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Abstract

This paper is the replication of Alizadeh and Nomikos (2008) *Performance of Statistical Arbitrage in Petroleum Futures Markets*. Cited methodology from the original paper, this paper investigates the linkages between commodities in the future markets and apply trading strategy based on statistical analysis. The trading strategy is established based on cointegration relationships between commodities and execute trading rules to determine long-short positions. The robustness of trading result will be implemented by using stationary bootstrap approach. From the result, we can see the trading strategy based on cointegration relationship analysis is efficient to set up trading strategies in given datasets.

Introduction

With the development of modern commodity economy and vast improvement of labor productivity, the change of market supply and demand tend to be complicated. For the price that continuously reflect the process of potential change of supply and demand, future markets plays essential part in daily production activities. Even though future markets are designed for lower trading risks, individual investors and market participants also facing high volatilities in trading some of the commercials, which means there are lots of arbitrage opportunities for investors by speculating on the future markets. However, this volatility can also cause huge loss if investors adapt wrong trading strategies. It is essential to create a trading strategy based on the signal that can alert the volatility of future price for commodities.

Referred from Alizadeh and Nomikos (2008), this paper also concentrate on issues about price discovery, market interrelationships and hedging effectiveness. The expected market prices in spreads of petroleum are incorporate inefficient has been proved by Alizadeh and Nomikos (2008). They also find the Sharpe ratios improved by implementing moving average trading strategy compared with traditional buy and hold strategy, which also gives a good evidence that statistical arbitrage opportunities exists in given combinations of petroleum future spreads. Other studies also find the price

inefficiency exists in commodity future markets. For example, the price inefficiency exists in hog, corn, and soybean meal future markets has been proved by Liu (2005). They created the ex-post trading simulations based on the spread among hog, corn, and soybean meal estimated by the multivariate cointegration test and the ex-ante trading simulations based on the predetermined hog spread based on the ratios in USDA documents. The tendencies from trading simulations shows these three commodity futures market are incorporate inefficient.

As we all know, the commodities are trading in future markets have some relationships between each other in daily production. These relationship will cause the price fluctuation of other commodities when one specific commodity price fluctuates, which means we need statistical methods to find the cointegration and causality between commodities. For example, Alizadeh and Nomikos (2008) investigated the interrelationships in petroleum future markets. They find the relationships between New York Mercantile Exchange (NYMEX) West Texas Intermediate (WTI) crude oil, NYMEX heating oil, Intercontinental Exchange (ICE) Brent crude oil, and ICE gas oil by using vector error correction model (VECM) (Johansen (1988)) to determine the cointegration relationships and using Granger causality test to determine the causality. The result by implementing VECM implies the existence of long run relationship in every pairs that set up by two petroleum commodities.

The trading strategy simulation result by simulating strategy back into original historical data is not convincing, which means there is possibility that the result is suffering data snooping bias. In order to discount the possibility of data snooping bias, Alizadeh and Nomikos (2008) implemented the bootstrap simulation to resample the original data. Implementing trading strategy back to bootstrapped data and compare the results with the results based on original data.

In this paper we started with looking into the time series properties of historical settlement price of NYMEX WTI crude oil and NYMEX heating oil. We find that the two future prices are integrated of order one. Then, using the vector error correction model to find cointegration vector. We also need to test causality by using Granger causality test (Granger 1986) if the cointegration relationship exists between two commodities. After confirming the cointegration relationship and causality of two commodities, We construct moving average (MA) trading strategy and test it with historical data. For the purpose of discount the influence of data snooping, We resample the dataset by using stationary bootstrap simulation () and test the trading strategy.

The structure of this paper is: the next section describes the statistical methodology and the model; the third section will be about the data and the empirical results; the last section will be about the empirical result after resampling methodology employed and the conclusion.

Statistical Methodology

This section we will focus on examine the time series properties of the NYMEX WTI crude oil and NYMEX heating oil future prices and their relationship. We will use vector error correction model (VECM) to find the long-run and short-run relationships:

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t \quad , \varepsilon_t \sim N(0, \Sigma) \qquad (1)$$

where X_t is a 2×1 vector of future prices; Δ denotes the first difference operator; Γ_i and Π is a 2×2 vector represents short run and long-run relationships; and ε_t is a stationary white noise processes with constant covariance matrix Σ.

The next part will be with the analysis. First, the future prices are being I(0) and the first differenced series are I(1). The existence of a stationary relationship between NYMEX WTI crude oil and NYMEX heating oil are examined in the equation (1). The rank (Π) will be also tested in equation (1) and the rank (Π) will determine the number of cointegrationg relationships. If $\Pi = 2$ which means full rank, all the variables in X_t are I(0) and vector autoregressive (VAR) model in levels will be the best statistical methodology to apply. If $\Pi = 0$, equation (1) will reduce to VAR model in I(1). The last condition will be Π has a reduced rank. For Π has a reduced rank, the existence of one cointegration vector will be confirmed and the coefficient matrix can be decompose as $\Pi = \alpha\beta^*$ where α and β^* are 2×1 vectors, α represents the error correction coefficients vector and β represents cointegration vector.

Then, after proof the cointegration relationship between WTI crude oil and heating oil, the causality must exist at least one direction. Finding the causality can help us find which time series cause another time series in a pair. Or in this paper, assume if there is one-way causality relationship, there will be WTI crude oil cause NYMEX heating oil if the present value of heating oil can be predicted accurately by the historical value of WTI crude oil. Also, if there is a two-way causality, there is going to be WTI crude oil and NYMEX heating oil cause each other. For testing the causality, VECM provides robustness evidence on either one-way or two-way causality exists between two commodities.

Trading Strategies

The purpose of cointegration analysis is to find the relationship between the commodities future in a pair. Then, we can develop a trading strategy that can identify investment timing opportunities by using this relationship. So we use historical correlation and cointegration of future prices as movement indicator and signal for trading activity.

For the purpose of study, we will just focus on simple moving average (MA) rule based on future spreads of commodities, which is the future spread of NYMEX WTI crude oil and NYMEX heating oil. The MA trading strategy are based on comparing one fast MA and one slow MA of the spread of future prices. For example, an one-week MA (MA1) of the future price spread will be compared with an one-month (four weeks) MA (MA4) of the future price spread of the same series. A positive difference between one-month MA and one-week MA of the spread (MA4-MA1) will be a buy decision which means one-month MA spread is greater than one-week MA and the spread (MA1) is less than the long-run spread (MA4). We can interpret this as the future price of the one commodity (MA1) are undervalued relative to the other (MA4).

Description of Data

This paper is to investigate the performance of future markets by using statistical methodology. For the purpose of methodology study, we will use NYMEX WTI crude oil and NYMEX heating oil future price data that gathered from U.S. Energy Information Administration (www.eia.gov). The time range is from April 4, 1983, to June 27, 2017, resulting 1717 weekly observations and for both crude oil future contract and heating oil contract are one month future contract. For crude oil, the contract expires on the third business day prior to the 25th calendar day of the month preceding the delivery month. If the 25th calendar day of the month is a non-business day, trading ceases on the third business day prior to the business day before the 25th calendar day. The remaining day of the month will be in the second following month. For heating oil, each contract expires on the last business day of the month before the delivery month.

In this paper we are going to assume both of NYMEX WTI crude oil and NYMEX heating oil contract expires at 30th business day of the contract starts. There are 1,000 barrels of crude oil per contract for NYMEX WTI crude oil future contract and there are 42,000 gallons of heating oil per contract for NYMEX heating oil contract.

Statistical Results and Analysis

Testing cointegration will show the long run relationship between NYMEX WTI crude oil and NYMEX heating oil by using Johansen cointegration test (). The lag length of equation (1) is chosen on the basis of the Schwarz Bayesian Information Criterion (Schwarz (1978)). The statistic test result presented, in table (1), indicates that for both NYMEX WTI crude oil and NYMEX heating oil future price have long run relationship with each other, which means there will be arbitrage opportunity. Because the asymptotic distributions of the cointegration test statistics are dependent in the VECM, we have to make sure the inclusion or not of constant and/or linear trends in the system (Alizadeh and Nomikos (2008)).

TABLE 1: Johansen cointegration test for NYMEX WTI crude oil and NYMEX heating oil

	Lags	H_0	λ_{max} test	λ_{trace} test	α_1	α_2
			Statistic		Error correction coefficients	
$HO_t - CL_t$	2	$R = 0$	69.75	72.44	-0.00182	0.003778
		$R = 1$	2.69	2.69	(0.00311)	(0.00319)

	Coefficient of Cointegration Vector			Causality test		
	1	β_0	β_2	$F_2 \rightarrow F_1$	$F_1 \rightarrow F_2$	
$HO_t - CL_t$	1	0.011966	-1.04599	33.781	0.964	
				{2.435e-15}	{0.3814}	

The future price of NYMEX heating oil and NYMEX WTI crude oil that we are using is log priced future price. The 5% critical value for H_0: r = 0 and H_0: r = 1 are 15.49 and 3.84. The number in parentheses are standard errors. The number in braces are the corresponding p-values.

Table (1) reports the estimated error correction coefficients from the VECM. From table (1), α_1 and α_2 are coefficients measure the speed of adjustment of future prices to their long-run relationship at period t -1 and it should be negative in the first equation and positive in the second equation. For example, the equation of error correction term is $F_{1,t-1} - \beta_2 F_{2,t-1} - \beta_0 > 0$ which implies the future price of the first (second) leg will decrease (increase) in value in order to restore the equilibrium.

According to the Granger (1986) theorem, if two prices are cointegrated, there will be at least one causality exists in the pair. The primary assumption is NYMEX WTI crude oil are expected to Granger cause of NYMEX heating oil because crude oil is the raw material of producing heating oil and crude oil prices are determined by the worldwide supply and demand. In fact from table (1), NYMEX heating oil is Granger cause NYMEX WTI crude oil. The reason of NYMEX heating oil is Granger cause NYMEX WTI crude oil in my opinion is that the heating oil price not only determined by supply of its raw material, but also determined by demand of itself. The reason that cause demand change of heating oil are vary, it could because some of the industry in order to expand their production, the inventory of heating oil will be required more than before. It also could be seasonal reason that industry of electricity or heating requires more heating oil to make sure their productivity during extreme weather. The demand of heating oil will be more sensitive than demand of crude oil that affected by the market because heating oil will be used widely than crude oil. Crude oil will be used as producing other kinds of oil like heating oil and gasoline mostly in the industry, but heating oil will be used as fuel to produce in most of heavy industry for energy supply.

Performance of Moving Average Trading Rules

The trading strategy in this paper combines the fundamental relationship between commodities is based on the deviation of the spread from its long-run mean. For locating when to proceed the transaction, we set up four moving average series of log future price difference. The four moving average series are one fast moving average [MA (1)] and three slow moving average [MA (4), MA (8), and MA (12)]. For 1, 4. 8, 12 in parentheses represents 1 week, 4 weeks, 8 weeks, and 12 weeks. The signals are based on the difference between fast moving average and one slow moving average. The price are construct as log price to proceed simulation. For example, for NYMEX heating oil and NYMEX WTI crude oil, if MA (4) – MA (1) > 0, then we will buy the NYMEX heating oil and sell NYMEX WTI crude oil. This position will be held until MA (4) – MA (1) <0. Simultaneously, the long position will be initiated by buying on NYMEX WTI crude oil, and short NYMEX heating oil by selling it.

An important part for evaluating trading strategy is the transaction cost are going to be involved in the simulation. For the purpose of study and referred from Alizadeh and Nomikos (2008), a transaction cost of 0.2% for every round trip of initiating and reversing trade will be added into the simulation.

TABLE 2 Trading Simulation of one-, two-, and three-month trading strategies.

	Mean Return	Standard Deviation	Sharpe Ratio
MA4 – MA1	-0.0053	0.1950	-0.0269
MA8 – MA1	-0.01	0.3986	-0.0251
MA12 – MA1	-0.0165	0.5593	-0.0296

TABLE 3 Buy and hold trading simulation

	Mean Return	Standard Deviation	Sharpe Ratio
Crude Oil	-0.0521	1.0372	-5.0235
Heating Oil	-0.03	0.9413	-3.1949

Mean return are the percentage annualized return and standard deviation are the % annualized standard deviations. Sharpe ratios are calculated using the R/STD.

The performance of different strategies is presented in table 2 and table 3. From the table 2, we can see the mean return of moving average simulation is slightly negative and return is not as high as Alizadeh and Nomikos (2008) presents in their paper. From Alizadeh and Nomikos (2008) paper, we can also see the NYMEX WTI crude oil and NYMEX heating oil pair has the lowest mean return among six of the pairs that tested in the moving average trading simulation. The highest return is from one-month to one-week moving average trading strategy and the lowest return is from three-month to one-week moving average trading strategy, which is same as the result in Alizadeh and Nomikos (2008)'s paper. Compare the performance of moving average trading

simulation and traditional buy and hold trading simulation, we can see the moving average trading strategy outperforms traditional buy and hold strategy. From table 2 and table 3, we can see the increase of Sharpe ratios in the moving average trading strategy.

The reason that the mean return of moving average trading simulation in NYMEX WTI crude oil and NYMEX heating oil is perhaps we still lack of information that will affect the change of future price in NYMEX WTI crude oil and NYMEX heating oil. We still need to adjust trading signal by involving more relevant information into analysis. For example, there are some other conditions will affect the supply and demand of these two commodities, like seasonal issues, but there are more information like sudden news or policy issues can also affect the future prices should be consider into trading signal when establishing trading signal.

Data Snooping and the Stationary Bootstrap

The result in last section is reasonable compare with Alizadeh and Nomikos (2008)'s result. However, an important issue exists in previous result is data snooping. According to Sullivan et al (1999) and White (2000), data snooping occurs when a data set is used more than once for data selection and inference purpose, which means using datasets frequently for testing moving average trading strategies will result to poor result satisfaction. However, using the ordinary bootstrap resampling technique will result to data nonstationary that will affect the accuracy of moving average trading simulation. Therefore, in order to assess the performance of moving average trading strategy and discount the influence of data snooping, we use the stationary bootstrap resampling technique to resample the future prices data. The basic idea of assess the performance of trading strategies are by implement the trading strategies into bootstrapped dataset to generate a distribution of trading statistics.

The process of stationary bootstrap simulation is: First, we bootstrap the log priced future price of NYMEX heating oil and NYMEX WTI crude oil. Then we construct the spreads that used to trigger buy and sell decisions based on moving average trading strategies. We also implement 0.2% transaction costs into trading simulation. For the purpose of comparison and function of benchmark, we will simulate buy and hold trading strategy by using bootstrapped data. We will bootstrap 1,000 times to make the result more accurate.

FIGURE 1 Bootstrapped histogram of returns of MA4 – MA1

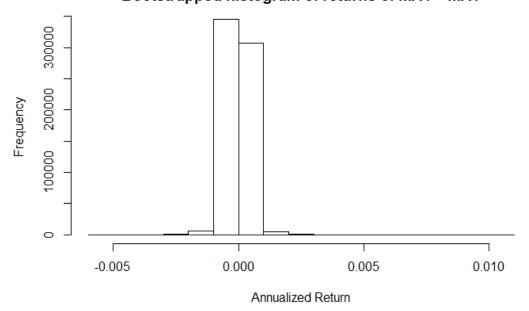**Bootstrapped histogram of returns of MA4 – MA1**

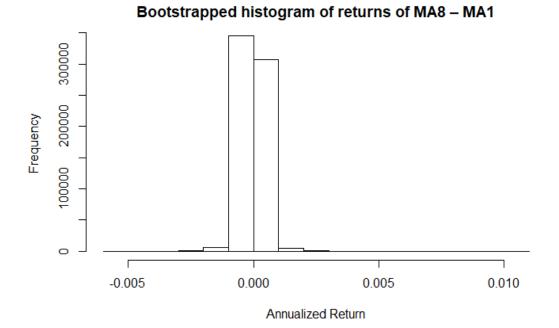FIGURE 2 Bootstrapped histogram of returns of MA8 – MA1

Bootstrapped histogram of returns of MA8 – MA1

FIGURE 3 Bootstrapped histogram of returns of MA12 – MA1
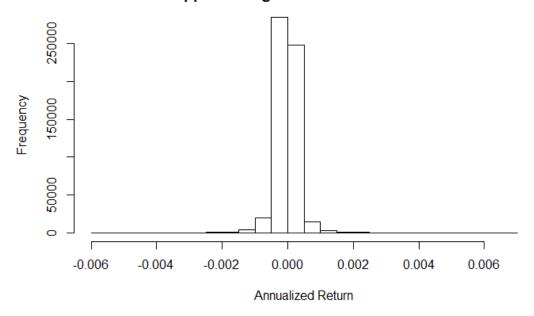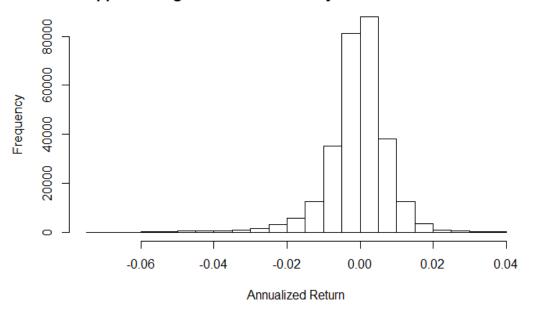
Bootstrapped histogram of returns of MA12 – MA1

FIGURE 4 Bootstrapped histogram of returns of buy and hold strategy

Bootstrapped histogram of returns of buy and hold NYMEX WTI crude oi

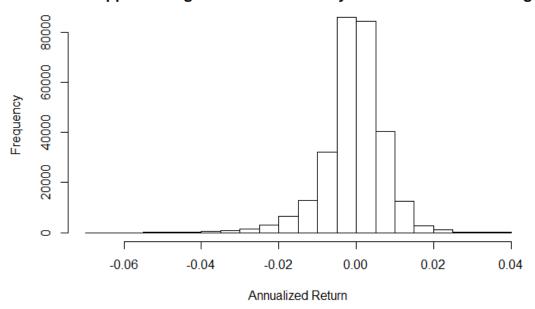## Bootstrapped histogram of returns of buy and hold NYMEX heating oil

TABLE 4 Moving average trading simulation with bootstrapped data

	Mean Return	Standard Deviation	Sharpe Ratio
MA4 – MA1	-0.0018	0.0379	-0.0473
MA8 – MA1	-0.0016	0.0309	-0.0518
MA12 – MA1	-0.0019	0.0293	-0.0633

TABLE 5 Buy and hold trading simulation with bootstrapped data

	Mean Return	Standard Deviation	Sharpe Ratio
Crude Oil	-0.0534	0.8336	-0.0641
Heating Oil	-0.0605	0.8138	-0.0744

For MA4 – MA1, annualized return lies between -0.75% ~ 0.86%. For MA8 – MA1, annualized return lies between -6.78% ~ 0.56%. For MA12 ~ MA1, annualized return lies between -0.55% ~ 0.66%. From the histogram, we can see the largest frequency of all trading strategies lies on the mean return that reported in the previous section. The mean return in each pair of moving average trading simulation in table 4 is larger than the mean return on previous section, which implies there are still the space for us to improve the vector error correction model (VECM) and reflect the future market more accurate. However, we can still see all of the moving average trading simulation outperforms the traditional buy and hold strategy no matter from mean return or Sharpe ratio.

Conclusion

In this study, we tested the performance of moving average trading strategies between NYMEX WTI crude oil and NYMEX heating oil based on examine the linkages between two commodities. Vector error correction model were used to discover the cointegration relationship, long-run, and short-run relationship. Under circumstances

of cointegration relationship exists between two commodities, we tested the causality relationship that shows NYMEX heating oil is Grange cause NYMEX WTI crude oil, which is an opposite result from Alizadeh and Nomikos (2008). After that, we identified the trading signal for whether buy or sell based on the deviation of one fast moving average and one slow moving average. The improvement of Sharpe ratio compared to traditional buy and hold strategy indicates that moving average trading strategy could get benefit for investors. Stationary bootstrap resampling process are employed to minimize the effect from data snooping. The result from moving average trading simulation based on stationary bootstrap provides a robust evidence that moving average strategy can improve the Sharpe ratio and return.

Based on the stationary bootstrap method, the methodology that included in this paper can be used to test any combination of commodities in the future market, as long as there are linkage between each other in daily life. Stationary bootstrap can surely provide a robustness result when investors apply trading strategy in it and help investors adjust their technical trading strategy. Overall, the result indicate that simple moving average strategy can improve return and Sharpe ratio, but we still need to adjust our trading signal in different condition in future markets.

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