STATISTICAL ARBITRAGE IN CRUDE OIL FUTURES MARKET

MEHMET NAZIM TAMKOÇ

BOĞAZİÇİ UNIVERSITY

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STATISTICAL ARBITRAGE IN CRUDE OIL FUTURES MARKET

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DECLARATION OF ORIGINALITY

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ABSTRACT

Statistical Arbitrage in Crude Oil Futures Market

In this study, we use crude oil futures contracts that differ in maturity to come up with a trading algorithm that takes forecasted convenience yields as a base. Because there is a liquidity constraint, we take 5 different futures contracts with a maximum maturity of 5 months from January 1985 to December 2012. By forecasting convenience yields of each contract day by day, we develop a profitable real life simulated trading strategy. The results indicate that there exist statistical arbitrage opportunity in crude oil futures market. After controlling for transaction cost and interest payments, our trading algorithm yields 19.11%, 16.37%, 15.45% and 11.92% annualized returns for the contracts 2-month, 3-month, 4-month and 5-month maturities respectively. In this respect it outperforms alternative trading strategies and generates statistical arbitrage.

ÖZET

Vadeli Ham Petrol Piyasası'nda İstatiksel Arbitraj

Bu çalışmada, farklı vadelerdeki ham petrol vadeli sözleşmelerini, uygunluk getirisinin tahminine dayalı bir ticaret algoritması geliştirmek için kullandık. Düşük likiditeden dolayı, vadesi en fazla 5 ay olan, Ocak 1985'den Aralık 2012'ye kadar, 5 farklı vadeli sözleşme kullandık. Her bir sözleşmenin uygunluk getirisini gün be gün tahmin ederek, gerçek hayatı temsil eden karlı bir ticaret stratejisi geliştirdik.Sonuçlar vadeli ham petrol piyasasında istatistiksel arbitraj imkanlarının varlığını gösteriyor. İşlem maliyetlerini ve faiz ödemelerini kontrol ettikten sonra, ticaret algoritmamız 2-ay, 3-ay, 4-ay ve 5-aylık vadesi olan sözleşmeler için sırasıyla %19.11, %16.37, %15.45 ve %11.92 yıllık olarak getiri üretiyor. Bu açıdan, bizim algoritmamız alternatif ticaret stratejilerinden daha üstündür ve istatistiksel arbitraj meydana getiriyor.

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CHAPTER 1

INTRODUCTION

The proliferation of computer usage in the finance industry has brought both opportunities and perils to the industry. On the one hand, it has allowed financial firms to incorporate complicated mathematical models into their trading strategies, and has accordingly made it possible to create innovative trading algorithms to exploit arbitrage opportunities conveniently and in an instant. On the other hand, it has brought more competitiveness to the industry which, in turn, necessitates creating more and more innovative algorithms to be the first to exploit arbitrage opportunities and make higher profits.

Although arbitrage is generally defined in broad terms as riskless profit, there are two kinds of arbitrage that are very distinct from each other. Deterministic arbitrage is defined as making riskless profit by taking long positions in some securities and short in others to take advantage of price discrepancies, whereas statistical arbitrage is defined as the exploitation of mathematical models to generate returns from systematic movements in securities prices (Pole, 2007). In this respect, statistical arbitrage is very different from the deterministic arbitrage in the sense that it has to satisfy certain mathematical conditions in order for an arbitrage to be classified as statistical. It is a long horizon trading opportunity designed to exploit persistent market anomalies to make a riskless profit (Hogan, Jarrow, Teo & Warachka,1994).

Gatev, Goetzmann and Rouwenhorst (1996) develop a pair trading algorithm in the US equity market and find that pair trading yields average annualized excess returns of 11%. They analyze cointegrated pairs in US equity markets and the spread between two normalized price series exceeds two standard deviations of the mean of the past spread then they take position by buying and selling these two contracts.

Bianchi, Drew and Zhu (2009) apply Gatev et al.'s (2009) pair trading strategy to the commodity market and find that the energy sector is the most profitable commodity group for pair trading, with a significant excess return of 1.48% per month, and precious metals is the least profitable commodity group, exhibiting an insignificant excess return of 0.50% per month. Cummins and Bucca (2012) examine 861 spreads on crude oil and refined products markets between 2003 and 2010, finding that daily returns range from 0.07 to 0.55% with a trade length of 9-55 days.

Jagadeesh and Titman (1993) apply momentum strategy, which is buying past winners and selling past losers on the stock market. And they found that momentum strategies realize a compounded excess return of 12% annually in the period from 1965 to 1989. On the other hand, Lakonishhok, Shleifer and Vishny (1994) use a contrarian investment strategy that buys past losers and sells past winner stocks on the New York Stock Exchange and the American Stock Exchange and they show that a contrarian strategy yields 10% and 11% in annual excess returns between 1968 and 1990.

Miffre and Rallis (2007) find that momentum strategy yields 9.38% excess returns in commodity futures markets by buying backwarded contracts and selling contangoed contracts from 1979 to 2004 but contararian strategies do not work for the commodity futures markets. Miffre and Rallis (2007) and Erb and Harvey (2006) also show that long-only strategies in commodity futures have negative returns and this feature distinguishes commodity markets from equity markets.

Fuertes, Miffre and Rallis (2010) investigate momentum strategy and term structure signals together on commodity futures markets. They find that momentum and term structure signal generate 10.14% and 12.66% returns respectively but they show that combination of these methods (double-shorting strategy) results with an abnormal return of 21.02%.

Marshall, Cahan and Cahan (2008) consider over 700 technical trading rules for the commodity market and find that trading strategies do not generate significant returns for 14 out of 15 commodities after controlling for transaction cost and data snooping bias. However Szakmary, Shen and Sharma (2010) show that the trend following strategies yield positive mean excess returns for the period 1972-1995. Moreover, Narayan, Ahmed and Narayan (2014) apply trend following strategies with momentum-based trading strategies and find that momentum-based trading strategies generate significant annualized return of 7.6% with monthly data and 4.8% with daily data.

Hogan et al. (2004) define statistical arbitrage mathematically and test whether momentum and contrarian strategies produce statistical arbitrage. They find that six of 16 momentum strategies employed in the Jagadeesh and Titman (1993) study and five of 12 contrarian strategies used in the Lakonishhok et al. (1994) produce statistical arbitrage. Statistical arbitrage tests for pair trading strategies conducted by other studies: See, for instance, Hoel (2013)-Oslo Stock Exchange, Zu (2005)-Interest rate swap contract, Avellaneda and Lee (2010)-US equity market, Rudy (2011)-Exchange Traded Funds. Also, Driaunys, Masteika and Sakalauskas (2014)-Natural Gas Futures Market.

In those papers, the models are based on mean-reverting behavior of securities and accordingly use pair-trading, momentum, and contrarian techniques in order to develop trading algorithms over different securities. In this study, we use instead futures contracts on a single commodity (crude oil) that differ in maturity. This study also differs from the aforementioned studies in the sense that our trading algorithm takes the forecast of convenience yield as a base.

The rest of the paper is organized as follows: Mathematical definition and testing procedure of statistical arbitrage will be given in Chapter 2; the trading algorithm, data and trading performance will be presented and examined in Chapter 3; and Chapter 4 concludes.

CHAPTER 2

STATISTICAL ARBITRAGE

Hogan et al. (2004) defines statistical arbitrage as a long horizon trading opportunity that generates a riskless profit and is designed to exploit persistent anomalies. Formally, a statistical arbitrage is a zero initial cost, self-financing trading strategy with a cumulative discounted value $v(t)$ such that:

1. $v(0) = 0$
2. $\lim_{t\to\infty} E^p[v(t)] > 0$
3. $\lim_{t\to\infty} P(v(t) < 0) = 0$
4. $\lim_{t\to\infty} \frac{Var^p[v(t)]}{t} = 0$ if $P(v(t) < 0) > 0 \; \forall t < \infty$

$$v(t_i) = \frac{L(t_i) - S(t_i) + V(t-1)[1 + r(t-1)]}{\exp\{\sum_{j=1}^{i} r(t_j)\}} \tag{1}$$

where $L(t_i)$ and $S(t_i)$ are respectively returns on long and short position when 1$ is invested in each position, and $V(t-1)$ is the previous period's profit. The first condition implies zero initial cost, and the second condition imposes a self-financing constraint requiring positive expected discounted profit in the limit. The third condition necessitates that the probability of loss converges to zero, and the last one states that if the probability of loss is greater than zero at any finite point in time, then time averaged variance converges to zero.

By assuming discounted incremental trading profits follows $\Delta v_i = \mu + \sigma i^{\lambda} z_i$ where z_i are iid N(0,1) random variables with $z_0 = 0$, $v(t_0) = 0$ and $\Delta v_0 = 0$, we can write cumulative discounted profits as follows:

$$v(t_n) = \sum_{i=1}^{n} \Delta v_i \sim dN\left(n\mu, \sigma^2 \sum_{i=1}^{n} i^{2\lambda}\right)$$

and log likelihood function of discounted incremental trading profits is

$$logL(\mu, \sigma^2, \lambda|\Delta v) = -\frac{1}{2}\sum_{i=1}^{n} log(\sigma^2 i^{2\lambda}) - \frac{1}{2\sigma^2}\sum_{i=1}^{n}\frac{1}{i^{2\lambda}}(\delta v - \mu)^2$$

Taking derivatives of log likelihood function with respect to four parameters gives MLE estimators, and statistical arbitrage test as follows:

A trading strategy generates a statistical arbitrage with $1 - \alpha$ percent confidence if the following conditions satisfied:

H1: $\hat{\mu} > 0$

H2: $\hat{\lambda} < 0$, and

Therefore, the sum of the p-values associated with the individual hypothesis must be below α. The first hypothesis is that the mean of discounted incremental trading profits is greater than zero and the second condition of statistical arbitrage is satisfied if this is the case. The second hypothesis which states that growth rate of standard deviation is smaller than zero, satisfies the third and fourth condition of statistical arbitrage definition if growth rate of mean is zero.

CHAPTER 3

TRADING ALGORITHM

We develop a trading algorithm using futures contracts on a single commodity with different maturities instead of different commodities and it is market neutral strategy i.e there are two possible positions, long future-short spot or long spot-short futures. Trading signals are generated by convenience yield forecasts. It is the benefit associated with holding an underlying product or physical good, rather than the contract or derivative product. Since we are not intended to receive any physical commodity, we assume there is no storage cost and calculate the convenience yields from the cost of carry model:

$$cy_{t,T} = r_t - \frac{ln(F_{t,T}) - ln(S_t)}{T - t} \tag{2}$$

where $cy_{t,T}$ is convenience yield of futures contract with maturity T at time t, r_t is risk free interest rate, $F_{t,T}$ is the price of future contract and S_t is the spot price which is the price of the nearest contract. We can interpret relative price chances of futures and spot contracts from the convenience yield formula. In order to see this, suppose $cy_{t+1,T}$ is greater (smaller) than $cy_{t,T}$. There are two possible explanations (assuming daily risk-free rate is constant): Either price of spot contract increases (decreases) while price of future contract decreases (increases) or increase in the price of spot contract is greater (smaller) than the increase in the price of future contract.

We forecast next period's convenience yield at each period and we generate trading signals according to forecasted convenience yield. Figure 1 illustrates our trading algorithm.

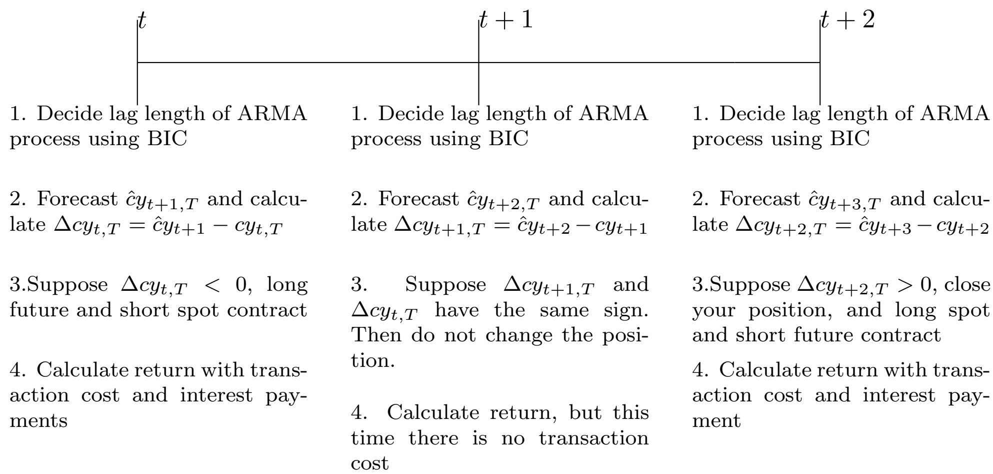

Fig. 1. Illustration of trading algorithm

At the end of the period t, using all past data our algorithm decides to ARMA(p,q) model by estimating all combinations of p and q up to 4 lags and choose the optimal lag length indicated by Bayesian Information Criteria (BIC). Then it forecasts convenience yields of period $t+1$, $\hat{c}y_{t+1}$, and calculate difference between $\hat{c}y_{t+1}$ and cy_t. Suppose this difference smaller than zero, it gives signal to long futures and short spot contract. At the end of the period $t+1$, it calculates excess returns with transaction cost and risk free interest rate. Also, algorithm calculates the true cy_{t+1}, adds it to the sample and forecasts next period's convenience yield, $\hat{c}y_{t+2}$ after choosing the optimal ARMA(p,q) model. Suppose sign of the difference between forecasted convenience yield and period $t+1$'s convenience yield is the same as the sign of difference calculated at previous period, then algorithm do not give any signal to change position. At the end of the period $t+2$, it calculates excess returns without transaction cost since no new position is taken. Again, algorithm calculates true cy_{t+2} and adds it to the sample and forecasts next period's convenience yield, $\hat{c}y_{t+3}$, using optimal ARMA(p,q) model. Suppose, however, $\hat{c}y_{t+3}$ is greater than cy_{t+2} at this period. Algorithm closes the previous position and take a new position that is long spot contract and short futures contract. Again it calculates excess returns with transaction cost at the end of the next period. Trading algorithm calculates returns with the following formula.

$$R_t = R_t^L - R_t^S + R_t^{roll} - 2.TC_t - r_t^f \tag{3}$$

where R_t^L is return of long position, R_t^S is return of short position, r_t^f is risk-free interest rate, R_t^{roll} is rolling return if t is rolling day (which will be explained in detail in the Data Subsection) and TC_t is transaction cost which estimated as percentage of notion contract (Szakmary et al. (2010)):

$$TC_t = \begin{cases} \dfrac{10 + (0.01x1000)}{Pricex1000}, & \text{if new position taken} \\ \quad 0 \quad , & \text{otherwise} \end{cases} \tag{4}$$

3.1 Data

We use daily transaction data for the crude oil (WTI) future contracts and the US Generic Government 3 Month Yield (as the risk free interest rate). The sample covers he period from January 2, 1985 to December 31, 2012. Since we are interested in contracts with different maturities, we construct four different futures contract prices with minimum two months and maximum five months by rolling each contract at 5^{th} business day of the month before expiry month. It is because of two reasons: first, although the future contract is trading on this day, we do not want to be on it as there might not be sufficient liquidity for us to exit on time; second, rolling rule ensures that physical commodity is never delivered for the entire period. For example, suppose we are constructing 2-month future contract prices starting from January 2, 1985. From transaction data for March 1985, we start to create our 2-month future contract prices until February 7, 1985 which is 5^{th} business day of the month (February) before expiry month (March) and we buy April contract at rolling day. As shown in the Table 1, price of April Contract is smaller than March Contract so there are rolling gain.

Table 1. End of Day Prices of Crude Oil March 1985 and April 1985 contracts

March Contract		April Contract	
1/30/1985	25.67	1/30/1985	25.37
1/31/1985	26.41	1/31/1985	25.83
2/1/1985	26.74	2/1/1985	26.26
2/4/1985	26.52	2/4/1985	26.19
2/5/1985	26.78	2/5/1985	26.38
2/6/1985	27.07	2/6/1985	26.68
2/7/1985	27.21	2/7/1985	26.71
2/8/1985	27.59	2/8/1985	26.92
2/11/1985	28.04	2/11/1985	27.42

After constructing price series we calculate the summary statistics of returns which we define as follow:

$$R_t = \begin{cases} \dfrac{F_{t,T} - F_{t-1,T}}{F_{t-1,T}} & \text{if t is not rolling day} \\ \dfrac{F_{t,T} - F_{t-1,T}}{F_{t-1},T} + \dfrac{F_{t,T} - F_{t,T+1}}{F_t,T} & \text{if t is rolling day} \end{cases} \tag{5}$$

where $F_{t,T}$ is the price of future contract at time t , $F_{t,T+1}$ is the price of rolled future contract at time t and R_t^{roll} is the second term in the case of rolling day. Summary statistics of the four different contracts are reported in Table 2 (Price and return graphs are reported in APPENDIX A).

Table 2. Summary statistics of future contracts

	2-month	3-month	4-month	5-month
mean	0.00053	0.00060	0.00062	0.00064
st. dev.	0.02316	0.02231	0.02200	0.02145
min.	-0.31892	-0.27979	-0.25515	-0.28872
max.	0.15690	0.18550	0.18252	0.14271
skewness	-0.38383	-0.28398	-0.40564	-0.45428
kurtosis	9.83226	8.64755	9.78524	10.43354
ADF-test	-82.67544	-82.20342	-81.90571	-81.72851
Obs. #	6994	6994	6971	6951

All futures contracts have positive mean return, and while volatility decreasing mean returns are increasing over the maturity. ADF test statistics rejects the null hypothesis of return series have unit root, for all maturities.

Table 3 reports the summary statistics of convenience yields calculated by using Equation (3).

Table 3. Summary statistics of convenience yields(%)

	cy_2	cy_3	cy_4	cy_5
mean	0.03755	0.04932	0.03470	0.06514
st. dev.	0.56293	0.54144	0.59894	0.62159
min.	-14.73311	-7.78116	-14.21700	-9.10033
max.	9.13261	10.49977	11.09150	19.24421
skewness	-2.11645	4.32904	1.66321	9.23857
kurtosis	157.30589	102.89562	150.71620	221.19648
ADF-test	-6.17866	-27.23738	-24.21926	-25.91468
Obs. #	6995	6995	6972	6952

All convenience yields are stationary and have positive mean that is holding physical crude oil benefits the holder on average. However high volatility indicates that sometimes holding futures contract instead of physical commodity benefits. Also convenience yields at all maturities have excess kurtosis and right skewed except cy_2.

3.2 Trading Performance Evaluation

Table 4 summarizes the performance of our trading algorithm in which the first column shows which futures contract is traded over the spot contract.

Table 4. Trading performance

maturities	daily mean return(%)	t-statistics	annualized return(%)	White RC p-value	RMSE
2-month	0.070	4.650	19.107	0.000	0.4943
3-month	0.061	3.567	16.366	0.004	0.4634
4-month	0.058	3.114	15.457	0.006	0.5400
5-month	0.045	2.107	11.921	0.082	0.4936

We estimate transaction cost for each trading day using Equation (4) and the average value is found as 0.07 %. Despite such a high transaction cost, all mean excess returns are significant at 1% significance level except for the one with the highest maturity. Put differently, our trading algorithm produces daily mean excess returns that are statistically greater than zero with a maximum of 0.07 % and minimum of 0.045 % on a daily basis. They correspond to annualized returns of 19.11% and 11.92%, respectively. The results also suggest that mean excess returns decrease in maturity together with a decrease in t-statistics. The trading performance of future contracts over the spot contract is presented for each maturity in APPENDIX B.

Root mean square errors (RMSE) of convenience yield forecasts are reported in the last column of Table 4. There seems to be no clear relationship between trading performance and forecast accuracy. More precisely, RMSE is the highest for the 4-month future contract but still its mean excess return is greater than the 5-month future with a difference of 3.54% on an annual basis. Besides, the highest mean excess return belongs to the futures contract with the nearest maturity, whose forecasts are, however, not as accurate as the futures contracts maturing in 4 and 5 months.

The length of position holding rises on average as maturity increases. Average lengths are 4.97, 7.81, 9.88 and 21.42 days in a respective order with maturity. It is likely resulted from the fact that the number of transactions decrease in maturity which in turn requires more time to take a new position or exit from an existing one.

We also do reality check to test whether our returns are generated by sheer luck or our trading algorithm is able to generate significant mean excess returns. The fifth column of Table 4 reports the p-values based on White Reality Check Test proposed by White (2000). In this framework, we use stationary bootstrap method of Politis and Romano (1994) to construct block samples with 500 observations for each return series. The test results indicate that mean excess returns are different from zero on 99% confidence intervals for the trades made with 2, 3, and 4-month futures contracts. But we fail to reject the null hypothesis of zero mean excess return for the trade made with 5-month futures contract. It produces a mean that is different from zero only if the confidence bands are narrowed to 90%.

These results demonstrate that trading based on convenience yield forecast outperforms the trading strategies used in the aforementioned studies, except for the double shorting strategy of Fuetre et. al (2010).

In order to test whether our trading algorithm generates statistical arbitrage or not, we first calculate cumulative trading profits based on Equation (1) (Graphs of cumulative discounted profits for each maturity are reported in APPENDIX C.).We then employ Maximum Likelihood Estimation method to estimate parameters of incremental profits. Estimated parameter values and their corresponding p-values are reported in Table 5.

Table 5. Parameter estimates and statistical arbitrage test

	μ (mean)	t-statistics	σ (standard deviation)	λ (growth rate of standard deviation)	H1 ($\mu > 0$)	H2 ($\lambda < 0$)	Sum (H1+H2)
2-month	0.000435	6.039	0.217	-0.449	0.000	0.000	0.000
3-month	0.000339	4.298	0.400	-0.512	0.000	0.000	0.000
4-month	0.000306	3.667	0.587	-0.552	0.000	0.000	0.000
5-month	0.000273	2.527	0.132	-0.340	0.006	0.000	0.006

According to Hogan et al. (2004) statistical arbitrage test, our trading algorithm meets the conditions of statistical arbitrage in the sense that it provides us with a zero cost and self financing trading strategy. The means of discounted incremental profits are significantly greater than zero for all maturities, and the minimum mean obtained here is grater than almost all of the momentum strategies' means that are tested in Hogan et al. (2004). More specifically, it is greater than 13 momentum strategies' means out of the 16. Although standard deviations are higher than momentum strategies, our trading strategy's growth rate of standard deviation is smaller than momentum strategy's growth rate of standard deviation and they are significantly smaller than zero.

CHAPTER 4

CONCLUSION

In this thesis, we develop a market neutral trading strategy which is based on the forecasted values of convenience yields. Positions are taken according to the difference between forecasted convenience yields and their corresponding current values. That is, the trading algorithm gives signal to long spot contract and short futures contract if forecasted convenience yield is greater than current convenience yield, and vice versa.

We apply our trading strategy on crude oil futures market and find that it generates significant excess return of 19.11%, 16.37%, 15.45% and 11.92% annually for the contracts 2-month, 3-month, 4-month and 5-month maturities respectively. Finally, we show that our trading algorithm provide statistical arbitrage by using Hogan et al. (2004) test.

APPENDIX A

CONTRACT PRICE AND RETURNS

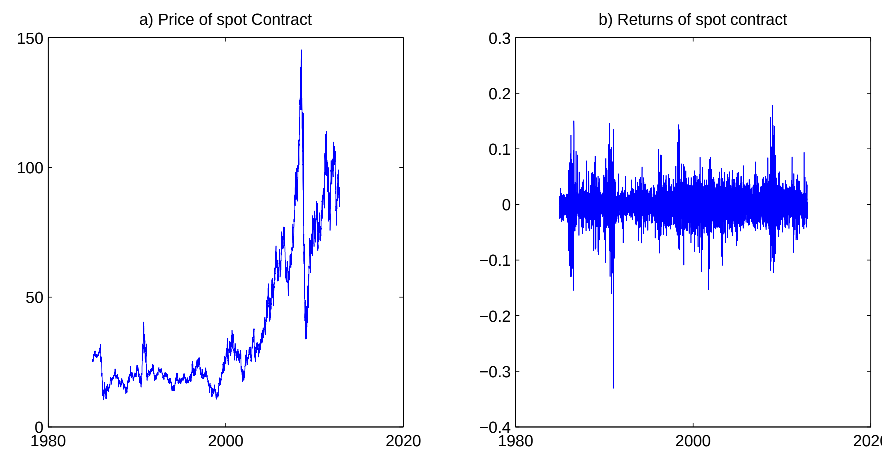

Fig. 2. Price and return series of spot contract.

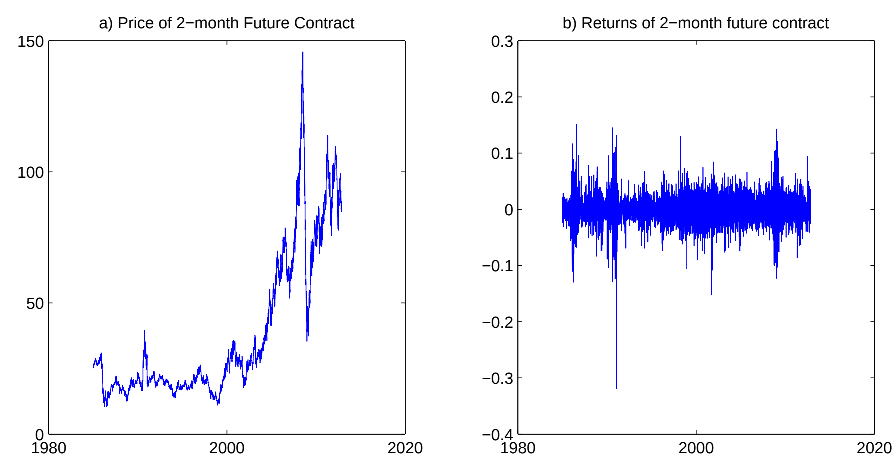

Fig. 3. Price and return series of 2-month future contract.

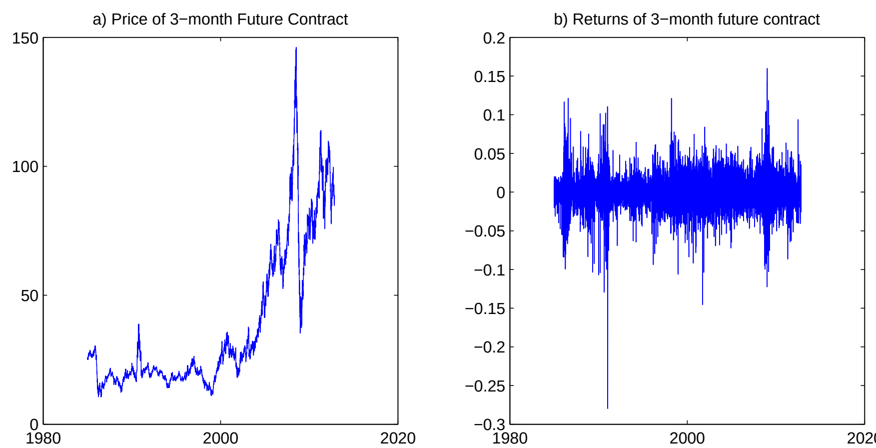

Fig. 4. Price and return series of 3-month future contract.

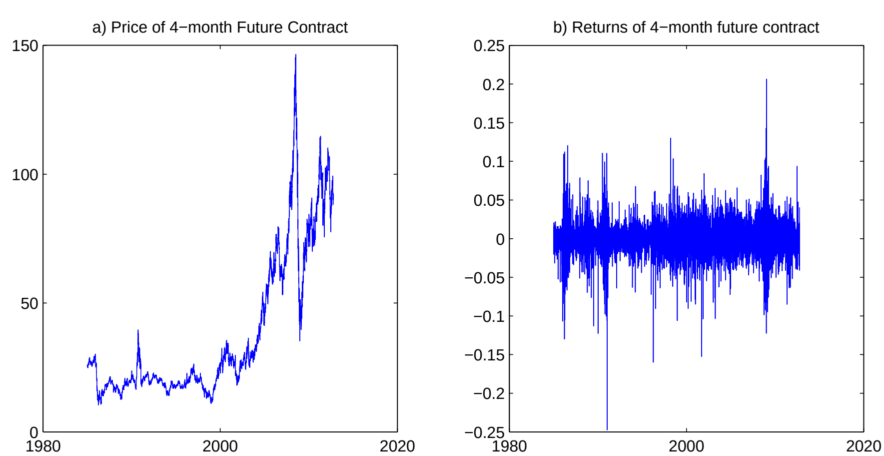

Fig. 5. Price and return series of 4-month future contract.

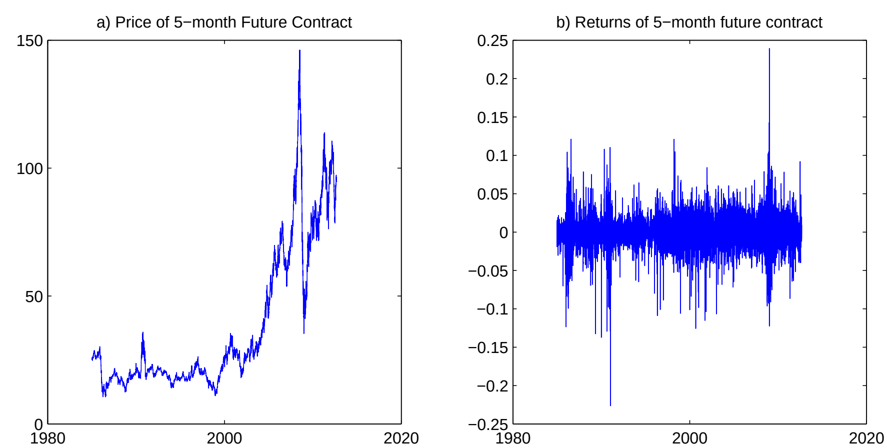

Fig. 6. Price and return series of 5-month future contract.

APPENDIX B

TRADING PERFORMANCE IN DETAIL

Table 6. Trading Performance of Trading with 2-month Future Contract

year	daily mean return (%)	t-statisitcs	annualized return (%)	RMSE
1987	0.119	1.864	34.637	0.338
1988	0.077	1.084	21.351	0.161
1989	0.318	2.832	120.926	0.844
1990	0.221	1.710	73.539	0.531
1991	0.034	0.415	8.823	0.637
1992	-0.018	-0.864	-4.354	0.129
1993	-0.073	-1.402	-16.674	0.245
1994	0.040	0.729	10.648	0.334
1995	0.100	2.130	28.432	0.106
1996	0.367	2.581	149.624	0.806
1997	0.022	0.530	5.650	0.174
1998	0.070	0.505	19.209	0.904
1999	-0.008	-0.194	-2.071	0.188
2000	0.276	3.093	99.181	0.624
2001	-0.034	-0.513	-8.243	0.301
2002	0.034	0.725	8.977	0.257
2003	0.255	3.127	89.228	0.438
2004	0.098	2.204	27.752	0.342
2005	-0.039	-1.071	-9.341	0.335
2006	-0.063	-1.141	-14.569	0.184
2007	-0.026	-0.605	-6.198	0.397
2008	0.013	0.105	3.274	0.372
2009	0.032	0.375	8.240	1.288
2010	0.012	0.498	3.125	0.087
2011	-0.022	-1.109	-5.297	0.267
2012	0.004	0.363	0.912	0.036

Table 7. Trading Performance of Trading with 3-month Future Contract

year	daily mean return (%)	t-statisitcs	annualized return (%)	RMSE
1987	0.098	1.497	27.757	0.244
1988	0.057	0.814	15.351	0.238
1989	0.242	1.820	83.215	0.562
1990	0.119	0.679	34.577	0.770
1991	0.097	1.013	27.357	0.128
1992	-0.024	-0.936	-5.899	0.122
1993	-0.135	-2.288	-28.593	0.472
1994	0.106	1.711	30.405	0.495
1995	0.065	1.212	17.674	0.232
1996	0.302	1.950	112.519	0.717
1997	-0.023	-0.427	-5.631	0.211
1998	0.140	1.106	41.810	0.229
1999	0.002	0.056	0.614	0.205
2000	0.227	1.652	76.329	1.083
2001	0.020	0.266	5.044	0.451
2002	0.040	0.867	10.573	0.201
2003	0.175	1.702	54.633	0.421
2004	0.043	0.761	11.330	0.305
2005	-0.008	-0.211	-2.030	0.065
2006	0.006	0.140	1.511	0.397
2007	-0.005	-0.149	-1.269	0.645
2008	0.005	0.046	1.383	0.757
2009	0.021	0.212	5.350	0.624
2010	0.010	0.434	2.633	0.159
2011	-0.022	-1.255	-5.321	0.263
2012	0.011	1.074	2.860	0.028

Table 8. Trading Performance of Trading with 4-month Future Contract

year	daily mean return (%)	t-statisitcs	annualized return (%)	RMSE
1987	0.078	1.069	21.636	0.565
1988	0.126	1.625	37.008	0.200
1989	0.282	1.929	102.386	0.807
1990	0.108	0.578	31.064	1.035
1991	0.043	0.371	11.409	0.739
1992	-0.014	-0.601	-3.478	0.135
1993	-0.055	-0.954	-12.822	0.245
1994	0.014	0.204	3.633	0.194
1995	0.014	0.304	3.643	0.234
1996	0.385	1.942	161.368	0.511
1997	0.050	0.690	13.237	0.153
1998	-0.001	-0.008	-0.273	1.269
1999	-0.005	-0.119	-1.306	0.057
2000	0.254	2.463	88.655	0.102
2001	0.062	0.751	16.713	0.322
2002	0.024	0.508	6.241	0.457
2003	0.045	0.398	11.806	1.119
2004	0.065	0.992	17.538	0.414
2005	-0.049	-1.046	-11.449	0.436
2006	-0.049	-1.245	-11.548	0.500
2007	-0.021	-0.614	-5.169	0.362
2008	0.082	0.692	22.620	0.184
2009	0.064	0.595	17.477	0.642
2010	-0.016	-0.636	-3.946	0.172
2011	-0.007	-0.302	-1.803	0.107
2012	0.002	0.176	0.400	0.054

Table 9. Trading Performance of Trading with 5-month Future Contract

year	daily mean return (%)	t-statisitcs	annualized return (%)	RMSE
1987	0.021	0.321	5.314	0.558
1988	0.075	1.016	20.560	0.257
1989	0.281	2.011	101.853	1.423
1990	0.192	1.063	61.657	0.936
1991	0.104	0.787	29.640	0.661
1992	-0.012	-0.360	-2.906	0.168
1993	-0.048	-0.692	-11.391	0.235
1994	-0.077	-1.111	-17.505	0.487
1995	0.064	0.944	17.480	0.284
1996	0.280	1.685	100.950	0.610
1997	0.081	0.891	22.339	0.185
1998	-0.091	-0.533	-20.427	0.507
1999	0.033	0.485	8.525	0.147
2000	0.120	0.918	34.846	0.839
2001	0.079	0.907	21.910	0.232
2002	0.025	0.378	6.443	0.286
2003	0.110	1.075	31.742	0.397
2004	0.094	1.305	26.575	0.173
2005	-0.029	-0.450	-7.032	0.201
2006	-0.078	-1.013	-17.690	0.188
2007	-0.033	-0.341	-7.990	0.247
2008	0.026	0.224	6.794	0.408
2009	-0.115	-0.482	-24.944	0.340
2010	0.047	1.733	12.517	0.031
2011	0.016	0.563	4.178	0.018
2012	-0.013	-0.655	-3.133	0.013

APPENDIX C

CUMULATIVE DISCOUNTED PROFITS

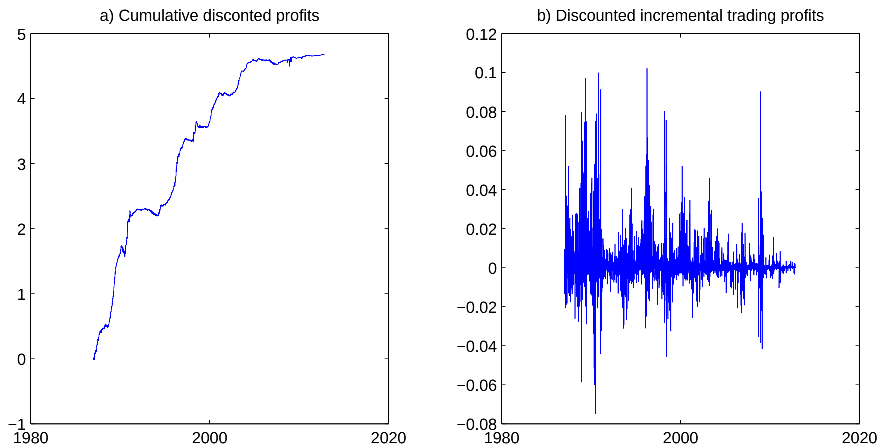

Fig. 7. Cumulative discounted and discounted incremental trading profits of trading with 2-month future contract .

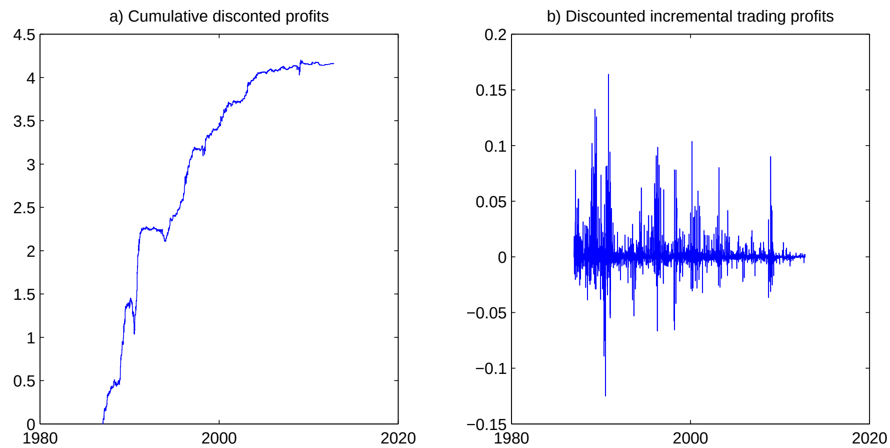

Fig. 8. Cumulative discounted and discounted incremental trading profits of trading with 3-month future contract .

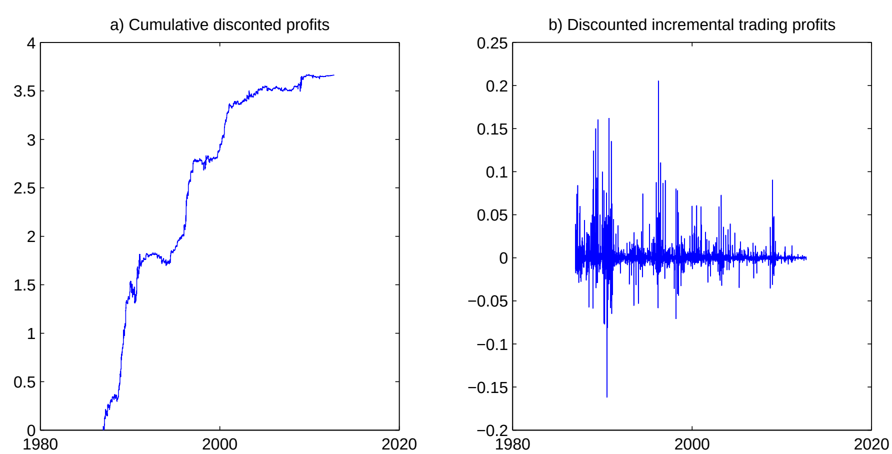

Fig. 9. Cumulative discounted and discounted incremental trading profits of trading with 4-month future contract .

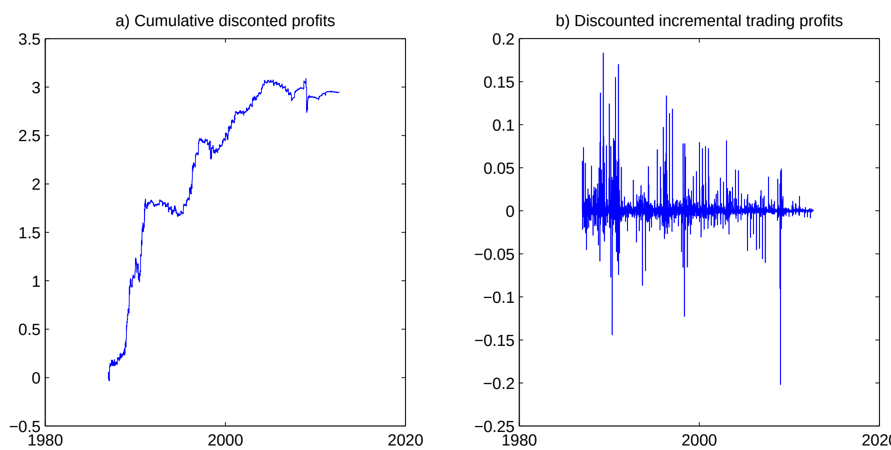

Fig. 10. Cumulative discounted and discounted incremental trading profits of trading with 5-month future contract .

REFERENCES

Avellaneda, M., & Lee, J. H. (2010). Statistical arbitrage in the US equities market. *Quantitative Finance*, 10(7), 761-782.

Bianchi, R., Drew, M., & Zhu, R. (2009). Pairs trading profits in commodity futures markets. *In Proceedings of Asian Finance Association 2009 International Conference* (pp. 1-26). University of Queensland.

Cummins, M., & Bucca, A. (2012). Quantitative spread trading on crude oil and refined products markets. *Quantitative Finance*, 12(12), 1857-1875.

Driaunys, K., Masteika, S., Sakalauskas, V., & Vaitonis, M. (2014). An algorithm-based statistical arbitrage high frequency trading system to forecast prices of natural gas futures. *Transformation in Business & Economics*, 13(3).

Erb, C. B., & Harvey, C. R. (2006). The strategic and tactical value of commodity futures. *Financial Analysts Journal*, 62(2), 69-97.

Fuertes, A. M., Miffre, J., & Rallis, G. (2010). Tactical allocation in commodity futures markets: Combining momentum and term structure signals. *Journal of Banking & Finance*, 34(10), 2530-2548.

Gatev, E., Goetzmann, W. N., & Rouwenhorst, K. G. (2006). Pairs trading: Performance of a relative-value arbitrage rule. *Review of Financial Studies*, 19(3), 797-827.

Hoel, C. H. (2013). Statistical arbitrage pairs: Can cointegration capture market neutral profits? (Master Thesis). Norwegian School of Economics, Bergen.

Hogan, S., Jarrow, R., Teo, M., & Warachka, M. (2004). Testing market efficiency using statistical arbitrage with applications to momentum and value strategies. *Journal of Financial economics*, 73(3), 525-565.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65-91.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, 49(5), 1541-1578.

Marshall, B. R., Cahan, R. H., & Cahan, J. M. (2008). Can commodity futures be profitably traded with quantitative market timing strategies? *Journal of Banking & Finance*, 32(9), 1810-1819.

Miffre, J., & Rallis, G. (2007). Momentum strategies in commodity futures markets. *Journal of Banking & Finance*, 31(6), 1863-1886.

Narayan, P. K., Ahmed, H. A., & Narayan, S. (2014). Do MomentumBased Trading Strategies Work in the Commodity Futures Markets? *Journal of Futures Markets*. doi: 10.1002/fut.21685

Pole, A. (2011). *Statistical arbitrage: Algorithmic trading insights and techniques*. Hoboken, N.J: John Wiley & Sons.

Politis, D. N., & Romano, J. P. (1994). The stationary bootstrap. *Journal of the American Statistical Association*, 89(428), 1303-1313.

Rudy, J. (2011). Four essays in statistical arbitrage in equity markets. (Doctoral dissertation). Liverpool John Moores University, Liverpool.

Szakmary, A. C., Shen, Q., & Sharma, S. C. (2010). Trend-following trading strategies in commodity futures: A re-examination. *Journal of Banking & Finance*, 34(2), 409-426.

White, H. (2000). A reality check for data snooping. *Econometrica*, 68(5), 1097-1126.

Zhu K., (2005), A statistical arbitrage strategy. (Masters Thesis). Royal Institute of Technology, Stockholm.