 0,87 |
| Buy-and-hold return | 6,4 | 6,4 | 6 |
| Over/(under) performance | -18,8 | -17,2 | -14,2 |
| No. of trades | 68 | 108 | 48 |
| **CDN/US $** (N=2421) | | | |
| Annual return | -1,5 | -2,8 | 0,8 |
| p-value | 0,43 | 0,52 | 0,07 |
| Buy-and-hold return | -2,2 | -2,2 | -2,2 |
| Over/(under) performance | 0,7 | -0,6 | 2,9 |
| No. of trades | 94 | 137 | 80 |

*Table A.4 Contra-Bollinger Band Profitability - Lento, Gardojevic, & Wright (2007)*

| MA (days)/ s.d. | . 20 / 2 | . 20 / 1 | . 30 / 2 |
|---|---|---|---|
| **TSX** (N=2421) | | | |
| Annual return | 13,2 | 19 | 16,3 |
| Buy and hold return | 9,1 | 9,1 | 9,2 |
| Over/(under) performance | 4,1 | 9,9 | 7,1 |
| No. of trades | 183 | 231 | 140 |
| **Dow Jones** (N=2421) | | | |
| Annual return | 5,2 | 2,8 | 5,1 |
| Buy and hold return | 10,8 | 10,8 | 11,3 |
| Over/(under) performance | -5,6 | -8 | -6,2 |
| No. of trades | 215 | 145 | 178 |
| **NASDAQ** (N=2195) | | | |
| Annual return | 19,6 | 15,9 | 14,9 |
| Buy and hold return | 6,4 | 6,4 | 6 |
| Over/(under) performance | 13,2 | 9,5 | 9 |
| No. of trades | 178 | 217 | 144 |
| **CDN/US $** (N=2421) | | | |
| Annual return | -1,7 | 2,2 | -3,2 |
| Buy and hold return | -2,2 | -2,2 | -2,2 |
| Over/(under) performance | 0,6 | 0 | -1 |
| No. of trades | 221 | 252 | 164 |

*Table A.5 Aggregate result Soybean Complex Spread - Poitras & Rechner (1993)*

| | 0 | 1 Cent | 2 Cent | 3 Cent |
|---|---|---|---|---|
| Mean profit per trade | -0,36 | 0,35 | 1,02 | 1,74 |
| Std. dev. Profit per trade | 2,71 | 2,97 | 3,40 | 4,00 |
| Skewness | 0,96 | 0,87 | 0,90 | 0,81 |
| Kurtosis | 6,94 | 7,22 | 6,67 | 5,62 |
| Rho | 0,010 | -0,061 | -0,077 | -0,068 |
| Chi-square (df=2) | 849 | 453 | 229 | 104 |
| Studentized range | 15,4 | 14,0 | 12,3 | 10,4 |
| t-value | -7,69 | 5,08 | 9,10 | 9,30 |
| number of trades | 3352 | 1861 | 922 | 457 |
| Percentage trades profitable | 39,6 | 52,3 | 62,3 | 69,0 |

*Table A.6 5 day Moving Average Crack spread results - Girma & Paulson (1999)*

| Std. Dev. | Total Profits | Avg. Profit | Std. Dev. | No of Trades | Avg.days in Trade | %Winning Trades | Std. Err. of Mean | T-Value |
|---|---|---|---|---|---|---|---|---|
| 3:2:1 Crack Spread | **Profitability of Five Day Moving Average Trading Strategy** | | | | | | | |
| ±1.50 | $155.212 | 281 | 920 | 552 | 4,2 | 77,7 | 39,157 | 7,176 |
| ±1.75 | $144.663 | 453 | 827 | 319 | 4,1 | 84,3 | 46,303 | 9,783 |
| ±2.00 | $97.142 | 552 | 870 | 176 | 4,2 | 85,2 | 65,579 | 8,417 |
| ±2.25 | $51.257 | 589 | 929 | 87 | 4,3 | 87,4 | 99,600 | 5,914 |
| ±2.50 | $20.048 | 557 | 946 | 36 | 4,3 | 88,9 | 157,667 | 3,533 |
| 1:1:0 Gasoline Crack Spread | | | | | | | | |
| ±1.50 | $138.959 | 307 | 1.204 | 453 | 4,3 | 74,4 | 56,569 | 5,427 |
| ±1.75 | $117.479 | 546 | 1.156 | 215 | 4,2 | 82,8 | 78,839 | 6,926 |
| ±2.00 | $68.199 | 662 | 987 | 103 | 4,0 | 84,5 | 97,252 | 6,807 |
| ±2.25 | $24.983 | 757 | 737 | 33 | 4,3 | 81,8 | 128,295 | 5,900 |
| ±2.50 | $12.967 | 997 | 621 | 13 | 3,9 | 100,0 | 172,234 | 5,789 |
| 1:01 Heating Oil Crack Spread | | | | | | | | |
| ±1,50 | $226.972 | 305 | 1.154 | 743 | 4,2 | 75,1 | 42,336 | 7,204 |
| ±1.75 | $124.195 | 409 | 1.467 | 304 | 4,5 | 81,3 | 84,138 | 4,861 |
| ±2.00 | $74.563 | 802 | 1.841 | 93 | 4,4 | 86,0 | 190,903 | 4,201 |
| ±2.25 | $27.098 | 934 | 1.604 | 29 | 4,4 | 82,8 | 297,855 | 3,136 |
| ±2.50 | $4.603 | 767 | 1.139 | 6 | 4,0 | 83,3 | 464,995 | 1,649 |
| 3:2:1 Crack Spread | **Profitability of Ten Day Moving Average Trading Strategy** | | | | | | | |
| ±1.50 | $185.211 | 372 | 1.044 | 498 | 5,2 | 82,1 | 46,783 | 7,952 |
| ±1.75 | $143.598 | 475 | 1.183 | 302 | 5,4 | 85,1 | 68,074 | 6,978 |
| ±2.00 | $103.741 | 644 | 1.349 | 161 | 5,8 | 86,3 | 106,316 | 6,057 |
| ±2.25 | $57.706 | 641 | 1.320 | 90 | 6,0 | 84,4 | 139,140 | 4,607 |
| ±2.50 | $25.136 | 474 | 1.359 | 53 | 6,0 | 81,1 | 186,673 | 2,539 |
| 1:1:0 Gasoline Crack Spread | | | | | | | | |
| ±1,50 | $163.778 | 402 | 1.213 | 407 | 5,2 | 79,6 | 60,126 | 6,686 |
| ±1.75 | $118.250 | 550 | 1.433 | 215 | 5,5 | 84,2 | 97,730 | 5,628 |
| ±2,00 | $84.280 | 826 | 1.378 | 102 | 5,7 | 83,3 | 136,442 | 6,054 |
| ±2.25 | $33.755 | 703 | 1.157 | 48 | 6,4 | 81,3 | 166,999 | 4,210 |
| ±2.50 | $20.230 | 1.012 | 1.272 | 20 | 6,4 | 80,0 | 284,428 | 3,558 |
| 1:0:1 Heating Oil Crack Spread | | | | | | | | |
| ±1.50 | $271.281 | 429 | 1.100 | 633 | 5,0 | 80,1 | 43,721 | 9,812 |
| ±1.75 | $157.654 | 569 | 1.436 | 277 | 6,0 | 83,0 | 86,281 | 6,595 |
| ±2.00 | $97.897 | 906 | 1.513 | 108 | 6,0 | 86,1 | 145,588 | 6,223 |
| ±2.25 | $59.383 | 1.485 | 2.398 | 40 | 6,0 | 82,5 | 379,157 | 3,917 |
| ±2.50 | $21.712 | 1.447 | 2.385 | 15 | 5,3 | 86,7 | 615,804 | 2,350 |

*Table A.7 1:1:0 Crack spread profitability – Poitras & Teoh (2003)*

| Filter (in cents) | 0 | 3 | 6 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|
| # profitable trades | 329 | 251 | 196 | 124 | 74 | 35 |
| % profitable trades | 46,21 | 47,63 | 51,44 | 57,41 | 61,67 | 71,43 |
| Mean % | -1,53 | 0,23 | 0,97 | 2,35 | 3,59 | 6,63 |
| Std. Dev. % | 20,96 | 21,18 | 21,81 | 22,36 | 23,80 | 28,25 |
| Filter (in cents) | 0 | -3 | -6 | -10 | -15 | -20 |
| # profitable trades | 337 | 258 | 188 | 124 | 79 | 49 |
| % profitable trades | 46,81 | 48,41 | 51,23 | 52,99 | 60,31 | 60,49 |
| Mean % | -1,87 | 1,28 | 0,21 | 0,13 | 3,50 | 4,52 |
| Std. Dev. % | 24,06 | 23,11 | 23,90 | 25,27 | 24,87 | 29,32 |

*Table A.8 1:0:1 Crack spread profitability – Poitras & Teoh (2003)*

| Filter (in cents) | 0 | 3 | 6 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|
| # profitable trades | 292 | 229 | 169 | 96 | 59 | 27 |
| % profitable trades | 41,01 | 43,45 | 44,36 | 44,44 | 49,17 | 55,10 |
| Mean % | -2,59 | -2,13 | -1,90 | -1,18 | 0,97 | 2,49 |
| Std. Dev. % | 14,77 | 14,82 | 15,01 | 15,56 | 15,20 | 15,31 |
| Filter (in cents) | 0 | -3 | -6 | -10 | -15 | -20 |
| # profitable trades | 361 | 273 | 202 | 134 | 81 | 52 |
| % profitable trades | 50,14 | 51,22 | 55,04 | 57,26 | 61,83 | 64,20 |
| Mean % | 0,22 | 0,93 | 2,29 | 2,90 | 3,65 | 5,74 |
| Std. Dev. % | 17,73 | 17,69 | 18,42 | 19,05 | 22,72 | 26,03 |

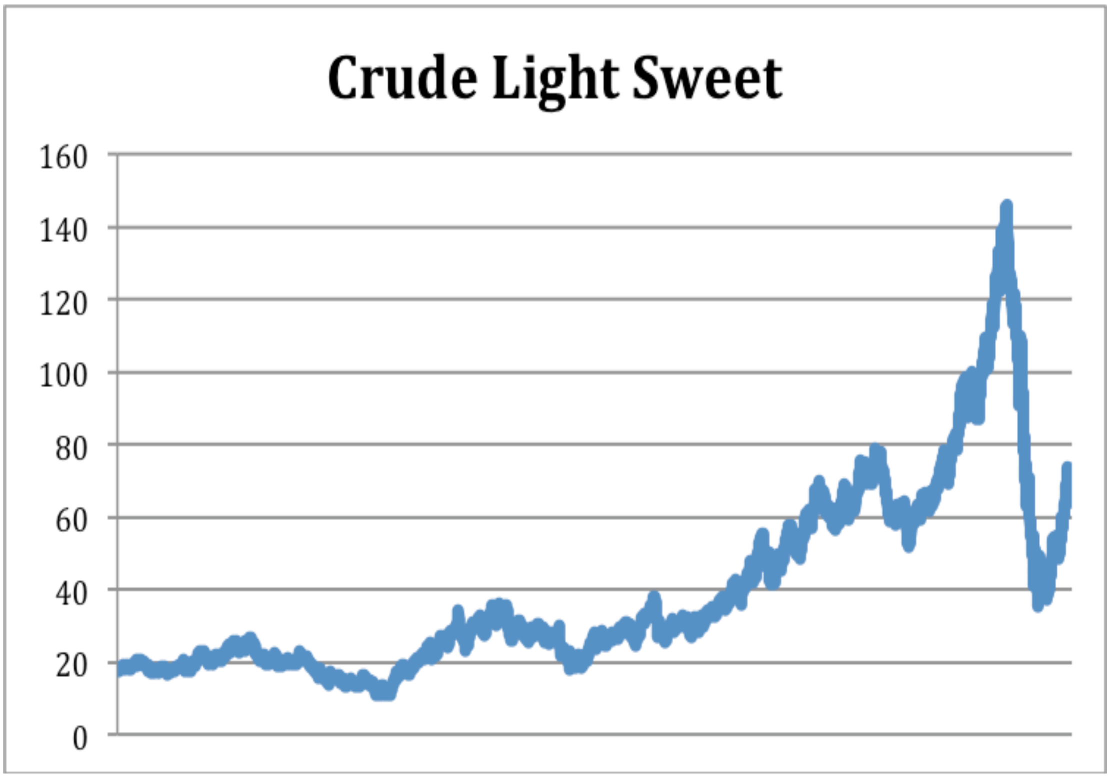
*Table A.9 Crack spread Neural Network profitability – Dunis, et al. (2005)*

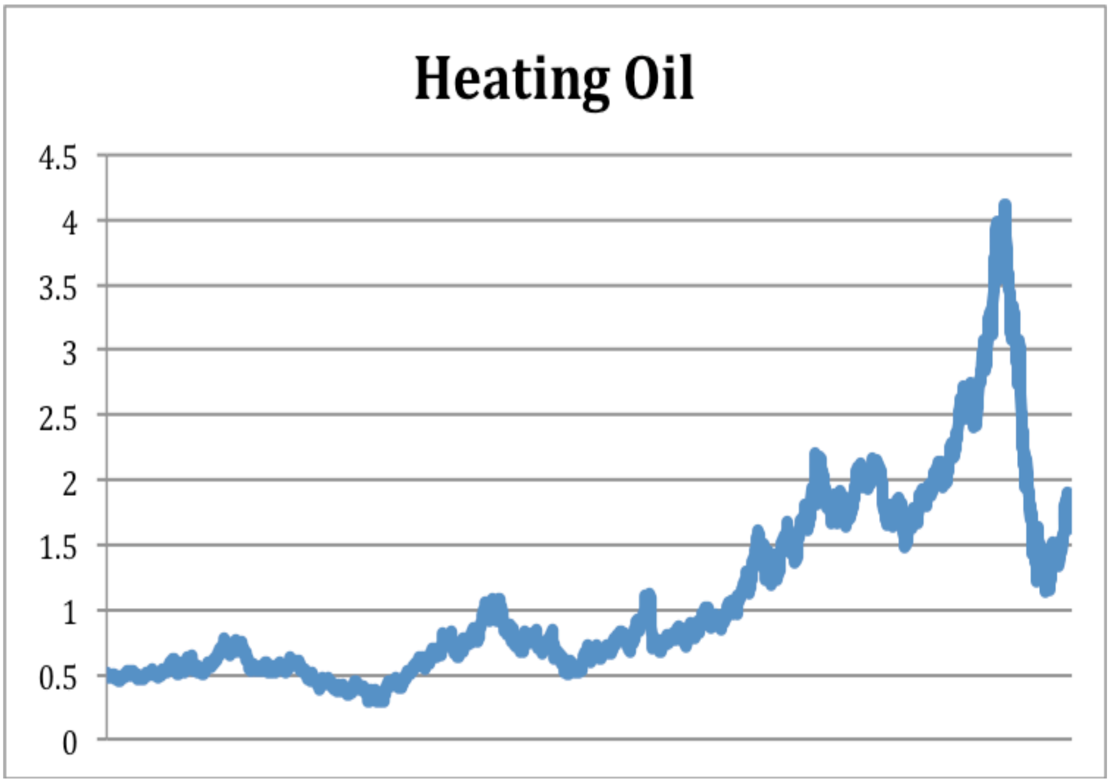
| | Filter Return | Stdev | MaxDD | Calmar | #Trades |
|---|---|---|---|---|---|
| Higher Order Neural Network - Out-of-Sample Trading Results | | | | | |
| BTC | 37,41% | 23,58% | -21,09% | 1,7738 | 105,38 |
| UnFiltered | 16,93% | 23,70% | -30,70% | 0,5513 | 105,38 |
| Threshold | 7,39% | 5,64% | -0,97% | 7,6097 | 10,88 |
| Correl | 9,22% | 15,42% | -22,50% | 0,4095 | 105,38 |
| Asymm | 2,84% | 4,77% | -1,82% | 1,5596 | 4,58 |
| Higher Order Neural Network - In-Sample Trading Results | | | | | |
| BTC | 21,43% | 22,66% | -46,22% | 0,4637 | 107,83 |
| UnFiltered | 0,48% | 22,76% | -60,08% | 0,008 | 107,83 |
| Threshold | 5,64% | 7,27% | -8,49% | 0,6638 | 9,87 |
| Correl | 11,48% | 13,85% | -28,11% | 0,4082 | 108,88 |
| Asymm | 1,97% | 3,11% | -1,67% | 1,1812 | 2,79 |
| Recurrent Neural Network - Out-of-Sample Trading Results | | | | | |
| BTC | 40,73% | 23,56% | -18,41% | 2,2118 | 100,23 |
| UnFiltered | 21,36% | 23,62% | -19,19% | 1,1128 | 100,23 |
| Threshold | 15,92% | 15,16% | -16,20% | 0,9829 | 97,36 |
| Correl | 21,36% | 23,62% | -19,19% | 1,1128 | 100,23 |
| Asymm | 4,93% | 11,97% | -17,82% | 0,2765 | 60,14 |
| Recurrent Neural Network - In-Sample Trading Results | | | | | |
| BTC | 25,88% | 22,64% | -35,54% | 0,7282 | 87,4 |
| UnFiltered | 8,90% | 22,72% | -56,70% | 0,1569 | 87,4 |
| Threshold | 6,76% | 9,95% | -14,80% | 0,4569 | 39 |
| Correl | 9,22% | 22,71% | -54,04% | 0,1706 | 88,1 |
| Asymm | 5,60% | 6,71% | -7,90% | 0,7095 | 21,47 |

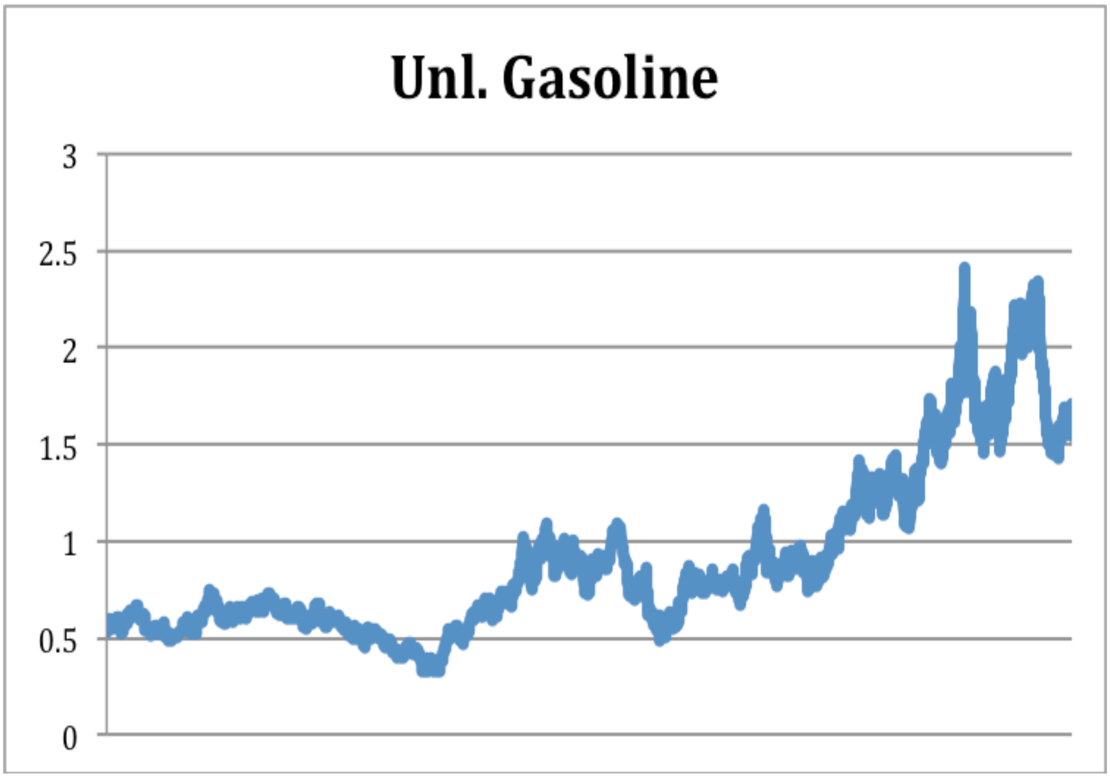
*Table A.10 Frac spread Bollinger Band profitability – Mougoué, (2007)*

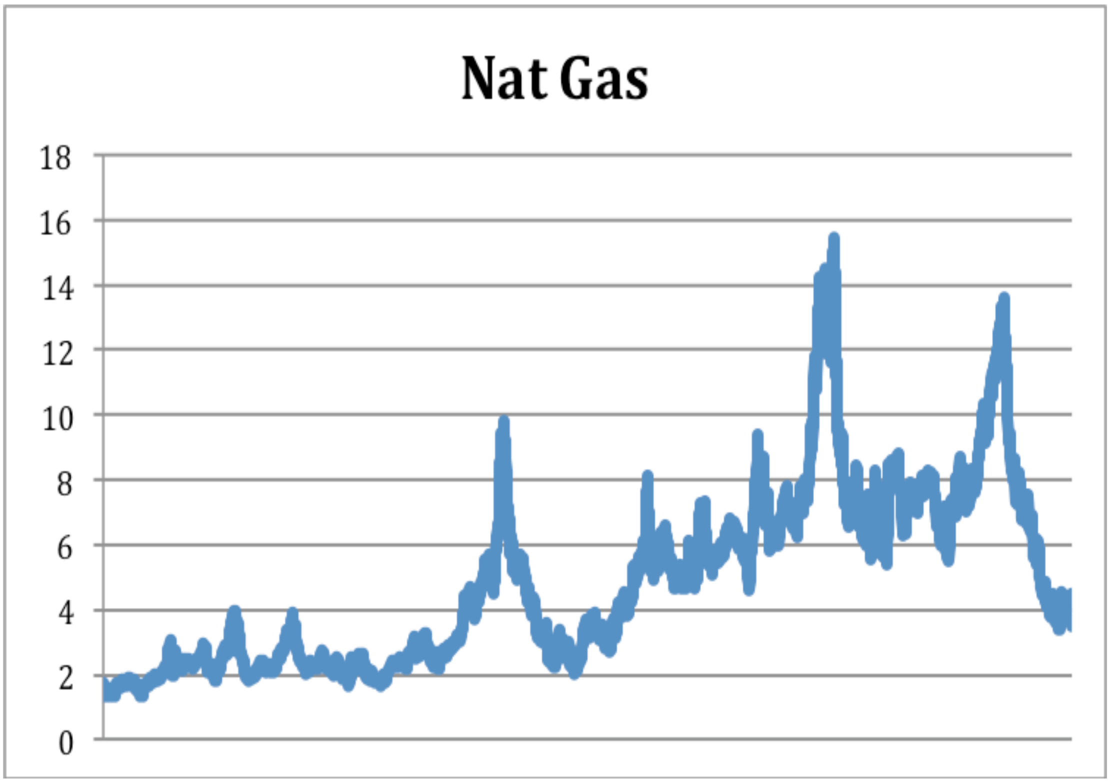
| | All trades | Long trades | Short trades |
|---|---|---|---|
| Initial capital | 100.000,00 | 100.000,00 | 100.000,00 |
| Ending capital | 325.974,38 | 250.081,14 | 175.893,24 |
| Net Profit | 225.974,38 | 150.081,14 | 75.893,24 |
| Net Profit % | 225,97% | 150,08% | 75,89% |
| Exposure % | 7,38% | 3,79% | 3,59% |
| Net Risk Adjusted | 3061,87% | 3956,47% | 2115,80% |
| Annual Return % | 25,59% | 19,33% | 11,50% |
| Risk Adjusted Return | 346,71% | 509,63% | 320,70% |
| All trades | 47 | 24 (51.06 %) | 23 (48.94 %) |
| Avg. Profit/Loss | 4.807,97 | 6.253,38 | 3.299,71 |
| Avg. Profit/Loss % | 19,25% | 25,04% | 13,21% |
| Avg. Bars Held | 10,98 | 10,46 | 11,52 |
| Winners | 31 (65.96 %) | 17 (36.17 %) | 14 (29.79 %) |
| Largest win | 58.944,63 | 58.944,63 | 21.460,68 |
| Largest loss | -17.464,09 | -17.464,09 | -11.914,52 |
| Max. trade drawdown | -34.601,02 | -24.295,70 | -34.601,02 |
| Max. system drawdown | -40.776,42 | -32.412,06 | -34.601,02 |
| Recovery Factor | 5,54 | 4,63 | 2,19 |
| Profit Factor | 3,17 | 3,94 | 2,43 |
| Payoff Ratio | 1,64 | 1,62 | 1,56 |
| Standard Error | 17.208,19 | 14.190,99 | 8.341,45 |
| Risk-Reward Ratio | 2,92 | 2,36 | 2,01 |
| Sharpe Ratio of trades | 1,7 | 1,89 | 1,45 |

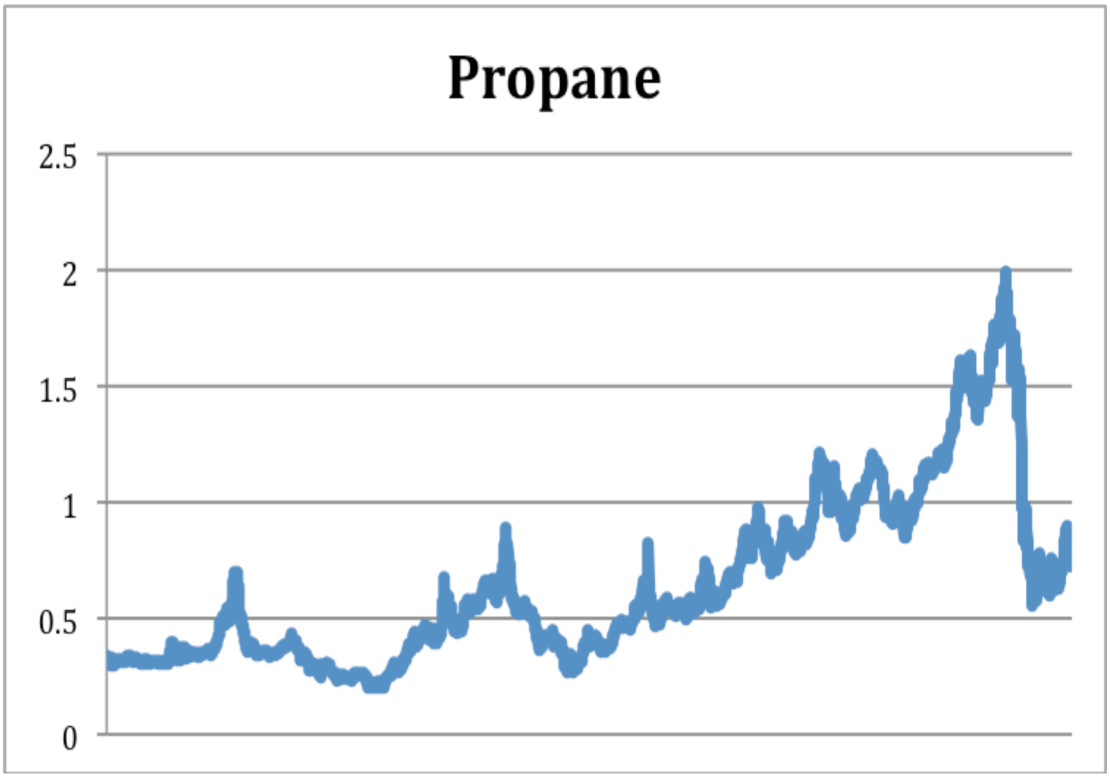
## **Appendix B – Data Graph** *(January 1995- July 2009)*




Unl. Gasoline
3
2.5
2
1.5
1
0.5
0


Nat Gas
18
16
14
12
10
8
6
4
2
0


Propane
2.5
2
1.5
1
0.5
0

# Appendix C – Descriptive Statistics Explained

Average Trade Net Profit: This represents the average profit (excluding costs) that one trade generates, in other words the mean
Formula = ∑ Total net profit / ∑ Total number of trades

Total Net Profit: Here the total return of the method over the tested period is presented. There return adds both positive and negative transactions.
Formula = ∑ (separate trade (from here: X) – transaction costs)

Gross Profit: The directly generated positive returns over the period added to create one result. Only the profitable trades are added together.
Formula = ∑ (positive resulting trades)

Gross Loss: The directly generated negative returns over the period added to create one results. Only the loss giving trades are added together.
Formula = ∑ (negative resulting trades)

Total Number of Trades: Expresses the number of trades the strategies executed over the specified time period.
Formula = Count nr. Of trades

Percent Profitable: illustrates the percentage of all trades that end profitable when considering net positions.
Formula = total number of profitable trades / total number of trades

Standard Deviation: The squared root of the variance which identifies how far, in general, the data moves from the mean.
Formula = square root( ∑ $(X – mean)^2$ )

t-Value: The probability that the resulting mean is statistically significantly different from zero. A result between -1.645 and 1.645 results in no significant difference from zero. 1.645 represents a 95% probability of significance and 2.576 a 99% significance level. the result has to be equal or higher.
Formula = ( X – mean {in this calculation mean = zero} ) / (standard deviation / Square root(total number of trades) )

Kurtosis: Illustrates if the data is distributed with a peak around the mean or more evenly distributed over the value range. A positive number represents data grouped around peak, a negative one more evenly distributed.
Formula = ( $\sum$ (X – mean) $^{4}$ ) / (total number of trades -1) * standard deviation $^{4}$ ) - 3

Skewness: exhibits how symmetrical the distribution is. A positive skewness means that the distribution has a bigger range to the right side, a negative to the left side, and zero an evenly distributed data set.
Formula = ( $\sum$ (X – mean) $^{3}$ ) / (total number of trades -1) * standard deviation $^{3}$ )

Maximum: Reveals the largest observation in the data set
Formula = display highest observation

Minimum: Reveals the smallest observation in the data set
Formula = display lowest observation

# Appendix D – Research Results

*Table D.1 Buy when cross back into band - Sell when cross out off opposite band*

| *Crack Spread 3;2;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 3.190,53 | -$ 675,38 | -$ 2.071,90 |
| Total Net Profit | -$ 245.670,80 | -$ 116.840,00 | -$ 124.314,00 |
| Total Generated Profit | $ 155.506,00 | $ 379.712,00 | $ 156.690,00 |
| Total Generated Loss | -$ 401.176,80 | -$ 496.552,00 | -$ 281.004,00 |
| Total Number of Trades | 77 | 173 | 60 |
| Percent Profitable | 25,97% | 35,26% | 35,00% |
| Total Transaction Costs | $ 7.700,00 | $ 17.300,00 | $ 6.000,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 10.360,67 | $ 7.746,92 | $ 10.910,35 |
| t-Value | -2,702 | -1,147 | -1,471 |
| Kurtosis | 5,194 | 8,936 | 7,345 |
| Skewness | -0,128 | 1,631 | 0,446 |
| Maximum | $ 36.434,00 | $ 44.696,00 | $ 42.782,00 |
| Minimum | -$ 43.864,00 | -$ 30.940,00 | -$ 43.906,00 |
| *Crack Spread 1;0;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 582,70 | -$ 429,85 | -$ 442,85 |
| Total Net Profit | -$ 51.278,00 | -$ 79.522,00 | -$ 20.814,00 |
| Total Generated Profit | $ 54.168,00 | $ 74.538,00 | $ 34.638,00 |
| Total Generated Loss | -$ 105.446,00 | -$ 154.060,00 | -$ 55.452,00 |
| Total Number of Trades | 88 | 185 | 47 |
| Percent Profitable | 25,00% | 28,11% | 40,43% |
| Total Transaction Costs | $ 3.520,00 | $ 7.400,00 | $ 1.880,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 2.490,00 | $ 1.771,17 | $ 2.496,80 |
| t-Value | -2,195 | -3,301 | -1,216 |
| Kurtosis | 2,921 | 8,335 | 1,690 |
| Skewness | 1,037 | 1,787 | 0,887 |
| Maximum | $ 8.406,00 | $ 9.486,00 | $ 7.592,00 |
| Minimum | -$ 5.640,00 | -$ 5.588,00 | -$ 4.976,00 |
| *Crack Spread 1;1;0* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 397,03 | -$ 421,33 | -$ 759,45 |
| Total Net Profit | -$ 30.174,00 | -$ 74.154,00 | -$ 35.694,00 |
| Total Generated Profit | $ 114.710,00 | $ 186.824,00 | $ 62.974,00 |
| Total Generated Loss | -$ 144.884,00 | -$ 260.978,00 | -$ 98.668,00 |
| Total Number of Trades | 76 | 176 | 47 |
| Percent Profitable | 35,53% | 39,77% | 38,30% |
| Total Transaction Costs | $ 3.040,00 | $ 7.040,00 | $ 1.880,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 5.195,79 | $ 3.944,84 | $ 5.280,61 |
| t-Value | -0,666 | -1,417 | -0,986 |
| Kurtosis | 4,681 | 6,350 | 6,239 |
| Skewness | 0,036 | -0,629 | -0,687 |
| Maximum | $ 15.988,00 | $ 12.332,00 | $ 13.760,00 |
| Minimum | -$ 21.352,00 | -$ 21.020,00 | -$ 21.856,00 |

| *Cracked Spread 0;2;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | $ 3.679,22 | -$ 63,02 | -$ 1.382,19 |
| Total Net Profit | $ 253.866,00 | -$ 11.406,00 | -$ 71.874,00 |
| Total Generated Profit | $ 488.370,00 | $ 604.242,00 | $ 177.012,00 |
| Total Generated Loss | -$ 234.504,00 | -$ 615.648,00 | -$ 248.886,00 |
| Total Number of Trades | 69 | 181 | 52 |
| Percent Profitable | 47,83% | 40,33% | 42,31% |
| Total Transaction Costs | $ 4.140,00 | $ 10.860,00 | $ 3.120,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 16.239,70 | $ 11.943,89 | $ 14.500,07 |
| t-Value | 1,882 | -0,071 | -0,687 |
| Kurtosis | 5,306 | 11,054 | 12,277 |
| Skewness | 1,898 | 1,765 | 1,694 |
| Maximum | $ 69.786,00 | $ 69.786,00 | $ 70.080,00 |
| Minimum | -$ 25.638,00 | -$ 44.328,00 | -$ 44.538,00 |
| *Cracked Spread 0;1;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 437,34 | -$ 129,79 | $ 775,29 |
| Total Net Profit | -$ 33.238,00 | -$ 22.584,00 | $ 39.540,00 |
| Total Generated Profit | $ 136.848,00 | $ 242.758,00 | $ 123.864,00 |
| Total Generated Loss | -$ 170.086,00 | -$ 265.342,00 | -$ 84.324,00 |
| Total Number of Trades | 76 | 174 | 51 |
| Percent Profitable | 35,53% | 35,63% | 47,06% |
| Total Transaction Costs | $ 3.040,00 | $ 6.960,00 | $ 2.040,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 5.506,51 | $ 4.469,63 | $ 5.281,23 |
| t-Value | -0,692 | -0,383 | 1,048 |
| Kurtosis | 2,161 | 4,727 | 1,225 |
| Skewness | 0,641 | 0,973 | 0,950 |
| Maximum | $ 19.616,00 | $ 20.204,00 | $ 16.802,00 |
| Minimum | -$ 16.000,00 | -$ 15.328,00 | -$ 9.070,00 |
| *Frac Spread 5;2* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | $ 450,28 | -$ 2.304,64 | $ 3.514,20 |
| Total Net Profit | $ 31.970,00 | -$ 477.060,00 | $ 175.710,00 |
| Total Generated Profit | $ 616.160,00 | $ 687.150,00 | $ 490.310,00 |
| Total Generated Loss | -$ 584.190,00 | -$ 1.164.210,00 | -$ 314.600,00 |
| Total Number of Trades | 71 | 207 | 50 |
| Percent Profitable | 38,03% | 25,60% | 38,00% |
| Total Transaction Costs | $ 9.940,00 | $ 28.980,00 | $ 7.000,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 27.438,44 | $ 15.325,81 | $ 28.814,24 |
| t-Value | 0,138 | -2,164 | 0,862 |
| Kurtosis | 8,571 | 27,887 | 8,144 |
| Skewness | 2,301 | 3,475 | 2,631 |
| Maximum | $ 127.290,00 | $ 128.490,00 | $ 125.580,00 |
| Minimum | -$ 49.620,00 | -$ 56.020,00 | -$ 37.340,00 |

| *Oil Frac Spread 1;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 466,84 | $ 174,88 | -$ 743,06 |
| Total Net Profit | -$ 42.016,00 | $ 30.778,00 | -$ 50.528,00 |
| Total Generated Profit | $ 97.278,00 | $ 173.740,00 | $ 73.724,00 |
| Total Generated Loss | -$ 139.294,00 | -$ 142.962,00 | -$ 124.252,00 |
| Total Number of Trades | 90 | 176 | 68 |
| Percent Profitable | 32,22% | 43,18% | 27,94% |
| Total Transaction Costs | $ 3.600,00 | $ 7.040,00 | $ 2.720,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 4.256,96 | $ 3.148,50 | $ 4.580,85 |
| t-Value | -1,040 | 0,737 | -1,338 |
| Kurtosis | 10,056 | 12,891 | 9,346 |
| Skewness | 1,967 | 2,278 | 2,007 |
| Maximum | $ 21.310,00 | $ 21.110,00 | $ 21.310,00 |
| Minimum | -$ 14.504,00 | -$ 10.180,00 | -$ 13.098,00 |

*Table D.2 Buy when cross out off band - Sell when cross out off opposite band*

| *Crack Spread 3;2;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 2.988,65 | -$ 1.910,84 | -$ 1.974,24 |
| Total Net Profit | -$ 230.126,00 | -$ 326.754,00 | -$ 116.480,00 |
| Total Generated Profit | $ 187.498,00 | $ 327.896,00 | $ 104.030,00 |
| Total Generated Loss | -$ 417.624,00 | -$ 654.650,00 | -$ 220.510,00 |
| Total Number of Trades | 77 | 171 | 59 |
| Percent Profitable | 29,87% | 30,41% | 32,20% |
| Total Transaction Costs | $ 7.700,00 | $ 17.100,00 | $ 5.900,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 10.650,97 | $ 8.649,65 | $ 7.381,99 |
| t-Value | -2,462 | -2,889 | -2,054 |
| Kurtosis | 4,405 | 9,612 | 3,297 |
| Skewness | 0,704 | 1,255 | 1,112 |
| Maximum | $ 39.212,00 | $ 49.562,00 | $ 26.726,00 |
| Minimum | -$ 39.508,00 | -$ 34.900,00 | -$ 16.546,00 |
| *Crack Spread 1;0;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 581,57 | -$ 389,31 | -$ 790,21 |
| Total Net Profit | -$ 51.178,00 | -$ 70.854,00 | -$ 37.140,00 |
| Total Generated Profit | $ 53.496,00 | $ 82.246,00 | $ 29.912,00 |
| Total Generated Loss | -$ 104.674,00 | -$ 153.100,00 | -$ 67.052,00 |
| Total Number of Trades | 88 | 182 | 47 |
| Percent Profitable | 26,14% | 30,77% | 40,43% |
| Total Transaction Costs | $ 3.520,00 | $ 7.280,00 | $ 1.880,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 2.438,27 | $ 1.913,85 | $ 2.578,45 |
| t-Value | -2,237 | -2,744 | -2,101 |
| Kurtosis | 3,296 | 7,419 | 1,125 |
| Skewness | 0,580 | 1,442 | 0,524 |
| Maximum | $ 7.262,00 | $ 9.702,00 | $ 7.336,00 |
| Minimum | -$ 9.320,00 | -$ 7.772,00 | -$ 5.524,00 |

| *Crack Spread 1;1;0* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 222,59 | -$ 495,99 | $ 4,13 |
| Total Net Profit | -$ 16.694,00 | -$ 85.806,00 | $ 194,00 |
| Total Generated Profit | $ 117.226,00 | $ 188.632,00 | $ 77.000,00 |
| Total Generated Loss | -$ 133.920,00 | -$ 274.438,00 | -$ 76.806,00 |
| Total Number of Trades | 75 | 173 | 47 |
| Percent Profitable | 37,33% | 36,99% | 44,68% |
| Total Transaction Costs | $ 3.000,00 | $ 6.920,00 | $ 1.880,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 4.729,68 | $ 3.849,27 | $ 4.567,91 |
| t-Value | -0,408 | -1,695 | 0,006 |
| Kurtosis | 2,990 | 3,412 | 2,494 |
| Skewness | 1,399 | 0,893 | 0,927 |
| Maximum | $ 17.506,00 | $ 14.260,00 | $ 15.944,00 |
| Minimum | -$ 7.528,00 | -$ 12.372,00 | -$ 9.190,00 |
| *Cracked Spread 0;2;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | $ 3.839,91 | -$ 386,25 | $ 2.613,18 |
| Total Net Profit | $ 264.954,00 | -$ 69.912,00 | $ 133.272,00 |
| Total Generated Profit | $ 489.096,00 | $ 568.014,00 | $ 318.450,00 |
| Total Generated Loss | -$ 224.142,00 | -$ 637.926,00 | -$ 185.178,00 |
| Total Number of Trades | 69 | 181 | 51 |
| Percent Profitable | 43,48% | 35,91% | 45,10% |
| Total Transaction Costs | $ 4.140,00 | $ 10.860,00 | $ 3.060,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 16.339,22 | $ 10.833,20 | $ 15.217,32 |
| t-Value | 1,952 | -0,480 | 1,226 |
| Kurtosis | 5,707 | 15,258 | 6,029 |
| Skewness | 2,186 | 2,836 | 2,060 |
| Maximum | $ 71.046,00 | $ 71.046,00 | $ 64.956,00 |
| Minimum | -$ 15.432,00 | -$ 25.890,00 | -$ 21.144,00 |
| *Cracked Spread 0;1;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | $ 197,08 | $ 18,95 | $ 710,12 |
| Total Net Profit | $ 14.978,00 | $ 3.240,00 | $ 35.506,00 |
| Total Generated Profit | $ 153.614,00 | $ 255.334,00 | $ 125.546,00 |
| Total Generated Loss | -$ 138.636,00 | -$ 252.094,00 | -$ 90.040,00 |
| Total Number of Trades | 76 | 171 | 50 |
| Percent Profitable | 40,79% | 41,52% | 50,00% |
| Total Transaction Costs | $ 3.040,00 | $ 6.840,00 | $ 2.000,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 5.553,34 | $ 4.345,93 | $ 5.971,15 |
| t-Value | 0,309 | 0,057 | 0,841 |
| Kurtosis | 3,206 | 4,095 | 1,367 |
| Skewness | 0,363 | 1,187 | 0,798 |
| Maximum | $ 19.238,00 | $ 20.204,00 | $ 18.188,00 |
| Minimum | -$ 19.444,00 | -$ 10.582,00 | -$ 10.624,00 |

| *Frac Spread 5;2* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 485,07 | -$ 3.158,66 | $ 1.837,00 |
| Total Net Profit | -$ 34.440,00 | -$ 634.890,00 | $ 91.850,00 |
| Total Generated Profit | $ 580.140,00 | $ 1.183.940,00 | $ 452.130,00 |
| Total Generated Loss | -$ 614.580,00 | -$ 1.818.830,00 | -$ 360.280,00 |
| Total Number of Trades | 71 | 201 | 50 |
| Percent Profitable | 36,62% | 33,33% | 32,00% |
| Total Transaction Costs | $ 9.940,00 | $ 28.140,00 | $ 7.000,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 26.711,09 | $ 24.654,01 | $ 26.491,50 |
| t-Value | -0,153 | -1,816 | 0,490 |
| Kurtosis | 7,057 | 12,428 | 5,446 |
| Skewness | 2,058 | 2,006 | 2,164 |
| Maximum | $ 110.110,00 | $ 148.100,00 | $ 90.750,00 |
| Minimum | -$ 47.580,00 | -$ 79.840,00 | -$ 39.400,00 |
| *Oil Frac Spread 1;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 285,57 | $ 114,07 | -$ 526,00 |
| Total Net Profit | -$ 25.416,00 | $ 20.076,00 | -$ 35.768,00 |
| Total Generated Profit | $ 108.560,00 | $ 175.028,00 | $ 85.264,00 |
| Total Generated Loss | -$ 133.976,00 | -$ 154.952,00 | -$ 121.032,00 |
| Total Number of Trades | 89 | 176 | 68 |
| Percent Profitable | 29,21% | 41,48% | 26,47% |
| Total Transaction Costs | $ 3.560,00 | $ 7.040,00 | $ 2.720,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 4.544,06 | $ 3.030,83 | $ 4.887,84 |
| t-Value | -0,593 | 0,499 | -0,887 |
| Kurtosis | 13,424 | 6,044 | 12,813 |
| Skewness | 2,976 | 1,510 | 2,791 |
| Maximum | $ 25.730,00 | $ 15.080,00 | $ 25.730,00 |
| Minimum | -$ 8.974,00 | -$ 8.900,00 | -$ 10.078,00 |

*Table D.3 Buy when cross back into band - Sell when cross of Moving Average*

| *Crack Spread 3;2;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 1.535,30 | -$ 807,48 | -$ 1.449,21 |
| Total Net Profit | -$ 191.912,00 | -$ 222.056,00 | -$ 153.616,00 |
| Total Generated Profit | $ 203.610,00 | $ 391.986,00 | $ 230.254,00 |
| Total Generated Loss | -$ 395.522,00 | -$ 614.042,00 | -$ 383.870,00 |
| Total Number of Trades | 125 | 275 | 60 |
| Percent Profitable | 31,20% | 37,09% | 53,33% |
| Total Transaction Costs | $ 12.500,00 | $ 27.500,00 | $ 6.000,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 7.400,04 | $ 5.742,69 | $ 9.438,69 |
| t-Value | -2,320 | -2,332 | -1,189 |
| Kurtosis | 9,788 | 12,147 | 11,090 |
| Skewness | -1,337 | -0,787 | 1,113 |
| Maximum | $ 22.016,00 | $ 22.016,00 | $ 43.862,00 |
| Minimum | -$ 43.252,00 | -$ 42.712,00 | -$ 43.252,00 |

| *Crack Spread 1;0;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 350,03 | -$ 291,97 | -$ 540,80 |
| Total Net Profit | -$ 48.304,00 | -$ 80.584,00 | -$ 49.754,00 |
| Total Generated Profit | $ 44.890,00 | $ 59.890,00 | $ 32.482,00 |
| Total Generated Loss | -$ 93.194,00 | -$ 140.474,00 | -$ 82.236,00 |
| Total Number of Trades | 138 | 276 | 92 |
| Percent Profitable | 34,06% | 26,09% | 22,83% |
| Total Transaction Costs | $ 5.520,00 | $ 11.040,00 | $ 3.680,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 1.410,19 | $ 1.116,33 | $ 1.614,15 |
| t-Value | -2,916 | -4,345 | -3,214 |
| Kurtosis | 5,039 | 17,075 | 2,463 |
| Skewness | 0,948 | 1,493 | 0,939 |
| Maximum | $ 6.668,00 | $ 8.580,00 | $ 5.112,00 |
| Minimum | -$ 4.052,00 | -$ 5.772,00 | -$ 3.976,00 |
| *Crack Spread 1;1;0* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 569,17 | -$ 450,25 | -$ 440,03 |
| Total Net Profit | -$ 72.854,00 | -$ 121.118,00 | -$ 37.843,00 |
| Total Generated Profit | $ 114.682,00 | $ 186.358,00 | $ 72.519,00 |
| Total Generated Loss | -$ 187.536,00 | -$ 307.476,00 | -$ 110.362,00 |
| Total Number of Trades | 128 | 269 | 86 |
| Percent Profitable | 34,38% | 35,69% | 32,56% |
| Total Transaction Costs | $ 5.120,00 | $ 10.760,00 | $ 3.440,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 3.653,46 | $ 2.936,46 | $ 3.078,68 |
| t-Value | -1,763 | -2,515 | -1,325 |
| Kurtosis | 8,864 | 12,524 | 4,559 |
| Skewness | -1,286 | -1,660 | 0,884 |
| Maximum | $ 9.656,00 | $ 9.656,00 | $ 13.098,00 |
| Minimum | -$ 21.452,00 | -$ 21.342,00 | -$ 8.922,00 |
| *Cracked Spread 0;2;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 99,74 | $ 56,34 | $ 157,88 |
| Total Net Profit | -$ 12.966,00 | $ 15.438,00 | $ 12.630,00 |
| Total Generated Profit | $ 373.026,00 | $ 566.352,00 | $ 309.252,00 |
| Total Generated Loss | -$ 385.992,00 | -$ 550.914,00 | -$ 296.622,00 |
| Total Number of Trades | 130 | 274 | 80 |
| Percent Profitable | 33,08% | 36,13% | 37,50% |
| Total Transaction Costs | $ 7.800,00 | $ 16.440,00 | $ 4.800,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 9.909,43 | $ 6.927,65 | $ 13.192,04 |
| t-Value | -0,115 | 0,135 | 0,107 |
| Kurtosis | 23,699 | 15,463 | 10,999 |
| Skewness | 3,424 | 2,622 | 1,803 |
| Maximum | $ 73.314,00 | $ 48.408,00 | $ 69.786,00 |
| Minimum | -$ 26.394,00 | -$ 29.292,00 | -$ 42.816,00 |

| *Cracked Spread 0;1;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 309,18 | -$ 171,27 | $ 702,69 |
| Total Net Profit | -$ 40.812,00 | -$ 48.298,77 | $ 58.323,40 |
| Total Generated Profit | $ 138.632,00 | $ 245.211,23 | $ 146.513,00 |
| Total Generated Loss | -$ 179.444,00 | -$ 293.510,00 | -$ 88.189,60 |
| Total Number of Trades | 132 | 282 | 83 |
| Percent Profitable | 43,94% | 42,91% | 48,19% |
| Total Transaction Costs | $ 5.280,00 | $ 11.280,00 | $ 3.320,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 3.343,13 | $ 3.053,26 | $ 4.445,67 |
| t-Value | -1,063 | -0,942 | 1,440 |
| Kurtosis | 4,817 | 8,025 | 6,799 |
| Skewness | 0,978 | 0,751 | 2,070 |
| Maximum | $ 15.500,00 | $ 15.273,20 | $ 21.842,00 |
| Minimum | -$ 10.372,00 | -$ 15.412,00 | -$ 6.802,00 |
| *Frac Spread 5;2* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 1.257,52 | -$ 2.163,49 | -$ 1.728,21 |
| Total Net Profit | -$ 167.250,00 | -$ 644.720,00 | -$ 164.180,00 |
| Total Generated Profit | $ 443.760,00 | $ 403.980,00 | $ 396.220,00 |
| Total Generated Loss | -$ 611.010,00 | -$ 1.048.700,00 | -$ 560.400,00 |
| Total Number of Trades | 133 | 298 | 95 |
| Percent Profitable | 22,56% | 22,48% | 23,16% |
| Total Transaction Costs | $ 18.620,00 | $ 41.720,00 | $ 13.300,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 15.978,87 | $ 7.459,60 | $ 19.111,88 |
| t-Value | -0,908 | -5,007 | -0,881 |
| Kurtosis | 45,988 | 12,360 | 33,018 |
| Skewness | 5,622 | 1,929 | 4,872 |
| Maximum | $ 139.080,00 | $ 44.490,00 | $ 140.130,00 |
| Minimum | -$ 29.750,00 | -$ 29.750,00 | -$ 32.780,00 |
| *Oil Frac Spread 1;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 299,24 | -$ 88,62 | -$ 277,21 |
| Total Net Profit | -$ 43.090,00 | -$ 25.878,00 | -$ 29.662,00 |
| Total Generated Profit | $ 72.226,00 | $ 147.084,00 | $ 73.946,00 |
| Total Generated Loss | -$ 115.316,00 | -$ 172.962,00 | -$ 103.608,00 |
| Total Number of Trades | 144 | 292 | 107 |
| Percent Profitable | 35,42% | 37,67% | 24,30% |
| Total Transaction Costs | $ 5.760,00 | $ 11.680,00 | $ 4.280,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 2.146,23 | $ 1.721,42 | $ 3.047,93 |
| t-Value | -1,673 | -0,880 | -0,941 |
| Kurtosis | 8,725 | 5,558 | 18,931 |
| Skewness | 1,275 | 0,362 | 3,620 |
| Maximum | $ 10.220,00 | $ 9.184,00 | $ 18.330,00 |
| Minimum | -$ 8.274,00 | -$ 7.696,00 | -$ 6.078,00 |

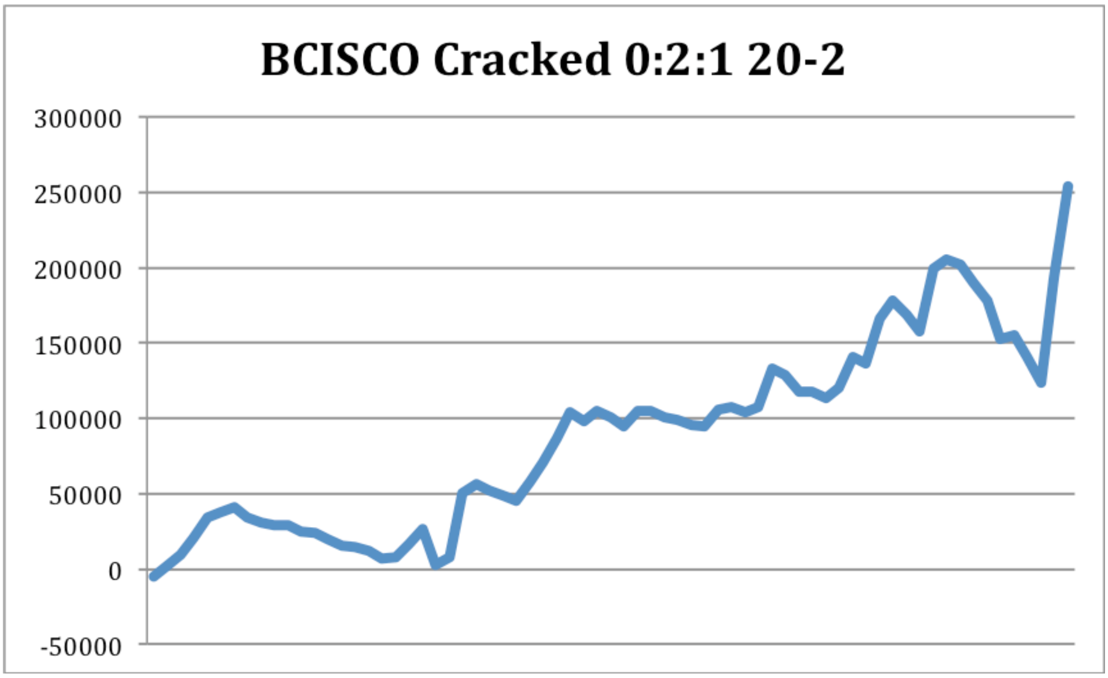
*Table D.4 Buy when cross out off band - Sell when cross of Moving Average*

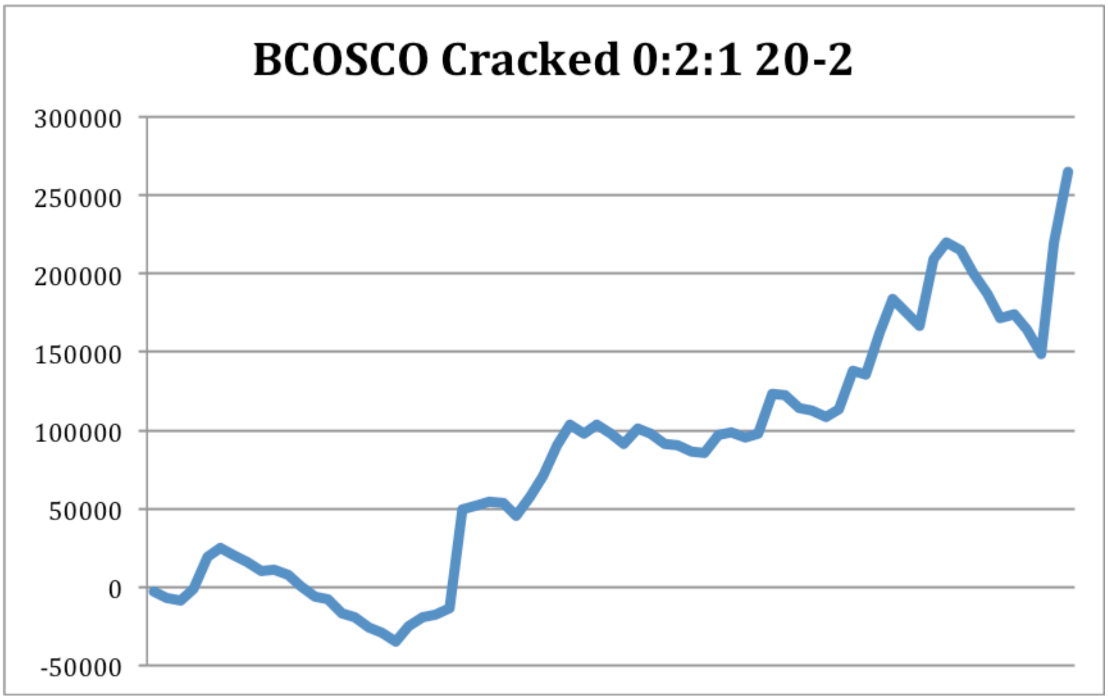
| *Crack Spread 3;2;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 1.952,78 | -$ 1.433,66 | -$ 1.790,99 |
| Total Net Profit | -$ 240.192,00 | -$ 384.220,00 | -$ 180.890,00 |
| Total Generated Profit | $ 191.702,00 | $ 340.466,00 | $ 160.950,00 |
| Total Generated Loss | -$ 431.894,00 | -$ 724.686,00 | -$ 341.840,00 |
| Total Number of Trades | 123 | 268 | 101 |
| Percent Profitable | 27,64% | 31,72% | 29,70% |
| Total Transaction Costs | $ 12.300,00 | $ 26.800,00 | $ 10.100,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 7.124,75 | $ 5.714,41 | $ 7.433,72 |
| t-Value | -3,040 | -4,107 | -2,421 |
| Kurtosis | 5,391 | 6,721 | 14,168 |
| Skewness | 1,106 | 1,059 | 2,445 |
| Maximum | $ 28.928,00 | $ 29.384,00 | $ 43.844,00 |
| Minimum | -$ 26.512,00 | -$ 19.546,00 | -$ 19.120,00 |
| *Crack Spread 1;0;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 408,53 | -$ 49,87 | -$ 819,54 |
| Total Net Profit | -$ 55.968,00 | -$ 13.364,00 | -$ 75.398,00 |
| Total Generated Profit | $ 48.208,00 | $ 219.314,00 | $ 30.014,00 |
| Total Generated Loss | -$ 104.176,00 | -$ 232.678,00 | -$ 105.412,00 |
| Total Number of Trades | 137 | 268 | 92 |
| Percent Profitable | 32,85% | 35,07% | 22,83% |
| Total Transaction Costs | $ 5.480,00 | $ 10.720,00 | $ 3.680,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 1.503,54 | $ 3.425,95 | $ 1.670,43 |
| t-Value | -3,180 | -0,238 | -4,706 |
| Kurtosis | 2,567 | 13,022 | 1,080 |
| Skewness | 0,200 | 0,195 | 0,049 |
| Maximum | $ 4.782,00 | $ 18.936,00 | $ 3.698,00 |
| Minimum | -$ 5.756,00 | -$ 19.200,00 | -$ 6.488,00 |
| *Crack Spread 1;1;0* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 276,25 | -$ 553,60 | $ 34,28 |
| Total Net Profit | -$ 34.808,00 | -$ 148.366,00 | $ 2.914,00 |
| Total Generated Profit | $ 122.114,00 | $ 184.568,00 | $ 122.642,00 |
| Total Generated Loss | -$ 156.922,00 | -$ 332.934,00 | -$ 119.728,00 |
| Total Number of Trades | 126 | 268 | 85 |
| Percent Profitable | 33,33% | 32,09% | 36,47% |
| Total Transaction Costs | $ 5.040,00 | $ 10.720,00 | $ 3.400,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 3.194,84 | $ 2.859,08 | $ 4.158,41 |
| t-Value | -0,971 | -3,170 | 0,076 |
| Kurtosis | 2,791 | 8,020 | 5,410 |
| Skewness | 0,811 | 1,112 | 1,693 |
| Maximum | $ 11.352,00 | $ 14.566,00 | $ 19.284,00 |
| Minimum | -$ 10.314,00 | -$ 13.030,00 | -$ 8.362,00 |

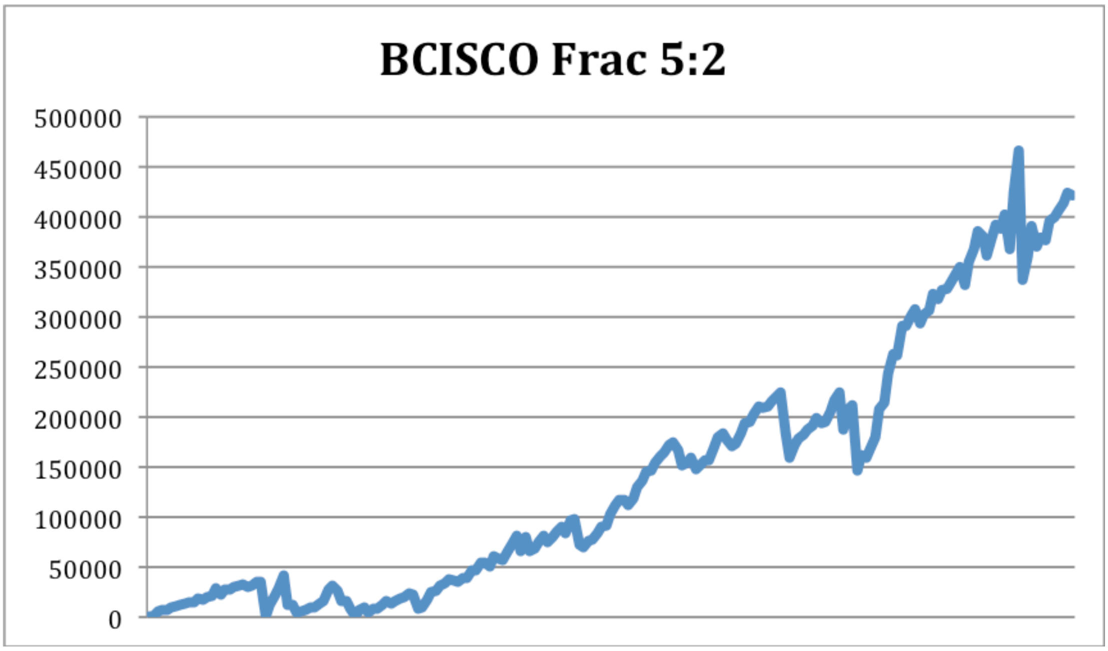
| *Cracked Spread 0;2;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | $ 927,58 | -$ 631,14 | $ 2.327,54 |
| Total Net Profit | $ 120.585,60 | -$ 169.776,00 | $ 181.548,00 |
| Total Generated Profit | $ 445.350,00 | $ 553.716,00 | $ 401.616,00 |
| Total Generated Loss | -$ 324.764,40 | -$ 723.492,00 | -$ 220.068,00 |
| Total Number of Trades | 130 | 269 | 78 |
| Percent Profitable | 38,46% | 32,34% | 41,03% |
| Total Transaction Costs | $ 7.800,00 | $ 16.140,00 | $ 4.680,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 10.709,01 | $ 7.521,67 | $ 13.521,88 |
| t-Value | 0,988 | -1,376 | 1,520 |
| Kurtosis | 18,669 | 12,816 | 9,148 |
| Skewness | 3,632 | 2,089 | 2,546 |
| Maximum | $ 64.536,00 | $ 45.258,00 | $ 71.046,00 |
| Minimum | -$ 20.304,00 | -$ 29.754,00 | -$ 19.422,00 |
| *Cracked Spread 0;1;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | $ 351,68 | -$ 2,80 | $ 383,07 |
| Total Net Profit | $ 46.422,00 | -$ 760,00 | $ 31.412,00 |
| Total Generated Profit | $ 206.968,00 | $ 298.082,00 | $ 153.910,00 |
| Total Generated Loss | -$ 160.546,00 | -$ 298.842,00 | -$ 122.498,00 |
| Total Number of Trades | 132 | 271 | 82 |
| Percent Profitable | 44,70% | 40,22% | 39,02% |
| Total Transaction Costs | $ 5.280,00 | $ 10.840,00 | $ 3.280,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 4.474,43 | $ 3.619,35 | $ 5.155,79 |
| t-Value | 0,903 | -0,013 | 0,673 |
| Kurtosis | 8,773 | 12,323 | 4,057 |
| Skewness | 1,986 | 2,148 | 1,783 |
| Maximum | $ 24.404,00 | $ 24.278,00 | $ 18.776,00 |
| Minimum | -$ 12.220,00 | -$ 13.312,00 | -$ 7.432,00 |
| *Frac Spread 5;2* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
| Average Net Profit Per Trade | -$ 1.732,76 | -$ 2.549,73 | -$ 2.104,89 |
| Total Net Profit | -$ 232.190,00 | -$ 757.270,00 | -$ 197.860,00 |
| Total Generated Profit | $ 449.730,00 | $ 572.020,00 | $ 413.970,00 |
| Total Generated Loss | -$ 681.920,00 | -$ 1.329.290,00 | -$ 611.830,00 |
| Total Number of Trades | 134 | 297 | 94 |
| Percent Profitable | 24,63% | 19,53% | 23,40% |
| Total Transaction Costs | $ 18.760,00 | $ 41.580,00 | $ 13.160,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 15.000,26 | $ 10.400,49 | $ 16.983,58 |
| t-Value | -1,337 | -4,225 | -1,202 |
| Kurtosis | 29,404 | 12,578 | 16,367 |
| Skewness | 4,104 | 2,323 | 3,318 |
| Maximum | $ 116.390,00 | $ 60.190,00 | $ 102.340,00 |
| Minimum | -$ 33.940,00 | -$ 35.960,00 | -$ 24.350,00 |

| *Oil Frac Spread 1;1* | *ma.20 sd.2* | *ma.12 sd.1.55* | *ma.50 sd.1.645* |
|---|---|---|---|
| Average Net Profit Per Trade | -$ 168,41 | -$ 78,66 | -$ 143,96 |
| Total Net Profit | -$ 23.914,00 | -$ 22.576,00 | -$ 15.548,00 |
| Total Generated Profit | $ 92.416,00 | $ 160.002,00 | $ 87.600,00 |
| Total Generated Loss | -$ 116.330,00 | -$ 182.578,00 | -$ 103.148,00 |
| Total Number of Trades | 142 | 287 | 108 |
| Percent Profitable | 33,10% | 37,28% | 27,78% |
| Total Transaction Costs | $ 5.680,00 | $ 11.480,00 | $ 4.320,00 |
| *Per Trade* | | | |
| Standard Deviation | $ 2.280,64 | $ 1.872,17 | $ 3.069,29 |
| t-Value | -0,880 | -0,712 | -0,487 |
| Kurtosis | 5,564 | 5,059 | 14,444 |
| Skewness | 1,345 | 0,855 | 3,109 |
| Maximum | $ 10.200,00 | $ 8.574,00 | $ 17.374,00 |
| Minimum | -$ 7.294,00 | -$ 6.820,00 | -$ 5.280,00 |

## Appendix E - Equity Curve *(January 1995- July 2009)*

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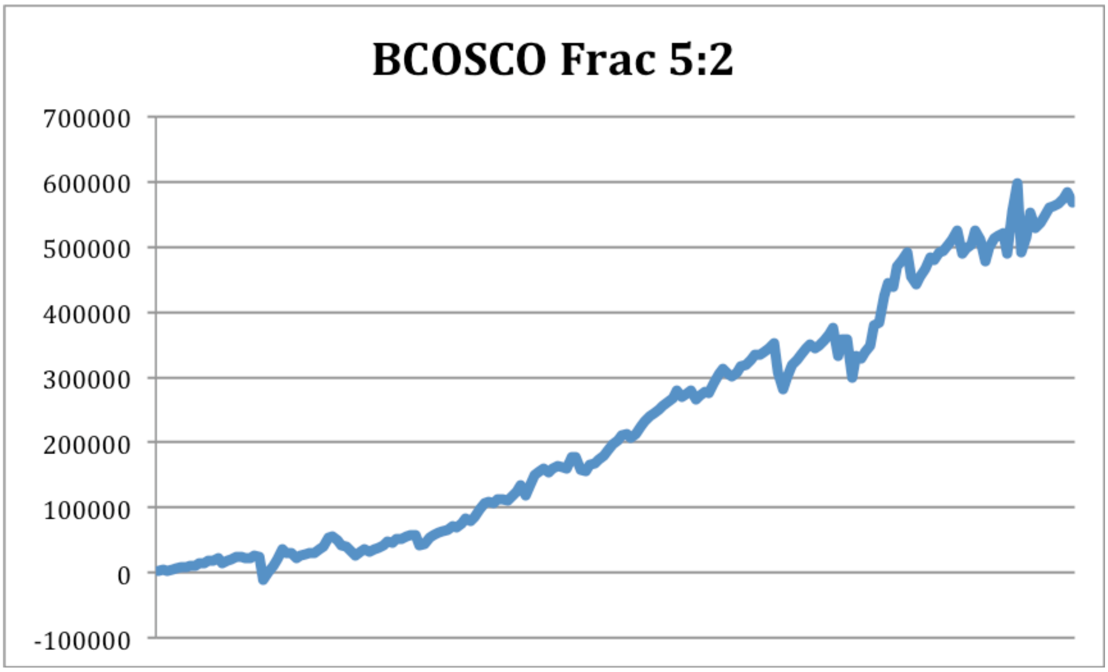
400000
350000
300000
250000
200000
150000
100000
50000
0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600000
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300000
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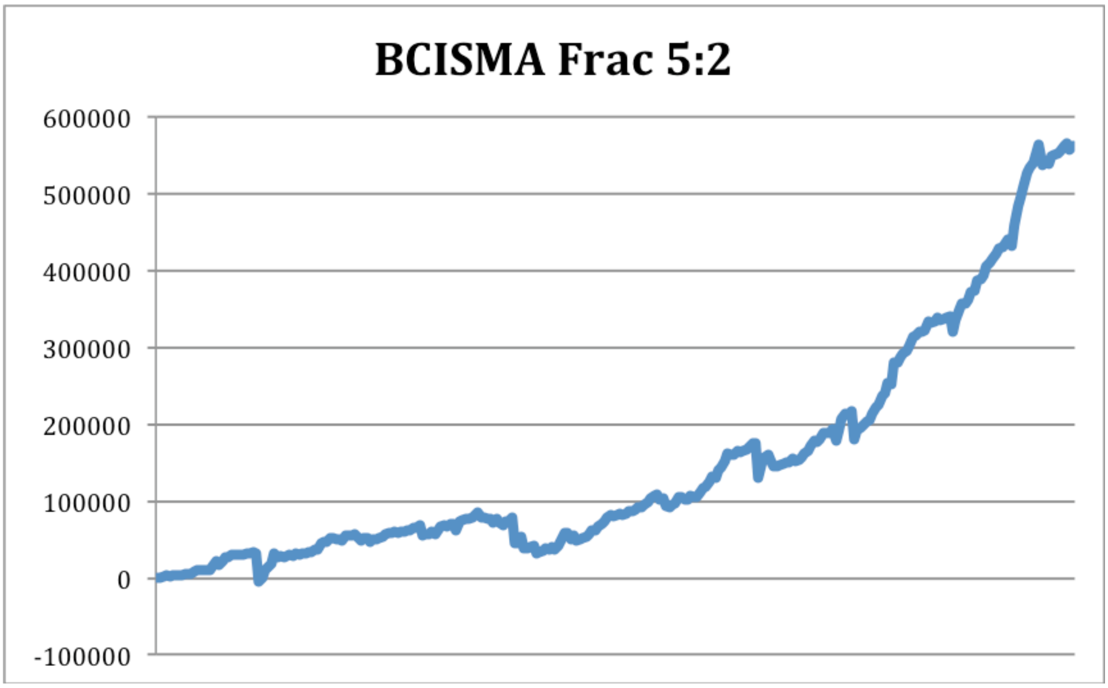
0
-100000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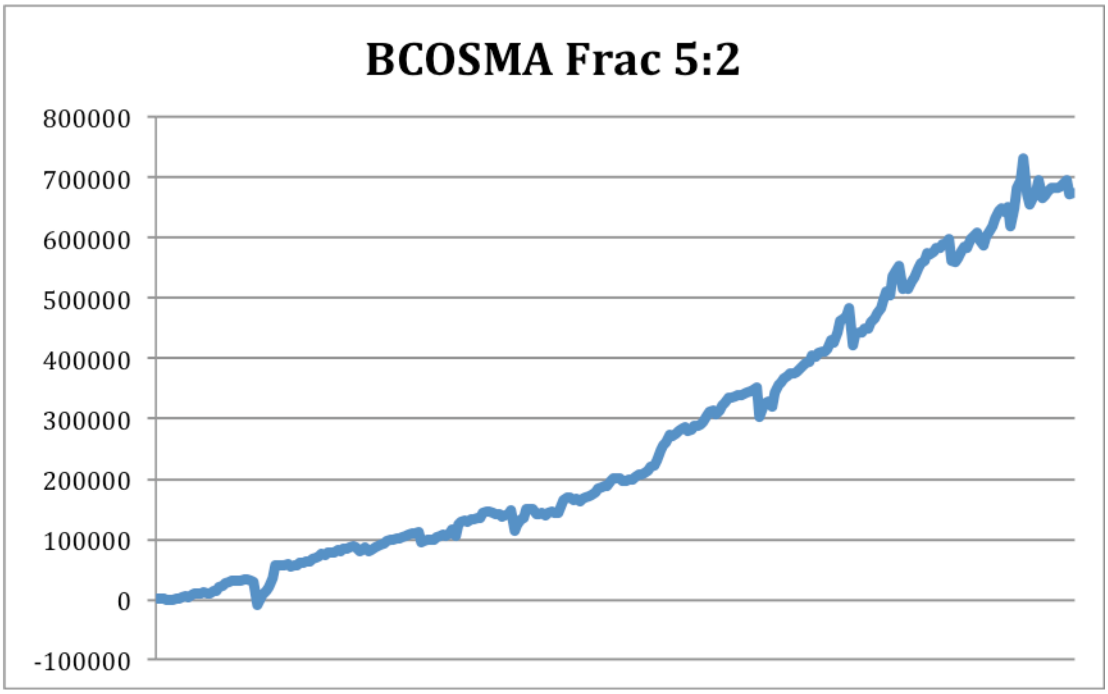
200000
100000
0
-100000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