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UNIVERSITY OF READING

ICM 301 – ENERGY FINANCE

Question 2

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Abstract

The main purpose of this paper is to shed light on the relationship between WTI and Brent, two primary standards in the oil market and accordingly, their price differential. Considering the unusual fluctuations in the pricing system over the last two decades, we investigate whether there has been a change in the long run relationship of the crudes and assess whether its spread can be profitably traded. We estimate a VECM model and hence test for cointegration between WTI and Brent for the period spanning from January 2000 to December 2019. Taking into account the 2011 structural break, our empirical findings reveal that a cointegrating relationship exists between the crudes. Additionally, we refer to previous studies on the WTI-Brent spread where we review three main approaches; the ARMA, MACD and NNR models and subsequently propose a cointegration model which incorporates the cointegration vectors generated via our Engle Granger test. From the returns generated by our strategy we hence deduce that the WTI-Brent spread can be traded for profits and a comparison made on the basis of performance metrics demarcated the MACD model as the best strategy to gain from the spread.

Contents

1. Introduction

As a significant production factor that fuels many of the world's leading economies, crude oil has in the last few decades, been featured as one of the most important and widely traded commodities (Fattouh, 2008). In addition to its extensive utilisation, from power generation to transportation (Liu, Schultz and Swieringa, 2015), dynamics of the oil market and consequently, price movements, substantially influences the performance of financial markets (Lescaroux and Mignon, 2008).

The global oil market is dominated by two competing benchmarks; the West Texas Intermediate (WTI) and Brent Crude (Chen, Huang and Yi, 2015; Shiyu and Karali, 2016), which have been established as reference crude oil prices in the petroleum industry (Fattouh, 2010; Scheitrum, Carter and Revoredo-Giha, 2018). Empirical studies considered, have suggested the oil market to be 'globalised', a theory, implying that crudes of similar compositions are expected to move closely together, in addition to displaying synergistic price fluctuations when exposed to an external shock (Tian and Lai, 2019). Correspondingly, as WTI and Brent are mostly considered as substitutes, (Wonstall, 2015; Shiyu and Karali, 2016), various studies conducted, have postulated that WTI and Brent should move in unison such that in the long run, their price differential should be nearly constant (Heier and Skoglund, 2014).

In line with the above literature, we therefore aim at investigating the 'one great pool' hypothesis. As such, we examine whether WTI and Brent exhibit a long-term cointegrating relationship, in addition to determining whether arbitrage opportunities exist between their spread. Hence, reviewing the existing literature, this study aims to examine the statistical association between WTI and Brent crudes, to consequently propose a trading strategy based on co-integration between the two commodities.

2. Literature Review

2.1 Properties of WTI and Brent

Primarily traded on the NYMEX, WTI serves as a standard to price oil, imported to the world's largest oil consumer, the US. WTI, a landlocked crude, is sourced in Cushing, Oklahoma, which has also served as main trade hub as well as storage and price settlement point for the crude since 1983 (Liu, Stevens and Vedenov, 2018). Conversely, Brent, a seaborne crude, is extracted from the North Sea and pumped onto the Sullom Voe terminal in the Shetlands Islands. Correspondingly, Brent is mostly traded on the Intercontinental Exchange (ICE) and as an international crude oil benchmark, has contributed in pricing around 70% of internationally traded oil (Liu, Schultz and Swieringa, 2015).

Different varieties of crudes are produced and traded internationally, with a market value pegged against their respective characteristics (Liu, Stevens and Vedenov, 2018). Crude oils are mainly defined by their API (American Petroleum Institute) gravity, a density measure and sulphur content, which are main properties used by refiners to grade them (Demirbas, Alidrisi and Balubaid, 2015). While a higher API (i.e. low density) indicates a lighter oil variety, its sweetness is assessed based on its impurity level, where sweeter oils are characterised by a lower sulphur content and vice versa (Heier and Skoglund, 2014). To this effect, crudes of low sulphur content combined with a high API gravity are easier to extract, less costly to refine and yield a higher percentage of the valuable petroleum product. Categorised as sweet-light oil, these crudes are the preferred norm in the global oil market and generally command a premium over heavy/ sour oils (Fattouh, 2008).

By virtue of their classification as sweet light crude oils, WTI and Brent are therefore used as influential price barometers in the oil industry, with WTI being sold at a slight premium relative to Brent, for its lower sulphur composition (Liu, Stevens and Vedenov, 2018).

Crude Oil	API Gravity	Sulfur Content
WTI	39.6°	0.24%
Brent	38.3°	0.37%

Table 1: API Gravity and Sulphur Content of WTI and Brent (Source: U.S.EIA)

2.2 WTI and Brent – Their dependence structure

Graph 1: WTI and Brent Spot Prices (2000 – 2020)

The pricing of these crudes has been widely reviewed in the energy economics literature, most specifically, to examine their dependence structure and relationship on a long term horizon (see e.g. Fattouh, 2008; Carollo, 2011; Amadeo, 2014; Scheitrum, Carter and Revoredo-Giha, 2018). Supporting the idea of a 'globalised' market, Weiner (1991) suggested that the crude oil market moves under 'one great pool'. A main implication of the theory, being that shocks applied to oil prices in a geographic location are expected to be quickly reflected into other regions causing the crudes price variations to also be in unison (Gulen, 1999; Wilmot, 2013; Liu, Stevens and Vedenov, 2018).

As such, commodities like WTI and Brent, linked by a fundamental relationship, have cause to be co integrated (Pfiffer, 2017). These findings thereby support Nordhaus, 2009, who postulated that in the long run, the price differential between the crudes, that is WTI and Brent spread, should differ mainly by quality differences and transportation costs (Scheitrum, Carter and Revoredo-Giha, 2018). In line with the above, Graph 1 thereby highlights the slight trading superiority of WTI over Brent for the last decade and most importantly, their co-movement throughout the past two decades. Corresponding to the findings of Reboredo (2011), It has been highlighted that WTI and Brent prices varied with similar intensities during bull and bear markets such as the financial crisis in 2008 and post the US Shale production shock in 2016, with the exception of 2011.

Termed as the ‘structural break’, the divergence in WTI prices in 2011 called into question the continued integration of the oil market (Galay, 2019) where arbitrage opportunities arose and conversely, Brent prices surpassed that of WTI. Mainly attributed to pipeline capacity constraints in Cushing, the increase in US Shale oil production and consequently, rising inventories in 2011 induced a downward pressure on WTI prices. On the other hand, the closure of nuclear facilities in Japan following the Fukushima incident, and subsequent production shortages in the North Sea, prompted Brent prices to rise in the period between 2011 to 2015 (The Economist, 2011, ; Heier and Skoglund, 2014, Liu, Stevens and Vedenov, 2018).

From Graph 1, we also highlight the profound impact of the recent pandemic, the COVID-19 virus, which caused the WTI price to plummet to a negative value of $37.63, the largest one-day drop in the US crude history. The pandemic, causing a worldwide lockdown and the temporary closure of oil industries, again triggered pipeline and oil transportation constraints in Cushing. Consequently, in the fear that storage capacity would run out, oil producers deemed more appropriate to sell WTI. On the other hand, it is noted that the same price shock was not reflected by Brent, since local conditions for the Seaborne crude allowed for better transportation and storage facilities (Nawaz, 2020).

Accordingly, various studies have found that the structural break period, significantly weakened the cointegrated characteristics of WTI and Brent (Carter and Smith, 2007). Through stationarity and cointegration tests, Fattouh (2010) and Liu, Stevens and Vedenov (2018) confirmed the existence of a structural mutation, where the WTI-Brent spread altered from a stationary series to one having a unit-root in 2010. However, with the US crude oil export embargo being lifted in 2015, the WTI-Brent spread gradually dampened, causing the short-term arbitrage space to die out. Therefore, it should be safe to assume that the co-movement between the two crudes, which post 2015, resumed to their earlier time pattern, should continue to grow with minimal spread differential (Tian and Lai, 2019).

The above literature is consistent with the empirical findings of academics, who stipulate that on a long- term horizon, WTI and Brent are therefore co-integrated. Using a SVAR approach, Zhang (2013) provides conclusive findings of co-integrating relations between the two commodities, which is further established by Hammoudeh et al. (2008), who used both the Engle Granger method and M-TAR approach. Correspondingly, using various models such as the ARMA, GARCH, VAR and VECM respectively, various academics have confirmed the existence of a co-integrating relationship (Gülen, 1997; Reboredo, 2011, Azar and Salha, 2017; Pfiffer, 2017; Caporin, Fontini and Talebbeydokhti, 2018; Caro, Golpe, Iglesias and Vides, 2020)

3. Methodology

To capture the evolution and interdependencies between the WTI and Brent series, we test for cointegrating relations by fitting the data over a general VAR model. To this effect, we conduct inference on the number of cointegrating relations between the crudes, without imposing a priori structural relations (Johansen, 1991). Additionally, it is highlighted that the model allows for the cointegrating relation to have a non-deterministic intercept while being stationary (Gogolin et al., 2018).

Subsequently, if stationarity tests conducted provide evidence in favour of cointegration, a Vector Error Correction Model (VECM) will be used to identify the long-run association between WTI and Brent while simultaneously taking into account the structural break of 2011 (Caporin, Fontini and Talebbeydokhti, 2018; Tian and Lai, 2019). In the case of WTI and Brent, we expect to identify a long-run (cointegrating) relationship between both crudes, where a more stable association between them (excluding the structural break phase) would yield the following equation:

$$WTI_t - \mu - \beta_1 Brent_t = \epsilon_t,$$

Where WTI_t and $Brent_t$ denote the logged prices of WTI and Brent respectively, ε_t representing the stationary error term and β_1 as the cointegrating coefficient.

3.1 Data Collection

We make use of the daily WTI and Brent closing spot prices for the last two decades, over the period spanning from 4th January 2000 up to 31st December 2019, yielding 5081 observations. For the purpose of this study, we exclude the period of 2020 given the largely irregular fluctuations caused by the Covid-19 pandemic that could potentially skew our results.

The dataset comprises Brent ('bp') and WTI ('wp') crude prices, denoted in dollars per barrel, which have been collected from the Energy Information Administration (EIA) database. Additionally, Python coding is used for our empirical analyses where statistical functions used were mainly imported from the 'statsmodels.api' and 'arch' library.

Date	bp	wp
2000-01-04	23.95	25.56
2000-01-05	23.72	24.65
2000-01-06	23.55	24.79
2000-01-07	23.35	24.79
2000-01-10	22.77	24.71
...	...	...
2019-12-24	69.26	61.17
2019-12-26	69.26	61.72
2019-12-27	68.91	61.76
2019-12-30	68.30	61.66
2019-12-31	67.77	61.14

5081 rows × 2 columns

Figure 1: WTI and Brent Prices (Years 2000 – 2019)

3.2 Empirical Tests

3.2.1 VAR Model

Taking a multivariate approach, a VAR model allows for the quantification of changes in multiple variables and as such, the interactions of the WTI and Brent time series. As such, we establish a VAR model using the OLS method, specifying an initial number of 2 lags.

The logarithmic difference of the crudes spot prices ('brentdiff' and 'wtidiff') are used, for they allow the coefficients of the estimated linear models to be interpreted as elasticities (Caporin, Fontini and Talebbeydokhti, 2018) (See table below)

Date	bp	wp	brentdiff	wtidiff
2000-01-05	23.72	24.65	-0.964975	-3.625173
2000-01-06	23.55	24.79	-0.719275	0.566345
2000-01-07	23.35	24.79	-0.852884	0.000000
2000-01-10	22.77	24.71	-2.515310	-0.323233
2000-01-11	23.93	25.69	4.968902	3.889379

Table 2: Logged price differences of the WTI and Brent Spot Prices

3.2.2 Lag Selection Order

Lag length selection is an important criterion to consider, not only when estimating a VAR model but also when conducting cointegration and stationarity tests, as these statistical assessments can be susceptible to an improper lag selection (Pfiffer, 2017; Brooks, 2019). Using too many lags can result in the coefficient estimates to be inflated while omitting lags may tend to an estimation bias. As such, we use a Multivariate Information Criteria approach and select a lag order that produces the most parsimonious model, that is, a lag length that minimises any of the below criteria.

VAR Order Selection (* highlights the minimums)

	AIC	BIC	FPE	HQIC
0	-6.794	-6.791	0.001121	-6.793
1	-15.49	-15.48	1.874e-07	-15.49
2	-15.65	-15.64	1.593e-07	-15.65
3	-15.67	-15.65*	1.565e-07	-15.66*
4	-15.67	-15.65	1.563e-07	-15.66
5	-15.67	-15.64	1.561e-07	-15.66
6	-15.67	-15.64	1.558e-07	-15.66
7	-15.68	-15.64	1.557e-07	-15.66
8	-15.68	-15.63	1.553e-07	-15.66
9	-15.68*	-15.63	1.549e-07*	-15.66
10	-15.68	-15.63	1.550e-07	-15.66

Table 3: Information Criteria Lag Length

From the lag selection table, we highlight that the lowest lag order of 3 is given by the BIC and HQIC criteria, which will be further used for the stationarity and co-integration tests.

3.2.3 Testing for Causality

We next examine the structure of the causal relationships between WTI and Brent, to determine whether one time series (i.e. WTI) is useful in predicting another (i.e. Brent) and vice versa. Correspondingly, we run a Granger-causality test for both crudes, estimating the pairwise combination by specifying a maximum lag order of 3:

Granger causality Wald-test. H_0: brentdiff does not Granger-cause wtidiff. Conclusion: reject H_0 at 5% significance level.

Test statistic	Critical value	p-value	df
13.58	7.815	0.004	3

Table 4: Granger Causality Test (Brent to WTI)

With Brent as the causing component in our first granger test (see table 4), we highlight a test statistic (13.58) above that of the critical value (7.815), which implies that we reject the null hypothesis of no granger causality at the 5% significance level.

Granger causality Wald-test. H_0: wtidiff does not Granger-cause brentdiff. Conclusion: reject H_0 at 5% significance level.

Test statistic	Critical value	p-value	df
557.4	7.815	0.000	3

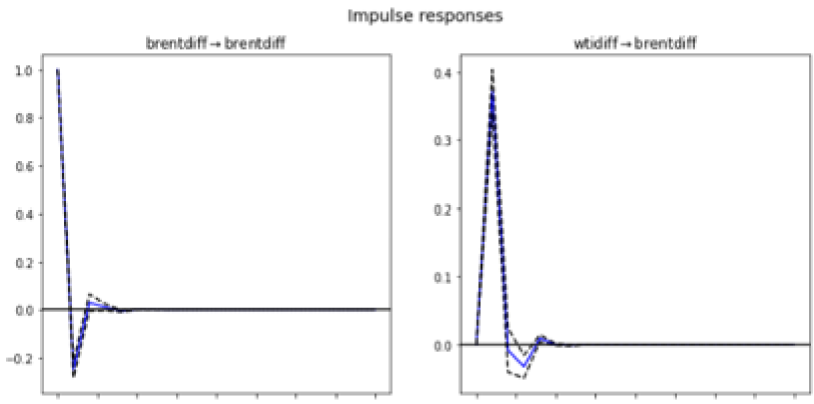
Table 5: Granger Causality Tests (WTI to Brent)

Similarly, granger causality test conducted with WTI as the causing component, yielded a test statistic far greater than its associated critical value. As such, the null hypothesis of no causality is again rejected at the 5% significance level.

From the above findings, we therefore infer that there is a bi-directional causality relationship between WTI and Brent, where WTI granger causes Brent and vice versa. In other words, this implies that WTI's historical prices contain useful information that can be used to predict Brent prices and vice versa.

3.2.4 Impulse Response Analysis and Forecast Error Variance Decomposition

To visualise the impact of shock absorptions between WTI and Brent, we plot the impulse response graphs for the estimated VAR model along with variance decompositions diagrams (see figure below)



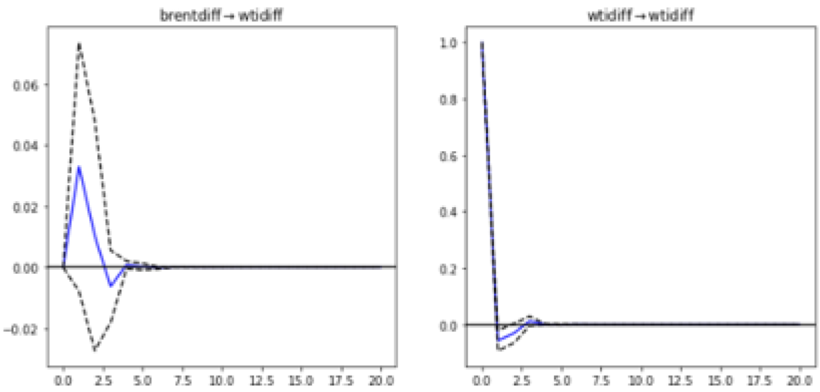


Figure 1: Impulse Response graphs of WTI and Brent

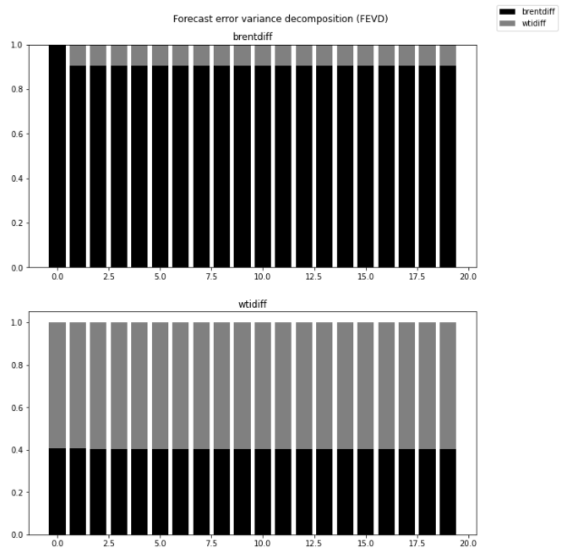


Figure 2: FEVD of Brent over WTI

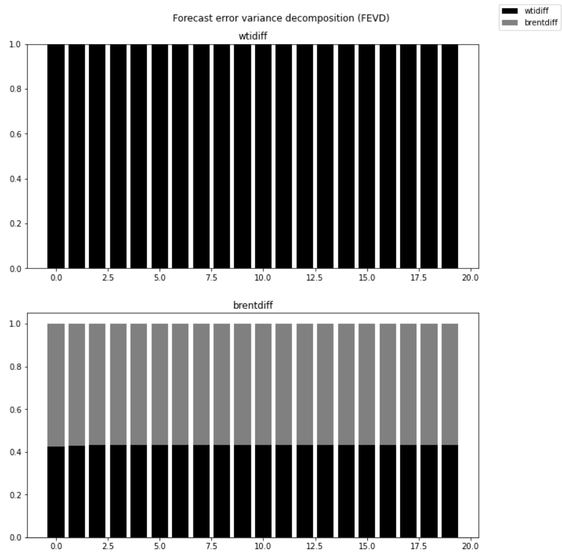


Figure 3: FEVD of WTI over Brent

From the above graphs, we find that the response shocks are small and dampen after 1 to 2 lags except for the variable's response to its own shock. The variance decomposition graphs on the other hand, demonstrates that both WTI and Brent, each explain around 40% of the variation in the other.

3.2.5 Testing for Stationarity

A first step in testing whether co-integration exists between the two crudes is to check whether they are stationary or characterised by a unit root (i.e. integrated of order one) (Fattouh, 2008). In other words, a linear combination of the series is required since no inferences about their long-term relationship can be made if the series are of different integrated order (Pfiffer, 2017; Brooks, 2019).

We apply the Dickey-Fuller test to both the WTI and Brent series and augment same by adding the lag order of 3, against the following hypotheses:

H_0: α = 0 ; Contains a unit root

H_1: α < 0 ; series is stationary

Augmented Dickey-Fuller Results

Test Statistic	-1.894
P-value	0.335
Lags	2

Augmented Dickey-Fuller Results

Test Statistic	-2.073
P-value	0.256
Lags	2

Trend: Constant
Critical Values: -3.43 (1%), -2.86 (5%), -2.57 (10%)
Null Hypothesis: The process contains a unit root.
Alternative Hypothesis: The process is weakly stationary.

Table 6: ADF test for WTI **Table 7: ADF test for Brent**

The outputs of the above tests (table 6 and 7) clearly indicate the presence of unit roots for both WTI and Brent at the 1% significance level, which confirms the findings of Fattouh (2008), Pfiffer (2017) and Liu, Stevens and Vedenov (2018) amongst others.

The first difference of both series is subsequently obtained, where a Dickey-Fuller test alongside a Phillips-Perron test are again run to verify whether both series are integrated of order 1.

ADF Tests

Augmented Dickey-Fuller Results

Test Statistic	-40.995
P-value	0.000
Lags	2

WTI

Augmented Dickey-Fuller Results

Test Statistic	-40.436
P-value	0.000
Lags	2

Brent

Trend: Constant
Critical Values: -3.43 (1%), -2.86 (5%), -2.57 (10%)
Null Hypothesis: The process contains a unit root.
Alternative Hypothesis: The process is weakly stationary.

Table 8: ADF tests for WTI and Brent

Phillips-Perron Tests

Phillips-Perron Test (Z-tau)

Test Statistic	-73.803
P-value	0.000
Lags	2

WTI

Phillips-Perron Test (Z-tau)

Test Statistic	-68.103
P-value	0.000
Lags	2

Brent

Trend: Constant
Critical Values: -3.43 (1%), -2.86 (5%), -2.57 (10%)
Null Hypothesis: The process contains a unit root.
Alternative Hypothesis: The process is weakly stationary.

Table 9: Phillips-Perron tests for WTI and Brent

As the unit root tests (ADF and Phillips-Perron) above suggests, we infer that both WTI and Brent prices become stationary at the integrated order of 1.

3.2.6 Testing for Cointegration

To determine whether there exists a common stochastic trend underlying WTI and Brent price movements, we first estimate the Vector Error Correction Model (VECM) (Liu, Stevens and Vedenov, 2018) and run cointegration tests. We specify the number of lags to be 2, based on the optimum lag selection criteria and utilise the stationary price series (first differenced values of WTI and Brent) for the VECM model.

As such, we turn the VAR model into a VECM, taking the form:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-1} + \mu_i,$$

where Y represents WTI/ Brent prices, Π being a 2x2 matrix further decomposed as $\Pi = \alpha\beta'$, where α and β denote 2 x r coefficient matrices to measure the respective short and long run adjustments of the pricing system and the error term μ_i that allows for the convergence of the prices back to 'equilibrium' (Johansen, 1991).

We refer to the two main methods used to test for cointegration; The Engle-Granger approach, used to obtain the cointegrating vector coefficients for the trading strategy (discussed in section 4), and the Johansen test, to obtain the trace statistics and eigenvalues in order to assess the crudes relationship. Given the WTI and Brent variables, we specify the number of cointegrating equations to be 2 and evaluate both tests using a constant to better account for the volatile period between 2011 to 2015.

The hypothesis tested are as follows:

$H_0 : r \leq R$ and $H_1 : r \geq R$;

where r is the cointegrating rank, such that $0 \leq r \leq 2$.

Johansen Cointegration Tests Statistics

Johansen cointegration test using trace test statistic with 1% significance level

r_0	r_1	test statistic	critical value
0	2	39.85	23.15
1	2	3.071	6.635

Table 10: Johansen Test – Trace statistics

The first column in Table 10 displays the number of cointegrating relationships for the WTI and Brent series, while the number of equations, totalling to 2 (i.e. WTI equation and Brent equation) are reported in the second column. The first row of the table tests the null hypothesis of at most one cointegrating vector, against an alternative of more than one cointegrating relationship. As such, it is noted that the λ_{trace} statistic for r_0 = 0, exceeds that of its corresponding critical value and hence, we reject the null of at most one cointegrating vector.

Alternatively, r_0=1 specifies a null of at most two cointegrating vectors and we note that its λ_{trace} statistic of 3.071 fares lesser to the critical value of 6.635. To this effect, the null of at most two cointegrating vectors is not rejected at the 1% significance level.

Johansen cointegration test using maximum eigenvalue test statistic with 1% significance level

r_0	r_1	test statistic	critical value
0	1	36.78	21.75
1	2	3.071	6.635

Table 11: Johansen Test – Eigenvalues

The eigen statistics on the other hand, stores eigenvalues in an order of decreasing magnitude, where they indicate the cointegrating relationship strength. The null hypothesis of the eigen tests assume that a given number of cointegrating relations, r exists against an alternative of r+1 cointegrating equations.

Engle-Granger Test Results

Dynamic OLS Cointegrating Vector Summary

Trend:	No Trend	**No. Observations:**	4245
Leads:	1	**R²:**	0.9996
Lags:	0	**Adjusted. R²:**	0.9996
Cov Type:	unadjusted	**Residual Variance:**	0.0072
Kernel:	Bartlett	**Long-run Variance:**	0.3487
Bandwidth:	55.241		

Cointegrating Vector

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
Brent	0.9956	0.0022	447.23	0.0000	0.9912	0.9999

Table 12: Engle-Granger test summary

WTI	1.000000
Brent	-0.995575

Table 13: Engle-Granger output (Cointegrating Vectors)

3.3 Empirical Findings

Therefore, confirming the above-mentioned literature, we infer from the Johansen tests conducted, that there indeed exists a cointegrating relationship between WTI and Brent. This implies that in the period from January 2000 to December 2019, a long-term relationship between WTI and Brent exists, characterised by unit elasticity, which suggests that movements in the Brent (WTI) price are reflected in the WTI (Brent) price (Fattouh, 2008; Pfiffer, 2017; Caporin, Fontini and Talebbeydokhti, 2018).

4. The WTI-Brent Differential

Another yet interesting aspect of the WTI and Brent relationship that has garnered researchers' attention is their price differential. Therefore, we aim at analysing the dynamic behaviour of the crude oil price spread (Heier and Skoglund, 2014) and make use of the above statistical results to examine whether the price differential of WTI and Brent can be leveraged for profitable opportunities.

4.1 The Cointegration Model

Building from Pfiffer's (2017) study, we make use of the cointegrating coefficients from the Engle-Granger test and propose an 'accumulate position' strategy. Correspondingly, we define the spread as follows:

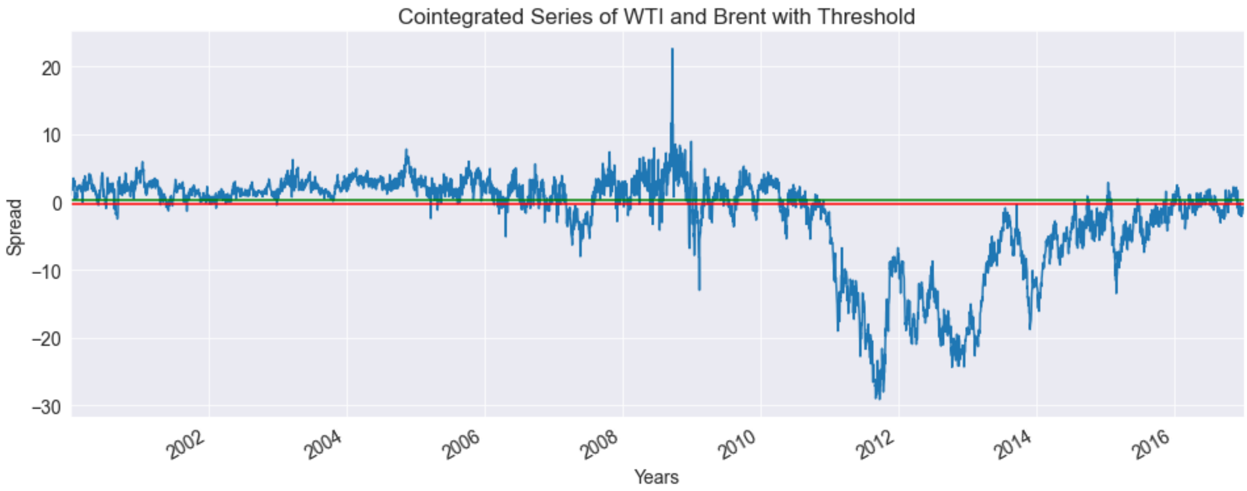
$$\text{spread}_t = \text{wti}_t - \beta_1 \text{brent}_t$$

We consequently integrate our previously found cointegrating vectors, to yield the equation below:

$$\text{Spread}_t = \text{WTI}_t - 0.99 \text{ Brent}_t$$

where Spread_t represents the stationary series, WTI_t and Brent_t denote the price of WTI and Brent at time t respectively and β_1 represents the cointegrating coefficient (Table 13: 0.99).

Consequently, we set an upper and lower threshold, such that the strategy buys WTI when the spread falls below the lower limit line (long the spread) and conversely trades Brent (short the spread) when the spread rises above upper threshold, as displayed in Graph 2. Following Dunis' et al. (2006) and Pfiffer' (2017) work, we utilise a threshold of +/- 0.3 which was chosen following an optimisation of their trading algorithm with the aim of maximising their in-sample Sharpe ratio.



Graph 2: WTI-Brent Spread with upper and lower thresholds

Based on the above spread equation, we build our accumulate position strategy which will function as such; for any given day that the spread moves outside the threshold boundaries, the strategy will result in 100 units of WTI being purchased/ sold, while an approximate opposite position of 99 Brent units (sold/ purchased) will be taken. Additionally, all taken positions are closed at the end of the investment trading period and we account for the bid/ask spread by impacting cashflows. However, we assess the strategy's performance on the assumption that no transaction costs or exchange fees have been incurred and as such, conclude that the portfolio returns estimated would be to some extent inflated.

We next split the dataset into an in-sample (train) and out-of-sample (test) set, where the train set contains data from January 2000 to December 2016 and the test set, made up of data from 2017 onwards (20% of dataset). Following the above equation, the spread was computed by applying the cointegrating coefficient of 0.99 to the train set prices (extract 1) and subsequently, given the upper and lower limits set, we obtained respective trading positions (Table 14: 'Daily PnL').

```
#Long the spread (below negative threshold)

for spread in test['Spread']:
    if spread < -0.3:
        test['Daily PnL'] = 99*test['Brent'] - 100*test['WTI']

#Short the spread (above the positive threshold)

    elif spread > 0.3:
        test['Daily PnL'] = 100*test['WTI'] - 99*test['Brent']
```

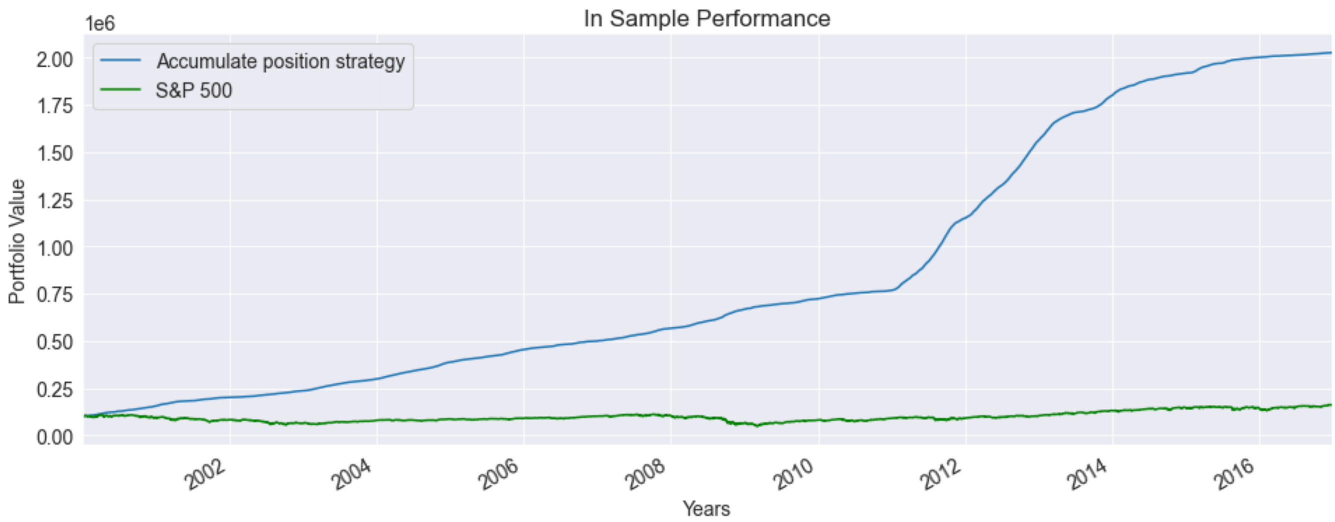
Extract 1: Generating trading positions

To test the viability of the strategy and as such determine whether the WTI-Brent price differential can be traded for profitability, we performed a back-test by simulating an initial portfolio investment of $100,000. Subsequently, using the train set generated positions, we calculate the portfolio returns using the mark-to-market sum of the position and use the S&P 500 as benchmark. As such, the accumulate position strategy cumulates the wealth following daily trading positions to then generate a terminal wealth value.

From graph 3 below, it can be highlighted that the strategy 's performance on the train set has largely outperformed the S&P 500 to generate profits from the WTI-Brent spread.

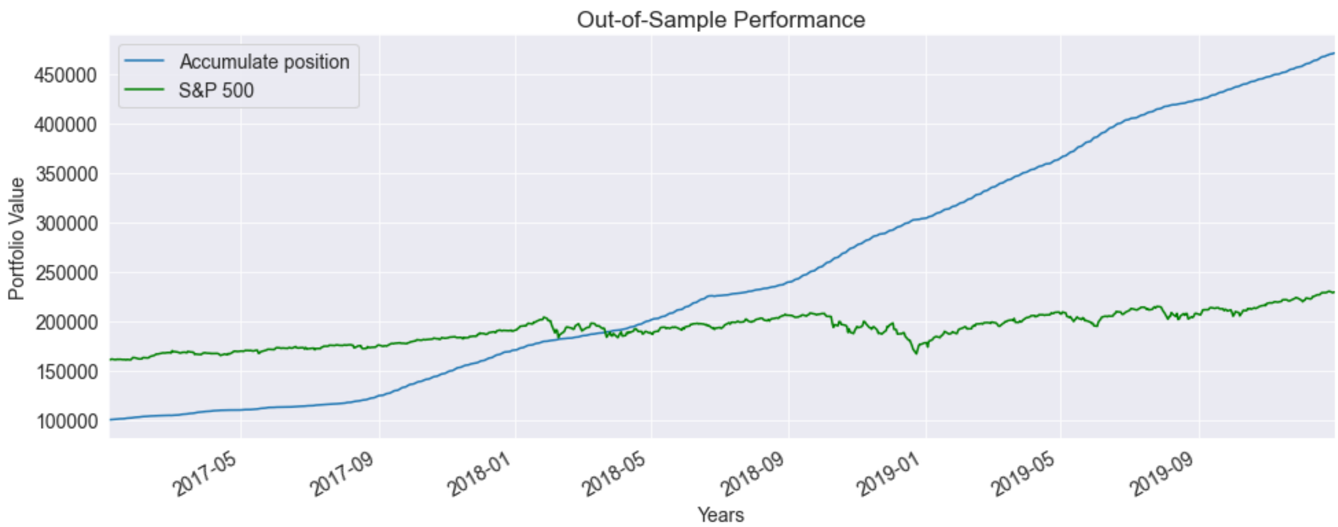
	WTI	Brent	Spread	Daily PnL	Terminal Wealth
Date					
2000-01-04	25.56	23.95	1.715380	184.95	100184.95
2000-01-05	24.65	23.72	1.034368	116.72	100301.67
2000-01-06	24.79	23.55	1.343620	147.55	100449.22
2000-01-07	24.79	23.35	1.542740	167.35	100616.57
2000-01-10	24.71	22.77	2.040188	216.77	100833.34
...	...	...	...	...	...
2016-12-22	51.98	54.04	1.822224	151.96	2025438.66
2016-12-23	52.01	53.93	1.682708	138.07	2025576.73
2016-12-28	54.01	54.95	0.698220	39.05	2025615.78
2016-12-29	53.80	54.97	0.928132	62.03	2025677.81
2016-12-30	53.75	54.96	0.968176	66.04	2025743.85

Table 14: Accumulated wealth based on trading positions (in-sample set)



Graph 3: In-sample performance of the Accumulate position strategy against S&P500 benchmark

We hence apply the strategy on the out of-sample set and similarly, highlight a good performance, with a wealth accumulation line that initially drops in the early 2017s but rises to a high profit-making margin trend.



Graph 4: Out of-sample performance of the Accumulate position strategy against S&P500 benchmark

For better comparison and a fairer assessment of our trading strategy, we compute the daily returns, standard deviation and using the US risk free rate of 1.79%, we obtain the Sharpe Ratio of both our strategy and the S&P 500 (see table below)

Accumulate Position Strategy Performance (in-sample)					
	Initial wealth	**Terminal Wealth**	**Compounded Annual Growth Rate (%)**	**Standard Deviation**	**Sharpe Ratio**
Accumulate Position	100,000	2,025,743	19.5	35.1	0.005
S&P500	100,000	158,956	2.8	0.012	0.82
Accumulate Position Strategy Performance (out-of-sample)					
	Initial wealth	**Terminal Wealth**	**Compounded Annual Growth Rate**	**Standard Deviation**	**Sharpe Ratio**
Accumulate Position	100,000	470,984	68.7	2.6	0.2
S&P500	100,000	229,385	12.7	0.008	13.5

Table 15: Accumulate Position Strategy Performance Metrics

The results demonstrate that compared to the S&P 500, the accumulate position yielded better returns (i.e. terminal wealth). However, from a risk-return perspective, it can be noted that the S&P 500 generated better returns for the amount of risk taken (Sharpe ratio: 0.82), which as outlined by the standard deviation was less volatile than our strategy. Our in-sample performance highlighted a riskier approach where a high standard deviation led to a huge profit margin. Conversely, the test set provided a more realistic view of the strategy's performance characterised by lower volatility and a higher annual growth rate.

4.2 A review of other trading strategies

We also discuss the possibility of trading the price differential based on the research conducted by Dunis, Laws and Evans (2006), where we refer to three trading strategies namely; the ARMA, the MACD and Neural Network Regression (NNR) models. The dataset used, covered the daily prices from 1995 to 2004 and the spread returns were used.

For the ARMA and MACD models, the dataset was divided into in-sample and out-of-sample sets where the former was used for training and optimising the model, which was subsequently applied on the out-of-sample set to test its accuracy. Conversely, the NNR model, being an algorithmic one, required the data sample to be further split into a train, test and validation set respectively. Following the testing of the model on the test set, the NNR strategy is applied on the validation set, which is a technique employed to avoid the model to overfit. In contrast to our accumulate position strategy, Dunis, Laws and Evans (2006), take into account additional factors such as commission fees against the price of Brent and also the bid-ask spread which has to be catered for to generate profitable returns.

4.2.1 ARMA Model

The ARMA model was devised based on a selection criterion where the model characterised with no significant autocorrelation was selected. The model was subsequently trained and tested, following which, a standard and correlation filters were each applied. In the case of the ARMA model, correlation comprised three optimising parameters which are the correlation's lag length, drawdown period and amount. As such, these enabled for the optimisation of the model by filtering out periods of static spread movements.

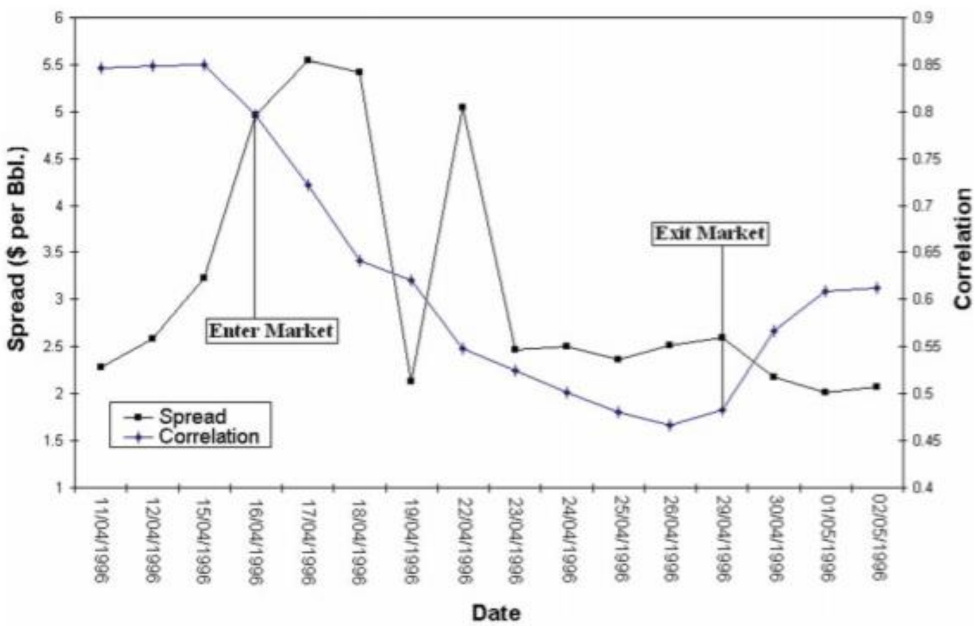


Figure 4: ARMA trading strategy using correlation filters

Figure 4 thereby displays the trading strategy such that:

$$\begin{aligned}&\text{If } p_t^e - X > p_{t-1}^a, \text{ then go long the spread}\\&\text{If } p_t^e + X < p_{t-1}^a, \text{ then go short the spread}\end{aligned}$$

where p^e_t denotes the price estimate at time t, p^a_{t-1} represents the current price at time t-1, and X, the filter size. An entry position is made the day following a correlation drop and conversely, following a rise, an exit trade is executed.

4.2.2 The MACD Model

This strategy entails the use of an n-day moving average where positions are taken when the market is mean-reverting, a feature that helps to circumvent situations characterised by large drawdowns which usually skews the results. The moving average is obtained via the following :

$$MA_t = \sum_{t-n}^{t} \frac{p_{t-n}}{N}$$

With MA as the moving average, p_{t-n} representing price at time t-n and N as the moving average duration (days). Therefore, unlike traditional moving average trading positions, the reverse moving strategy is executed such that the spread is shorted when price exceeds the MA limit while a long position is held when price falls below the MA. Correspondingly, the standard and correlation thresholds are applied to optimise the trading outcome.

4.2.3 The NNR Model

The Neural Network Regression model on the other hand, is made up of multilayer networks where the spread data is passed into an input layer (x_t), processed and filtered through nodes in the hidden layer (h_t with activation function as threshold) and hence generated via the outermost layer (y_t) (see figure 5). Differing from the previous two models by virtue of its ability to learn from the training data sample, the NNR is hence applied on a test and validation sets so the accuracy of its predictions is enhanced.

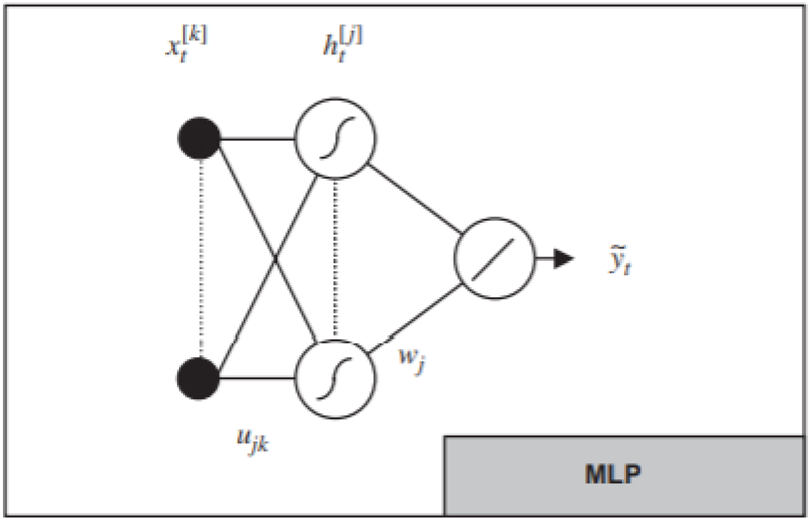


Figure 5: NNR model

4.3 Discussion

Based on the various strategies discussed above and our proposed strategy, we therefore deduce that one can profitably trade on the price differential between WTI and Brent (Dunis, Laws and Evans, 2006; Pfiffer, 2017; Caro, Golpe, Iglesias and Vides, 2020), albeit their shortcomings which is to be addressed.

As per the below figures, Dunis, Laws and Evans (2006) make the following findings:

ARMA Model

Period	Filter	Returns (%)	Drawdown (%)	St. dev. (%)	Sharpe	Parameters			
						RMSE (%)	Level (X)	Period (Y)	Cor. length (Z)
In-sample	None	26.47	−19.15	21.34	1.24	0.8038	–	–	–
Out-of-sample	None	25.06	−10.26	17.41	1.44	0.8274			
In-sample	Standard	26.47	−19.15	21.34	1.24	0.8038	0	–	–
Out-of-sample	Standard	25.06	−10.26	17.41	1.44	0.8274			
In-sample	Correlation	26.47	−19.15	21.34	1.24	0.8038	1	–	–
Out-of-sample	Correlation	25.06	−10.26	17.41	1.44	0.8274			

Figure 6: ARMA Model results

It is found that the usage of neither the standard nor correlation filters illustrate any enhancements to the in-sample statistics output and given that the ARMA model did not respond to these filters, we assume the best in-sample model to be the unfiltered one.

On the other hand, the out of-sample performance of all the filters generate identical outputs as evidenced by the Sharpe ratios of the out-of-sample (1.44) and in-samples (1.24) displayed in Figure 6, respectively.

MACD Model

Period	Filter	Returns (%)	Drawdown (%)	St. dev. (%)	Sharpe	Parameters RMSE (%)	Level (X)	Period (Y)	Cor. length (Z)
In-sample	None	32.52	−14.13	21.68	1.50	1.2615	–	–	–
Out-of-sample	None	26.15	−8.45	18.10	1.44	1.3007			
In-sample	Standard	22.31	−10.93	14.85	1.50	2.6343	0.62	–	–
Out-of-sample	Standard	26.35	−5.68	13.37	1.97	2.1184			
In-sample	Correlation	32.38	−14.84	21.64	1.50	1.2670	0.08	1 day	30 days
Out-of-sample	Correlation	26.15	−8.45	18.10	1.44	1.3328			

Figure 7: MACD Model results

Comparatively, the MACD gives the better trading statistics. The single 20-day reverse moving average mode used, has been found to be the best suited. The out of sample period with the standard filter generated a return of 26.35% with the lowest drawdown of 5.68% and standard of 13.37% and Sharpe ratio of 1.97.

NNR Model

Period	Filter	Returns (%)	Drawdown (%)	St. dev. (%)	Sharpe	Parameters RMSE (%)	Level (X)	Period (Y)	Cor. length (Z)
In-sample	None	16.26	−16.89	20.91	0.7777	0.7914	–	–	–
Out-of-sample	None	15.65	−19.13	17.86	0.8760	0.7920			
In-sample	Standard	9.66	−6.20	10.25	0.9424	2.2948	0.25	–	–
Out-of-sample	Standard	3.64	−1.50	4.74	0.7686	1.5346			
In-sample	Correlation	16.59	−16.01	20.85	0.7958	0.7950	0.01	1 days	30 days
Out-of-sample	Correlation	15.65	−19.13	17.86	0.8760	0.8090			

Figure 8: NNR Model results

Surprisingly, the NNR fared the lowest in terms of its Sharpe ratio and was outperformed by both the ARMA and MACD models. This may have been mainly attributed to the occurrence of an overfit on the training set.

With regards to the accumulate position strategy, a main influencing factor is the cointegrating vector, estimated by taking into consideration the past two decades, where stable co-movements were displayed by the WTI-Brent spread. We also highlight that the abnormally high profit margin generated on the in-sample set may have been mainly due to the period of high volatility between 2011 to 2015 (i.e. the structural break) and therefore, would be less consistent when the market stabilises. This is evidenced by our out of sample performance whereby the returns generated alongside the risk associated were reduced. As mentioned above, we did not consider additional elements such as transaction costs, exchange fees, brokerage fees amongst others, which may have been contributory toward the windfall profits of the strategy. Given the addition of transaction and other relevant deductions, the MACD, followed by the ARMA model have been found to have outperformed, both in terms of their in-sample and out of-sample yields.

5. Conclusion

As competing benchmarks in the oil market, WTI and Brent have hence, received garnered interest for their pricing structure, including their long-term relation and price differential. Building from a VECM model, we hence provide support to the theory of a 'globalised' market, where we find that WTI- Brent have a long-term equilibrium relationship. An interesting feature of their pricing system, however, has been the structural break in 2011. Despite their new cointegrated relationship, WTI is still weighed down by the pipeline constraints, that still prevail in Cushing. We identified various strategies, the MACD, ARMA and NNR, that profit from those divergences and as such propose an accumulate position approach that yields considerable returns. Nevertheless, we highlight that arbitrage across the oil market is not costless and hence, improvements could be made such that the cointegration between these leading crudes can be better leveraged as trading signals.

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Appendix 1

Python codes

```
#importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from statsmodels.tsa.api import VAR
from statsmodels.tsa.stattools import adfuller
from statsmodels.tools.eval_measures import rmse, aic
import pickle

#import dataset
oil = pd.read_excel(r'C:\Users\Sandhyana\Desktop\wb.xls', sheet_name='Data
oil1=oil.dropna()


#filter prices for the last two decades
oil1 = oil[(oil['Date' ] > '1999-12-31') & (oil['Date' ] <= '2019-12-31')]
oil1['Date'] = pd.to_datetime(oil1['Date'])
oil1.set_index('Date', inplace=True)
```

```
#log the prices
oil1['brentdiff']=np.log(oil1['bp'])
oil1['wtidiff']=np.log(oil1['wp'])
oil2=oil1.dropna()

#retain the log prices from the dataframe
oil3= oil2.iloc[:, 2:]
oil3

#Constructing the VAR model
import statsmodels.tsa.api as smt
model=smt.VAR(oil3)
res=model.fit(maxlags=2)
res.summary()

#first step in construction of any VAR model, is to determine
#the appropriate lag length
#we employ a multivariate information criteria
res= model.select_order(maxlags=10)
res.summary()

# we next run a Granger causality test
model = smt.VAR(oil3)
res = model.fit(maxlags=2)
res_causality=res.test_causality(causing=['brentdiff'],caused=['wtidiff'],
              kind='wald',signif=0.05)
res_causality.summary()

model1 = smt.VAR(oil3)
res1 = model1.fit(maxlags=8)
res_causality1=res1.test_causality(causing=['wtidiff'],
              caused=['brentdiff'], kind='wald',signif=0.05)
res_causality1.summary()


# Impulse response analysis
model=smt.VAR(oil3)
res=model.fit(maxlags=3)

#impulse response plots
irf=res1.irf(20)
irf.plot()

#FEVD plots
fevd=res.fevd(20)
fevd.plot()
```

```
#we reverse the columns to check for the effect of WTI on brent
oil4=oil3[['wtidiff','brentdiff']]
oil4

model=smt.VAR(oil4)
res=model.fit(maxlags=2)

fevd=res.fevd(20)
fevd.plot()

# Unit Root testing
import pickle
from arch.unitroot import DFGLS, ADF,PhillipsPerron
oil5= oil1.iloc[:, :2]

#we obtain the first difference for ADF test
oil5['bp_diff'] = oil5['bp'].diff(periods=1)
oil5['wp_diff'] = oil5['wp'].diff(periods=1)
oil5

oil6=oil5.dropna()

#ADF test for brent
res=ADF(oil6['bp'],lags=3)
res.summary()

#ADF test for WTI
res=ADF(oil6['wp'],lags=3)
res.summary()


#ADF test for brent after first difference
res=ADF(oil6['bp_diff'],lags=3)
res.summary()

#ADF test for WTI after first difference
res=ADF(oil6['wp_diff'],lags=3)
res.summary()


# Phillips Perron tests for the first differences
res=PhillipsPerron(oil6['bp_diff'],lags=3)
res.summary()

res=PhillipsPerron(oil6['wp_diff'],lags=3)
res.summary()
```

```
# Cointegration tests
import statsmodels.formula.api as smf
import matplotlib.pyplot as plt
from arch.unitroot import DFGLS

oil7= oil6.iloc[:, :2]
oil7

# we need to ensure that variables are non stationary

#VECM model
from statsmodels.tsa.vector_ar import vecm
model=vecm.select_order(oil7,maxlags=12)
model.summary()

#Cointegration test - trace test
vec_rank1=vecm.select_coint_rank(oil7,det_order=1,k_ar_diff=1,
          method='trace',signif=0.01)
vec_rank1.summary()

#eigen values test
vec_rank2=vecm.select_coint_rank(oil7,det_order=1,k_ar_diff=1,
          method='maxeig',signif=0.01)
vec_rank2.summary()

#VECM model summary
model=vecm.VECM(oil7,k_ar_diff=1,coint_rank=2,deterministic='co')
res=model.fit()
res.summary()

#obtain cointegrating vectors

#import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from pandas.plotting import register_matplotlib_converters
register_matplotlib_converters()

from statsmodels.tsa.api import VAR
from statsmodels.tsa.stattools import adfuller
from statsmodels.tools.eval_measures import rmse, aic
import pickle
```

```
#import dataset
#Read in Dataset
data = pd.read_excel('/Users/admin/OneDrive/Energy Finance/
                     Crude Oil Data.xls',index_col='Date')

#split data into train and test sets
train = data[(data.index > '2000-01-03') & (data.index <= '2016-12-31')]
train

test = data[(data.index > '2016-12-31')]
test


import warnings
warnings.simplefilter('ignore')

get_ipython().run_line_magic('matplotlib', 'inline')
import seaborn

seaborn.set_style('darkgrid')
plt.rc("figure", figsize=(16, 6))
plt.rc("savefig", dpi=90)
plt.rc("font",family="sans-serif")
plt.rc("font",size=14)

#log prices of both WTI and Brent
log_price = np.log(train)

ax = log_price.plot()
xl = ax.set_xlim(log_price.index.min(), log_price.index.max())


# engle granger test
from arch.unitroot import engle_granger
eg_test = engle_granger(log_price.WTI, log_price.Brent, trend="n")
fig = eg_test.plot()

eg_test.cointegrating_vector

#get summary from dynamic OLS

from arch.unitroot.cointegration import Dynamic OLS
vector_est = DynamicOLS(log_price.WTI, log_price.Brent, trend="n")
ve = vector_est.fit()
ve.summary()
```

```
#Having computed the cointegrating vector, we can now compute the spread
#based on the equation: spreadt = wtit âˆ' Î²1brentt + Î±, where
#beta = -0.995575

train['Spread'] = train['WTI'] - train['Brent'].apply(lambda x: x*0.9956)
train

#Plot the spread based on the equation (cointegration vectors)
train['Spread'].plot(title='Cointegrated Series of WTI and Brent
                     with Threshold')
plt.axhline(y=0.3, color='g', linestyle='-')
plt.axhline(y=-0.3, color='r', linestyle='-')
plt.ylabel('Spread')

# The Accumulation Approach
#Long the spread (below negative threshold)

for spread in train['Spread']:
    if spread < -0.3:
        train['Daily PnL'] = 99*train['Brent'] - 100*train['WTI']

#Short the spread (above the positive threshold)

    elif spread > 0.3:
        train['Daily PnL'] = 100*train['WTI'] - 99*train['Brent']
train

train.to_excel('/Users/admin/Desktop/t.xlsx')
train2 = pd.read_excel('/Users/admin/Desktop/t.xlsx', index_col='Date')


#backtesting

initial_capital = float(100000)

#Portfolio Value
train2['Terminal Wealth'] = initial_capital + train2['Daily PnL'].cumsum()

#import S&P 500 prices
import yfinance as yf

sandp = yf.download('^GSPC', start='2000-01-05', end='2016-12-31',
                   group_by='Close')
sandp500 = sandp['Close']
sandp500 = pd.DataFrame(sandp500)

#plots
sandp500['Terminal Wealth'] = sandp500['Close']*71
sandp500['Terminal Wealth'].plot()

train2['Terminal Wealth'].plot(label='Accumulate position')
sandp500['Terminal Wealth'].plot(label='S&P 500', color='g')
plt.ylabel('Portfolio Value')
plt.title('In Sample Performance')
plt.legend(loc='best')
```

```
#Performance of test set

test['Spread'] = test['WTI'] - test['Brent'].apply(lambda x: x*0.9956)
test


#Long the spread (below negative threshold)

for spread in test['Spread']:
    if spread < -0.3:
        test['Daily PnL'] = 99*test['Brent'] - 100*test['WTI']

#Short the spread (above the positive threshold)

    elif spread > 0.3:
        test['Daily PnL'] = 100*test['WTI'] - 99*test['Brent']

test

#testing S&P 500 test sample
sandp2 = yf.download('^GSPC', start='2017-01-04', end='2020-01-01',
                     group_by='Close')
sandp5002 = sandp2['Close']
sandp5002 = pd.DataFrame(sandp5002)

sandp5002['Terminal Wealth'] = sandp5002['Close']*71
sandp5002


#generating plots
test['Terminal Wealth'].plot(label='Accumulate position')
sandp5002['Terminal Wealth'].plot(label='S&P 500')
plt.ylabel('Portfolio Value')
plt.title('Out-of-Sample Performance')
plt.legend(loc='best')

#performance metrics (this was repeated for our strategy and S&P500
# in sample and out of sample sets)

#CAGR
def CAGR():
     start_value=(test['Terminal Wealth'].iloc[0])
     end_value=(test['Terminal Wealth'].iloc[-1])
     num_periods=len(test) #dataframe length
     Compounded_Rate=(((end_value/start_value)**(252/(num_periods)))-1)
                      *100 #252 is the number of trading days
     return Compounded_Rate

print(CAGR())
```

```
#daily returns
drt=test['Daily PnL'].pct_change()
drt

#standard deviation
sd=np.std(drt,axis=0)
sd

#Sharpe Ratio
def Sharpe1 ():
    rf=0.0179 #1.79%% annual rate
    Sharpe_Ratio=((CAGR1()/100)-rf)/sd1
    return Sharpe_Ratio

print(Sharpe Ratio())
```