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A Traders Guide to the Predictive Universe- A Model for Predicting Oil Price Targets and Trading on them

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Abstract:

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At heart every trader loves volatility; this is where return on investment comes from, this is what drives the proverbial "positive alpha." As a trader, understanding the probabilities related to the volatility of prices is key, however if you could also predict future prices with reliability the world would be your oyster. To this end, I have achieved three goals with this dissertation, to develop a model to predict future short term prices (direction and magnitude), to effectively test this by generating consistent profits utilizing a trading model developed for this purpose, and to write a paper that anyone with basic knowledge of markets and finance can readily understand.

To address my first goal a well-quoted and tradable asset was required. To create a model that traders can use to make money it needed to be volatile with significant short and longer-term price swings. After some analysis, a review of macroeconomic impacts, and drawing in some part on experience, oil emerged as a fitting test, in particular Brent Crude Oil. For simplicity, and to further my third goal, "Oil" as used within this paper will represent Brent Crude Oil unless otherwise specified.

While some dissertations and other scholarly works set out to discern theoretical truths this dissertation is much simpler, this is all about the money. Though I am certainly interested, as I am sure many traders are, in discovering the "Holy Grail" of how to trade any type of asset, the scope of my analysis will be confined to Brent Crude Oil prices within a sampling period of January 2002 thru May 2016. The findings indicate that there are factors that are predictive of

the price of Oil and the research has allowed several conclusions. These conclusions culminate in a model that consistently generates profitable long and short trading opportunities.

The model created spans over 13 years, from January 2003 thru May of 2016, and achieves a trading success ratio (profit generation) exceeding 94% of the trades opened, with the successful per trade average return exceeding 6.5% and the majority of the trades held for less than 60 calendar days (2 months) with an average holding period of 33 days for successful trades, exponentially larger than profits that might be realized by simply holding a single investment in Oil over the period of the analysis. The data contained in the paper will provide the details on the construction of both the prediction model and development of a trading model, variables utilized, and results achieved. The variables in this case are of significant interest and likely not as intuitive as might be expected. Chen, Rogoff, and Rossi (2008) provide some direction, although commodity currencies are utilized, finding that "commodities tend to be less of a barometer of future conditions than are exchange rates."

It should be noted that the time period analyzed is the complete period for which some of the variable data is available; this period includes magnitudes of volatility rarely witnessed. The reason for creating a model during such a challenging environment is that as a trader, we do not get to "cherry pick" dates that we would like to trade, but have to be equipped to deal with the dynamics of the marketplace.

Acknowledgements

First and foremost I have to thank my wife Kim for her support, patience, and understanding during this program. This has altered our lives in a number of ways, something neither of us was aware of at the outset, I truly will not ever be able to thank her enough. My daughters, Caitlin and Kelsey and son-in-law James, have been persistent supporters, providing encouragement throughout and were constant cheerleaders, something often needed and much appreciated.

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The faculty at Washington University have been a pleasure to work with but none more so than Radha Gopalan. Radha has spent an extraordinary amount of time during the preparation of this dissertation, but also prior to it in the classroom and out, it has truly been an honor to work with him. The other committee members, Todd Milbourn and Guofu Zhou, have provided me with direction in this and other undertakings, for which I am in their debt.

I'm not sure how to successfully acknowledge the Olin School for providing me this opportunity, I continue to be humbled by my inclusion in this institution and the association I have been afforded with the faculty and students whom are Olin. Lastly I would be remiss if I didn't thank a number of individuals that have made this the experience that it has been, among them: Anjan Thakor, Ohad Kadan, Hong Liu, Matt Ringgenberg, Phil Dybvig, Rich Ryffel, and Jim Horn.

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Background

The volatility of the price of oil is not a recent phenomenon; a review of the history of oil prices reveals that volatility is a constant. Oil is one of the most sought after commodities in the world, driving engines of growth and supporting, from both the supply and demand perspective, economies around the world. Many think of Oil as just another commodity, and as a result, oil pricing is usually understood as conforming to the to the laws of supply and demand that date to Adam Smith, and that volatility in oil, therefore, must necessarily come from volatility in its co-determinants, the supply and demand of oil. This belief is widespread, in the financial media it is not uncommon to see headlines that read, "Oil price down on inventory buildup, or "oil price surges after new, lower rig counts". The media is not alone as there are countless academic works that attribute pricing solely or primarily to the effects of supply and demand.[1] However, given the general, and more recently the very volatile, price movement of Oil observed during the period analyzed from a high of $145.49 to a low of $23.74, and considering the inelasticity (supply and demand) there appear to be factors beyond simple supply and demand economics that must exist.

To understand the factors that would provide a trader with the ability to predict price movements, to do so with a high degree of probability, and to make a profitable trading model from my investigation is the goal of the analysis. While finding the variables may seem like the Holy Grail I have found that it's a bit more straightforward; diligent analysis combined with a practitioners understanding of the markets. As discussed previously an understanding of the predictive variables, and the reason behind them was key. The approach taken was to utilize

[1] For example, Dees, Gasteuil, Kaufmann, and Mann (2008) "Although a linear relationship could be a reasonable approximation under normal circumstances, extreme events may shift the market equilibrium between supply and demand towards different types of market functioning in which prices are much more sensitive to shocks than under normal conditions."

historical data to create a model that "predicted" success based on realized "future" events, while in the real world this of course is not plausible sans a crystal ball, it would provide an understanding of the predictive variables and how they would be applied.

The variables found to have the significant predictive quality have little to do with what we traditionally think of as Oil supply or demand, but instead are in large part driven by trade (in more general terms) and the valuation of different currencies. Engel and West (2005), demonstrate that if nominal exchange rates indicate changes in economic conditions they should also be predictive of them. The relationship between commodities, currencies, and interest rates has been explored and validated in several papers. Akram (2009) found that "shocks to interest rates and the dollar are found to account for substantial shares of fluctuations in commodity prices." This notion of a dependency on currency valuation raised the question of whether Oil was in fact a type of currency in itself, one whose value is more associated with its buying power than with its intrinsic value as a commodity, a placeholder of value if you will. This idea of a placeholder of value as well as a commodity is in need of additional analysis, but in actuality is more realistic than the value associated with sovereign currencies that have nothing more than faith backing them. This relationship with currencies also addressed another aspect of the extreme short term volatility of Oil prices, and which may be better illustrated in light of the Efficient Market Hypothesis, simply that it should not occur if Oil prices observed were indeed the result of supply and demand.

The variables utilized for this paper lead me to the conclusion that Oil might better be described as a placeholder of value, a quasi-currency. The research involved in this paper focused on price prediction for trading purposes, however in the process of discovering the variables utilized an understanding of the forces that affect the price of Oil was necessary. This process challenged some notions about both Oil pricing in particular and possibly asset pricing in general. This relationship was also found by Tang and Xiong (2008) in part that a significant correlation between non-energy commodities and oil after 2004, as well as changes in commodity prices that were in some part independent of supply and demand driven by emerging markets.

Reports of macro supply and demand for Oil are primarily released and published monthly, with other types of economic releases, are often used to extrapolate likely supply and demand. If the price of Oil was primarily dependent on supply and demand this periodically released information could never account for the daily volatility (exceeding 1.4% during the period analyzed) of prices in the marketplace, and certainly would not validate the EMH. However, if the variables that are used to evaluate Oil in terms of EMH expectations are not related to supply and demand then there may be no need to discount the hypothesis. The finding in this paper that currencies, which are highly liquid and volatile, are among the predictive variables with which to predict Oil prices then the EMH seems to hold true. This may be due to the fact that Oil prices are reflective of the market process of establishing exchange rate parities.

Now that these relationships have been discovered the only question is if they can be used to make money, and if so how consistently. This short term effect was found in Yan (2012) noting "that each increase in the dollar exchange rate by 1% drops the international price by 1.82%.

The time frame utilized to create this predictive price model utilized data from January 2002 until August of 2016, this difference between this time period and the model period tested accounts for the twelve months needed for the rolling coefficient calculation at the start, and the forward looking closing date high at the conclusion. This difference will become more apparent as I discuss the predictive model. The time frame contains all of the data available for some of the variables utilized in the model, making out of sample testing a bit more challenging. I note this limitation because this constraint will preclude certain out of sample testing, however, an alternative testing approach was devised and applied.[2]

Approach to Predictive Model

To achieve the goals set out at for this paper it was necessary to first develop a short term predictive price model. The predictive model seeks to determine both the direction and magnitude of prices of Oil, again with a 12 month maximum time period but emphasizing the short term. The predictive model that was developed utilizes a "rolling" twelve-month calculation approach to create coefficients based on the first trading day closing price of each month during the period analyzed. Chen, Rogoff, and Rossi (2008) utilized a similar rolling model, however the model they employed used half of their data set, in this model I utilize a much smaller portion of the data set (less than 10%) in the "roll."[3] The coefficients for the rolling calculations were created using the least squares method to provide the regression coefficients for the best fit of the variables utilized. These coefficients utilize the closing price and additional variables detailed later to predict the future short term price of Oil. In this case, "future" is the maximum twelve months; during this period, every trade opened is closed. If the price predicted was not reached during the twelve months following the opening of the trade, the trade would be closed at the closing price of the day preceding the date of the first anniversary of the trade opening. It's important to remind the reader that this twelve month limit is a realistic parameter for a trader, after which a trade must be closed. Traders often operate in a "year-over-year" mode that in effect is a twelve month rolling window, thus the findings that twelve month rolling coefficients provide significant predictive value may be intuitive to some readers. While

[2] The alternative will be described in detail and utilizes a method of testing different periods during the study to assess consistent performance, a measure of the models performance consistency.

[3] Although this paper is cited the idea of rolling calculations for trading applications is well documented in a number of sources and in practice.

a trader would likely also have a downside threshold, this is a constraint that I felt would mask the true results, and thus such a limitation was not applied.[4] It is important to note that the tact taken is extremely conservative in other elements which very likely skew some of the results lower or even to losses in the analysis in order to highlight the true value of this approach.[5]

The literature provides a good understanding of the type of variables that would likely contribute to the analysis and ultimately the model, although none of those reviewed in the available research were utilized for the same type of application as was being sought here. Sadorsky (2000) shows that there is an equilibrium between different types of energy futures and a trade weighted index of exchange rates. He also finds that exogenous shocks to energy futures can be manifested through these exchange rates. This also validated the thought that the variables had to reflect the fact that to be predictive the analysis had to incorporate global influences. The variables below were chosen and tested:

MSCI Commodity Producers Index, used the closing monthly price for the entire period, January 2002 thru July 2016 as reported on the last day of the month, this was lagged one month, essentially a single day.

Real Trade Weighted U.S. Dollar Index: Major Currencies used the closing monthly price for the entire period, January 2002 thru July 2016 as reported on the last trading day of the month, this was lagged one month, essentially one day.

The Closing Price of Brent Crude on the first Trading Day of the Month utilized the daily closing prices for the entire period, January 2002 thru July 2016.

[4] Given the level of risk aversion following Dodd Frank the notion of a downside threshold for any type of trade has been institutionalized, however, this may provide a false sense of value in this analysis.

[5] Utilizing the arbitrary closing price of oil on the first day of the month in the analysis instead of high/low prices which may have been achieved intraday to open transactions.

Brent Crude Options and Commodity Aggregate Monthly Volume this utilized monthly Intercontinental Exchange (ICE) data for the entire period, January 2002 thru July 2016 and aggregates reported option and futures volumes, these are lagged one month.

These variables were assessed using a linear regression.

$$m = \frac{n\sum(xy) - \sum x \sum y}{n\sum(x^2) - (\sum x)^2}$$

$$b = \frac{\sum y - m\sum x}{n}$$

$$r = \frac{n\sum(xy) - \sum x \sum y}{\sqrt{\left[n\sum(x^2) - (\sum x)^2\right]\left[n\sum(y^2) - (\sum y)^2\right]}}$$

The outcome of this can be found below

	Coefficients	t Stat	P-value
Intercept	0.8831	3.9625	0.000112576
Ln Commodity Producers	0.1708	4.0236	8.9128E-05
Ln Real Dollar Weighted	-0.5869	-5.9470	1.73023E-08
Ln Closing Price	0.7316	22.8380	1.28788E-51
Ln Futures Volume	0.0323	3.1454	0.001986812

This predicted environment was based on historical values of the variables outlined, this allowed for the testing of various approaches utilizing actual prices, in particular the model utilized the *future* 60 day closing high price, observed in the data as my dependent variable. The natural log of the Y and X variables and then regressed over the period analyzed. This approach yielded an *R squared* of 0.977 and an *adjusted R squared* of 0.954 with a *P-value* of 4.69E-89. As you ca see, an adjusted R squared of 95% is nothing to scoff at, especially considering the idiosyncratic shocks to the global financial system observed over this time frame. It is reasonable to suspect that some of the explanatory power of this model may be coming from some autocorrelation in the data, so a Durban Watson test was performed to evaluate the level of auto correlation in the sample.

The Real Statistics Durban-Watson test was utilized and analysis was conducted to test for autocorrelation using the following statistic:

$$d = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2}$$

where the $e_i = y_i - \hat{y}_i$ are the residuals, n = the number elements in the sample and k = the number of independent variables. The results of the analysis can be found below:

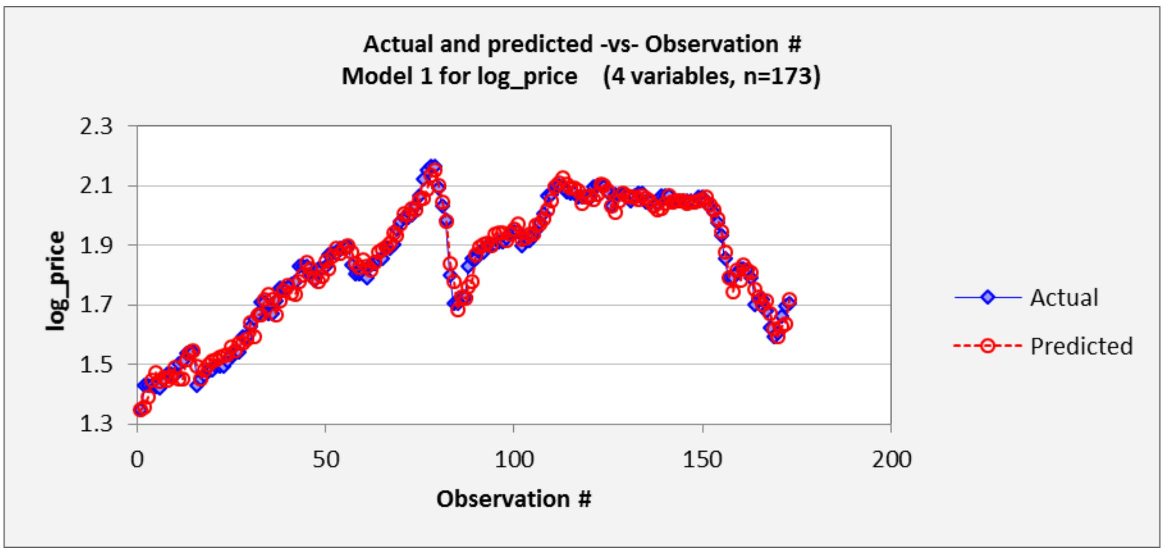
Durbin-Watson Test	
Alpha	0.05
D-stat	0.550421
D-lower	1.66418
D-upper	1.78243
significant	yes

The findings that the D-stat = 0.550421 < 1.66418 = D-lower demonstrate there is significant autocorrelation.[6]

The question of whether autocorrelation exists is clearly that it does and as a result the T scores are likely biased, but please keep in mind that the dependent variable is not really observable. I

[6] Durbin and Watson (1950, 1951)

have already stated that the gauge by which my model will be judged is not by its explanatory power, or by its ability to divine the "actual" econometric factors underlying oil pricing, but in its ability to make money. If the model developed can be shown to perform, then I care not whether the standard errors are somewhat epistemically biased. To better understand the impact of the analysis and resulting auto correlation a visual analysis of the predicted prices versus the actual was created. The chart below provides a comparison of actual and predicted prices for the time period analyzed. As an aside please note the dramatic changes in pricing for the period as well as the actual fit.



This graphical representation illustrates the predictive ability of the model versus the actual prices observed in the data.

At this point, the reasonable reader may still raise the point that these numbers are indicative of a problem that has not been addressed, but please keep in mind this model is utilizing a dependent variable that would not be possible to know in the real world, since the *future* 60 day high has not yet occurred. The actual and predicted prices detailed in the chart confirm the choice of variables and their explanatory value. The results of the approach yielded the following variables, approach, and coefficient calculation methodology. Additionally the aforementioned autocorrelation finding that resulted from the Durbin-Watson test may provide an increased level of confidence. It should also be understood that with regard to securities autocorrelation still remains helpful in understanding relationships between prices. Autocorrelation has also been found to illustrate momentum or certain pricing tendencies for securities. This momentum will be addressed in the second model developed for trading. However, the tests on actual performance, that is dollars and cents, are the most robust test a trader is motivated by.

Illustration 1 below provides additional details to illustrate the success of the approach outlined for the predictive model described. The transactions illustrated reflect both long buys and short sells, returns reflect none of the transaction costs or spreads that might be incurred by an investor executing these transactions. While these costs can be a factor in overall return of investments, as recently shown in Frazzini, Israel, and Moskowitz (2012) these costs are much lower than has traditionally been accounted for in academic literature and are dependent on factors (e.g. type of trading entity) that this paper does not distinguish between.

The variables are used to create the rolling twelve-month coefficients described previously and similar to those described in Chen, Rogoff, and Rossi (2008). The calculation of the coefficients was achieved by utilizing the below returning statistical information on the line of best fit, through a supplied set of x- and y- values.

The basic statistical information returned is the array of constants, $\mathbf{m_n, m_{n-1}, \ldots, b}$ for the equation:

$$\mathbf{y = m_1x_1 + m_2x_2 + \ldots + b}$$

Where the constant "b" is treated normally.

The equation for best line fit uses the least squares method to calculate the line of best fit for the set of y- and x- values, given there are multiple ranges of x-values, the line of best fit satisfies the equation above.

Where,

- the x's are the independent variable ranges;
- y is the dependent variable;
- the m's are constant multipliers for each x range;
- b is a constant.

The above is the basis for the LINEST function within Microsoft Excel which is utilized in the model to calculate the coefficients from which the predictive prices are created.

The result of the analysis being used to create the predictive model is found in Panel 1 below. This applies no trading rules and illustrates the "raw" results of the coefficients described previously. As this model emphasizes short term trades, always preferable for a trader, the fact that over half of the trades are opened and closed in less than 2 months and almost ¾ within six months is significant, note that the returns shown are not annualized. Trades not opened were due to anticipated price changes of less than 1%.[7]

Illustration 1

There are 161 (n=161) data points observed, from January of 2003 through May 2016. Of the 161 months in the analysis the price predicted was achieved about 88% of the time within twelve months, 20 months had a predicted return of less than 1% and no trade was opened, the detailed distribution is shown below.

Closing trade period	0-60 Days	61-180 Days	181-360Days	Did not return a profit	No Trade Executed
Number of months	81	31	14	15	20
% of Months	54.73%	20.95%	9.46%	10.14%	13.51%
% of Trades Executed	63.28%	24.22%	10.94%	11.72%	
Average Return per trade	6.20%	Return for non-loss Trades	6.94%		

[7] Instances that did not achieve the target price within the twelve month period were "closed" at the closing price the day prior to the 1 year anniversary.

Alternative to Out of Sample Testing of the Model

The previous sections provide insight into the goals and results of the model that was used to test the variables and the methodology that have been applied to create the predictive pricing model. As noted previously an out of sample test is not possible due to the inclusion of all available data for some variables, as an alternative the analysis was divided into three concurrent time series in order to judge the consistency of the model from period to period across the entire span of time incorporated. Illustration 2 below illustrates the performance in terms of returns that resulted in a profit, losses and months in which no trades were undertaken were excluded.

Illustration 2

In order to understand the consistency of the approach to predict price targets an analysis of equal but separate time periods was conducted to illustrate the value of this approach during various economic and political cycles.

Time periods	**1/2003-11/2006**	**12/2006-7/2011**	**8/2011-5/2016**
Months Achieved	42	42	42
Average Yield	6.97%	7.33%	6.50%

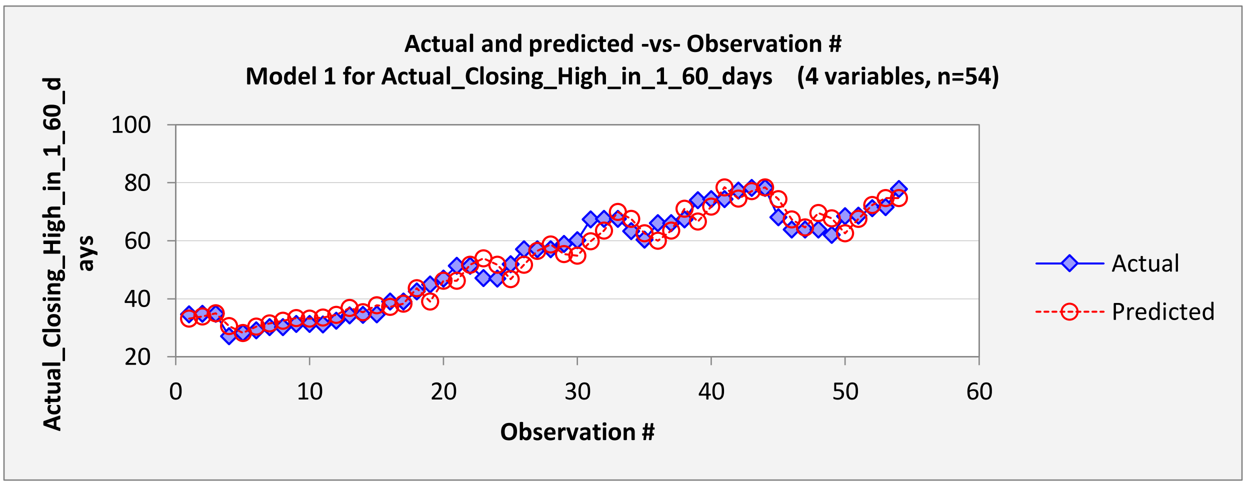
As the data in the panel illustrates the yield throughout the different periods appears to remain relatively consistent. The second period (P2) is characterized by Federal Reserve actions, notably the "Quantitative Easing" programs, that I believe skews the yield somewhat accounting for what may be viewed as an inconsistency.[8] The effect of interest rates on prices of Oil may

[8] The Federal Reserve Bank actions following the Financial Crises resulted in a 1 year Treasury rate fluctuation from a high of 4.91% to a low of 0.12% during the second period (P2) as sourced from Factset.

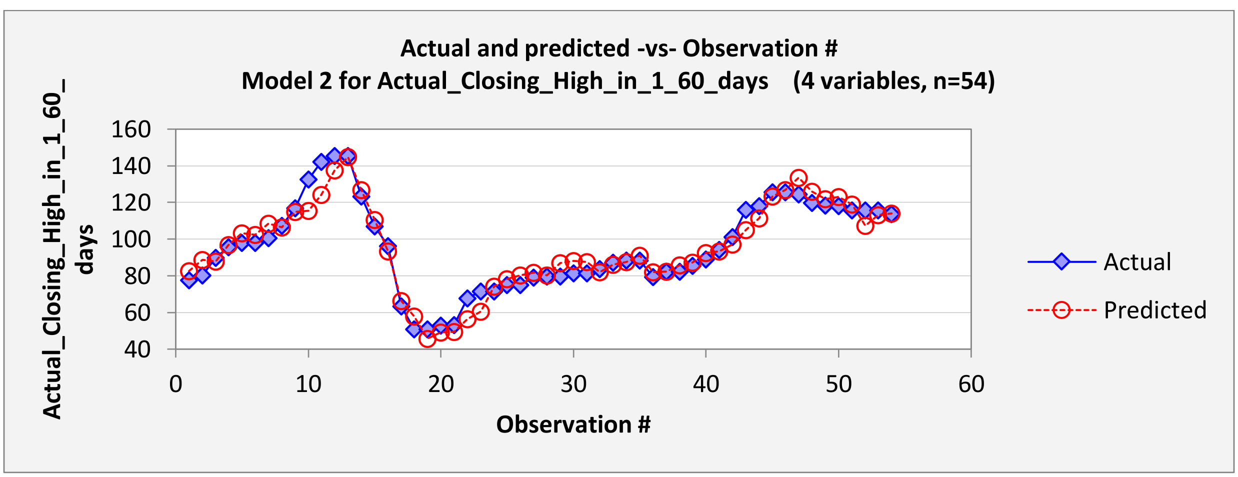
seem intuitive, but are well documented in Grisse (2010) “We also find the Dollar depreciation is associated with higher Oil prices in the short run. US short-term interest rates explain much of the long-run variation in Oil prices and the Dollar exchange rate.”

The actual versus the predicted are found for each period below to better illustrate the points made here.

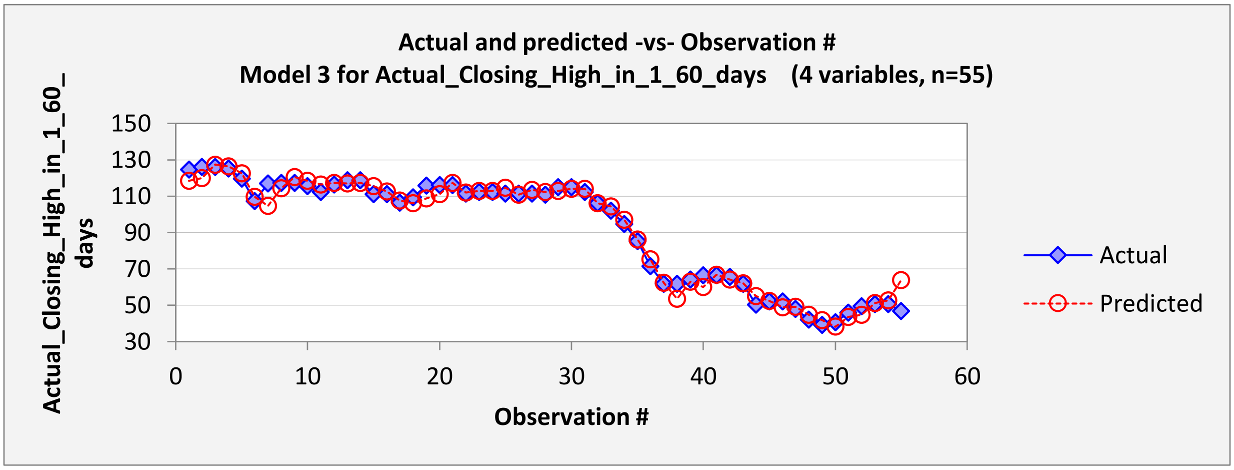
Period 1/2003-6/2007



Period 7/2007-12/2011



Period 1/2012-7/2016



These three charts illustrate the performance of the model that was used to create the working predictive model; they also illustrate the aforementioned volatility, in particular during the second and third periods.

A detailed spreadsheet of the Predictive Price Model can be found in Appendix 1 provides an example of elements involved in the calculations.

Trading Model

As discussed the ability to test, and in the case of a trader, utilize the predictive model is dependent on real world application in a trading environment. In the real world capital is at risk, both when trades are opened as well as when they are not, thus developing a trading model required the implementation of certain rules that would insure the test was both objective and realistic. The model developed for trading utilizes two predictive prices, which will be referred to as predictive price A (P_a) and predictive price B(P_b), this is the predicted future price that will be reached within 12 months, and optimally sooner. The “current price” is the closing price of the first trading day of the month. The model facilitates trading in a straightforward fashion that provides a trader with all of the information needed. If the P_a is at least 1% higher than the current price this is a signal for a long buy opening trade. If the P_a is at least 1% lower than the current price this signals a short sell opening trade. If less than a 1% price movement is predicted no transaction will be initiated. If the P_a is achieved within the first two months the trade is closed at that price. If the trade is not closed within the first two months P_a is adjusted to the original models 60-day look *forward* methodology is applied and P_b becomes the new target price at which the trade will be closed. If a trade is not closed within 12 months, the trade will be closed at the closing price on the day preceding the date of the first anniversary of the opening of the position.[9]

Development of the Trading Model to test the Predictions

Variables

While the success of the predictive pricing model was promising, in order to put the findings that resulted into a working model that a trader could use and profit from, there were changes that have to be made. The most significant change that is necessitated involves the dependent variable used, the forward looking 60 day closing high is replaced with the previous 40 day high price for the calculation of P_a at which a trader must decide on whether or not to open a position. The sixty day high price is incorporated into the first 10 of the 12 months rolling calculation, since this is historical in nature. P_b is calculated two months following the original calculation of P_a when the 60 day closing high becomes available. Both of these factors are important to the development of the working model.

The replacement of the dependent variable is primary in developing a model that would match the performance of the predictive price model.

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[9] Instances in which $P_a$and P_b provided conflicting buy long/sell short signals maintained the initial target P_a but were otherwise treated as any other transaction.

The complete replacement of the dependent variable is a problem when calculating the two most current consecutive months; remember this variable is the 60-day *forward-looking* closing high price. In the 12 month rolling calculation months 1 – 10 will employ the high for the following 60 days, as this has proven most effective in the testing and performance of the model. The problem lies in months 11 and 12 (the most current month), which will “roll” the next month, such that the current month 12 will next month become month 11. This idea of utilizing a previous months volatility, in our case the result of which is the predicted price, was explored by Moreira and Muir (2016) finding there was a “strong relationship between lagged volatility and current volatility.”

The approach found to be most effective is to utilize the previous 40 day high as the dependent variable for months 11 and 12 respectively with which to calculate the coefficient used for the calculation of the P_a. As previously mentioned P_a is captured in the model at this point and utilized for the current and following month as the target price.

A description and discussion of the independent variables used in both models are below.

The closing price of Oil on the first trading day of the month is straightforward and utilized in both models as a part of the coefficient calculation for the particular month as well as for the predicted price calculation (sourced from Factset).

The Futures/Options variable is the aggregated traded volume reported by the Intercontinental Exchange (ICE). Because options on Oil futures represent single contracts, the aggregation provides a more complete picture than futures alone. These volumes are reported at the end of the month, this allows for a total number to be used the following month, which is in actuality to next trading day.

The variable Real Trade Weighted U.S. Dollar Index: Major Currencies; is produced by the Board of Governors of the Federal Reserve System (US). This index is a weighted average of the foreign exchange value of the U.S. dollar against a subset of the broad index currencies that circulate widely outside the country of issue. Major currencies index includes the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. This is produced monthly allowing for the result of the previous month to be applied the following trading day in the model.

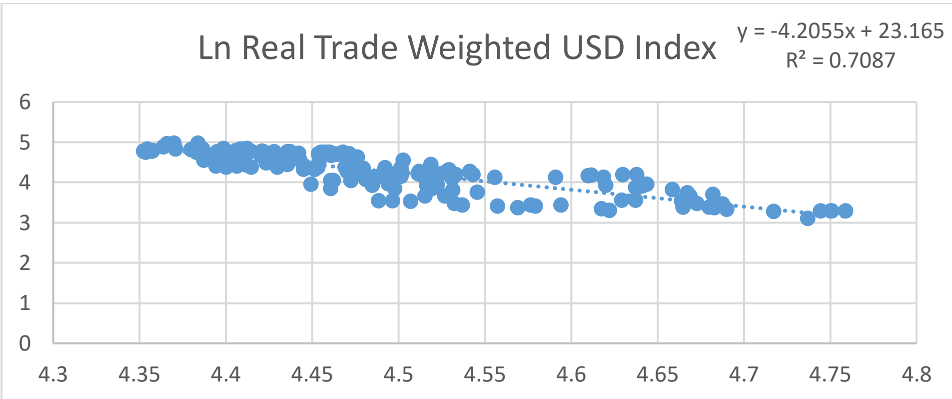
The MSCI AC World Commodity Producers Index captures the Global opportunity set of commodity producers in the energy, metal, and agricultural sectors. Nine of the top ten constituents are in the energy sector, comprising over 68% of the index. Country weightings are primarily the United States, United Kingdom, Canada, Australia, and France.

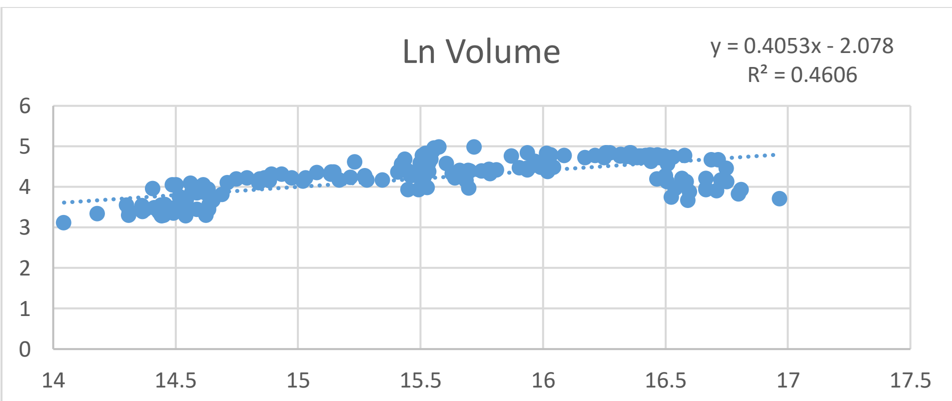
A detailed regression analysis of the variables is located in appendix 2.

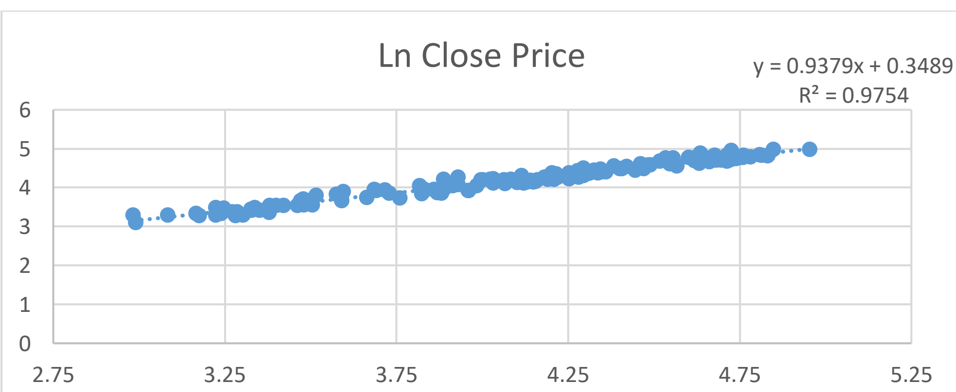
As noted similar variables have been employed in other papers seeking to understand energy price relationships, e.g. Sadorsky (2000). Specifically as related to currencies, in this case the US Dollar, Bloomberg and Harris (1995) noted a correlation to multiple commodity indexes. While I have used a dollar index in this research, I have also illustrated the value of a global producer price index that takes into account those factors that will affect currencies and thus the price of Oil expanding on Akram (2009) findings that related higher oil prices to a weaker US Dollar.

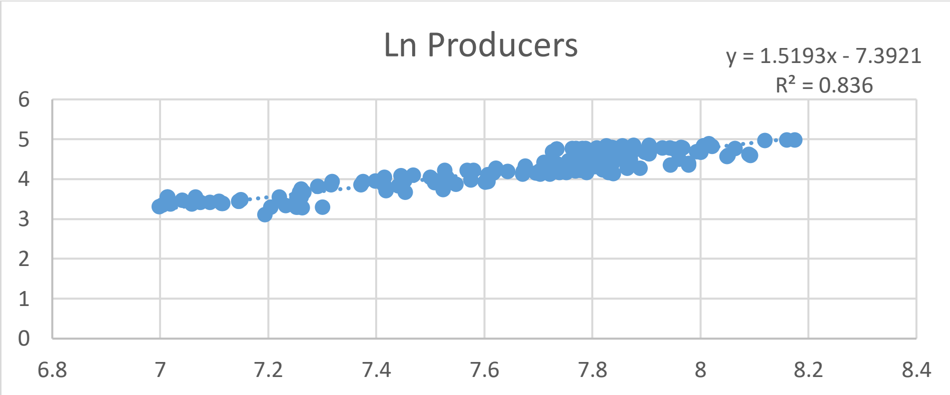
Variable analysis

A simple linear regression analysis of the individual variables was conducted to understand the value versus that of the multivariate approach utilized in the predictive model. The results of the individual variables can be found in the charts below along with the R^2 values.









The significant R^2 and line fit of the Closing Price variable, while somewhat intuitive provided raised questions concerning the predictive nature, and how this might be realized in actual trading situations. As observed in the data the price of Oil is extremely volatile over a variety of time periods. As such a question that must be addressed, is it possible that the predictive model is just capturing gains by happenstance, those that would naturally have been captured by a passive investor employing a short term strategy? After all since the long-term trend in the Oil price data has been positive, it makes sense that a buy-and-hold strategy, on average, would make money over time regardless of when it was bought and sold. To test this theory a short term, ninety days, passive strategy was constructed utilizing historic pricing information. In order to minimize any possible bias the strategy would have no rules beyond a set time frame in which trades would be opened and closed.

The strategy established an "opening" trade at the closing price on the first trading day of the month, exactly as employed by the predictive model. Unlike the predictive model the passive strategy would "close" the trade three months later, again at the closing price of the first trading day of the third month following the opening, the difference in the price would then be used to calculate the return.

$$(\boldsymbol{t_1 - t_4})/\boldsymbol{t_1}$$

The cumulative return of -16.48 was calculated for the complete time of the analysis, January 2003 thru May 2016, so that the time frame replicated that of the predictive model. Clearly the predictive model outperformed a passive short term buy and hold strategy. The detailed results can be found in appendix 3.

Testing Trading Model Performance

Like any trading model the complete environment must be taken into account, this includes flags for trades should not be opened due to an unreasonably low predicted yield and/or in which momentum may skew the prediction. The issue of unreasonably low predicted yields, in this case less than 1%, is relatively easy to address the trades are simply not opened as the risk reward is not justified. The second problem is well understood in trading circles and is often characterized as trying to "catch a falling knife." This notion of equilibrium control is articulated in Spiegel (1996) "an equilibrium change may require simultaneous control over the trading environment."

In order to avoid those trades in which the predicted price is obscured by adverse momentum systematic rules were required.[10] These variables and the associated percentage movements were designed to filter out "noise" and identify actual momentum events, when the noise is identified by the rule no trade is implemented. The percentages were identified by taking the percentage changes for each variable for each month, squaring these, and then taking the square root to find the absolute changes. The standard deviation was then calculated to provide

[10] Detecting those instances required a working understanding of the variables and the nuances, the rules used are as follows; Monthly increase in day one closing price by 103% of the previous month, 102% change in P_a over the previous month high, Monthly day one close that is 104% of previous month high, and a month over month average price change of 117%.

additional direction and testing parameters. The results of the rules impact on the overall performance of the model, the results are found in Illustration 3 below.

The ability of the model to detect this noise, along with the ability to provide short sell (as well as buy long) signals is significant. As Moreira and Muir (2016) found in their analysis by "cashing out" in the Fall of 2008 was the correct move when the popular view was that of a buying opportunity, in a similar approach our signals provided short selling and trade avoidance opportunities, making money on the short sells and avoiding losses in trades avoided.

Illustration 3

The results of the systematic rules constructed to detect those predicted prices that may be overly affected by momentum and to alert the trader not to open these trades are found in this chart.	
Losses avoided	7
Average Loss Averted	40.8%
False positives	8

The 8 losses averted with average declines exceeding 40%, which significant to the trading models performance.[11] Indeed, these results somewhat validate the old trader's adage to "never try to catch a falling knife." If you did try to catch a falling knife in Brent Crude over the time period, you'd have lost your shirt.

[11] Declines of this magnitude, depending on the financial instrument used, would likely violate company risk limits and a traders sensibility and thus even if not averted with such a rule would have been mitigated.

The objective for developing the model is to make profits, the preceding information provides the necessary background on how the model was developed and tested, but the proof is in the profits. The Illustration below provides insight into the actual performance of the model over the period analyzed.

Illustration 4

There are 161 data points observed, from January of 2003 through May 2016. Of the 161 months in the analysis the price predicted was achieved about 94% of the time within twelve months, 36 months had a predicted return of less than 1% or the momentum rule was triggered and no trade was opened, the detailed distribution is shown below.

Closing trade period	0-60 Days	61-180 Days	181-360Days	Did not return a profit	No Trade Executed
Number of months	81	27	11	7	35
% of Months	50.31%	16.77%	6.83%	4.35%	21.74%
% of Trades Executed	64.29%	21.43%	8.73%	5.56%	
Average return	5.29%	8.76%	11.06%		
Average Return per trade	6.61%		Return including losses	5.24%	

While the panel results are impressive, the extreme market volatility during this period including the Financial Crisis, the Oil route, and of course the resulting Federal Reserve Bank and European Central Reserve makes it even more so.

The average holding period for all successful trades (long and short) was 33 days. The shortest period was a single day and the longest, with the exception of the forced closures at 12 months, was 218 days, the holding period has a standard deviation of 42 days.

Because the model facilitates both long and short positions the question of holding both a long and short at the same time must be addressed. This occurs only once during the time of the analysis in March of 2009, when the previous months long position is still open. If the long position were to be closed out it would have resulted in a loss of less than 1% instead of a gain exceeding 23%. The notion of a long and short position in the same security (shorting against the box) is an established concept in trading, albeit rare. In short this single position would have de minimis impact on the overall performance.

The model's performance was also evaluated in terms of losses realized to understand the totality of "drawdowns" that may have occurred during rolling twelve month periods throughout the entire period analyzed. To accomplish this a theoretical investor with $1,000,000 to invest in the strategy was utilized. All profits were returned to the portfolio such that 1/12 (.08333) of the current portfolio balance was reinvested for the month, with the balance reflecting gains or losses when they were realized. The reason that only 1/12 of the balance was invested is that the portfolio positions could be held up to 12 months necessitating funds be available to consistently invest. Again the complete time frame from January 2003 thru May of 2016 was analyzed for portfolios drawdowns, applying the trading rules discussed previously to insure consistency.

The most significant result of the test was a drawdown realized on September 1 of 2015 for $71,120, at this point the theoretical $1,000,000 portfolio had a balance of $1,617,883 prior to the realization. This loss was related to a single trade opened 12 months earlier and subject to the forced closure rules established for the trading model. It is also the largest loss in any rolling twelve month period of the analysis.

As in the test model out of sample testing is difficult given that the data utilized to construct the model incorporates almost the entire period for which variable information is available. Therefore, a test was conducted to compare three consecutive periods with a similar number of months (42, 42, 43) in which trades were executed. The purpose of this test was to understand the consistency of the predictive ability of the model, and most importantly the performance of the model. The return performance is detailed in Illustration 5 below, the risk free rate is provided as context. While the context of the risk free rate is important as a basis of comparison between the periods, it would likely be viewed in a different light by a trader tasked with this particular asset class. Within the time of the analysis Treasury rates fluctuated significantly in very short periods of time, this is particularly the case within the second period which experienced rate fluctuations from 4.93% to 0.10%. I believe this rather significant movement accounts for what may be viewed as an inconsistency in the second period.

The “trade blotter” in the appendix provides the complete details of the individual transactions that make up the panel data in illustration 5 as well as the associated variable values on the days in which the transactions were undertaken.

Illustration 5

In order to understand the consistency of the approach to predict price targets an analysis of equal but separate time periods was conducted to illustrate the value of this approach during various economic and political cycles. To provide a bit more context the 6 Month US Treasury Constant Maturity Yield is included as a risk free rate benchmark, the fluctuations in this rate throughout some of the periods are significant.			
Time period	**1/2003-5/2007**	**6/2007-11/2011**	**12/2011-5/2016**
Months Reviewed	42	42	43
Average Return per Trade	6.28%	5.88%	3.80%
Risk Free Rate	2.79%	0.85%	0.17%
Return net of RFR	3.490%	5.030%	3.630%
Months with losses	0	2	5

Sharpe Ratio

This would not be complete without some measure of the risk and return profile of the investments undertaken through the trading model. . The approach was to take the return generated over the holding period of the trade and then to invest in the risk free asset for the balance of a one year holding period. The purpose was to provide a consistent basis of comparison with which to evaluate using the Sharpe Ratio. In this case the risk free asset utilized was the 1 year US Treasury Constant Maturity. Such that:

$$A_r + R_r^{f\,1/(365/(365-(T-t_1))}$$

Where,

- A_r is the return on the asset
- R_r^f is the risk free rate, the continuous maturity 1 year Treasury
- $^{T\text{-}t}{}_1$ the difference between trade opening and closing dates, the holding period

I have mixed feelings in addressing this question, as an energy trader has few options other than trading energy, or even more specifically if Oil trading is the sole purview of the trader. However, to provide some context to this question the Sharpe ratio

$$\frac{r_p - r_f}{\sigma_p}$$

was calculated for each complete year and the portion of 2016 included in the analysis. The results of this analysis can be found in the chart below.

Illustration 6

Year	Risk Free Rate	Average Return	Excess Return
2003	0.0124	1.0917	0.0792
2004	0.0193	1.0882	0.0689
2005	0.0369	1.1173	0.0805
2006	0.0494	1.0900	0.0406
2007	0.0445	1.0776	0.0331
2008	0.0172	1.0279	0.0107
2009	0.0048	1.0892	0.0844
2010	0.0031	1.0656	0.0625
2011	0.0018	0.9984	-0.0034
2012	0.0018	1.0783	0.0766
2013	0.0013	1.0330	0.0317
2014	0.0013	0.9449	-0.0564
2015	0.0033	1.0503	0.0470
2016	0.0058	1.1480	0.1422
	Average		**0.0498**
	Standard Deviation		**0.047325**
	Sharpe Ratio		**1.052869**

Alternative to Out of Sample Testing the Trading Model

Like the passive test used to validate the predictive model, a test of the trading model was needed to understand the value of the trading model, in other words was the success of the predictive model primarily related to the trading model. In order to insure the test had no new bias that might influence the outcome the exact same rules utilized previously were applied to this test, with of course the exception of the target prices. To keep this as straightforward as possible a simple 5.24% increase (the average gain realized in the trading model) of the opening trade price was used in place of the predicted price. After a trade is opened, again at the closing price on the first day of the month, the predicted price (P_c) is now the closing price on the first day on the month (T_p) multiplied by 105.24%,

$P_c = T_p * 105.24$

P_c is the target price at which a trade is closed. The outcome can be viewed in the chart below.

Illustration 7

In order to understand the consistency of the trading model an analysis of equal but separate time periods was conducted to illustrate the value of the model using passive target prices based on a 5.24% increase in the opening price, during various economic and political cycles. To provide a bit more context the 13 week Treasury rate average for the period is included as a risk free rate benchmark.

Time periods	**I**	**II**	**III**
Average Yield	5.08%	2.87%	-1.41%
Risk Free Rate	2.79%	0.85%	0.17%
Net of Risk Free Rate	2.29%	2.02%	-1.58%

As the analysis in the chart illustrates not only are the returns utilizing a buy-and-hold strategy much lower than those utilizing the predicted pricing models and in one period the average yield was a loss. Given the results the trading model and the simple rules associated with it cannot be deemed the cause of the extraordinary results detailed in Illustration 4.

The results presented would not be complete without a risk adjusted return context in which to view them. However, given the nature of this this paper as that of a tool for a trader, an appropriate measure is challenging. In reviewing the literature much is concerned with specific instruments (e.g. futures) as detailed by Pagano and Pisani (2009) or as an “inflation insurance” as in Amenc, Martellini, and Ziemann (2009), neither of these approaches seemed appropriate given the instrument specificity and purpose. Applying an approach borne out of practical experience appeared to provide a better, and more realistic measure.

As a trader, the focus of this work, the environment that can be traded is very often limited by industry, capitalization, or some other parameters. Traders, portfolio managers and other investment professionals will usually specialize in certain sub-groups. As such a relative measure would need to be limited to those alternative investments available to an oil trader.

Conclusion

As was the intent of this paper I have successfully designed a model to predict price targets for Brent crude Oil in short term scenarios through the use of a multivariate model. The model has, in part, illustrated the findings of other academic papers, but has also advanced the practical application of this work. By utilizing a "passive" pricing approach the value of the predictive model has been shown to be valid. But as I stated at the outset the true bar of success was that of a trader's perspective, could the model make money, in the real world and not in a finance laboratory. The testing of the model in a trading environment provided an other than perfect world laboratory in which to apply the predictive prices and to demonstrate the predictive models success. A trading model was constructed, rules established and the predicted prices put to the test. The trading model not only made money, with successful transactions returning over 6.5% on average within 6 months, but did this in a number of different economic cycles. This is particularly significant because the predictive model, substantially outperforms a buy-and-hold strategy, both over the entire period, as well as over the period in which Oil prices experienced substantial declines. The consistency with which the model operates in the trading environment validates the consistency that is required in a real trading environment, and it should be noted this was over a period exceeding 13 years. This period is marked not only by the financial crisis but also by huge levels of both short and long-term volatility in the underlying asset being analyzed. From the outset the objective of this paper was to make money, and while there are certainly other statistical measure that can be used to judge the success of such model, the "profits" generated in this case are the best indicator of the performance of both the predictive and trading models.

Appendix 1

Date	MSCI COMMODITY PRODUCERS Index (Lagged)	Real Trade Weighted U.S. Dollar Index (Lagged)	Closing Price on first of month	Futures volume (Lagged)	Coefficients					Predicted Price a	Predicted Price b	Return Predicted Price a
1/2/02	1332.03	114.117	19.9	1256602	4.06E-06	0.209597	-0.31728	-0.00615	59.31014	22.9879268	24.1865267	0.1551722

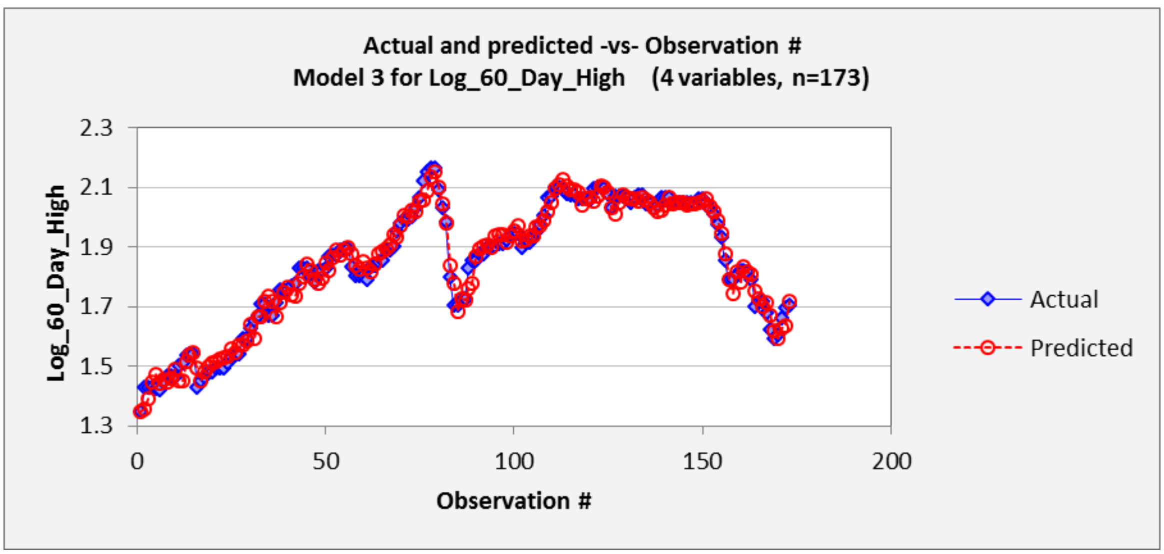
Appendix 2

Regression Statistics: Model 1 for Ln_1_60_Day_High (4 variables, n=173)

	R-Squared	Adj.R-Sqr.	Std.Err.Reg.	Std. Dev.	# Cases	# Missing	t(2.50%,168)	Conf. level
	0.980	0.980	0.069	0.481	173	0	1.974	95.0%

Coefficient Estimates: Model 1 for Ln_1_60_Day_High (4 variables, n=173)

Variable	Coefficient	Std.Err.	t-Stat.	P-value	Lower95%	Upper95%	Std. Dev.	Std. Coeff.
Constant	2.025	0.587	3.447	0.001	0.865	3.184		
Ln_Close	0.735	0.035	20.720	0.000	0.665	0.805	0.507	0.774
LN_Producers	0.167	0.043	3.870	0.000	0.082	0.252	0.290	0.100
Ln_Real_Trade	-0.559	0.114	-4.898	0.000	-0.785	-0.334	0.096	-0.112
Ln_Volume	0.026	0.011	2.449	0.015	0.005034	0.047	0.806	0.043



Appendix 3

	Closing Price	(t-t3)/t	Return on $100
1/2/03	30.64	-0.11195	88.80548
2/3/03	32.5	-0.26954	64.86899
3/3/03	33.29	-0.20757	51.40414
4/1/03	27.21	0.025726	52.72656
5/1/03	23.74	0.203033	63.43178
6/2/03	26.38	0.058757	67.15882
7/1/03	27.91	0.011465	67.92882
8/1/03	28.56	-0.02486	66.24012
9/2/03	27.93	0.008235	66.7856
10/1/03	28.23	0.061637	70.90203
11/3/03	27.85	0.056373	74.89902
12/1/03	28.16	0.132813	84.84655
1/2/04	29.97	0.074074	91.13148
2/2/04	29.42	0.121686	102.2209
3/1/04	31.9	0.222571	124.9723
4/1/04	32.19	0.045045	130.6016
5/3/04	33	0.26303	164.9538
6/1/04	39	0.054359	173.9205
7/1/04	33.64	0.376338	239.3734
8/2/04	41.68	0.163388	278.4841
9/1/04	41.12	0.114543	310.3824
10/1/04	46.3	-0.13823	267.4786
11/1/04	48.49	-0.06104	251.1508
12/1/04	45.83	0.093389	274.6054
1/3/05	39.9	0.347118	369.9258
2/1/05	45.53	0.117725	413.4751
3/1/05	50.11	0.006586	416.1981
4/1/05	53.75	0.038884	432.3814
5/2/05	50.89	0.166044	504.1759
6/1/05	50.44	0.335052	673.1009
7/1/05	55.84	0.13485	763.8682
8/1/05	59.34	-0.01618	751.5104
9/1/05	67.34	-0.19142	607.6588

10/3/05	63.37	-0.08222	557.6998
11/1/05	58.38	0.132922	631.8305
12/1/05	54.45	0.125069	710.8528
1/3/06	58.16	0.142194	811.9317
2/1/06	66.14	0.109314	900.6869
3/1/06	61.26	0.148057	1034.04
4/3/06	66.43	0.101611	1139.11
5/1/06	73.37	0.013493	1154.48
6/1/06	70.33	0.000142	1154.644
7/3/06	73.18	-0.15195	979.1914
8/1/06	74.36	-0.21436	769.2894
9/1/06	70.34	-0.09312	697.6539
10/2/06	62.06	-0.0253	680.0046
11/1/06	58.42	-0.03458	656.4919
12/1/06	63.79	-0.04264	628.4991
1/3/07	60.49	0.102662	693.0219
2/1/07	56.4	0.207447	836.787
3/1/07	61.07	0.110201	929.0022
4/2/07	66.7	0.061019	985.6894
5/1/07	68.1	0.123642	1107.562
6/1/07	67.8	0.082006	1198.388
7/2/07	70.77	0.133107	1357.902
8/1/07	76.52	0.163879	1580.434
9/4/07	73.36	0.208288	1909.619
10/1/07	80.19	0.175957	2245.63
11/1/07	89.06	0.028296	2309.171
12/3/07	88.64	0.133687	2617.877
1/2/08	94.3	0.094168	2864.396
2/1/08	91.58	0.231164	3526.542
3/3/08	100.49	0.268783	4474.416
4/1/08	103.18	0.373425	6145.275
5/1/08	112.75	0.112106	6834.2
6/2/08	127.5	-0.12549	5976.575
7/1/08	141.71	-0.32101	4058.048
8/1/08	125.39	-0.50355	2014.622
9/2/08	111.5	-0.52924	948.4083
10/1/08	96.22	-0.58273	395.7451
11/3/08	62.25	-0.2612	292.3746
12/1/08	52.49	-0.12993	254.3865
1/2/09	40.15	0.216438	309.4455
2/2/09	45.99	0.10698	342.5499
3/2/09	45.67	0.433983	491.2107
4/1/09	48.84	0.435504	705.1348

5/1/09	50.91	0.374975	969.543
6/1/09	65.49	0.073904	1041.197
7/1/09	70.11	-0.04593	993.3766
8/3/09	70	0.092714	1085.477
9/1/09	70.33	0.099957	1193.978
10/1/09	66.89	0.169682	1396.574
11/2/09	76.49	-0.05779	1315.873
12/1/09	77.36	-0.00414	1310.43
1/4/10	78.24	0.049208	1374.913
2/1/10	72.07	0.213681	1668.706
3/1/10	77.04	-0.0305	1617.804
4/1/10	82.09	-0.08003	1488.325
5/3/10	87.47	-0.11787	1312.897
6/1/10	74.69	0.012719	1329.596
7/1/10	75.52	0.080111	1436.112
8/2/10	77.16	0.077372	1547.226
9/1/10	75.64	0.145426	1772.233
10/1/10	81.57	0.142577	2024.912
11/1/10	83.13	0.198605	2427.069
12/1/10	86.64	0.297899	3150.092
1/3/11	93.2	0.254185	3950.796
2/1/11	99.64	0.260036	4978.146
3/1/11	112.45	0.037172	5163.194
4/1/11	116.89	-0.04064	4953.38
5/2/11	125.55	-0.06993	4606.979
6/1/11	116.63	-0.01895	4519.682
7/1/11	112.14	-0.07883	4163.395
8/1/11	116.77	-0.06431	3895.629
9/1/11	114.42	-0.03242	3769.315
10/3/11	103.3	0.040852	3923.299
11/1/11	109.26	0.022241	4010.555
12/1/11	110.71	0.106585	4438.019
1/3/12	107.52	0.146577	5088.532
2/1/12	111.69	0.068762	5438.429
3/1/12	122.51	-0.15786	4579.893
4/2/12	123.28	-0.22713	3539.684
5/1/12	119.37	-0.11267	3140.85
6/1/12	103.17	0.115828	3504.649
7/2/12	95.28	0.18178	4141.725
8/1/12	105.92	0.031911	4273.891
9/4/12	115.12	-0.03614	4119.449
10/1/12	112.6	-0.01918	4040.425
11/1/12	109.3	0.052882	4254.091

12/3/12	110.96	0.010094	4297.031
1/2/13	110.44	-0.00779	4263.57
2/1/13	115.08	-0.10306	3824.171
3/1/13	112.08	-0.09636	3455.675
4/1/13	109.58	-0.06133	3243.756
5/1/13	103.22	0.033811	3353.431
6/3/13	101.28	0.128456	3784.199
7/1/13	102.86	0.050068	3973.666
8/1/13	106.71	0.023334	4066.389
9/3/13	114.29	-0.03106	3940.082
10/1/13	108.01	0.027035	4046.6
11/1/13	109.2	-0.01969	3966.928
12/2/13	110.74	-0.01716	3898.866
1/2/14	110.93	-0.02975	3782.881
2/3/14	107.05	0.010462	3822.459
3/3/14	108.84	0.008912	3856.525
4/1/14	107.63	0.046455	4035.682
5/1/14	108.17	-0.02099	3950.991
6/2/14	109.81	-0.06457	3695.891
7/1/14	112.63	-0.14525	3159.047
8/1/14	105.9	-0.19518	2542.451
9/2/14	102.72	-0.29614	1789.517
10/1/14	96.27	-0.41436	1048.021
11/3/14	85.23	-0.41863	609.2859
12/1/14	72.3	-0.14924	518.3565
1/2/15	56.38	-0.03051	502.5428
2/2/15	49.55	0.294248	650.4152
3/2/15	61.51	0.02211	664.796
4/1/15	54.66	0.127881	749.8111
5/1/15	64.13	-0.18213	613.248
6/1/15	62.87	-0.2238	476.0061
7/1/15	61.65	-0.22985	366.598
8/3/15	52.45	-0.08656	334.8658
9/1/15	48.8	-0.11947	294.8603
10/1/15	47.48	-0.23589	225.3061
11/2/15	47.91	-0.32269	152.6024
12/1/15	42.97	-0.16849	126.8905
01/04/16	36.28	0.003859	127.3801
02/01/16	32.45	-0.4151	74.50463
03/01/16	35.73	-0.46795	39.63988
04/01/16	36.42	-0.47446	20.83216
05/02/16	45.82	-0.57115	8.933915

Return	-0.16475

References

Akram, Q. (2009), "Commodity Prices, Interest Rates, and the Dollar", *Energy Economics* volume 31, issue 6, 838-851

Amenc, N., L. Martellini, and V. Ziemann (2009) "Inflation-Hedging Properties of Real Assets and Implications for Asset-Liability Management Decisions", *Journal of Portfolio Management* Vol. 35 No. 4 94-110

Bloomberg, S., E. Harris (1995) "The Commodity-Consumer Price Connection: Fact or Fable?" Federal Reserve Board NY Economic Policy Rev., October, 31-38

Caplan, K., R. Cohen, J. Lenz, and C. Pullano (2009) "Dark Pools of Liquidity", Price Waterhouse Coopers Alternatives

Chin, Y., K. Rogoff, B. Rossi (2008) "Can Exchange Rates Forecast Commodity Prices,"

Dees, S., A. Gasteuil, R. Kaufmann, and M. Mann (2008) "Assessing The Factors Behind Oil Price Changes", European Central Bank *Working Papers Series, NO 855 January 2008*

Engle, C. and K. West (2005), “Exchange Rates and Fundamentals”, *The Journal of Political Economy* 113(3), 485-517

Frazzini, A., R. Israel, and T. Moskowitz (2012) “Trading Costs of Asset Pricing Anomalies”, Yale University

Grisse, C. (2010), “What Drives the Oil Dollar Correlation?”

Moreira, A. and T. Muir (2016) “Volatility Managed Portfolios”, Yale School of Management

Pigono, P and M. Pisani (2009) “Risk Adjusted Returns of Oil Prices” European Central Bank

Sadorsky, P. (2000) “The Empirical Relationship Between Energy Futures Prices and Exchange Rates”, *Energy Economics* 22, 253-266

Spiegel, M. (1996) “Stock Price Volatility in a Multiple Security Overlapping Generation Model,” *EconPapers*

Tang, K. and W. Xiong (2008) “Index Investment and the Financialization of Commodities”, *Financial analysts Journal* Vol 68 Number 6 2012

Yan, L. (2012) “Analysis of the International Oil Price Fluctuations and Its Influencing Factors,” *American Journal of Industrial and Business Management* 2, 39-46