

Cointegration in Crude Prices

Trading strategies to take advantage of a long-term equilibrium relationship between Brent and WTI.

Cameron Pfiffer

August 2017

Contents

1	Introduction	2
2	Literature Review	2
2.1	Cointegration	2
2.2	Trading Strategy and Transaction Costs	3
3	Data and Statistical Tests	3
3.1	Data	3
3.2	Lag Length Selection	4
3.3	Stationarity	4
3.4	Testing for Cointegration	5
4	Results	6
5	Discussion	10
6	Conclusion	10
	References	12

1 Introduction

Are Brent and West Texas Intermediate (WTI) crude oils co-integrated? An economic case could be made for the two oil grades to be co-integrated – they are essentially substitutes, with similar specific gravities and sulfur content. Indeed, Adelman (1984) famously claimed that “The world oil market, like the world ocean, is one great pool.” This study reviews existing literature, examines the statistical relationship between Brent crude and WTI crude, proposes a trading strategy based on co-integration between the two securities, and concludes with a discussion of findings and areas of further study.

2 Literature Review

2.1 Cointegration

Co-integration as a concept was first introduced by Granger (1981), and later expanded upon to include methodology for testing co-integration (Engle and Granger, 1987). The theory states that non-stationary series integrated of the same order may have a co-integrating vector that reduces the resulting series to a stationary process, in which case the series are said to be *cointegrated*. Assets linked by a fundamental relationship (such as being substitutes) have cause to be co-integrated, and the crude oil markets are no exception. WTI and Brent crudes are both highly similar commodities, with proximate specific gravity and sulfur content. It makes sense that two nearly fungible assets would be linked in a fundamental way, ignoring cost of carry and transit costs. Johansen (1991) later expanded upon the Engle-Granger methodology to expand to multivariate co-integrating relationships, and offered a solution to several issues that arise from the Engle-Granger approach.

There are consistent findings among academics that WTI and Brent are co-integrated. Hammoudeh et al. (2008) found co-integrating relationships in Brent and WTI (as well as Dubai and Maya crudes) using both the Engle-Granger method (1987) and the M-TAR approach (Enders and Granger, 1998; Enders and Siklos, 2001) which permits asymmetry in the return to equilibrium levels¹. Fattouh (2010) finds similar co-integrating relationships, though notes the presence of structural breaks and non-stationarity in crude price differentials in some extraordinary time periods. Numerous other academics have confirmed the existence of co-integration (Azar and Salha, 2017; Gülen, 1997; Kim et al., 2009; Reboredo, 2011) using a variety of methodologies.

¹Hammoudeh (2008) notes that there is cause to suspect asymmetrical returns to equilibrium; he cites the heterogeneity in global trader’s expectations, compulsive and noisy trading, and transaction costs as potential factors. Asymmetry is highly important for trading strategies, though for simplicity, the co-integrating relationship between Brent and WTI used in the trading strategies that follow is assumed to be symmetric.

2.2 Trading Strategy and Transaction Costs

Developing a trading strategy requires the awareness of several key facts. First, in a world absent transaction costs, any deviation from the mean should spur immediate mean reversion no matter how small, as noted by Balke and Famby (1997). However, as we do not live in a world absent transaction costs and this is an empirical study (and thus subject to the whims of reality), and appropriate transaction cost must be assumed to evaluate the profitability of any trade. In this study, transaction costs are included by construction, as the trading simulation assumes that all purchases are made on the ask and all sales made on the bid. This is an overly simplified assumption, as this merely accounts for explicit transaction costs, and not implicit costs such as opportunity cost and market impact, among others.

Dunis et al. (2006) forms the primary inspiration for the trading strategies employed below. They designed strategies that trade when the co-integrated spread between Brent and WTI was larger or smaller than a given threshold, a methodology expanded upon in this paper. Other authors, such as Kawasaki et al. (2003) study contrarian and momentum trading strategies in co-integrated equities. They find Sharpe ratios of approximately 0.90 for a momentum strategy, and 0.59 for a contrarian strategy. The results presented below demonstrate moderately more subdued returns, though results are in line with expectations.

3 Data and Statistical Tests

3.1 Data

The data used are daily close bid, ask, and midpoint prices for Dated Brent FOB and West Texas Intermediate FOB between January 1st, 1995 and July 14th, 2017, composing a total of 5,571 observations. Days when prices for either security was not available are removed, so that only days when both securities are traded are used. Furthermore, the data is segmented into two parts; an in-sample and out-of-sample set. The co-integrating relationships, threshold optimization, and model estimates are performed on the in-sample data between January 1st, 1995 and July 14th, 2015. The remaining two years (July 15th, 2015 through July 14th, 2017) of data is used to evaluate the trading strategy using the co-integrating vectors found in the preceding period. The bid and ask prices are used to determine the closing bid ask spread for an approximation of transaction costs.

Additional data includes S&P 500 prices for the same period in order to compare the algorithm to a benchmark. The bid yield of US Treasury 1 year bonds are converted to daily interest rates to determine excess returns.

3.2 Lag Length Selection

It has been shown that lag length selection can have important effects on a VAR model's impulse response and variance decomposition² (Braun and Mittnik, 1993), and Brooks (2014) notes that Johansen tests and Augmented Dickey-Fuller tests can be susceptible to improper lag selection. Thus, we select a lag length that creates produces the most parsimonious model, i.e., the smallest lag length. The `vars` package for R (Pfaff et al., 2013) contains a built in function for multivariate information criterion. Table 1 presents the lag lengths suggested by four information criteria tests. All criteria suggest a lag length of 5, and this is used for further tests. A procedure evaluating the results from the Johansen test and the ADF test demonstrate that the same results are found using lags up to 60, at which point further testing is beyond reason, and we can be highly certain that the results are appropriate.

Table 1: Information Criteria Lag Length

	Lag Length
AIC(n)	5
HQ(n)	5
SC(n)	5

3.3 Stationarity

The first step in determining whether two assets are co-integrated is to find whether they are both $I(0)$. It is important to find unit roots in the levels of each potentially co-integrated series – if only one of two series is $I(1)$ and the other is $I(0)$, there can be no co-integrating vector and no inferences about the long term relationship between the two assets can be made.

Table 2 presents summary statistics for each series using lag $k = 5$, with the results clearly showing unit roots in both series. This is the expected result for a series of prices, though it now remains to be seen if they can be co-integrated.

Table 2: Augmented Dickey-Fuller Summary

	Augmented Dickey-Fulley Statistic	P Value
WTI	-2.004603	0.5763956
Brent	-1.778735	0.6720475

²This paper presents neither form of VAR analysis, as it is primarily concerned with the co-integrating vector given by the Johansen test, though it is good practice regardless to select appropriate lag lengths.

3.4 Testing for Cointegration

Two common methodologies in testing for co-integration are the Engle-Granger methodology, and the Johansen test. The Engle-Granger procedure is simple, though it suffers from some issues that cannot be solved by large sample sizes. The Engle-Granger method is thus used only to confirm that the two series are cointegrated, while the Johansen test determines the cointegrating vector for the trading strategies. Both tests are evaluated with a constant in an effort to better account for high volatility periods in between 2008 and 2012. Table 3 displays the results of the residuals test, and Table 4 summarizes the results of the Engle-Granger error correction model. Table 5 and Table 6 present the cointegrating vector found in the Johansen test and the relevant test statistics respectively.

Table 3: Engle-Granger Residuals Test

Augmented Dickey-Fulley	
Statistic	P Value
-4.296	0.01

Table 4: Engle-Granger Error Correction Model Summary

	Estimate	Std. Error	t value	Pr(> t)
Intercept	0.0001362	0.01141	0.01193	0.9905
Brent	0.8263	0.008906	92.77	0
Residuals	-0.01435	0.002367	-6.06	0.000000001459

Table 5: Johansen Cointegration Vector

	WTI	Brent	Constant
Cointegrating Vector	1	-0.8733	-5.426

Table 6: Johansen Test Statistics

	10%	5%	1%	Test Statistic
$r \leq 1$	7.52	9.24	12.97	2.34
$r = 0$	13.75	15.67	20.2	24.17

The results of these two tests both show that there is indeed a cointegrating vector between Brent and WTI prices. The Johansen test shows that the null hypothesis that there is no cointegrating vector is rejected at even the 1% level, and the ADF test from the Engle-Granger approach shows a similarly strong relationship.

4 Results

The overview the two trading strategies utilized is as follow:

1. Calculate a stationary series using a given cointegrating vector.
2. Take an appropriate long/short position when the spread is outside a threshold.
3. Close out position when the spread reaches the opposite threshold.
4. Repeat until end of series, and then close out positions.

Using the Johansen test's cointegrating vector from Table 5, a spread variable is created by calculating the below equation:

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

Using the cointegrating vector found previously:

$$\text{spread}_t = \text{wti}_t - 0.873 \text{brent}_t - 5.425$$

Where spread_t is the stationary series created by an intercept (α), the price of WTI at time t , and the price of Brent at time t multiplied by a cointegrating coefficient (β_1). Figure 1 plots this series for the entire data set. A threshold is then utilized as in Dunis et al. (2006), whereby a signal to purchase WTI and sell Brent if the spread is below the negative threshold (long the spread) or the opposite (short the spread) if the spread is above the positive threshold. Figure 1 also shows this threshold set at ± 0.3 in dark blue. This threshold was selected by running an optimization problem through the trading algorithm to maximize Sharpe ratio in the in-sample period, and was averaged between the best threshold for the two strategies.

Two primary strategies are utilized under this threshold approach. The first, is the *accumulate position* approach, because it purchases or sells 100 units of WTI and takes an opposite position in approximately 87 units of Brent (as given by the β_1 coefficient) for each day that the spread is outside the boundaries of the threshold. The second strategy, the *buy and hold*, purchases or sells 5,000 units of WTI and takes an opposite position in approximately 4,350 units of Brent, selling only when the spread reaches the opposite threshold from when the position was entered. Both strategies close out all positions at the end of the sample period. The bid/ask spread is assumed to be symmetric about the midpoint, and is accounted for in the strategy by impacting cash flows. For every transaction made the algorithm, half of the

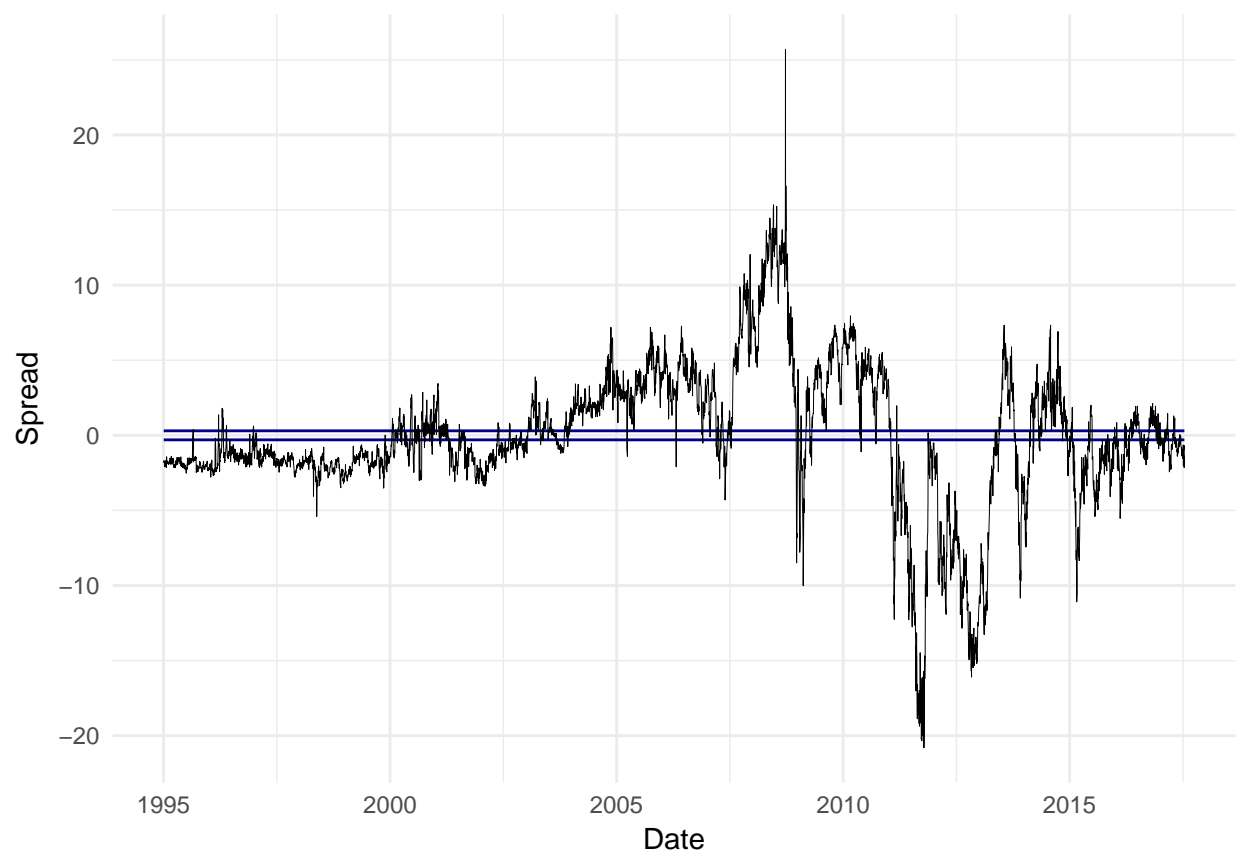


Figure 1: Cointegrated Series of WTI and Brent with Treshold

bid ask spread for the time of the trade per asset is assessed to the cash flow. No other transaction costs, such as brokerage, commission, exchange fees, settlement, market impact, or other implicit costs are considered, and thus the portfolio return should be considered an overestimate. Portfolio returns are calculated by the mark-to-market sum of the position in Brent and WTI, and cash holdings. Standard deviation is calculated using a daily risk-free rate derived from the 1 year US Treasury bond midpoint yield. Tables Table 7 and Table 8 present summary statistics for the two strategies.

Table 7: Strategy Performance In Sample (January 1st, 1995-July 13th, 2015)

	Initial Wealth	Terminal Wealth	Log Return	Geometric Return	Minimum Value	Sharpe Ratio
Accumulate position	100,000	2,115,245	3.052	0.05518	78,209	0.03137
Buy and hold	100,000	897,687	2.195	0.06059	95,641	0.03982
S&P 500	100,000	459,357	1.525	0.05475	100,000	0.02116

Table 8: Strategy Performance Out of Sample (July 14th, 2015-July 14th, 2017)

	Initial Wealth	Terminal Wealth	Log Return	Geometric Return	Minimum Value	Sharpe Ratio
Accumulate position	100,000	175,500	0.5625	0.0754	84,618	0.06911
Buy and hold	100,000	213,372	0.7579	0.1155	93,135	0.08319
S&P 500	100,000	116,697	0.1544	0.05236	86,793	0.039

The results demonstrate that while the accumulate position portfolio had higher absolute returns (terminal wealth), it was significantly more volatile and has a smaller Sharpe ratio than the buy and hold portfolio. Both strategies outperformed buying and holding \$100,000 worth of the S&P during the sample periods, in absolute terms and in risk-adjusted measures. The buy and hold strategy performed best overall in risk-adjusted measures and in absolute terms in the out-of-sample period. Figures 2 and 3 both demonstrate the out performance in terms of portfolio value of the trading strategies as compared to an investment in the S&P 500.

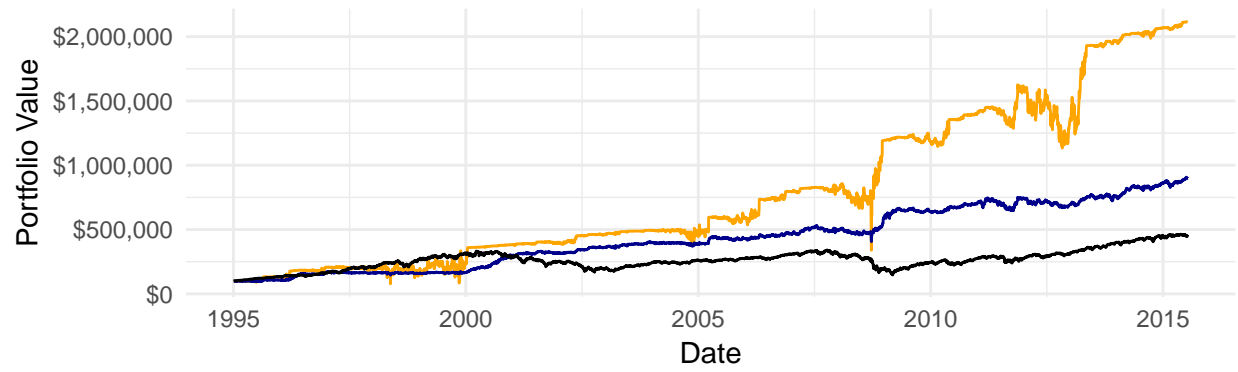


Figure 2: In-sample Performance

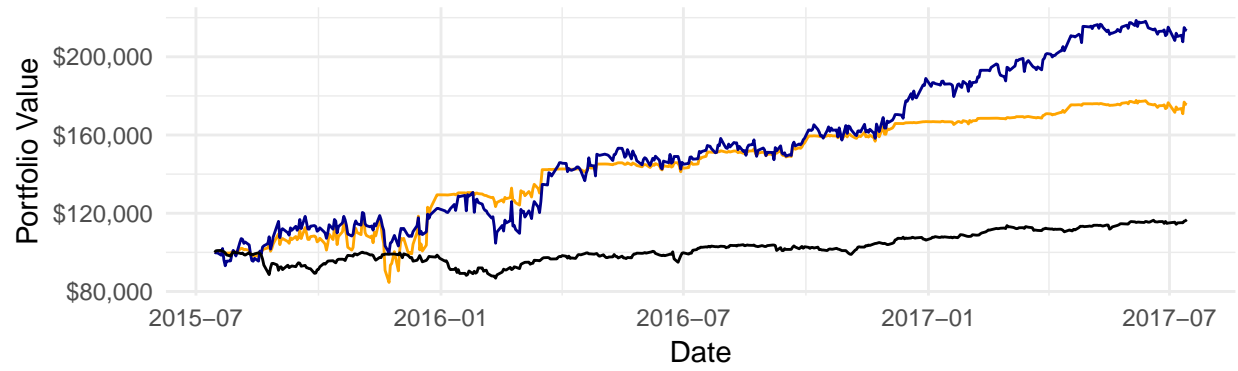


Figure 3: Out-of-sample Performance

5 Discussion

As the results in the previous section illustrate, it is possible to take advantage of the cointegrating relationship between two assets, though it is important to address several shortcomings in the strategies used.

First, a large portion of the cointegrating vector was estimated during an incredibly stable period for crude prices, and the long term relationship may have changed since what appears to be a structural break between 2008-2015. If this is the case, the relatively short out-of-sample testing period of two years may fail to capture the nature of the modified relationship and the strategy may go from consistently profitable to consistently loss taking.

Second, the strategies fail to consider multiple elements of market microstructure, such as implicit transaction costs, brokerage fees, short selling fees, exchange fees, and other such costs that may affect the decision making process. It is also assumed that an asset can be transacted at the close price, both long and short, and ignores liquidity provisions and market impact. Such transaction costs cannot be so easily discounted, and can have out-sized effects on highly active strategies such as the accumulate position strategy, which made 4,792 trades in the test period as compared to the buy and hold strategy which only traded 182 times. It follows then that an implementation of this strategy in actual trading conditions would suffer dampened returns.

Third, both the buy and hold and accumulate position strategies suffer from a scale problem - they often hold a large amount of cash and do not properly utilize all cash holdings. Assets are purchased as a fixed amount, and do not adapt to performance. This is less important than in a pure long-only strategy, as going long in one asset and short another often keeps net changes in cash very low. Utilizing more cash reserves and increasing purchasing scale would be similar to leveraging and magnifying returns and losses, and would allow the strategies to modulate the number of securities transacted to keep holdings in line with cash reserves. It may be more advantageous to purchase more assets the farther away from the spread one is, particularly for the accumulate position strategy, as it would bring the average spread price farther from the mean and increase profits.

6 Conclusion

The two trading strategies based on a cointegrating relationship have demonstrated abnormal returns both in and out of sample, though it should be noted that there is room for improvement in algorithm design and implementation. Numerous improvements beyond the scope of this paper could be made to the algorithm, such as modeling asymmetric returns to the mean, including more comprehensive transaction cost analysis, fixing the scaling problem, and accounting for structural breaks. Each of these has the potential to improve the

performance of the strategies and shed further light on the way that cointegration can be utilized as an effective trading signal.

References

- Adelman, M.A., 1984. International oil agreements. *The Energy Journal* 5, 1–9.
- Azar, S.A., Salha, A., 2017. The bias in the long run relation between the prices of brent and wti crude oils. *International Journal of Energy Economics and Policy* 7.
- Balke, N.S., Fomby, T.B., 1997. Threshold cointegration. *International Economic Review* 38, 627–645.
- Braun, P., Mittnik, S., 1993. Misspecifications in vector autoregressions and their effects on impulse responses and variance decompositions. *Journal of Econometrics* 59, 319–341. doi:10.1016/0304-4076(93)90029-5
- Brooks, C., 2014. *Introductory econometrics for finance*. Cambridge university press.
- Dunis, C., Laws, J., Evans, B., 2006. Trading futures spreads: An application of correlation and threshold filters. *Applied Financial Economics* 16, 903–914. doi:10.1080/09603100500426432
- Enders, W., Granger, C.W.J., 1998. Unit-root tests and asymmetric adjustment with an example using the term structure of interest rates. *Journal of Business & Economic Statistics* 16, 304–311. doi:10.1080/07350015.1998.10524769
- Enders, W., Siklos, P., 2001. Cointegration and threshold adjustment. *Journal of Business & Economic Statistics* 19, 166–76.
- Engle, R.F., Granger, C.W., 1987. Co-integration and error correction: Representation, estimation, and testing. *Econometrica: journal of the Econometric Society* 251–276.
- Fattouh, B., 2010. The dynamics of crude oil price differentials. *Energy Economics* 32, 334–342. doi:http://dx.doi.org/10.1016/j.eneco.2009.06.007
- Granger, C.W., 1981. Some properties of time series data and their use in econometric model specification. *Journal of econometrics* 16, 121–130.
- Gülen, S.G., 1997. Regionalization in the world crude oil market. *The Energy Journal* 18, 109–126.
- Hammoudeh, S.M., Ewing, B.T., Thompson, M.A., 2008. Threshold cointegration analysis of crude oil benchmarks. *The Energy Journal* 29, 79–95.
- Johansen, S., 1991. Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. *Econometrica* 59, 1551–1580.
- Kawasaki, Y., Tachiki, S., Udaka, H., Hirano, T., 2003. A characterization of long-short trading strategies based on cointegration, in: *Computational Intelligence for Financial Engineering, 2003. Proceedings. 2003 Ieee International Conference on*. IEEE, pp. 411–416.
- Kim, J., Oh, S., Heo, E., 2009. A study on integration of the world crude oil markets using

price asymmetry model. *Geosystem Engineering* 12, 1–4.

Pfaff, B., Stigler, M., Pfaff, M.B., 2013. Package “vars”.

Reboredo, J.C., 2011. How do crude oil prices co-move? *Energy Economics* 33, 948–955.
doi:<http://dx.doi.org/10.1016/j.eneco.2011.04.006>