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Statistical Arbitrage Opportunities in Crude Futures Markets

Evidence from WTI and Brent Inter-Market Spreads

Statistisk Arbitrasjemuligheter mellom markeder som omsetter fremtidskontrakter på råolje.

Bevis fra WTI og Brent Inter-Marked Futures Spreads

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Veileder: Stein Frydenberg



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Selve prosessen tok noe lengre tid enn antatt, men endelig er jeg i mål.

Jeg vil rette en takk til Stein Frydenberg som i sin rolle som veileder har kommet med gode råd, innspill og tilbakemeldinger. Deretter vil jeg rette en stor takk til foreldre, besteforeldre og resterende familie og venner som har støttet med gjennom hele utdanningsløpet.

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Summary of study

The purpose with this study was 1.) Discover arbitrage opportunities in Inter-Market futures spread for the Crude Benchmarks West Texas Intermediate (WTI) and Brent Crude by using statistical models and 2.) Testing the profitability of any statistical arbitrage opportunity found with a long/short Hedge Fund strategy known as Pairs trading to assess if the arbitrage opportunity found is tradable.

The Engle-Granger Cointegration analysis *Engle-Granger (1987)* was implemented as the statistical model to investigate possible statistical arbitrage opportunities. In the formation-period chosen in this study, July 1st 2014 – June 30th 2015 The cointegration analysis found the following spreads to be Cointegrated: ICE Brent – NYM Brent, RTS Brent – NYM Brent, RTS Brent – ICE Brent, ICE WTI – NYM WTI, DGCX WTI – NYM WTI and DGCX WTI – ICE WTI. The Cointegration test did not reject cointegration in spreads against ROFEX, but evidence support that there were some non-stationary trends in the residual for the spreads ROFEX -NYM, ROFEX – ICE and DGCX - ROFEX. The profitability in trades executed in those spreads suggested the trends to only be short-term and could be because of low trading activity in ROFEX.

The hypothesis of Statistical Arbitrage opportunities in daily closing prices for WTI and Brent Futures spreads were confirmed by the positive annualized returns after a 0,5% transaction fee was subtracted generated in the out-of-sample (trading) period; July 1st 2015 – July 15th 2016 for all spreads. The long-short strategy generated an 7,22% annualized profit (5,5% Post Transaction costs) in the ICE-NYM Brent spread, 8,48% (6,18% post TC) profit in the ICE-NYM WTI spread, 15,4% (10,7% post TC) in the DGCX-NYM and 17,6% (12,9% post TC) in the DGCX-ICE WTI Spreads. But due to the low numbers of trades (3,8-10,3) in 273 trading days, further research on intra -day data is warranted before any wider conclusions can be drawn. The average profits pr. trade (1,7%-2,14%) from the daily settlement data suggests that if the transaction fee is small enough, implementing a StatArb strategy on intra-day data could also be profitable. The Pairs Trading strategy was also found to be profitable between the other markets, but it is not possible to determine without the intra-day data if the profits came from trading activity or just time-zone differences. The one-day waiting rule from *Gatev et al (,2006)* was tested on Brent spreads to see if the spreads still were profitable (still outside its range) after waiting one day

after the trigger for opening positions were met. It was found that this rule generated results similar to the spreads between ICE, NYM and DGCX. The average number of trades decreased to 7,5 in the RTS-ICE spread and 8 in the RTS-NYM spread. The strategies generated an average 25,495 % annual profits post TC for RTS-NYM and 23,435 % annual profits between RTS and ICE. The results from the rule suggest that it could also be statistical arbitrage opportunities to exploit in those markets, since the speed of correction in those markets are slower than for ICE, NYM and DGCX spreads which continues the mispricing from the relative – value between those markets into the next few trading sessions, but this relationship must also be investigated further using intra-day data. The returns from the pairs trading strategy had for all spreads low correlation with the return of the S&P 500 and S&P GSCI All Crudes Index, highlighting the tactical value of using a pairs trading strategy in WTI and Brent Crude Futures as a tool for diversification in an investment portfolio.

Sammendrag av studie

Formålet med denne studien var 1.) avdekke mulige arbitrasjemuligheter mellom markedsplasser hvor fremtidskontrakter på WTI og Brent er omsatt ved hjelp av statistiske modeller og 2.) teste den eventuelle avdekkede arbitrasjemulighetenes profitabilitet med en lang/kort strategi kjent som Pairs Trading.

Engle-Granger Ko-integrasjonsanalyse *Engle-Granger (1987)* ble valgt som statistisk modell for å finne den relative- verdien til de forskjellige markedene i forhold til hverandre. Analysen fant at i formeringsperioden 1. Juli 2014 – 30. Juni 2015 var følgende markeder ko-integrerte; ICE Brent – NYM Brent, RTS Brent – NYM Brent, RTS Brent – ICE Brent, ICE WTI – NYM WTI, DGCX WTI – NYM WTI og DGCX WTI – ICE WTI. Ko-integrasjons analysen avsto ikke ko-integrasjon mellom ROFEX og de andre markedene som omsatt WTI fremtidskontrakter, men ut fra residualplottet så ser det ut som det var noen ikke-stasjonære trender i formeringsperioden mellom ROFEX -ICE, ROFEX – NYM og DGCX – ROFEX. Avkastningen fra lang/kort strategien mellom disse markedene tilsier at denne trenden med ikke-stasjonære residualer bare var forbigående og kan komme av lavt aktivitetsnivå på ROFEX i formeringsperioden.

Hypotesen om at det finnes arbitrasjemuligheter mellom markeder som omsetter WTI og Brent ble bekreftet av den årlige avkastningen etter at transaksjonskostnader fra trukket fra i handelsperioden 1 juli 2015 – 15. Juli 2016. Strategien genererte en årlig avkastning på 7,22% (5,5% Post Transaksjonskostnader) mellom ICE -NYM Brent, 8,48% (6,18% post TK) i ICE– NYM WTI, 15,4% (10,7% post TK) i DGCX – NYM WTI og 17,6% (12,9% post TK) i DGCX – ICE WTI, men på grunn av det lave antallet gjennomsnittlige handler i løpet av handelsperioden (3,8 – 10,3) så bør analysen bli gjort med intradag data før noen videre konklusjon kan trekkes. Men den gjennomsnittlige avkastningen per- handel mellom disse markedene (1,7% - 2,14%) tilsier at om transaksjonskostnaden er liten nok så kan en intradag StatArb strategi gi positiv avkastning.

Lang/kort analysen ble også implementert mellom de andre markedene, men store forskjeller mellom tidspunktene for daglig oppgjør gjorde det vanskelig å avgjøre om avkastningen kommer fra tidsforskjeller eller fra handelsaktivitet. Handelsregelen fra Gatev et al (2006) hvor man venter 1 dag etter at signalet for åpning av posisjoner er nådd før man tar en posisjon, hvis markedene fortsatt er feilpriset, ble implementert mellom RTS – ICE og RTS – NYM for Brent.

Regelen gav lignende resultat som for strategien mellom DGCX, ICE og NYM med ett lavere gjennomsnittlig antall handler. Strategien genererte 25,49% årlig avkastning i RTS – NYM og 23,45% årlig avkastning mellom RTS og ICE etter transaksjonskostnader var trukket fra.

Resultatet fra denne regelen tilsier at det kan finnes arbitrasje mellom disse markedene som ikke bare kommer fra forskjeller i tidssoner, siden korreksjons hastighet mellom disse markedene er lavere enn de nevnt tidligere, men også dette bør analyseres videre med intradag data for å være sikker. Avkastningen fra strategiene og indeksene S&P 500 og S&P GSCI All Crudes viser den taktiske verdien av å bruke en pairs-trading strategi som et diversifiseringsverktøy i en investeringsportefølje.

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1. Introduction

1.1 Literature review

Pairs trading is a long-short equity strategy where the profits are generated by the relative performance of the two components in the spread, called *legs* in a situation where they trade outside of their historical range, found by statistical models, under the assumption that there are some kind of mean-reverting mechanism that ensures that the pairs converges back to their historical mean. The earliest cases of pairs -trading were mostly based on finding highly correlated pairs of stocks that moved in the same correction, and then take a long position in the undervalued and a short position in the overvalued stock when the correlation weakened. Most literature on pairs trading in the equity market are influenced by the early work of *Gatev et al (2006)*. They found excess returns generated through pairs trading to be a compensation to arbitrageurs for enforcing the law of one price (LOP), and by doing that, ensuring market efficiency. They also found the excess returns to be unrelated to market-risk factors (uncorrelated), which suggest that pairs trading should be profitable even in periods with declining prices in markets. Evidence from papers such as *Ungever (2015)*, *Fuertes, Miffre and Rallis (2008)*, *Miffre and Rallis (2006)*, *Dunis et al (2006)*, *Dunis et al (2008)*, *Desai et al(2012)*, *Girma and Paulson(1999)* and the most recent study by *Yang et al.(2016)* suggests that the findings from Gatev et al(2006) should also be valid when a pairs trading strategy is implemented in the commodity futures markets. *Ungever (2015)* tested a pairs trading strategy using cointegration approach on the 10 most popular agricultural futures markets. He continued to find two Cointegrated pairs (Cotton – Coffee and Cotton -Live cattle) which the pairs trading strategy was implemented on. The strategy was successful in both the in-sample period and trading – period for both pairs. *Fuertes, Miffre and Rallis (2008)* found an average 21,02% excess returns in calendar spreads in different commodities using trading signals based on momentum (Contango/ “normal” backwardation) and term structure (carrying cost *Working (1948)*).*Miffre and Rallis(2006)* investigated 56 momentum and contrarian strategies for futures spread trading. They identified 13 profitable momentum strategies were the backwardated contracts was bought and the contangoed contracts were sold, and captured an annualized average profit of 9,38%. *Dunis et al (2006)* tested a Neural Neutral Network (NNR), Cointegration “Fair – value” and a Moving Averages Convergence Divergence (MACD) model on the WTI-Brent Futures Spread with different threshold and correlation

filters. They found the MACD model to be most profitable model with a 26,35% return with the threshold filter, and 26,15% with the correlation filter. In *Dunis et al (2008)* the previous study was further developed with the models used in the previous study and the addition of a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model on portfolios of oil futures spreads. The NRR model was found to be the best model on portfolios of oil future spreads with its 10,76% annualized profit. *Desai et al (2012)* applied the Stochastic pairs trading approach to the Gold and Silver markets which turned out a 100% success rate and a 44,45% profit in the test period. *Girma and Paulson (1999)* investigated the long-term relationship and risk-arbitrage opportunities in Crack spreads, spreads between Crude Oil Futures and refined products produced from Crude. They found cointegration in the 3:2:1 Crack spread, 1:1:0 gasoline spread and the 1:0:1 Heating Oil Spread and implementing a successful long-short strategy on those spreads. *Yang et al. (2016)* implemented a profitable pairs trading strategy in the Chinese commodity futures markets using a similar approach as *Gatev et al(2006)* on data from the time period January 1st 2005- June 1st 2016 .The study found the high profit generated by the strategy too be a compensation for the spread divergence risk in longer holding periods, since the profits decreased if the maximum holding period was decreased.

The focus in academic literature on the commodity futures markets has primarily been on relationships between spot and futures contract, and the relationship between futures contracts with different time to maturity. Research into other types of futures spreads, such as spreads between markets in the same commodity has not gotten much attention. The same goes for cointegration analysis between different markets. Due to the massive evidence on stationarity and cointegration found in other studies, such as in *Mosivuk & Smyth (2008)* , that found spot and futures prices for WTI and Brent to contain a unit root (non – stationary) between 1991 – 2004, *Lin & Liang (2010)* tested and found cointegration between spot and futures prices between January 2nd 2001 and October 15th 2006 using the Momentum Threshold Autoregressive Consistent (M-TAR-C) method, and the studies that traded futures spreads using the cointegration approach mentioned earlier , it was assumed that futures contracts on the same underlying crude could be Cointegrated with futures contracts in the same underlying, but traded at a different futures exchange. The small difference in prices quoted between different markets indicates that this assumption could be correct.

1.2 Pairs Trading

The use of statistical models to develop quantitative arbitrage strategies (STATARB) had its beginning at Wall Street in the mid 1980's. A group of analysts under the command of Nunzio Tartaglia started to trade pairs using statistical techniques and automatic trading systems carried out with computers. The trading system designed by Nunzio Tartaglia and his team at Morgan Stanley is the base for the more sophisticated, automated, high-frequency statistical trading system used today. The framework of pairs trading strategies can be divided into two sub categories; Statistical Arbitrage Pairs trading (STATARB) and Risk-arbitrage Pairs trading strategies. *Vidyamurthy (2004)*

The Statistical Arbitrage Pairs trading framework is driven purely by the relative -value established by statistical models between the two *legs* of the pair, but risk-arbitrage pairs are an event-driven strategy, such as merger-arbitrage and other risk-arbitrage events, where the arbitrageurs are betting on the outcome of the event. STATARB pairs-trading strategies are typical long-short equity trades where the profits from the strategy is derived from the relative-mispricing between the pairs. The arbitrageurs use statistical measures to establish a long-term relationship between the two components, and take offsetting positions under the assumption that there exist an Error Correction Mechanism (ECM) that brings the spread between the two component back to its historical range. Pairs trading strategies are considered as self-financing, market neutral strategies that are less risky than other relative -value strategies due to the hedging aspect with going both long-and short at the same time. Profitability in a Relative- value pairs trading strategy that implies that the underlying assumption in the *Arbitrage Pricing Theory (APT)* introduced by Stephen Ross in *Ross (1976)* is correct *Gatev et al(2006)*. He argues that if two securities that have exactly the same exposure to common risk factors, the expected return to the two securities should be the same. This aligns with the *Law of one Price* introduced by David Ricardo in the early part of the 19th century. He argued that if there was free movement between markets, and the exactly same goods traded at different prices in the two markets, arbitrageurs could earn risk free profits from buying the goods in the cheap market and then sell with a profit in the expensive market. By doing so, the price in the cheap market would increase, due to the increased demand, and the price in the expensive market would decrease due to the increased supply. Eventually, this disequilibrium between the supply and demand in the two markets would bring the prices in

the two markets back to a price level were the only difference between the two markets would be the price difference of transporting the goods to the markets making it impossible for arbitrageurs to make a profit. *Ingersoll (1986)* formulated this law applied to financial markets as “*Two assets with the same payoff in every state, should sell for the same price*». Under this assumption, two similar assets like WTI Crude and Brent Crude should sell for the same, or almost the same since WTI is of a higher quality than Brent. Historically WTI traded with a premium towards Brent due to being of a higher quality until August 2010. This has in later years changed due to a change in non-economic factors that made the relationship change, and making Brent trade with a premium compared to WTI. *Büyüksahin et al (2012)* found significant evidence that infrastructure bottlenecks could be one of the main factors on why Brent overtook WTI’s throne. WTI is a land-based crude, and it is transported to the markets (Cushing, Oklahoma) by road, railroad and pipeline. Since WTI and Brent are substitutes of each other, the bottleneck issues with WTI did not make the price sky-rocket for WTI due to the disequilibrium between supply and demand, but the consumers shifted their consumption over from WTI to Brent and instead increasing the price for Brent. The pairs -trading framework offers a number of approaches on how to identify related pairs, such as the distance approach tested by *Gatev et al 2006*) and *Yang et al.(2016)* where pairs are identified by their “Closeness”, the sum of squared deviations between two normalized price series.

$$SSD = \sum_{i=1}^i (NP_t^A - NP_t^B)^2$$

The price series for all possible pairs are normalized and the return from each normalized stock are added to a profit index. The pair with the smallest SSD are considered the “closest” pairs.

The stochastic spread approach, as in *Boguslavskaya & Boguslavsky(2003)* and *Kanamura(2009)* were the spread is modeled as a mean-reverting Ornstein-Uhlenbeck Process

$$\text{Ornstein – Uhlenbeck: } dX_t = -kX_t dt + \sigma dB_t$$

The last of the main three approaches is the Cointegration approach, which also is the most common approach in academic research on pairs trading in the commodity futures market. One of the advantages of using cointegration analysis to model long-term relationships are that having Cointegrated pairs implies mean-reversion. The main idea behind pairs trading is to capture profits from short-term deviations in pairs that have a stable long-run relationships and their reversion back to their long-run relationship, dynamics that Cointegrated pairs implies. The cointegration error correction model allows for limited drift away from the historical mean before the prices revert back to the mean. This implied mean-reversion makes the cointegration approach a far more robust approach to pairs trading than the distance approach used by Gatev et al(2006), where it is only assumed that the historical trend will continue after the divergence from the historical long-run relationship, no model for mean-reversion is modeled in the analysis.

Due to the success in a number of earlier studies such as *Girma & Paulson (1999)* that found cointegration in the *3:2:1 Crack spread*, the *1:0:1 Heating Oil Crack spread* and the *1:1:0 Gasoline Crack spread* between 1983-1994., *Dunis et al (2006)* found the WTI-Brent spread to be Cointegrated and *Lin&Lian (2010)* found that there are cointegration between futures and spot prices. Not much attention in the Academic literature has been given to Crude Inter-Market spreads and cointegration between futures markets in the same underlying commodity, but the evidence found in other studies suggest that there could be found cointegration relationship inside Crude Inter-Market Futures spreads, due to the large evidence on non- stationarity in futures prices for Brent and WTI.

1.3 Pairs trading in the commodity futures market.

In order to trade pairs successful, the pairs must be designed in a way that their exposure to movements in the market are eliminated. This market neutrality can according to *Erhman (2006)* be achieved in three ways:

1. *Dollar neutral*

The trader invests the same amount of dollar value in each leg for the trade. The number of shares in each leg is calculated by the price-ratio between the two assets.

$$\frac{n_x}{n_y} = \frac{P_x}{P_y}$$

Investing the same amount in each *leg* eliminates the effects of movements in the market as a whole, but the trader can still profit from movements away from the relative- value in the two legs.

2. *Beta Neutral*

This can be achieved in two ways; i.) Picking two pairs with identical betas to the market, or ii.) Use the beta-ratio to choose what number of shares to invest in each *leg*.

3. *Share neutral*

Pairs with prices that are close, can become *share-neutral* by investing the equal numbers of shares in each leg. Using close prices and equal number of shares in each leg eliminates some of the smaller market-movement as long as the betas are not to different.

Becoming market neutral when trading commodity futures are done in a similar way.

Commodity Futures does not have a beta to the market portfolio, since they are not included in the market portfolio, but they have exposure to movements in the currency which they trade in. By going for the dollar-neutral approach or the share neutral approach in two commodity futures that trades in the same currency the trader eliminates any exposure to currency movements, and the position is neutral to movements in the market, which for commodity futures are movements in currency rates. *Erhman (2006)* describes the differences between a spread-trade (a pairs-trade using commodity futures) and a typical pairs trade in stocks as;” *A Spread trade is a market bet with a hedging feature built in, while a pairs trade is a market neutral position*”. He argues that becoming neutral to movements in the underlying currency is not enough to classify the trade as a market neutral trade, and this

approach should be considered a riskier approach than a pairs trade. Even though a Spread trader cannot achieve the same amount of “market neutrality” as a pairs trader, the approach is still considered a less risky strategy, something the reduced initial marginal requirements from buying the WTI-Brent Spread compared to just buying one side of the pair proves. CME¹ list the initial Margin on buying the Brent – Dubai crude spread in the period 07/16 – 08/16 at \$770, and the margin on buying just one side of the spread, the Brent futures is listed with a \$3850. When it comes to the market neutrality aspect for intra-market spreads, it seems as most of the spreads fulfill the dollar neutral and share neutral approach to market neutrality, since the price differential between most markets are really small.

One of the biggest benefits to using futures in a pairs trading strategy is the reduced initial margin or “deposit of good faith” which allows traders to use the gearing effect by using a higher degree of leverage. Let’s say a spread trades 5% outside its historical range and the initial margin on the spread is 5%, when the spread converges back to its historical range, the trader would have a 100% ROI if only the initial margin is posted, and an initial deposit on 10 % would yield a 50% ROI. The option to use a higher degree of leverage allows the traders to multiple their profits, but also multiple their potential losses. Both CME² and ICE³ operates with an initial margin that is 110% of the maintenance level for futures contracts. That means that in situations where only the initial margin is posted after the triggers to open positions are met, and the spread continues to widen, the trader would soon receive margin calls from his Broker. If the trader is unable to meet the margin call, his positions are liquidated immediately in order to cover his debt. The backside with using leverage in trades is that the trader has to cover the total loss of his positions, even in situations where the losses is greater than the total margin posted.

Schleifer & Vishny(1997) discussed the agency problem that could occur when Money-Managers where chasing arbitrage opportunities using other people’s money. Since most of the professional arbitrageurs are speculating with other investors money, there is a limit on how much loss the investors are willing to take in order to lock in the ultimate profit, even if taking a short term loss means that their profits by the time of convergence would be even greater. In a situation where the spread continues to widen even more after the trigger for opening a trade is met, a well-informed rational money-manager increase his position even

¹ <http://www.cmegroup.com/clearing/margins/>

² <http://www.cmegroup.com/clearing/margins/componentised/initial-margin-requirements.html>

³ <https://www.theice.com/margins>

more (for spread trading, open a position at a higher threshold) even if this means that additional margins has to be deposited. From an investors perspective, a growing spread and deposits due to margin calls, looks like they are losing money even though that is not the case. If the investors sit the same set of information that the money -managers are having, then we will not have any agency problems. But as long as the arbitrageurs are having investors that is not informed at the same degree as him, he could face problems with bringing in the money needed in order to meet the margin calls or investors could take their money out of the found. The case of the problem here is information. As long as the investors have the same information as the arbitrageur, then they would not have any agency- problems. If not, the money-manager are telling the investors that they are making money, but the investor is seeing that they are losing money due to margin calls or negative positions, and this could lead to problems. Schleifer and Vishny also argued that pairs-trading strategies should not be considered self-financing, even though sale of the overvalued contracts covers going long in the undervalued contract, the managers still need capital to cover possible margin-calls if the mispricing continues to grow. The manager would need a large amount of capital in order to ensure that we have the money needed if the broker makes a margin call.

Schleifer&Vishny(1997) The biggest risk factor to relative value trading is a situation where the prices between the two legs of the trade does not go back to its historical price range. There can be a number of reasons on why the long-run relationship between the two assets has changed to a degree where the prices do not run inside the historical range, such as micro and macro-economic factors. The WTI – BRENT relationship went through a change like this. Historically the Brent traded at a discount compare to WTI but this relationship has since changed. *Büyüksahin et al (2012)* found empirical significant evidence that infrastructure bottlenecks were one of the biggest factors behind this change. WTI being a land based is more prone to this kind of bottleneck problems since all the transportation from the field to the storage area happens on land. Brent on the other hand is a sea based crude and is transported its basically moved directed from the field to the storage area, the oil tanker. This allows for more flexibility when it comes to storage and which market the crude is going to. *Girma & Paulson (1998)* found empirical evidence on seasonality in prices for some commodities. Demand for heating oil and gas increases in the winter season, and a colder/warmer winter than expected could influence the demand for crude oil since heating oil is a derivative of crude. Commodities like crude oil or its derivative products like heating oil, tend to have periods or season where the demand increases due to non-economic factors like

the weather. This illustrates some of the degree of sensitivity crude oil and crude products has to micro economic, macro-economic factors, and the risk that is associated with trading a crude oil futures spread based on historical stable long-run relationships. A relative value investment strategy is based on the assumption that the price differences between the two legs are only temporary, but if the changes are long-term, the trader can end up with a significant loss. The risk factors associated with a pairs trading strategy proves that profits earned should not be considered risk-free returns due to the agency issues described in *Schleifer & Vishny(1997)* and the possibility of a situation where the spread continues to grow apart to a degree where the long-term equilibrium distance between the two pairs has changed it should also not be considered capital – free arbitrage or a self-financing strategy since the trader would need capital in cause of a margin call.

1.5 Price behavior for commodity futures

Some terms that is often confused when it comes to Commodity Futures markets are normal/inverted markets and contango/backwarded futures. The difference between those two set of terms are that normal/inverted describes the relationship between futures with different time to maturity, and backwarded/ Contango describes the difference between the spot price or the expected future spot price and the futures contract. If the short -term contracts on a commodity trades at a lower level then the long-term contracts, the markets are said to be in contango. In a contango market, the “yield”-curve between futures with different time to maturity is increasing, meaning $F_{jan} < F_{feb} < F_{june}$ and so on. If the shorter term contracts trade higher than the longer terms contracts, the market is said to be inverted. The yield curve on the commodity shows a downward sloping curve between the short term contracts and the long-term contracts. This relationship is often describing as a function of changes in short -term supply of the commodity, which increases the price on short-term delivery.

The terms Contango and Backwardation (Normal – Backwardation) refers to the difference in price (Basis) between the Futures price and the expected future spot price $E(s)$ If the Futures contract trades at a premium towards the expected future price on delivery, the future market are said to be in Contango. A Contango Futures market implies that the price will decrease for that commodity, since the price of futures contracts tend to move towards the expected spot price as closer to maturity you come. A futures contracts that trades with a discount towards the expected future spot price $E(s)$ are said to be in backwardation or in “normal”

backwardation and were expected to raise. *Keynes (1930)* argued that futures prices should always be in backwardation towards the expected future spot price to compensate investors that goes “long” in the future contract. This implies that futures contracts do have a “risk premium to investors that does go long in the commodity contract, or an “insurance” premium to the producers of the commodity. A risk-averse producer can hedge his exposure to price movements by selling a future in the market and thus remove any exposure to price movements: The difference between the expected future spot rate or today's spot price and the futures contract can be seen as the price of insurance. Contrary to Keynes theory that assumes that the hedgers that sells the futures contracts forward sits on a long position on the underlying commodity, Cootner(1960) viewed hedgers as both risk-averse producers that sits on the underlying commodity and risk-averse consumers that wants to limit their exposure to upwards price movements and explains contangoed and backwardated futures prices as a function of hedgers net short/long positions. If the hedgers net positions are short, meaning more short positions than long, the prices are expected to raise, a backwardated futures market. Net Long positions by the hedgers means that prices were expected to fall, contangoed prices. In the Theory of Storage, introduced by Working (1933) modified by Kaldor (1939) and Working (1948), found the reason for why markets were in backwardation or Contango as a result of the inventory levels of the consumers and the benefit of holding the commodity, called the Convenience Yield. In this theory, the price of the futures contract is decided by the storage cost (c), the interest rate (r), the spot price and the benefits by holding the commodity (q). $F = S + r + C - q$

The size of the benefit (q) followed the inventory levels of the consumers. When inventories are low, the benefit of holding the commodity are high, and then inventories where high, the benefit of holding the commodity where low. A Convenience yield that exceeds the interest rate and storage costs causes backwardated futures markets and a low convenience yield causes contangoed markets. Working (1948) argued that backwardated markets could be seen as a result of the carry-costs associated by holding the commodity. He explained the positive spread between the near month contract and the next month contract (Calendar Spread) as the cost of holding the commodity. If the cost of carry was negative, inverse carry cost, meaning backwardated prices, the benefit for owning the commodity is greater than the interest rate and storage costs. Like in Kaldor's contribution, the size of the inventory is decided the levels of inventories in the consumers, but also upon the possibility of shortages. A high possibility of shortage means a high convenience yield and commodities that often is difficult to storage,

or have a short “shelf” life often tend to have a large convenience yield. In the cost of carry model, the futures price is expressed as a sum of the variables risk free rate (r), the storage cost (c), and the convenience yield (q) expressed in percentage of the spot price. $F = Se^{(r+c-q)t}$

1.6 Types of futures spreads

The main focus in commodity futures spreads has primary been on spreads that are either categorized as intra-commodity spreads or inter-commodity spreads.

Intra Commodity Spread

A spread where the two legs in the spread is both on the same underlying commodity, the same exchange but different delivery (expiration) date. This spreads are commonly known as “calendar” spreads. Traders that implements a pairs-trading strategy on a calendar spread tries to take advantage of the difference in the implied volatility between the different months also known as carrying costs.

Inter – Commodity Spread.

A spread between two related commodities, like a Natural Gas -Heating Oil spread or spreads between a commodity and the derivatives that comes from that commodity, like the Crack Spread or the Crush spread. The Crack spread is the spread between Crude Oil and the petroleum products produced by it, and the crush spread is the spread between Soya Beans and the product extracted from that. Traders that trades an inter-commodity spread takes advantage of the implied economic relationship between the two commodities. One way to implement a pairs trading strategy in an inter-commodity spread is to trade two substitutes like the WTI and Brent Crude and make trade on the distance between the two.

Except from these two categories of spreads, there is also a category of spreads that have received less attention: Spreads between markets(exchanges). The futures-spreads investigated in this study are inter-market, intra commodity futures spreads on WTI and Brent. Spreads between different exchanges such as ICE or RTS, in the same commodity futures with the same expiration date. If Futures contracts on WTI and Brent follows the *Law of one Price* the spread between the price quoted in the different markets should only reflect the transportation costs associated with shipping the crudes to the markets.

Any deviations from this relationship leaves arbitrageurs the opportunity to earn a profit by buying a futures contract in one market and simultaneous sell a futures contract in the other market. That means that if a long run equilibrium can be established using statistical models such as cointegration, there is likely that the *Law of one Price* holds between those markets. and the distance found between the two markets are the implied transportation costs between the two markets. As discussed earlier, there are other factors then just the transportation costs that decides the price in the markets, such as changes in the convenience yield due to increased/decreased demand or changes in paper market condition in that particular market, something that is more likely to be the reason on why the price of a liquid product as Crude Oil expire prices that lies outside the long-run equilibrium.

2. Data, methodology and trading rules

2.1 The data sample

Daily WTI and Brent Continuous price series (CS00) on the near-month futures contracts were collected from DataStream of the following exchanges in the time period 2011 – July 2016.

Brent Crude Futures:

- Russian Trading Systems (RTS) – Russia and Central Asia
- New York Mercantile Exchange (NYM) -North America
- Intercontinental Exchange Europe (ICEU) - Europe

West Texas intermediate(WTI) light sweet crude futures:

- New York Mercantile Exchange (NYM) – North America
- Intercontinental Exchange Europe (ICEU) - Europe
- The Rosario Futures Exchange (ROFEX) – Latin America
- Dubai Gold & Commodities Exchange (DGCX) – Middle East

This selection of exchanges represents almost all markets, as markets are divided in the ENI World Gas and Oil review 2015⁴, with the exception of the African Market and the Asian Market. Comparing exchanges that is located in different part of the world comes with the issue of trading in different time zones. Using Intra-day data, this is easily fixed with only trade and analyze data from when both exchanges is open for trading, but for daily closing quotes it is a bit more difficult. *Gataev et al (2006)* proposed a one-day waiting rule to deal with the bid/ask spreads, *Bianchi et al(2009)* expanded this rule to serve as a proxy for trading in different time zones. That meant that they waited one day after the opening signal was triggered before taking a position. If the spread was still outside its historical range after waiting one day, they opened positions on the spread.

⁴ <http://www.eninorge.com/no/>

Figure 1. The trading hours at the different exchanges

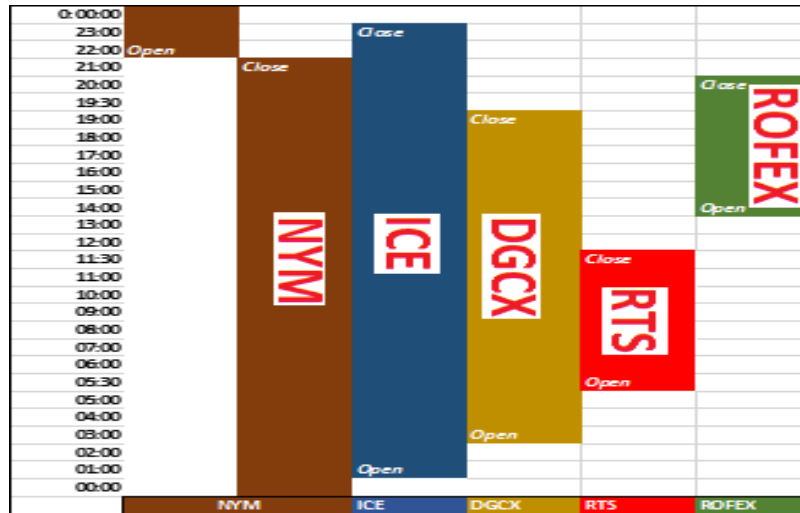


Figure 1 shows the trading hours for WTI and Brent collected from the different exchanges and converted to Greenwich Middle Time (GMT). Since both ICE and NYM have online trading platforms, they offer trading almost around the clock. ICE, NYM and DGCX calculates their daily settlement quote at around the same time, around 19 GMT so that means that there is good overlap in spreads between these three exchanges. The other two exchanges overlaps also in terms of trading hours, but their daily settlement time differs from the ones at ICE, NYM and DGCX. The only two exchanges where the trading hours do not overlap are RTS and ROFEX. But since the WTI-Brent spread is not investigated in this study, having no overlap in trading hours in those two markets are not an issue. Implementing the *Gataev et al (2006)* rule was reviewed as a fix for the issue with different settlement times, later dropped as a general rule since there is some overlap to a degree in trading hours between the exchanges.

Table 1. Descriptive Statistics Formation Period 1st July 2014 – 30th June 2015

	<i>Obs</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>Std.dev</i>	<i>Kurt</i>	<i>Skew</i>	<i>Implied Vol</i>
RTSb	261	75,311	112,220	47,400	1,2094	1,235	0,503	1,873 %
Log RTSb	261	4,289	4,720	3,859	0,0157	1,296	0,286	
NYMb	261	74,924	112,290	46,590	1,2082	1,236	0,501	2,308 %
Log NYMb	261	4,284	4,721	3,841	0,0157	1,300	0,284	
ICEb	261	74,896	112,290	46,590	1,2083	1,234	0,502	2,261 %
Log ICEb	261	4,283	4,721	3,841	0,0157	1,297	0,284	
ICEw	261	69,384	105,340	43,460	1,2062	1,336	0,455	2,411 %
Log ICEw	261	4,201	4,657	3,772	0,0170	1,430	0,255	
NYMw	261	69,406	105,340	43,460	1,2063	1,338	0,453	2,462 %
Log NYMw	261	4,202	4,657	3,772	0,0170	1,432	0,253	
DGCXw	261	69,395	105,340	43,460	1,2063	1,336	0,454	2,408 %
Log DGCXw	261	4,202	4,657	3,772	0,0170	1,430	0,254	
ROFEXw	261	71,827	104,110	49,480	1,0668	1,270	0,469	1,978 %
Log ROFEXw	261	4,246	4,645	3,902	0,0145	1,407	0,290	

The data sample for all contracts are based on a continuous price series (CS00) for near-month futures contract daily settlement quotes. These price-series are rolled over to the next month on the last day in the month, or if it is not a trading day, the last trading day of the month. That means that the prices quoted are for the next month contract. A continuous price series where chosen since the roll over return are in these series taken mathematically out for the series. The rollover return is a return from the price gap between the last trading day before delivery and the first trading of the next near-month contract. All contracts start to

trade at levels either higher than the expected future spot rate on delivery (Contango) or lower than the expected future spot rate on delivery (Backwardation / “normal”-backwardation.) if the market are in backwardation, a trader that rolls over a long only would receive a small negative rollover return, and a positive rollover-return in backwardated markets.

Since pairs trading strategies base their profit from relative – mispricing between the two components in the pair, and not from market movements, it was decided to test the strategy in the worst possible market conditions for Brent and WTI, the period with declining crude prices (2014-2016). The formation period was set to 12 months’ form July 1st 2014 – June 30th 2015. The trading period, or out of sample period was also around one year, July 1st – July 15th 2015. Before any stationarity test were done, the price-series was log transformed in order to normalize the series. Another benefit by using log prices are that when running the regression Cointegration Regression in the Engle-Granger Two-Step method $\log x_t = \alpha + \beta \log y_t + \varepsilon_t$, ε_t becomes returns and the coefficients are allocation weights Alexander(1999)

Table 2. Descriptive Statistics Brent and WTI intra Market Spreads, 1st July 2014 – 30th June 2015

	<i>n</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>N avg. Spread ≠ 0</i>	<i>ρ</i>
B_0	261	0,0277	5,17	-0,15	1,433	99,986 %
B_1	261	0,38736	3,18	-3,41	n/a	99,875 %
B_2	261	0,43084	3,68	-3,41	n/a	99,880 %
W_0	261	-0,0223	0,11	-4,67	1,433	99,989 %
W_1	261	-0,011	2,12	-4,24	1,427	99,988 %
W_2	261	2,42092	12,16	-4,06	n/a	99,195 %
W_3	261	2,44318	12,16	-4,06	n/a	99,188 %
W_4	261	0,01126	2,12	-0,14	1,438	99,998 %
W_5	261	-2,4319	4,06	-12,16	n/a	99,197 %

The strong correlation between all markets for both WTI and Brent Spread shows that WTI and Brent shows WTI and Brent Inter-market spreads are good candidates for both a pairs trading strategy and a cointegration relationship. The spreads with a mean close to zero ICE-NYM Brent (B_0), ICE-NYM WTI (W_0), DGCX-ICE (W_4) and DGCX- NYM (W_1) was also checked to see how many days it took the spread to converge back to zero. In all of those spread, the spreads between the markets had converged back to zero after 1,4 days.

2.2 Methodology

2.2.1 Cointegration and testing for unit roots

Two non-stationary time series $I(1)$, F_{NYM}^{Brent} and F_{ICE}^{Brent} are said to be Cointegrated if there exist a linear representation of the two time-series that is stationary and integrated in levels ($I(0)$). If two futures markets, like NYM and ICE are cointegrated, that means that the spread between the two markets has a limited deviation before it is corrected back to the historical mean, due to the error-corrective mechanism between Cointegrated time series. The concept of cointegration was introduced by Engle-Granger *Engle Granger (1987)* and were soon applied to financial data. The Engle-Granger two step method for testing cointegration is a method to determine the relative value between to financial assets. The mean reverting mechanism built into cointegrated pairs make it a good framework to base long-short strategies and other relative-value strategies on. There are two main frameworks for testing cointegration, the Engle-Granger Two Step method *Engle -Granger (1987)* and the Johansen-method *Johansen (1991)*. The two methods differ in how they measure cointegration and how many cointegration relationships that can be investigated at the same time. The Johansen method aims to find the most stationary combinations between the variables, and also allows for testing more than one cointegration relationship at the same time. The Engle-Granger framework aims to find the combinations of the variables with the lowest variance. The Engle-Granger framework only allows for one cointegration relationship to be investigated. If more than one cointegration relationship is to be investigated, the Johansen framework is preferred. Even though the Johansen framework is superior to the EG-two step framework for investigate cointegration relationships, the EG-two step still receives a lot of attention. *Alexander (1999)* credits this to the fact that the EG – two step is easier to implement, all is done by OLS regressions, and the criterion of minimum variance has greater financial applications then maximum stationarity.

The *Engle-Granger* framework was implemented in this study due to the criterion of minimum variance and since it is quite simple to implement.

The Engle-Granger Two-Step method was implemented in three steps:

1. Testing for stationarity using Augmented Dicky-Fuller test, and optimal lags chosen by Schwarz-Bayesian Information Criterion to determine order of integration
2. First step in the Engle-Granger Two step method: Running the Cointegration regression and testing the residual for stationarity using Augmented Dicky – Fuller (ADF) test
3. Second step in the Engle- Granger Two-Step method: Formulate the Error Correction Model (ECM) for each cointegration relationship

2.2.2 Testing for stationarity

The number of times a time – series that follows a random – walk is differenced before it becomes stationary, integrated by order zero $I(0)$, decides the order of integration in the time – series. A time – series that are stationary when differenced one time, is integrated by order one $I(1)$, and a time – series that is not stationary in first difference but it second are known as integrated by order two $I(2)$. There are a number of frameworks available when testing for unit roots, like the Phillips- Peron (PP), Dickey- Fuller or Augmented Dicky – Fuller test and the ADF test was chosen in his paper.

The Augmented Dickey- Fuller test is a transformation of the original model described in *Dickey – Fuller (1979)* to allow for lagged variables in order to reduce problems with autocorrelation.

The DF test runs a regression on the model : $\Delta x_t = \alpha + \theta x_{t-1} + \delta t + \sum_{t=1}^p \Delta x_{t-1} + u_t$ and test the properties of θ .

If $\theta=1$, the process contains a unit root and is non-stationary

If $\theta < 1$, the process is stationary

If $\theta > 1$, Process is what is called an Explosive process

Were α is a constant coefficient, and δ is the trend coefficient

The null hypothesis H_0 In the DF and ADF test are that the time-series are non-stationary ($\theta=1$), with the alternate hypothesis that the time – series are stationary ($\theta < 1$).

The data sample was tested for stationarity to see if there were any changes between time-periods with a stable Crude price (2011-2013) and a period with declining Crude prices (2014-2015) and a combination of stable and declining crude prices (2013-2015).

The number of lags used in the ADF test were chosen by the Schwartz Bayesian Information criteria (SBIC) and was set at 1 for all log levels except from ROFEX WTI log level (11-13) where two lags were chosen.

For the first differenced log level, named log returns the SBIC found that the log return series should run without lags, except for ROFEX WTI log returns (11-13) where one lag was chosen. For the log levels, the trend variable was not suppressed after visual inspections of the data, but in log returns (the first differenced) the trend variable was suppressed.

Table 3. Results from Augmented Dickey - Fuller (ADF) test

	2011-2013		2014-2015		2013-2015	
	<i>Log Level</i>	<i>Return</i>	<i>Log Level</i>	<i>Return</i>	<i>Log Level</i>	<i>Return</i>
<i>RTS Brent</i>	-1,54	-18,92	-1,97	-14,44	-2,87	-20,2
<i>NYM Brent</i>	-0,82	-20,33	-1,55	-15,25	-2,33	-21,49
<i>ICE Brent</i>	-0,77	-20,59	-1,62	-14,86	-2,39	-21,01
<i>NYM WTI</i>	-1,35	-21,72	-0,83	-16,37	-1,71	-22,59
<i>ICE WTI</i>	-1,34	-22,04	-0,89	-16,16	-1,74	-22,35
<i>DGCX WTI</i>	-1,43	-21,76	-0,88	-16,23	-1,75	-22,4
<i>ROFEX WTI</i>	-2,08	-12,9	-0,78	-15,53	-1,72	-21,18

The ADF test found Log Prices in level to be non-stationary, just a random walk since none of the test statistics were outside the critical range. The first difference of Log Price, log return had all test statistics that were outside the critical range, and non-stationary were rejected for the first differenced series of log Prices. This concludes that the time-series in the sample are integrated by the first order $I(1)$. A Phillips -Peron test was also run on the sample and the conclusion from the PP test was the same as for the ADF test. There were some differences in ADF statistics between the three time periods. 2013-2015 had both the highest average ADF statistics in both levels and in the first differenced series, called returns, while the 2014-2015 period had the lowest ADF statistics in levels and returns.

2.2.3 Engle-Granger Two Step Method.

Engle-Granger (1987) defines cointegration as:

..”A vector φ_t that consist of $N \times r$ time – series are Cointegrated if i.) All elements in φ_t are non-stationary in its price levels and integrated by the same order $I(d)$ and ii.) there exist a vector $w, w \neq 0$ such that $w\varphi_t$ is stationary $I(0)$. The vector w is also known as the cointegration vector. $\varphi_t \sim I(d), w_i' \varphi_t \sim I(d - b), w_i \neq 0 \rightarrow \varphi_t \sim CI(d, b), d \geq b > 0$ “..

If there exist a cointegration relationship between two variables, model that describes the long-term dynamics between the two variables, there must also be a dynamic between the two variables that corrects short – term deviations from the historical long run dynamics, an error correction model (ECM).

The first step is to run a simple OLS regression on the two components in the spread by using this model: $y_t = \alpha + \beta x_t + \epsilon_t$, and then test the residuals from the OLS for cointegration using an Augmented Dickey- Fuller (ADF) test. The model used was the ADF test with the constant not suppressed, two lags of the differenced residuals and no trend. ADF: $\Delta \epsilon_t = \alpha + \theta \epsilon_{t-1} + \sum_{t=1}^p \Delta \epsilon_{t-1} + u_t$

If the ADF tests reject the null hypothesis of no-stationarity, the time series are said to be Cointegrated $CI(1,1)$ of order one. The Granger representation theorem states that if a two variables are Cointegrated, there is also an Error Correction Model Representation (ECM) of the two variables.

$$\begin{aligned}\Delta x_t &= \alpha_1 + \beta_1 \Delta y_t - \vartheta_1 (x_{t-1} - \alpha y_{t-1}) + \epsilon_1 \\ \Delta y_t &= \alpha_2 + \beta_2 \Delta x_t + \theta_2 (x_{t-1} - \alpha y_{t-1}) + \epsilon_2\end{aligned}$$

What makes this an error correction model is the second part or the rights hand side in the equation, the cointegration vector $\vartheta (x_{t-1} - \alpha y_{t-1})$. This ensures that the spread converges sine $\vartheta_1 < 0$ and $\vartheta_2 > 0$. The size of ϑ decides the speed of the reversion. The bigger the ϑ , the faster the mean-reversion when the mispricing is large.

2.2.4 Results from the Engle-Granger Two-Step Cointegration Analysis

The regression $x_t = \alpha + \beta y_t + \varepsilon_t$, the residual from the regression ε_t was tested for stationarity using ADF with two lags of the first difference of the residual series. In the EG-Framework, there is no difference between which variable that are chosen as dependent and which variable is independent when testing for Cointegration, contrary to a system were more than one cointegration is tested for at the same time such as the Johansen framework. To make things simple, the variable chosen as dependent in the Cointegraion OLS regression was also the first *leg* in the trading strategy and the dependent variable in the ECM model.

Table 4. Results from Cointegration Regression ADF test

	B_0	B_1	B_2	W_0	W_1	W_2	W_3	W_4	W_5
<i>CI test</i>						-			
<i>statistic</i>	-9,35	-7,69	-7,61	-9,31	13,76	-4,06	-4,05	-7,73	-4,03

The regression $x_t = \alpha + \beta y_t + \varepsilon_t$, the residual from the regression ε_t was tested for stationarity using ADF with two lags of the first difference of the residual series. In the EG-Framework, there is no difference between which variable that are chosen as dependent and which variable is independent when testing for Cointegration, contrary to a system were more than one cointegration is tested for at the same time, such as the Johansen framework. To make things simple, the variable chosen as dependent in the Cointegraion OLS regression was also the first *leg* in the trading strategy and the dependent variable in the ECM model. Since the critical values for stationarity with two variables are different than for just using one, the *Engle & Yoo (1987)* critical values for cointegration tests using OLS regression were used. The stationarity test on the residual series rejected the null hypothesis of no-Cointegration in all spreads, and concludes that all spreads are Cointegrated during the formation period July 1st 2014- June 30th 2015. All spreads regarding ROFEX (W_2 , W_3 and W_5) does have the lowest Cointegration statistics, just barely above the 1% critical value [1%:4,00, 5%:3,37].

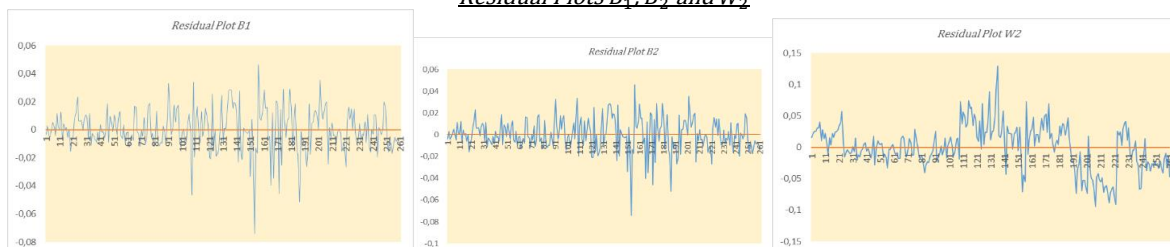
Table 5. Cointegration vectors from OLS Regression:

$B_0: \mu_t = \text{LogICE} - 1,00014484 \text{LogNYM}$
$B_1: \mu_t = \text{LogRTS} - 0,99378367 \text{LogNYM} - 0,03207328 (*)$
$B_2: \mu_t = \text{LogRTS} - 0,99354374 \text{LogICE} - 0,03349115 (*)$
$W_0: \mu_t = \text{LogICE} - 0,99981811 \text{LogNYM}$
$W_1: \mu_t = \text{LogDGCX} - 0,99990853 \text{LogNYM}$
$W_2: \mu_t = \text{LogROFEX} - 0,84206396 \text{LogNYM} - 0,70833739$
$W_3: \mu_t = \text{LogROFEX} - 0,84206429 \text{LogICE} - 0,70860804$
$W_4: \mu_t = \text{LogDGCX} - 1,00007297 \text{LogICE}$
$W_5: \mu_t = \text{LogDGCX} - 1,16098281 \text{LogROFEX} + 0,72850251$

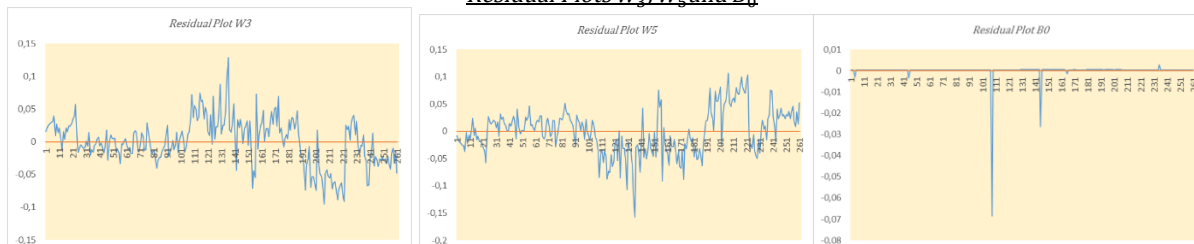
(*) Significant on 5% level

Figure 2. Residual Plots

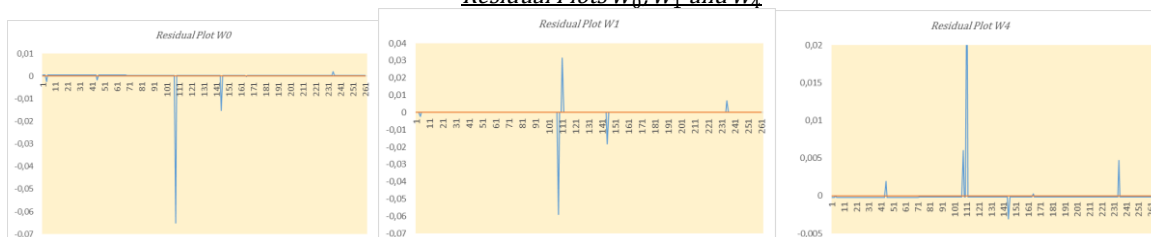
Residual Plots B_1, B_2 and W_2



Residual Plots W_3, W_5 and B_0



Residual Plots W_0, W_1 and W_4



The visual inspection of the Residual plots shows that the Spreads with a high Cointegration statistic, appears to have the strongest error correction. In all these spreads, it only takes one day before the markets have corrected itself, but the trading opportunities are limited due to a low number of observations the spread trades outside its range. In both the ICE-NYM WTI and ICE-NYM Brent spreads the mispricing appears come in most cases due to “overvalued” prices in NYM (Negative Residuals), the same trend can also be found against DGCX. Both of the Brent spread against RTS (B_1 and B_2) appears to be highly tradable spreads with frequent miss-pricing and mean reverting. Contrary to WTI spreads, the source of the miss-

pricing seems to the Russian Market (RTS) and not mispricing from ICE or NYM. The speed of the mean – reversion also appears to be a little slower than in the ICE-NYM and DGCX-ICE/NYM spreads, perhaps an average 2-3 days.

All spread against ROFEX, the spreads with the lowest CI statistic (W_2 , W_3 and W_4) does seem to have some issues. The residual plots in figure 2 illustrated some trends in the residuals, which can explain the low test statistics from the Cointegration analysis. The Cointegration Vector found in cointegration OLS regression for spreads against ROFEX all had a significant constant coefficient, something that is not really that strange, but in the spread against ICE and NYM this constant coefficient implies that ROFEX should trade at a lower level than ICE and NYM, something that does not make any economic sense. If the law of one price holds for spreads against ROFEX, NYM should trade lower than ROFEX ($F_{ROFEX} = F_{NYM} + c$, $c = \text{transportation costs}$) and not the other way around.

With this in mind, the ECM models were specified for all spreads. No constant was included in the Cointegration Vector of the ECM model. The ECM model was specified with first the *leg(component)* as the dependent variable.

$$\Delta y_t = \alpha_1 + \beta_1 \Delta x_t - \theta(y_{t-1} - \alpha x_{t-1})$$

The other side is found by rearranging the model with the second leg on the left hand side of the equation.

Table 6. Error Correction Model (ECM)

$W_0: \Delta ICE = 0,998813\Delta NYM + 1,0042(ICE_{t-1} - 0,99980NYM_{t-1}) + \epsilon$
$B_0: \Delta ICE = 0,99887\Delta NYM - 1,00580702((ICE_{t-1} - 1,00013766NYM_{t-1})) + \epsilon$
$B_1: \Delta RTS = 0,02554 + 0,56023103\Delta NYM + 0,739272(RTS_{t-1} - 0,992904NYM_{t-1}) + \epsilon$
$B_2: \Delta RTS = 0,026699 + 0,56034835\Delta ICE + 0,74524244(RTS_{t-1} - 0,99270205ICE_{t-1}) + \epsilon$
$W_1: \Delta DGCX = 0,992683\Delta NYM + 0,990609(DGCX_{t-1} - 0,99989NYM_{t-1}) + \epsilon$
$W_2: \Delta ROFEX = 0,0623NYM(*) + 0,310155(ROFEX_{t-1} - 0,839430NYM_{t-1}) + \epsilon$
$W_3: \Delta ROFEX = 0,06573\Delta ICE(*) + 0,30850(ROFEX_{t-1} - 0,83955ICE_{t-1}) + \epsilon$
$W_4: \Delta DGCX = 0,991876\Delta ICE + 1,00702(DGCX_{t-1} - 1,00006ICE_{t-1}) + \epsilon$
$W_5: \Delta DGCX = 0,1327\Delta ROFEX(*) + 0,02462(DGCX_{t-1} - 0,772353ROFEX_{t-1}) + \epsilon$

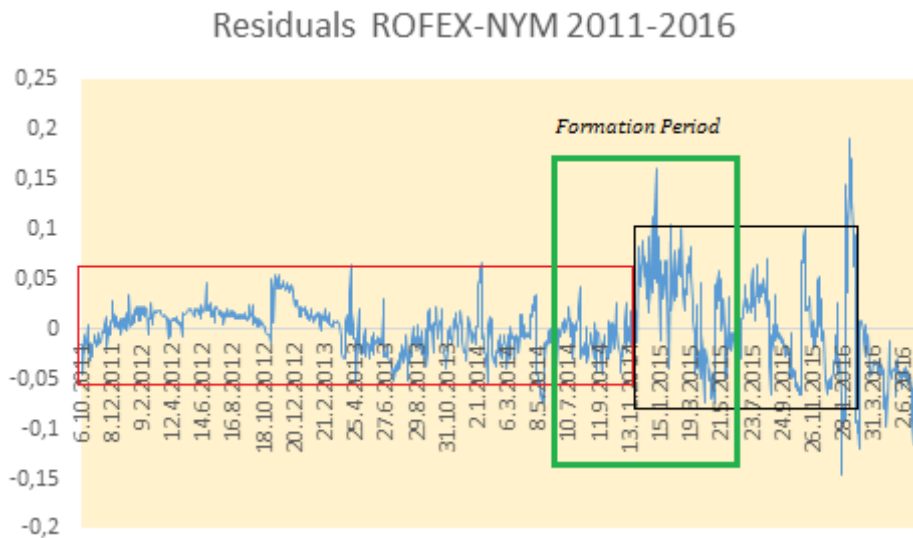
All coefficients on the on the lagged dependent variable came back negative. This means that the Cointegration Vector is added for when the first *leg* is the dependent variable, and subtracted when the second *leg* is the dependent variable in the ECM.

There were some issues regarding the significance of coefficients in spreads against ROFEX. None of the coefficients on a_1 , a_2 , β_1 and β_2 were significant different from Zero on a 5% level in all spreads. This means that the “Fair – value “cointegration trading strategy used by

Dunis (2006) $\alpha + (Leg_1 * \beta) - 1Leg_2 = \mu_t$ are not going to be used when trading the spreads. This issue with the ECM representation is most likely due to the weak Cointegration statistics in the ROFEX spreads. In all three of the spreads, the test statistic are barely more extreme than the critical values [4,00 1%, 3,37 5%] listed in *Engle&Yoo(1987)*.

The formation period for ROFEX spread were increased by one year (July 1st 2013-June 30th 2015) before another cointegration analysis were done on the spread. The increased formation period improved the test statistic from the cointegration tests for all spread but only had little effects on the significance of the ECM coefficients. In all spreads except for the DGCX-ROFEX (W_5) the ECM coefficients became significant different from zero on a 5 % level, but in the W5 spread all coefficients was still not significant on a 1% or 5% level. Including more lags in the stationarity test of the residuals on the original data-sample did reject Cointegration on an 1% level, but on a 5% level, the test still concluded cointegration. After inspecting the raw prices used in the cointegration, it seems as this issue can be related to a period close to the end of the formation period where the price quoted for ROFEX did not change over some time. I suspect that this can be related to low trading activity on WTI futures at ROFEX during the formation period. the residual plot from the whole duration of the data sample (2011-2016) between ROFEX and NYM shows that up until 2015 the residuals moved inside the 0,05 an-0,05 range but from 2015-2016 the range has increased significantly.

Figure 3. Residual Plots ROFEX – NYM 2011-2016



Even though Cointegration was not rejected in the Cointegration tests on ROFEX spreads, all the issues with the ECM and the Cointegration Vector in ROFEX spreads implies that using a cointegration model when trading that particular spreads should be done with caution. The residual plots in the ROFEX spread does imply mean reversion and cointegration during periods when the trading activity is high, but weaker mean -reversion and Cointegration in periods with low activity. From the ROFEX-NYM 2011-2016 residual series, it seems as the residuals becomes more stationary in the winter/spring for 2016. With this in mind, those spreads were still included as the sample for testing trading strategies.

2.3 Trading the spreads

Two trading strategies are tested on the different futures spreads; one strategy based with a static component, and one strategy with a dynamic component. The spreads were normalized using a z-score (z_t) in order to capture the situations where one side of the spread was overvalued compared to the other side.

If z_t is not equal to zero and higher than the threshold p , the first component in the spread (A) is overvalued compared to the second (B). The response to this is to take a short position in the first component (A) and a long position in the second (B) until the prices converge or z_t crosses the threshold b .

If z_t is less than zero and less than the threshold $(-p)$, the second component two (B) is overvalued in relation to the first component (A). A short position is taken in component two (B) and a long position in component one (A) until the two prices converge or z_t crosses the threshold $(-b)$.

If z_t is between the threshold p and $(-p)$, no actions are taken, since this implies that the two components in the spread, A and B, trade inside its “fair value” range (historical range).

2.3.1 Static trading Strategy

In the first strategy, a z-score is calculated by using the standard deviation and mean from the spread in the formation period (July 2014 – June 2015). Using a static component, the mean from the formation period, is a proxy for the cointegration distance found in the cointegration vector. The mean is a proxy for the cointegration “fair – value”. The z-score is calculated the following way:

$$\mu_t = f_t^A - f_t^B, \quad z_t = \frac{\mu_t - \bar{\mu}_{1-12}}{\sigma_{\mu_{1-12}}}$$

Adding a model with a dynamic component is done because of the limitations to the cointegration approach. The distance between the two components in the spread, found by cointegration analysis, is static. If there is a change in the underlying relationship between the two components of the spread during the trading period, it can lead to great losses, or to a situation where no trades are executed because the z-value does not cross the threshold.

2.3.2 Dynamic Trading Strategy

$$\mu_t = f_t^A - f_t^B, \quad z_t = \frac{\mu_t - (n \text{ day } MA_t^\mu)}{\sigma_t^{n \text{ day } \mu_t^{AB}}}$$

The z score is calculated the same way as in the other model.

A 20 and a 50 day moving averages was used in this model. In technical Analytics, the 20-day moving averages and the 50 day moving averages are used as indicators on short and medium- term momentum and trends. The MA's are calculated the following way;

$$\mu_t = f_t^A - f_t^B, \quad n - \text{day } MA = \sum_{t=1}^n \frac{\mu_t + \mu_{t-1} + \mu_{t-2} + \mu_{t-3} + \dots + \mu_{t-n}}{n}$$

2.3.3 The trading rules.

The same trading rules and triggers was used in all spreads in both the static and the dynamic models.

If $z_t > p$, open a “buy”, long position in B and short position in A

If $z_t < -p$, open a “sell”, a long position in A and a short in B

If z_t is between p and $-p$, no actions are taken

If a “buy” position is open, the position is closed when the spread crosses a trigger, b

If a “sell” position is open, the position is closed when the spread crosses a trigger, $-b$

For positive z-scores, the thresholds 1 and 2 where used to open positions and 0,5, 1 for closing them again. For negative Z-scores the thresholds where -2, -1 for opening a position and -1 and -0,5 for closing the position in all strategies and spreads.

Since the price - series used in this paper are based of continuous contract series, where the contracts are rolled over to the next one the last day of the month, there is set a limit upon trading close to month's end. No positions are opened during the three (3) last trading days in the month. If there is a position still active when the contracts are rolled over, the contracts are liquidated and a new position is opened on the first day of trading in the next month if the prices haven't converged from the last trading day in the previous month – first trading day of the month. *Girma & Paulson (1999)* used a similar rule where no trades were executed within the last 20 days before expiration on the underlying futures contracts but this limits the trading too much, since the spreads in question is on the exactly the same underlying product, and for close spreads like DG CX-NYM or DG CX-ICE a tradable relative - mispricing does not occur that often. There was also tested a rule where no trades are executed during the last 10 trading days of the month on the 50-day Moving Averages in order to see if number of

times the contracts were liquidated due to running out of days stayed the same, or went down.

The number of positions opened in each contract is set to one (1). This means that if a signal is triggered when a position is open, no actions are taken upon the signals until the open position is closed. Having multiple positions opened in spreads where the trigger is set high ($2 * z_t$) could yield a higher profit in cases where the z_t -score is growing, but in cases where the trigger is set low it can lead to just running up the transaction costs without improving the average profit per trade. In cases where the z_t score is decreasing, and an additional signal is triggered could lead to losses if the z_t score is close to the closing trigger value.

2.3.4 Calculating the returns from the trading strategies

The returns in the trades are calculated based on the daily performance of the two components in the spread in this way;

$$\text{Profit/loss from trade } \pi_t = \left(\frac{Long_2 - Long_1}{Long_1} \right) + \left(\frac{Short_2 - Short_1}{Short_1} \right) - TC (0,5\%)$$

Before added to the profit index, the transaction cost is subtracted from the trades profit or loss.

$$\pi_{Profit\ Index} = \sum_{n=1}^n \pi_n + 1$$

2.3.5 The transaction fee

There was also added a transaction cost (TC) in order to see if the spread could be profitable. The total transaction cost for each time the trade was executed was 0,5% and subtracted from the profits generated from each trade before the profits were added to the *Trade Profit Index*. The transaction cost estimate was calculated by the average transaction costs from opening and closing two positions on ICE, DGCX and NYMEX. The average transaction cost between these three exchanges was found to be 0,382% and an extra 0,117% was added on to in order to adjust for estimates in the other exchanges.

2.3.6 Measure for performance

The information Ratio where chosen for measuring the performance of the different spreads and strategies. The ratio Measures the risk-adjusted excess return in the profit portfolios return.

$$\text{Information Ratio (IR)} = \frac{\alpha}{\omega} = \frac{\pi_p - \pi_i}{\sigma_{\pi_p - \pi_i}},$$

Excess return α , the difference between the portfolios return and the return from a benchmark index. The index used here the *S & P GSCI All Crudes index* from July 1st 2015 – July 15th 2016 and during that period the GSCI All Crude index saw a 60.53 % decrease Some other indexes were also under consideration, such as the HFRX Absolute Return Index, HFRX Relative Value Arbitrage Index or the Eureka Hedge Relative Value Hedge Fund Index. but the access to data from these indexes were limited. The advantage by using the All Crudes index is that the return from the index reflects the return from a buy and hold strategy in the same commodity during the trading period.

3. Empirical Results and Conclusion

3.1 Average results from trading

Table 7. Results from Trading, All strategies

	B_0	W_0	B_1	B_2	W_1	W_2	W_3	W_4	W_5
Average profits pre TC	7,85 %	9,22 %	85,2 %	75,8 %	16,8 %	40,1 %	38,4 %	19,3 %	36,4 %
<i>Average profits Pre TC, Annualized</i>	7,22 %	8,48 %	76,1 %	67,9 %	15,4 %	36,5 %	35,0 %	17,6 %	33,2 %
Transactioncosts, 0,5%	1,88 %	2,50 %	12,5 %	11,7 %	5,1 %	5,9 %	6,3 %	5,2 %	7,1 %
Average Profits Post TC, Annualized	5,50 %	6,18 %	65,2 %	57,7 %	10,7 %	31,2 %	29,4 %	12,9 %	26,7 %
average number of days in position	1,0	1,0	1,3	2,1	3,8	6,0	6,8	3,7	6,8
Average number of trades	3,8	5,0	25,0	23,4	10,2	11,8	12,5	10,3	14,2
Success Ratio	100,0%	100,0 %	99,6 %	96,7 %	92,6 %	87,6 %	88,0 %	93,3 %	84,1 %
Success Ratio post TC	83,7 %	90,0 %	98,9 %	96,7 %	75,7 %	84,6 %	82,4 %	83,7 %	84,1 %
$\sigma_{Profit\ Index}$	0,0164	0,0181	0,2374	0,2148	0,0444	0,1232	0,1227	0,0499	0,1101
$Volatility_{Profit\ Index}$	0,26 %	0,24 %	0,7 %	0,7 %	0,4 %	0,8 %	1,0 %	0,4 %	0,9 %
$Volatility_{Annualized}^{Profit\ Index}$	0,24 %	0,22 %	0,7 %	0,7 %	0,3 %	0,7 %	0,9 %	0,4 %	0,8 %
Average Profit pr. Trade	1,64 %	1,43 %	3,4 %	3,3 %	1,2 %	5,0 %	4,9 %	1,4 %	2,7 %
Correlation with Market Return	7,46 %	3,42 %	2,76 %	8,68 %	-4,43 %	0,19 %	4,54 %	-2,43 %	0,10 %
Information Ratio (IR)	0,0840	0,0844	0,1361	0,1305	0,0879	0,1078	0,1062	0,0907	0,1024

B_0 : ICE – NYM, B_1 : RTS – NYM t, B_2 : RTS – ICE, W_0 : ICE – NYM, W_1 : DGCX – NYM, W_2 : ROFEX – NYM, W_3 : ROFEX – ICE, W_4 : DGCX – ICE, W_5 : DGCX – ROFEX

Table 7. shows the average performance for all the different strategies tested on each spread. The performance for each strategy is found in section 5. Graphs and Tables.

Table 7 shows the average performance of the different spreads. The table shows the average results and the annualized average results from trading before the transaction fee is subtracted. The average transaction fee, average numbers of days in positions, average number of days, success ratio both pre and post transaction fee. The standard deviation for the profit index, the implied volatility and implied annualized volatility and the correlation between returns and the S&P GSCI All Crudes Index and the information ratios.

Only 1 out for 47 strategies ended up with a negative return from the trading period, the Dynamic Model with the 20-day moving averages and the lowest thresholds for the ROFEX-DGCX spread (W_5). The Spread generated a 9,9% profit pre transaction costs, but only a 68,2% success rate Post Transaction costs, which meant that the spread generated a -1,1% return after the transaction fee was subtracted. It seems that there is a correlation between numbers of days in position, and the success ratio for positions opened. The Spreads with the lowest average number of days in position also has the highest success rate pre transaction costs. The Brent ICE-NYM spreads has a 1-day average in position, and a 100% success rate, the WTI spreads ROFEX-ICE (W_3) and DGCX-ROFEX (W_5) has the highest average number of days in position, and also has some of the lowest success rates pre TC with an

88,0% for W_3 and 84,1% for W_5 . Most of this loss was due to the closing triggers not being met before the end of the trading period (month), and the positions were closed before the spread had converged. When the rule of not trading within the last 3 trading days in the month was increased to 10 days in the dynamic model with the 50-day moving averages, the success rate increased by 5,1% pre TC and 7,27% Post TC in the WTI spreads. Due to the already high success rate in Brent spreads, the 10-day rule was not implemented there. The 0,5% transaction cost used in this paper is just an estimate in order to see the effects of Transaction costs for an Intra-market spread. The actual Transaction costs in the spreads tested could both be higher and lower than the estimate used in this paper. The average profit generated PR trade gives some pointers upon the profitability of the different spreads. The spreads with the lowest implied correlation also seems to have the lowest profit PR trade, and the spreads with the highest implied volatility tend to have some of the highest profits PR trade, except for the spread with the second highest implied volatility (0,8%), the DGCX-ROFEX (W_5) spread, which has a lower average profit PR trade than the spread with the highest volatility, ROFEX-ICE (W_3), due to the low number of successful trades. The average profit pr trades implies that there is room for an even higher estimate on the transaction costs. Increasing the transaction cost to 1% means that the spread with the lowest average profit pr trade, the WTI DGCK-NYM spread (W_1) still would generate an average 0,7% profit pr trade. The measure for risk-adjusted excess return, the Information Ratio, find the Brent Intra-market spreads B_1 and B_2 to outperform their WTI counterparts, but the WTI ICE-NYM spread performs slightly better than the Brent ICE-NYM spread. When comparing which of “home” or “foreign” markets for Brent and ICE that performed better, it seems as there is a slight advantage to the “foreign” market in inter-market spreads. The “foreign” market, NYM, performed better than the “home” market ICE against RTS in the Brent Inter-market spreads. In the WTI inter-market spreads, the “foreign” market, ICE, performed better against DGCX and the “home” market and “home” performed better against ROFEX.. The ROFEX spreads were the only spreads where the home market outperformed the foreign, but the difference in information ratios between the two markets are only 0,0016, almost half the difference as in the DGCX spreads.

3.2 Implementing the one-day waiting rule in RTS – ICE and NYM spreads

Due to the high profits in the Brent spreads against RTS, the *Gatev et al (2006)* one-day waiting rule was implemented in those spreads in order to try to figure out if the high returns came due to time-zone differences or due to trading activity. The two best performing trading strategies for the Brent intra-market spreads, the 50-day Moving Averages and the 20 day Moving averages were chosen as the strategies to test the rule on. If a signal for opening a positions was triggered, a position was opened the next day if the spreads was still outside its range.

Table 8. Results from Trading, One-day Waiting Rule

	B_1 50 MA	B_2 50MA	B_1 Static	B_2 Static
<i>Profit post TC , Annualized</i>	29,49 %	27,49 %	21,50 %	19,38 %
<i>Profits pre TC, Annualized</i>	34,16 %	32,01 %	30,01 %	28,02 %
<i>Average n-days in position</i>	2,4	2,4	1,2	2,8
<i>Average number of trades</i>	10	10	6	5
<i>Success ratio</i>	100%	100%	100%	100%
<i>Success ratio post TC</i>	100%	100%	100%	100%
$\sigma_{Profit\ index}$	0,1047	0,1166	0,0891	0,0828
<i>Volatility_{Annualized}</i>	0,54 %	0,57 %	0,41 %	0,39 %
<i>Average Profits pr. trade</i>	3,23 %	3,01 %	3,92 %	4,23 %
<i>Information Ratio (IR)</i>	0,107	0,105	0,100	0,098

Implementing the waiting rule brought the results of the strategies closer to the results from the DGCX, ICE and NYM spreads, with a lower profit and a lower number of trades. The rule also improved the average profits pr. trade to 3,575% +0,5% (TC) for the RTS-NYM spread, and 3,62% + 0,5% (TC) for the RTS – ICE spreads. The success ratio both pre transaction cost and post transaction cost improved. None of the trades failed to cover the transaction cost, an improvement from the average success ratio of 98,9% in the RTS – NYM spread and 96,7% in the RTS – ICE spread.

3.3 Performance of the different strategies

Table 9. Strategies by IR

	<i>STATIC</i>	<i>20MA</i>	<i>50MA</i>
B_0	0,0841	0,0841	0,0841
B_1	0,1201	0,1394	0,1615
B_2	0,1256	0,1228	0,1559
W_0	0,0844	0,0844	0,0844
W_1	0,0999	0,0805	0,0833
W_2	0,1061	0,1087	0,1087
W_3	0,1061	0,1017	0,1108
W_4	0,0980	0,0882	0,0858
W_5	0,1153	0,0907	0,1077

The strategies were also ranked by the information ratio (IR). B_0 and W_0 performed the same in all strategies. It appears that it doesn't matter which strategy that is used when dealing with spreads as volatile as the ICE- NYM spreads. B_1 , B_2 , and W_3 all performed best with the 50-day moving averages, and W_3 had the same performance in the 20 day moving averages as in the 50 day moving averages. Those four spreads were also the ones with the most volatility in residuals from the cointegration analysis. Both WTI spreads against DGCX performed best with the static model. The DGCX-ROFEX spread, also a spread with a lot of volatility in the residuals, performed the best with the static model. Overall, the spreads with the lowest Cointegration Statistics tend to perform better when a medium trend is used as a proxy for the cointegration "fair value" then for shorter-term trends (20 MA) or the one-year trend (static). The relative low annual returns and total numbers of trades executed in spreads between ICE and NYM implies that maybe most of the mispricing that occurs during trading hours between these markets are corrected for before the daily settlement time.

3.4 Correlation with market returns

The correlation between the returns of the trading strategies and the returns of the indexes S&P 500 and S&P GSCI All Crudes were estimated for the spreads between ICE, NYM and DGCX.

	B_0	W_0	W_1	W_4
ρ	10.141 %	11.600 %	-3.122 %	-3.258 %

	B_0	W_0	W_1	W_4
ρ	7,46 %	3,42 %	-4,43 %	-2,43 %

One of the assumption for a pairs trading strategy are neutrality for market movements. Erhman (2006) argued that in order to be completely market neutral, the pairs have to be designed in a to achieve complete market neutrality by either matching pairs with the same beta or investing the same amount of dollar value in each leg. Ensuring complete market-neutrality in the commodities market is more difficult than for stock something that the correlation between S&P 500 and S&P GSCI All crudes shows. The returns from the strategies have a low positive correlation towards both indexes for the spreads between ICE – NYM, and a low negative correlation in the spreads between DGCX – ICE/NYM. The low correlations towards the indexes highlight's the tactical value of adding a pairs trading strategy into the investment portfolio for diversification purposes.

3.5 Concluding remarks from trading

In all spreads between ICE and NYM, the average days in position were only one day, meaning that they had converged back to their relative – value the following day. The tradable mispricing in a spread with daily settlement quotes represents only the extreme causes of mispricing, it is assumed that most of the mispricing in that market is corrected for during the daily trading session. Further study of ICE-NYM spreads with Intra-day data must be done in order to see if there is a possibility to generate a profit from the intra-day mispricing. There is some evidence that an intra-day StatArb strategy could work, since the average return from each trade is $(1,64\% + 0,5\%) = 2,14\%$ in the Brent B_0 spread and $(1,34\%+0,5\%)=1,84\%$ in WTI spread for the extreme causes, but there is no way to determine this without inspecting the intra-day data. It all depends on the size of the transaction costs. The high success rate for positions (100%) in each trade and the low implied volatility (0,24% for B_0 and 0,22% for W_0) implies that a trader that only wants to chase the extreme cases i.e the cases of mispricing that continues into the next trading session, could still earn a decent profit by leveraging his position. Receiving a 5,5% profits for a 90% leveraged positions means that the trader would earn a 55% ROI during that period. If a 95% leverage was used, the ROI in the B_0 ICE – NYM spread would be 110%. Increasing the profits could also be done by opening more than one position at each time the trigger was met.

This study limited the total position on each contracts to one, but in the real world of trading, the trader could open as many positions as he like in each contracts, as long as he has the required capital to maintenance his positions and cover the initial margins required. As long as the speed of corrections and distance between those markets stays in the same range as in the formation and trading period, a trader could profit from a pairs trading strategy when the mispricing is extreme between those two markets for WTI and Brent. Spreads between DGCX and ICE or NYM also shows promise in cases with extreme mispricing. The correction speed was lower than for ICE-NYM spreads with average days in positions at 3,8 and 3,7 days with the triggers used which also meant a higher volatility and higher annual profit adjusted for transaction costs compared to the zero spreads. The average profit per trade in those spreads were lower than for ICE-NYM spreads, $(1,2\%+0,5\%) = 1,7\%$ in the spread against NYM and $(1,4\%+0,5\%)= 1,9\%$ against ICE but with a higher implied annual Volatility. When it comes to the issue with probability for success, the DGCX spreads have a

lower success rate than their ICE-NYM counterpart. The success rate pre TC decreased from 100% in the ICE-NYM spread to 96,7% in DGCX-NYM and 93,3% in DGCX-ICE. The post TC rate did also decrease from 90% to 75,7% in DGCX-NYM and 83,7% in DGCX-ICE. But it is still possible to generate a profit with a low volatility and high probability in those spreads. The three markets ICE, NYM and DGCX were the ones most integrated by trading hours and by their cointegration statistic, which makes spreads between these markets the best measure for statistical arbitrage opportunities. Even though the other spreads like B_1 and B_2 was better ranked by information ratio, the profits and conclusion drawn from trading in other spreads than ICE, NYM and DGCX spread does not holds as much water as the findings from the ICE, NYM and DGCX since the trading hours and settlement time in those markets are too different from ICE, NYM and DGCX settlement times. Without further research using intra-day data and testing time periods with overlapping trading hours, it is not possible to know if the profits earned in those spreads comes simply from time-zones differences or from trading activity even though the implementation of the one-day waiting rule shows promising results.

3.6 Discussion

Historical long-term relationships were discovered between the markets ICE, NYM, RTS, DGCX and ROFEX with the cointegration analysis. The coefficients from the cointegration vector in the ECM models (Table 6.) were rearranged to find the implied transportation costs between the two markets in the spread.

Table 12. Implied transportation costs from ECM model (Table 6.)

	ICE - NYM WTI	ICE - NYM Brent	RTS - NYM Brent	RTS - ICE Brent	DGCX - NYM WTI	ROFEX (*) - NYM WTI	ROFEX (*) - ICE WTI	DGCX - ICE WTI	DGCX - ROFEX (*) WTI
Transportation costs	0,020 %	-0,014 %	0,710 %	0,730 %	0,011 %	16,057 %	16,045 %	-0,006 %	22,765 %

Table 12 shows the implied transportation costs in percentage of the first leg of the spread. A positive percentage transportation costs implies that transportation to the first market is more expensive, and a negative percentage transportation cost implies that the second market is more expensive.

(*) The coefficients in the ECM models (Table 6.) in spreads against ROFEX were not significant.

In the spread between ICE and NYM for Brent Crude futures, it was found that NYM traded with a premium towards ICE, implying that the transportation cost to deliver to NYM is larger than for delivery to ICE. This relationship with a lower price in the “home” market than for the foreign was also found for WTI between ICE and NYM. DGCX did also trade with a

premium towards NYM, implying the existence of a transportation costs between those two markets. The spread with the lowest implied transportation cost were the spread between DGCX and ICE. From the ECM model, the historical transportation costs between DGCX – ICE were only - 0,0006%, a small premium on delivery to ICE. Those two markets are also the two closest markets when ICE, NYM and DGCX are considered. It makes sense that the transportation cost between those two should be small. The only thing that could be a little confusing are the direction of the premium, with ICE being a closer market in geographic location than DGCX, but when comparing the implied transportation costs between ICE – NYM and DGCX – NYM, the implied costs are greater between ICE – NYM then DGCX – NYM, implying that it is more expensive to “deliver” WTI to the European market then to “deliver” it to the Middle East market. Is assumed that this difference may come from a shorter route by sea to the middle east, compared to Europe.

The results from the pairs trading strategies, were a profit between the markets ICE, NYM and DGCX could be generated with a high degree of certainty and low implied annualized volatility and finding a stable long-term relationship between the markets supports the view that the futures prices for Brent and WTI follows the Law of one prices

Gatev et al (2006) credits the source of the excess return in a pairs trading strategies as a compensation to arbitrageurs to enforcing the law of one price.

Bianchi et al (2009) implemented a pairs trading strategy in the commodities futures market, and found significant evidence that supported that view that the excess return is a compensation for enforcing the law of one price in the commodities market. Yang et al (2016) implemented a pairs trading strategy on the Chinese commodity futures markets and found higher profits in spreads when the maximum holding period was increased, and lower profits in shorter maximum holding periods. They credited the higher levels of excess returns in longer periods as a compensation to arbitrageurs for ensuring that the spreads converged, rather than a compensation for ensuring market efficiency by enforcing the law of one price.

Contrary to the results by Yang et al (2016) the returns and success-ratio in pairs trading strategies on Brent and WTI decreased when the average holding period increased. The spreads with the highest average number of days in positions had the lowest success-rates both before and after the transaction costs were subtracted. The probability of success in a position decreased significant when the “holding” period was longer then one day.

A pairs trading strategy implemented on an inter-market futures spread has the goal of capturing the relative mispricing in transportation costs between the two markets, arbitrage in its purest form. Generating an average positive return in all spreads tested supports Gatev et al(2006) and Binachi et al (2009)’s view that the excess return captured in a pairs trading strategy are a compensation to the arbitrageur for enforcing the law of one price.

3.6 Conclusion

In this study, an implementation of a pairs trading strategy based on statistical long-run relationships found by Cointegration was done on Brent Crude futures spreads between the markets Russian Trading System (RTS), New York Mercantile Exchange (NYMEX), The Intercontinental Exchange Europe (ICEU) and WTI Light Sweet Crude futures spreads between New York Mercantile Exchange (NYMEX), The Intercontinental Exchange Europe (ICEU), Dubai Gold & Commodities Exchange (DGCX) and The Rosario Futures Exchange (ROFEX). The pairs trading strategy generated profits in three different spreads of Brent Crude and six different WTI Crude spreads with low correlation to market returns, but concluded that the evidence found from trading is only valid for spreads between ICE, NYM and DGCX when daily settlement quotes are analyzed, due to the difference in settlement time with other markets. I conclude based on the evidence I have presented that in cases of extreme mispricing, cases where the disequilibrium from the relative value are not adjusted for during one trading session, implementing a pairs trading strategies could yield decent profits with high rate of success, confirming that there could be statistical arbitrage opportunity between those markets. Due to the low number for tradable days, research should be done on those markets using intra-day data should be drawn before any conclusions upon profitability in intra-day data are drawn. This study finds also some evidence on statistical arbitrage opportunities in the other spreads when the one-day waiting rule is implemented, but further research using intraday data in an overlapping time period must be done. The low correlation to both the S&P 500 and S&P GSCI All Crudes Index highlights the tactical value of using a pairs trading strategies on WTI and Brent Crude Futures as a tool for diversification in an investment portfolio.

4. References

- Alexander, C (1999) – *Optimal Hedging using Cointegration*, The Royal Society (1999)
- Bianchi,R.J , Drew,M.E,Zhu,R.(2009) *Pairs Trading Profits in Commodity Futures Markets*, Retrieved From <http://www98.griffith.edu.au/>, April 2016
- Büyüksahin, B., Lee, T.K.,Moser,J.T,Robe,M.A. – *Physical Markets, Paper markets and the WTI-Brent Spread*, Energy Journal, Vol.34 , issue 3. (2013)
- Boguslavaskaya,E , Boguslavasky,M (2003) *Optimal Arbitrage Trading*
- Cootner,P.H (1960) *Returns to Speculators:Tesler versus Keynes* , Journal of Political Economy, Vol.68, No.4 (August 1960)
- Desai,Dr. J., Trivedi,A.,Joshi,N.A (2012) *The case of Gold and Silver: A New Algorithm for Pairs Trading*,
- Dickey, D.A, Fuller, W.A (1979) *Distribution of the Estimators for Autoregressive Time Series with a Unit Root*. Journal of the American Statistical Association, Vol. 74, Issue 366 (June 1979), pp 427-431
- Dunis, C.L, Laws, J., Evans,B (2006) – *Trading Futures Spreads: An application of Correlation and Threshold filters*, Applied Financial Economics, 16:12,pp 903-914
- Dunis, C.L, Laws, J., Evans,B(2008) – *Trading and filtering futures spread portfolios: Further applications of threshold and correlation filters*,
- Engle,R. F., Granger,W.J (1987) – *Co-integration and Error Correction: Representation, Estimation and Testing*, Econometrica, Vol.2 (March 1987) , pp 251-276
- Engle,R.F.Yoo,B.S (1987) – *Forecasting And Testing In Co-integrated Systems*, Journal of Econometrics 35 (1987), pp 142-159
- Erhman, D.S. (2006) *The handbook of Pairs Trading*, John Wiley & Sons,Inc., pp 17-73
- Fuertes, A., Miffre, J., Rallis,G. (2008) *Tactical Allocation In Commodity Futures Markets: Combining Momentum and Term Structure Signals*, EDHEC Risk and Assets Management Centre.
- Gatev, E.G., Goetzman, W.N., Rouwenhorst, K.G. (2006) - *Pairs trading: Performance of a relative-value arbitrage rule*, Review of Financial Studies vol.19 issue 3 (2006), pp 797-827
- Girma,P.B, Paulson, A.(1998) - *Risk Arbitrage Opportunities in Petroleum Spreads* , The Journal of Futures Markets, Vol.19 issue 8 (1999), pp 931-955
- Ingersoll, J.E.jr (1986) – *Theory of Financial Decision Making*, Yale University, chapter 2.8, pp 34-35

- Johansen, Søren (1991) – *Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models*, *Econometrica* Vol.59, No.6(November, 1991), pp 1551-1580
- Kanamura, T., Rachev, S.T., Fabozzi, F.J. (2009) *A Profit Model for Spread Trading with an Application to Energy Futures*, Karlsruhe Institute für Technologie (KIT) Working paper series in Economics, No.27(May 2011)
- Keynes, J.M (1930) *A Treatise on Money*, The applied Theory Of money, Vol. 2 (1930), pp 47-142
- Lin, J.B., Liang, C.C (2010) *Testing for threshold Cointegration and Error correction: Evidence in the petroleum futures market*, *Applied Economics*, Vol. 44 , Issue 22 (2010)
- Maslyuk , S., Smyth, R. (2008)– *Unit Root Properties of Crude oil spot and futures prices – Energy Policy* 36 (2008) 2591-2600
- Miffre, J., Rallis, G. (2006) – *Momentum strategies in Commodity Futures Markets*, *Journal of Banking and Finance*, Vol.31, No.9(2007)
- Ross, S. (1976) *The Arbitrage Theory of Capital Assets*, *Journal of Economic Theory* No. 13 (1976), pp 341-360
- Shleifer, A., Vishny, R.W (1997) – *The limits of Arbitrage*, *The Journal of Finance*, Vol.52 No.1 (March 1997), pp 35-55
- Ungever, C. (2015) – *Pairs Trading to the Commodities Futures Market Using Cointegration*, *The International Journal of Commerce and Finance*, Vol. 1, Issue 1 (2015), pp 25-38
- Vidyamurthy, G (2004) *Pairs Trading : Quantitative Methods and Analysis* , John Wiley & Sons, Inc.
- Working, H (1933) *Wheat Studies of The Food Research Institute*, Vol 9. No.6, (march 1933)
- Working, H (1948) *Theory of the inverse Carrying Charge in Futures markets*, *Journal of Farm Economics*, Vol. 30, No.1 (February 1948)
- Yang, Y., Goncu, A., Pantelous, A.A. (2016) – *Pairs Trading with Commodity Futures: Evidence from the Chinese Market*,

5. Tables and Graphs

Table 10 - 15. Results from the different trading rules.

Results from Trading Static P=2,b=1							
	B1	b2	w1	w2	w3	w4	w5(*)
Profit from Spread	11,014 %	18,108 %	25,601 %	13,818 %	13,818 %	28,952 %	
Profit annualized	10,125 %	16,606 %	23,418 %	12,691 %	12,691 %	26,455 %	
TC (0,5%)	1,000 %	1,500 %	4,000 %	0,500 %	0,500 %	5,500 %	
Profit adj for TC annualize	9,209 %	15,238 %	19,785 %	12,234 %	12,234 %	21,468 %	
average n-days in position	1	1	5,25	7	7	3,18181818	
n-trades	2	3	8	1	1	11	
n strades sucess	100,00 %	100,00 %	87,50 %	100,00 %	100,00 %	90,91 %	
n trades sucess (TC)	100,00 %	100,00 %	87,50 %	100,00 %	100,00 %	90,91 %	
sdddev Profit Index	0,03875631	0,06317675	0,07922757	0,06508179	0,06508179	0,08977191	
volatility Profit Index	0,4075 %	0,5425 %	0,5577 %	0,7553 %	0,7553 %	0,5589 %	
annualized volatility Profit	0,3761 %	0,5007 %	0,5147 %	0,6970 %	0,6970 %	0,5158 %	
Average Profit pr. Trade	5,007 %	5,536 %	2,700 %	13,318 %	13,318 %	2,132 %	
Information Ratio (IR)	0,08727774	0,09647141	0,09778654	0,08989249	0,08989249	0,09961618	
(against S&P GSCI All Crudes Index) Buy and hold , (*) No trades							
Results from Trading Static 1=2,b=0,5							
	B1	b2	w1	w2	w3	w4	w5
Profit from Spread	105,61 %	107,59 %	32,30 %	53,54 %	48,07 %	25,85 %	46,98 %
Profit annualized	94,52 %	96,25 %	29,48 %	48,56 %	43,67 %	23,65 %	42,69 %
TC (0,5%)	14,00 %	13,50 %	6,50 %	3,50 %	3,50 %	6,00 %	4,00 %
Profit adj for TC annualize	82,26 %	84,43 %	23,59 %	45,43 %	40,53 %	18,20 %	39,10 %
average n-days in position	1,57142857	2,25925926	3,53846154	6,71428571	9	3,91666667	8,25
n-trades	28	27	13	7	7	12	8
n strades sucess	100,0 %	100,0 %	92,3 %	100,0 %	100,0 %	91,7 %	100,0 %
n trades sucess (TC)	96,4 %	100,0 %	92,3 %	100,0 %	100,0 %	83,3 %	100,0 %
sdddev Profit Index	0,30393659	0,32673836	0,09559415	0,19139021	0,158797	0,08142616	0,16344272
volatility Profit Index	0,8272 %	0,8336 %	0,5642 %	1,0897 %	1,0550 %	0,5351 %	0,8269 %
annualized volatility Profit	0,7633 %	0,7692 %	0,5207 %	1,0054 %	0,9734 %	0,4939 %	0,7631 %
Average Profit pr. Trade	3,272 %	3,485 %	1,984 %	7,148 %	6,368 %	1,654 %	5,372 %
Information Ratio (IR)	0,15	0,15	0,10	0,12	0,12	0,10	0,12
(against S&P GSCI All Crudes Index) Buy and hold							

Results from Trading 20-day MA P=2,b=1							
	B1	b2	w1	w2	w3	w4	w5
Profit from Spread	41,9 %	31,8 %	11,9 %	39,8 %	33,2 %	22,6 %	41,0 %
Profit annualized	38,1 %	29,0 %	11,0 %	36,2 %	30,3 %	20,7 %	37,3 %
TC (0,5%)	5,5 %	5,5 %	5,0 %	5,5 %	4,0 %	6,0 %	5,0 %
Profit adj for TC annualized	33,1 %	24,0 %	6,4 %	31,3 %	26,7 %	15,2 %	32,8 %
average n-days in position	1,2	2,3	3,3	3,4	3,6	3,0	3,9
n-trades	11	11	10	11	8	12	10
n trades success	100,0 %	90,9 %	90,0 %	90,9 %	100,0 %	91,7 %	90,0 %
n trades success (TC)	100,0 %	90,9 %	50,0 %	90,9 %	87,5 %	75,0 %	90,0 %
sdddev Profit Index	0,112	0,078	0,027	0,131	0,120	0,056	0,139
volatility Profit Index	0,622 %	0,519 %	0,416 %	0,649 %	0,658 %	0,486 %	0,723 %
annualized volatility Profit Index	0,574 %	0,479 %	0,384 %	0,599 %	0,607 %	0,448 %	0,667 %
Average Profit pr. Trade	3,306 %	2,391 %	0,693 %	3,118 %	3,651 %	1,385 %	3,602 %
Information Ratio (IR)	0,114	0,102	0,084	0,111	0,107	0,094	0,110

(against S&P GSCI All Crudes Index) Buy and hold

Results from Trading 20-day MA 1=2,b=0,5									
	B1	b2	w1	w2	w3	w4	w5 (*)		
Profit from Spread	139,4 %	107,1 %	8,6 %	38,2 %	32,6 %	12,8 %	9,9 %		
Profit annualized	123,8 %	95,8 %	7,9 %	34,8 %	29,8 %	11,7 %	9,1 %		
TC (0,5%)	24,5 %	20,5 %	7,0 %	7,5 %	12,0 %	7,0 %	11,0 %		
Profit adj for TC annualized	102,6 %	77,9 %	1,5 %	28,0 %	18,9 %	5,3 %	-1,1 %		
average n-days in position	1,3	3,1	4,2	5,3	4,9	4,2	5,4		
n-trades	49	41	14	15	24	14	22		
n trades success	98,0 %	92,7 %	85,7 %	86,7 %	70,8 %	85,7 %	68,2 %		
n trades success (TC)	98,0 %	92,7 %	50,0 %	80,0 %	70,8 %	64,3 %	68,2 %		
sdddev Profit Index	0,367	0,284	0,012	0,100	0,095	0,017	0,039		
volatility Profit Index	0,893 %	1,037 %	0,205 %	0,618 %	1,007 %	0,284 %	0,993 %		
annualized volatility Profit Index	0,824 %	0,957 %	0,190 %	0,570 %	0,929 %	0,262 %	0,916 %		
Average Profit pr. Trade	2,344 %	2,112 %	0,115 %	2,046 %	0,860 %	0,411 %	-0,052 %		
Information Ratio (IR)	0,1647581	0,14385245	0,07732449	0,10600103	0,09669921	0,08229392	0,07196078		

(against S&P GSCI All Crudes Index) Buy and hold

Results from Trading 50-day MA P=1,b=0,5, 3 day rule							
	B1	b2	w1	w2	w3	w4	w5
Profit from Spread	128,2 %	114,2 %	12,0 %	53,3 %	50,5 %	16,8 %	42,0 %
Profit annualized	114,1 %	102,0 %	11,0 %	48,4 %	45,9 %	15,4 %	38,3 %
TC (0,5%)	17,5 %	17,5 %	4,5 %	11,5 %	11,0 %	4,5 %	9,5 %
Profit adj for TC annualized	98,9 %	86,7 %	6,9 %	38,1 %	36,0 %	11,3 %	29,7 %
average n-days in position	1,7	1,8	2,8	5,8	6,0	2,8	7,0
n-trades	35	35	9	23	22	9	19
n trades success	100,0 %	100,0 %	100,0 %	69,6 %	72,7 %	100,0 %	78,9 %
n trades success (TC)	100,0 %	100,0 %	88,9 %	65,2 %	59,1 %	88,9 %	78,9 %
sdddev Profit Index	0,366	0,322	0,026	0,134	0,123	0,037	0,097
volatility Profit Index	0,813 %	0,753 %	0,263 %	0,913 %	1,233 %	0,344 %	0,956 %
annualized volatility Profit Index	0,750 %	0,695 %	0,243 %	0,842 %	1,138 %	0,317 %	0,882 %
Average Profit pr. Trade	3,162 %	2,762 %	0,831 %	1,819 %	1,797 %	1,364 %	1,713 %
Information Ratio (IR)	0,16	0,16	0,08	0,11	0,11	0,09	0,11

(against S&P GSCI All Crudes Index) Buy and hold

Results from Trading 50-day MA 1=2,b=0,5 , 10 day rule							
	B1	b2	w1	w2	w3	w4	w5
Profit from Spread	0,00 %	0,00 %	10,41 %	42,14 %	52,44 %	8,55 %	42,33 %
Profit annualized	0,00 %	0,00 %	9,58 %	38,35 %	47,57 %	7,87 %	38,52 %
TC (0,5%)	0,00 %	0,00 %	3,50 %	7,00 %	6,50 %	2,00 %	6,00 %
Profit adj for TC annualized	0,00 %	0,00 %	6,36 %	32,04 %	41,76 %	6,03 %	33,12 %
average n-days in position	0,0	0,0	3,6	7,9	10,2	5,3	9,3
n-trades	0	0	7	14	13	4	12
n trades success	0	0	100,0 %	78,6 %	84,6 %	100,0 %	83,3 %
n trades success (TC)	0	0	85,7 %	71,4 %	76,9 %	100,0 %	83,3 %
sdddev Profit Index	0	0	0,0257	0,1177	0,1740	0,0183	0,1123
volatility Profit Index	0	0	0,262 %	0,841 %	1,059 %	0,243 %	0,867 %
annualized volatility Profit Index	0	0	0,242 %	0,776 %	0,977 %	0,225 %	0,800 %
Average Profit pr. Trade	#DIV/0!	#DIV/0!	0,988 %	2,510 %	3,534 %	1,638 %	3,028 %
Information Ratio (IR)	0,00	0,00	0,08	0,11	0,12	0,08	0,11

(against S&P GSCI All Crudes Index) Buy and hold

Table 16. Results from ICE- NYM spreads

	ICE-NYM spreads, WTI and Brent							
	WO stat	BO stat	WO 20MA	BO 20 MA	WO 50 MA 3 d	WO 50 MA 10	BO 50 MA 3 d	BO 50 MA 10 c
Profit from Spread	8,98 %	5,43 %	9,45 %	8,88 %	9,45 %	8,98 %	8,79 %	8,29 %
Profit annualized	8,26 %	5,00 %	8,69 %	8,17 %	8,69 %	8,26 %	8,08 %	7,63 %
TC (0,5%)	2,00 %	1,50 %	3,50 %	2,50 %	2,50 %	2,00 %	2,00 %	1,50 %
Profit adj for TC annualized	6,43 %	3,62 %	5,48 %	5,87 %	6,40 %	6,43 %	6,25 %	6,25 %
average n-days in position	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
n-trades	4	3	7	5	5	4	4	3
n strades sucess	100,0 %	100,0 %	100,0 %	100,0 %	100,0 %	100,0 %	100,0 %	100,0 %
n trades sucess (TC)	100,0 %	100,0 %	80,0 %	60,0 %	80,0 %	100,0 %	75,0 %	100,0 %
sdddev Profit Index	0,01821153	0,01676353	0,0182	0,0158	0,0179	0,0182	0,0165	0,0168
volatility Profit Index	0,241 %	0,255 %	0,241 %	0,256 %	0,241 %	0,241 %	0,255 %	0,255 %
annualized volatility Profit Index	0,222 %	0,235 %	0,223 %	0,237 %	0,223 %	0,223 %	0,235 %	0,235 %
Average Profit pr. Trade	1,745 %	1,310 %	0,850 %	1,275 %	1,390 %	1,745 %	1,697 %	2,263 %
Information Ratio (IR)	0,08	0,08	0,08	0,08	0,08	0,08	0,08	0,08

(against S&P GSCI All Crudes Index) Buy and hold

