VARIATION IN OIL PRICE RISK
IN THE ENERGY SECTOR

by

Nicole Carmody

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Project Approved:

Supervising Professor: Steve Mann, Ph.D.
Department of Finance

Susan Kleiser, Ph.D.
Department of Marketing
ABSTRACT

Mixed findings have resulted from the analyses of oil price risk as a systematic risk factor. Studies in the past have researched the effects of oil shocks on various macroeconomic variables; however, this paper is primarily concerned with the effect of oil prices on company share price returns within the energy sector due to the dramatic decrease in oil prices beginning in June 2014. By using statistical testing, including multivariate regressions, the relationship between the share prices of energy industry subsector companies and oil prices will be examined. This paper will present evidence that WTI crude and Brent crude does play a systematic role in the oilfield services, exploration and production, midstream, and integrated company share price returns, and will examine the differing levels of exposure to oil price risk between the different energy industry subsectors. The tests do not support the presence of oil price risk in the downstream subsector.
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INTRODUCTION

In 2014, oil prices declined in value by over 50%. From WTI crude’s June high of $108, to its $44 low in January, an unusual amount of stockpiling caused this “crash” in prices. Energy prices play a key role in the modern United States economy, attributed to the fact that oil is the primary energy source for the global economy (Susan & Waititu, 2015). Often shaping the outcome of consumer sentiment, oil is also an important commodity and input to many petroleum based products. Oil is a macro-economic variable, and it has been hypothesized that macro-economic variables do affect stock market returns (Bodie, Kane, & Marcus, 2014). With the recent drop in oil prices during 2014, falling to less than half of what they had been, the effect crude prices have on the economy becomes even more relevant due to the high level of integration oil has within the economy.

Since the decline in crude prices, questions surrounding the commodity begin to emerge. What will happen to demand? What will happen to production? When will prices rise again? How will this new pricing environment affect cash flow? Opinions range from one extreme to the other.

Due to the focus on oil prices, some research has been devoted to the study of energy and its effects on various macro-economic variables. Further, research also covers the subject of how energy shocks affect the economy. NYMEX futures returns (Huang, Masulis, & Stoll, 1996), cash flows (Jones & Kaul, 1996), and size (Alsalman & Herrera, 2015) have been studied in this research.

Not only does uncertainty surround the actual commodity itself, but one should be sure to ask how this decrease in prices will affect various energy sector companies, and more
specifically, their stock price rate of return. An increase in the price of energy raises the marginal cost of production (Edelstein & Kilian, 2007), so more than likely, changes in the cost of crude will have an effect on the rate of return of oil companies as well.

Though research is available on the effects of oil on certain parts of the economy, little research has been conducted on how oil prices affect various energy sector companies, and more specifically, their rate of return. There is still a large opportunity to research this topic. To study how changes in the commodity price affects stock returns, I will be examining whether or not oil price risk is systematic using the arbitrage pricing theory as an underlying theory (Ross, 1976). The APT is a multi-factor model, unlike the capital asset pricing model (CAPM), that would allow for a systematic oil price variable (Bodie, Kane, & Marcus, 2014). Many studies have been done on the APT which suggest its superiority to other forms of predicting rate of return (Roll & Ross, 1980). Further, research regarding oil sensitivity and systematic risk have used the APT as a means of comparing sensitivity in stock returns to changes in various macro-economic factors with their sensitivity to oil prices (Hammoudeh & Huimin, 2004). Therefore, the APT is an appropriate approach to predicting stock returns based on oil price risk. At the time of this study, there has been no theory developed for oil price risk in conjunction with systematic risk.

My research will examine U.S. energy sector companies. In this paper, the reader will first encounter a review of available relevant literature followed by a data description. The results of my analysis, including multivariate regressions and t-tests, will be discussed. Finally, I will present my conclusion based on the results of my analysis.
LITERATURE REVIEW

Literature has been devoted to the research of energy shocks on the economy, but little has been researched regarding oil price as a systematic risk factor. Financial theory suggests that the spread between long and short interest rates, expected and unexpected inflation, industrial production, and the spread between high and low grade bonds should play a systematic role in the movement of stock returns (Chen, Roll, & Ross, 1986). Further, stock prices are generally considered as responding to external variables (Chen, Roll, & Ross, 1986). Truly exogenous variables are natural forces, however, in the context of this paper, I will not consider physical factors in my research, because the ability to predict, for example, a hurricane’s effect on stock market returns, is beyond the scope of modern finance. Because of its pervasive nature in the current economy, oil price as a systematic risk factor will be examined. I will examine the effect of this macro-economic variable and its returns against equity returns.

Pricing a Stock

The focus of this paper is on the effects of changes in oil prices on the return of U.S. energy sector stocks. The price of a stock is given by the equation,

\[ p = \frac{E(c)}{E(r)} \]

where \( p \) is the stock price, \( c \) is the cash flow stream, and \( r \) is the discount rate. Realized stock returns, \( R \), can be written as,

\[ R = \frac{d(E(c))}{E(c)} - \frac{d(E(r))}{E(r)} \]
Therefore, movements in cash flow and the discount rate affect stock returns (Huang et al, 1996). An increase in the price of energy raises the marginal cost of production (Edelstein & Kilian, 2007), and it is therefore possible that a change in energy prices may also affect the cash flow of a company, and thus the stock price. Oil is a real resource and is often an input to the production of many goods. Since oil is an input, as oil prices expectedly change, the costs of a firm will expectedly change as well (Huang et al, 1996). For specific firms, the effect on stock price would depend on whether the firm was a consumer or producer of oil. However, for the economy as a whole, oil is an input and increases in oil prices would likely depress stock prices due to the increase in costs.

A second factor that can affect stock price is the discount rate. Theoretically, the discount rate is composed of the expected inflation rate and the expected real interest rate. Both of these components could be affected by expected oil prices. The United States is a net importer of oil, and higher oil prices would cause a balance of payments deficit (Huang, Masulis, & Stoll, 1996). This would put downward pressure on the dollar’s FX rate and consequently put upward pressure on the domestic inflation rate. Therefore, a higher inflation rate is positively related to the discount rate and is negatively related to stock returns (Huang, Masulis, & Stoll, 1996). As oil is a commodity, it acts as a proxy for the expected inflation rate. Therefore, if the expected inflation rate has a negative relationship with stock returns, oil can also be assumed to have a negative correlation with stock returns. Oil prices could also influence the real interest rate, which is the second component of the discount rate, as oil is a major economic resource (Huang, Masulis, & Stoll, 1996).

Generally, the capital asset pricing model is used to calculate the discount rate, however, in this study, the arbitrage pricing theory will be used.
Arbitrage Pricing Theory

An important concept in examining the effect of oil price risk on energy sector returns is understanding the arbitrage pricing theory (APT). The APT is an alternative to the capital asset pricing model (CAPM), which is the most widely accepted model used for determining the expected return of a security and accounting for one variable: market risk (Bodie, Kane, & Marcus, 2014).

CAPM is the most widely used model for predicting the discount rate, and is used in conjunction with modern portfolio theory by professionals in the financial world. Modern portfolio theory is defined as Markowitz portfolio theory, in which the ideal portfolio is a function of the means, variances, and correlations of assets (Duchin & Levy, 2009). However, there has been a growing concern regarding CAPM’s usability as an accurate predictor of returns. This is supported by the number of related but different theories and by anomalous empirical evidence (Roll & Ross, 1980).

However, there is a good reason for CAPM’s wide usage among financial professionals. It is compatible with asset returns’ common variability, and attributes this common variation to a single factor with a stochastic disturbance, which generates returns for each asset through a linear relationship (Roll & Ross, 1980). This linear relationship which is based on diversifiable and non-diversifiable risk, is the underlying rationalization for the CAPM theory, not the CAPM originally derived from utility theory (Roll & Ross, 1980). Despite CAPM’s functionality, the APT proves an appropriate alternative because it still agrees with the rationale behind CAPM and is based on a linear return generating process; further, it does not rely on utility assumptions beyond monotonicity and concavity (Roll & Ross, 1980). APT is also useful across periods and is not restricted to a single period, unlike CAPM.
The structure of CAPM also presents a drawback in my research. CAPM is an example of a single factor model. Single factor models decompose risk into two portions: a common or macroeconomic factor, and firm-specific events. These are generally known as systematic risk and idiosyncratic risk. Idiosyncratic risk can be diversified away from within a portfolio, but systematic risk, the underlying idea of this research, cannot be diversified. The APT is a multifactor model which takes into account exposure to various macroeconomic risks; in other words, systematic risk is not restricted to a single factor in the APT (Bodie, Kane, & Marcus, 2014).

Any investor will want to take as large a position as possible in an arbitrage opportunity to maximize wealth, and modern theory holds that if an arbitrage opportunity is present, investors will take advantage of it until equilibrium price is once again achieved. There are two arguments regarding equilibrium price relationships. The dominance argument states that when an arbitrage opportunity is present, many investors will make limited portfolio changes. On the contrary, the other argument holds that arbitrage opportunities will entice investors to take as large a position as possible regardless of their risk aversion, resulting in few investors restoring the equilibrium price. No arbitrage arguments hold stronger than the risk-return dominance argument. The CAPM is an example of a risk-return dominance argument, implying all investors hold mean-variance efficient portfolios. However, it can be assumed that not all investors hold mean-variance portfolios. The APT frees us of this assumption, providing an advantage over the CAPM (Bodie, Kane, & Marcus, 2014).

It should be noted that while applying the APT, three key assumptions hold (Bodie, Kane, & Marcus, 2014):

1.) Security returns can be described by a factor model
2.) There are sufficient securities to diversify away idiosyncratic risk

3.) Well-functioning security markets do not allow for the persistence of arbitrage opportunities

The arbitrage pricing theory model is as follows:

\[ R_i = E(R_i) + \beta_{i1}F_1 + \beta_{i2}F_2 + e_i \]

where:

- \( E(R_i) \) is the expected return on the \( i^{th} \) asset (Roll & Ross, 1980)
- \( F \) is the deviation of the common factor from its expected value
- \( \beta_i \) is the sensitivity of firm \( i \) to that factor
- \( e_i \) is the firm-specific disturbance; i.e. the idiosyncratic risk

Note that above, the model is shown as a two-factor model, but can allow for multiple “loadings” or risk factors.

Much research has been done on the viability of the APT as an alternative to CAPM. Though the APT allows for multiple risk factors, it does not specify what those factors are (Huberman & Gur, 2005). Some testing suggests that the APT could be a four factor model (Roll & Ross, 1980), however, that is just a suggestion. The APT has been used in research on studying the effects of changing oil prices on the market as well, and the results were consistent with those of other models, such as a VEC model, supporting the APTs usage in the context of this paper (Hammoudeh & Huimin, 2004). The two loadings, or risk factors, I will use in conjunction with the APT are S&P 500 returns and oil price changes.
Oil Price Risk

The effects of oil price risk on the market have been studied in the past, but the studies focus on one specific part of the market. For example, one study found that in the airline industry, the average beta including oil price risk was higher than the beta excluding oil price. However, for the marine and land industries, the opposite was found. The impact of oil price risk is larger in the airlines industry than the marine and land industries (Chen & Lu, 2008). The testing was done using multiple models which returned slightly varying results, suggesting further testing of alternative sub-industries. Another study found that oil futures returns are not correlated with stock market returns, except in the case of oil price returns (Huang, Masulis, & Stoll, 1996). This suggests that further testing of energy subsectors would provide useful.

Further, geographic location has been studied in conjunction with oil price risk. Different indexes were used depending on which locations were being studied. Regarding the market as a whole, one study suggests that on a daily basis, there is a negative bi-directional dynamic relationship between the oil futures price growth and the return of the world capital market (as represented by the MSCI index). Higher oil prices are bad for the world capital market as a whole, but oil price growth has a positive impact on the oil-related stocks (Hammoudeh & Huimin, 2004).

One caveat to be aware of is the seemingly economic comparability of different geographic locations. In regards to oil price shocks, one study found varying results in comparing the U.S and Canada with the UK and Japan (Jones & Kaul, 1996). It is important to avoid assumptions when comparing testing results from the studies of different locations to the results of this paper.
Oil shocks also play a key role in studying oil price as a systematic risk factor. Although studies in the past have found that there is no evidence of a negative relationship between oil prices and stock returns, more recent studies have conflicted these views and pointed towards a negative relationship between oil prices and stock returns (Alsalman & Herrera, 2015). However, the nature of the negative relationship depends on the underlying nature of the oil shock (Alsalman & Herrera, 2015). An oil shock occurs when the supply or demand of oil dramatically increases, and through economic theory, can explain a change in the commodity’s pricing. As established previously, exogenous factors affect changes in stock market returns, and in the case of this paper, a change in oil prices acts as an exogenous factor. The change in oil prices are assumed exogenous to the market because oil prices are affected by shocks, which are exogenous to the world economy (Jones & Kaul, 1996). Essentially, this means that changes in oil prices could be explained by oil shocks. Further, a causal interpretation must be given to the correlation between oil prices and macroeconomic phenomena (Hamilton, 1983).

Despite the lack of evidence that supports oil price shocks having an effect on stock returns, oil price shocks do affect other macroeconomic variables within the economy. At the individual firm level, there is evidence that demonstrates significant correlations between oil price shocks and output, employment, or real wages. Ferderer found empirical evidence that supports oil price shocks’ adverse impact on macroeconomic factors, because a change in oil price due to oil shocks will increase oil price volatility. He then found that oil price volatility can help forecast aggregate output movements within the U.S. (Ferderer, 1996). However, despite these findings, correlations between oil price shocks and macroeconomic factors is weaker in data obtained since 1985 (Hamilton, 2003).
One important feature of oil shocks is their Granger-precedence. The expression that oil price changes Granger-precede implies that oil price changes are not Granger-caused by other variables, and therefore presents considering oil price shocks as a potential exogenous cause for oil price changes (Jones & Kaul, 1996). Granger causality is a statistical concept based on prediction, which essentially states that if all thresholds are met, one variable should be able to forecast values of another variable more accurately than the historical values of the variable alone.

One study found that U.S. stock prices rationally reflect the impact of oil shocks on current and future real cash flows (Jones & Kaul, 1996). Given the equation for the price of a stock, it is predicted that anything affecting cash flows could affect the returns of a stock. And since oil price increases have been found to be caused by oil shocks (Jones & Kaul, 1996), these events could play a major role in predicting stock market returns.

In recent years, some studies have argued that changes in stock prices could be caused by speculative news or fads, in addition to simply changes in current and future cash flows (Jones & Kaul, 1996). Given the recent concern, it is important to note that oil shocks are unlikely to suffer from fads due to the few, sharp movements induced by exogenous events such as wars and OPEC embargoes (Jones & Kaul, 1996). Therefore, oil prices could accurately reflect oil shocks.

Another factor to consider is whether the size and sign of oil price changes play a role in oil price risk as a systematic risk factor. Previous studies have found that the sign of oil price shocks only mattered in determining the sign of the response (increase versus decrease), but not the magnitude of the stock market responses (Alsalman & Herrera, 2015). Further, this study found that the size of the oil price shock affected stock returns, but only in determining the scale of the effect. This study suggests that a linear model proves fit in predicting the response of real
stock returns to the changes in real oil prices. Relating this study to the modern economy, in the first quarter of 2014, stockpiling of crude oil accelerated around the world at an unusual rate, most likely caused by the shale revolution (O’Keefe, 2014). Because a supply shock caused the recent drop in oil prices, paying attention to the effect of shocks on oil prices will be important to energy companies as they plan for the future.

Though the economic consensus on oil shocks and stock markets has been mixed, there is a focus on the underlying cause of energy shocks (Kilian & Park, 2007). Whether a shock is demand side or supply side driven has an impact on aggregate stock returns, presumably through oil prices. Understanding the cause of oil price shocks is pivotal to this research because of the emphasis popular press places on changes in oil prices. For example, on August 21, 2006, the Financial Times attributed the decline of the U.S. stock market to an increase in crude oil prices caused by concerns about the political stability in the Middle East. In October 2006, the Financial Times argued that the rally in global equity markets was an effect of a decrease in oil prices that same day. Despite the fact that economists hold no clear consensus on the negative relationship between oil shocks and stock returns, popular press has voiced its clear consensus. Because popular press has an established view, it is important to address this in my research.

Perhaps popular press is right, and oil prices do play a role in determining stock returns. One study adds some clarity to the concept of oil price shocks and the stock market by studying both demand and supply shocks in the global crude oil market. The negative response of stock returns to changes in oil prices, as commonly referred to in financial press, is present only when oil prices rise due to an oil-market specific demand shock (Kilian & Park, 2007). This type of demand shock can include precautionary demand driven by concerns about future supply. The research also found that supply side oil shocks have no effect on cumulative stock returns (Kilian}
& Park, 2007). Demand shocks explain a larger fraction of stock returns over supply shocks. When studying oil price as a systematic risk factor, it will be important to keep this concept in mind.

Finally, research has been done on oil price risk acting as a systematic risk factor (Chen, Roll, & Ross, 1986). This study found no relationship between oil prices and stock returns. The last study done on this subject was over 30 years ago; since 1986, the United States has experienced two major bubbles—the Dot-Com Bubble in the early 2000s and the Great Recession in 2008. Since the dynamics of the domestic and world market have changed, it is appropriate to re-test oil price risk as systematic risk factor that plays a role in stock market returns.

Indices

I am going to be performing tests of regression and t-tests in order to determine whether oil price risk is a systematic risk factor in affecting the returns of United States equities. The process includes running regression tests against two factors—market risk, which is assumed systematic, and oil price risk. I will test multiple indices against these two factors, and then specifically test different subsectors within the energy sector: oilfield services (OFS), exploration and production (E&P), midstream, downstream, and integrated. However, first I must define which indices I will use and the reasoning behind using them.

Systematic risk is defined as risk that is inherent to the entire market. Generally, in the United States, a beta coefficient is derived from regressing equity returns against the S&P 500. This beta coefficient measures volatility of the equity against the market (S&P 500) as a whole. In my study, I will be using the S&P 500 as a proxy for market returns. The S&P 500 is an appropriate choice because it fits the geography limitations. The S&P 500 is a leading indicator
of United States equities. Second, the S&P 500 is a market value weighted index and therefore reflects the risk / return characteristics of the large cap universe. Studies that have previously tested the effects of oil price shocks on stock market returns have used the S&P 500 as a proxy for the market, reaffirming its appropriateness for my tests (Jones & Kaul, 1996).

Further, in CAPM, the market portfolio plays an important role. The market portfolio is defined as a portfolio that includes every asset available in the market and is value weighted. In the CAPM, the market portfolio plays an important role in theory and in testing that all of the assets available be included in the market portfolio (Roll & Ross, 1980). In other words, the CAPM will not work correctly when tested against subsets of assets. The APT, in contrast, yields a statement of relative pricing on subsets of assets in the entire universe of available assets (Roll & Ross, 1980). For this reason, it is appropriate to test multiple indices acting as proxies for subsectors against oil price risk and market risk. The sector I am testing is defined by the S&P 500 as the energy sector. It is important to test different subsectors because oil price risk may not play a significant role in all areas of the energy sector. Further, each subsector could respond differently to different variables. For example, one study found that oil and gas firm returns, market betas, oil betas, and return variances respond asymmetrically to oil price changes. Interestingly, oil betas and return variances are more affected by oil price increases rather than decreases. Further, responses to changes in oil prices depend on a firm’s specific qualities, such as ROA, firm size, firm leverage (Mohanty, S.K. et al, 2013). Breaking down my analysis into subsectors help isolate differentiating factors.

The energy sector is an obvious choice because these companies use oil as resources for inputs and produce oil or petroleum products as outputs. Oil sits at the center of the energy sector. The S&P 500 defines its energy sector as “companies included in the S&P 500 that are
classified as members of the GICS sector.” The Global Industry Classification Standard energy sector is defined as “companies engaged in exploration & production, refining & marketing and storage & transportation of oil & gas and coal & consumable fuels.

The ticker for the S&P 500 energy sector is “SPN.”

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<th>CONSTITUENT TOTAL MARKET CAP [USD MILLIONS]</th>
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<tr>
<td>Max Market Cap</td>
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<tr>
<td>Min Market Cap</td>
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<tr>
<td>Mean Market Cap</td>
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<tr>
<td>Median Market Cap</td>
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</table>

I will further break down the energy sector into five different indices, based on subsectors: oilfield services, exploration and production, midstream, downstream, and integrated. These five custom indices will best represent each subsector and I will define them in terms of Bloomberg subsector definition and market cap. It is important for my research to study the different subsectors because a variety of questions surrounding the decrease in returns arises. For example, why did midstream returns decrease so much during the year of 2015? It was assumed that midstream companies would have supposed little exposure to a downfall in oil prices since the business model is set up comparable to a toll road, and contracts with exploration and production companies are generally long-term. Shouldn’t midstream companies be protected from this risk? Testing a midstream subsector could reveal if the decrease in midstream returns was due to oil price risk or some other risk factor.

In terms of oil price returns, I will use West Texas Intermediate (WTI) historical spot prices quoted in dollars obtained from NYMEX. The underlying physical asset is domestic crude...
oil, which is quoted for immediate delivery in the Cushing, Oklahoma trading center. WTI is light and sweet, produced in Texas and Oklahoma (Hammoudeh & Huimin, 2004).

By analyzing the varying exposure to oil price risk through these subsectors, companies can better prepare for falls in oil prices in terms of maintaining returns.

**DATA**

The data used in this study include time-series monthly return data covering a 72-month period from January, 2010 through December, 2015, for The Standard & Poor’s 500 Index, West Texas Intermediate crude, Brent crude, and individual companies, sourced from Bloomberg.

The Standard & Poor’s 500 Index (SPX) was used as a proxy for the market, comprising 500 companies chosen by the S&P Index Committee based on size, liquidity, and industry grouping. The SPX is designed to act as a leading indicator of U.S. equities and therefore provides a good representation of the U.S. market.

West Texas Intermediate (WTI) crude oil is considered light and sweet crude that can easily be refined. WTI crude acts as the underlying commodity of NYMEX’s oil futures contracts, and is deliverable in Cushing, Oklahoma. The futures price is quoted for delivering a specific quantity of WTI crude at a specific time and place in the future. The futures price, rather than the spot price, was used as markets are forward looking. WTI spot price refers to the price quoted for immediate delivery at the Cushing, Oklahoma trading center. The data was pulled from Bloomberg over a 72-month historical period, quoted in dollars and cents. The Bloomberg ticker is CL1 COMB COMDTY.

Brent crude oil is considered sweet and easy to refine. The Brent crude commodity used as the underlying commodity for ICE futures contracts refers to the North Sea forward and spot
market, representing Brent, Forties, Oseberg, and Ekofisk crudes. The data was pulled from Bloomberg over a 72-month historical period, quoted in dollars and cents. The Bloomberg ticker is CO1 COMDTY.

In mid-2010, WTI began trading at a discount to Brent due to the unconventional shale oil revolution, resulting in an oversupply of WTI and arbitrage. However, pipeline conversions and new pipelines reduced this issue and stabilized WTI to fall just below parity. I calculated the spread between Brent and WTI as the difference between the CO1 COMDTY and the CL1 COMB COMDTY. Then, I calculated monthly returns based off the spread prices.

Finally, the data that makes up my five subsector indices was pulled from Bloomberg over a 72-month historical period. These companies include: Schlumberger Ltd (SLB), Halliburton Co (HAL), Baker Hughes Inc (BHI), National Oilwell Varco Inc (NOV), Cameron International Corp (CAM), ConocoPhillips (COP), Occidental Petroleum Corp (OXY), Anadarko Petroleum Corp (APC), Chesapeake Energy Corp (CHK), Apache Corp (APA), Plains All American Pipeline LP (PAA), Enterprise Products Partners (EPD), Energy Transfer Equity LP (ETE), Sunoco Logistics Partners LP (SXL), NGL Energy Partners (NGL), Global Partners LP (GLP), Kinder Morgan Inc (KMI), Oneok Inc (OKE), Williams Companies Inc (WMB), Enbridge Energy Partners LP (EEP), Targa Resources Partners LP (NGLS), Phillips 66 (PSX), Valero Energy Corp (VLO), Marathon Petroleum Corp (MPC), World Fuel Services Corp (INT), Tesoro Corp (TSO), Exxon Mobil Corp (XOM), Chevron Corp (CVX), Murphy Oil Corp (MUR), CVR Energy (CVI), and HollyFrontier Corp (HFC).

All subsectors include the five largest companies based on market capitalization as categorized by Bloomberg; however, the midstream subsector contains 11 companies. The reasoning behind this decision stems from the significant unexpected drop in the returns from
major midstream companies following the drastic decline in oil prices in June 2014. One would expect exploration and production companies to have the most exposure to a decline in oil prices, but the midstream sector still took a significant hit as well. Since midstream companies provide piping services, and essentially act as a highway, a decline in midstream returns such as the decline actually experienced is perplexing. By adding more companies to my midstream index, the analysis covers a more accurate set of midstream data. Also, note that some midstream companies are master limited partnerships (MLPs).

**HYPOTHESES**

My background research led me to test two sets of hypotheses. For the first test, I analyzed the significance of the S&P 500 and oil variables against my indexes. This also set up my second hypothesis and allowed for analysis. Testing the second hypothesis analyzed the difference in exposure to oil price risk between different indices.

_Hypothesis 1: The S&P 500 and the oil price variables have a statistically significant effect on energy subsector equity returns._

\[ H_0: \beta_1 = 0 \quad H_A: \beta_1 \neq 0 \quad \text{at } \alpha = 0.05 \]

\[ \beta_2 = 0 \quad \beta_2 \neq 0 \]

where:

\( \beta_1 \) is the beta associated with the SPX factor

\( \beta_2 \) is the beta associated with the oil price risk factor

_Hypothesis 2: Different energy industry subsectors face differing levels of oil price risk._

\[ H_0: \beta_i = \beta_j \quad H_A: \beta_i \neq \beta_j \quad \text{at } \alpha = 0.05 \]

where:
$\beta_i$ is the beta associated with subsector $i$

$\beta_j$ is the beta associated with subsector $j$

Subsector $i$ is either the oilfield services, exploration & production, midstream, downstream, or integrated subsector

Subsector $j$ is either the oilfield services, exploration & production, midstream, downstream, or integrated subsector

**METHODOLOGY**

The analysis of the relationship between independent and dependent variables in my study requires two tests: regressions and t-tests. The first test I performed was a regression analysis.

Regression analysis is the statistical process for measuring the relationship among variables in time series data. Regressions are performed to observe the variation of a response variable through one or more explanatory variables (Hardle & Simar, 2015). Single variable regression uses one dependent and one independent variable, while multivariate regression tests one dependent variable against two or more independent variables. I ran three multivariate regressions for each subsector, with the SPX index as a proxy for the market. The secondary independent variables include WTI crude historical six year monthly returns, Brent crude historical six year monthly returns, and the Brent-WTI crude spread historical six year monthly returns. Moving forward, I will classify these tests through three scenarios:

<table>
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<th>Scenarios</th>
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<td>(1)</td>
<td>SPX</td>
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<tr>
<td>(2)</td>
<td>SPX</td>
<td>Brent</td>
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<tr>
<td>(3)</td>
<td>SPX</td>
<td>Spread</td>
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</tbody>
</table>
I used a multivariate approach because in the CAPM, market risk is the only systemic risk factor accounted for. Although my study focuses on the APT, CAPM is still regarded as the most widely accepted pricing model, which makes including a market proxy in regression analysis relevant.

After I ran my regressions using Microsoft Excel, there were two resulting betas—one beta for each x (independent) variable. These betas could explain the relationship between the independent and dependent variables. Put in other words, the betas describe to us how much the independent variables affect the returns of each of the five indices. However, betas must also be tested for statistical significance to see if they really do differ from zero.

To test this, I performed a t-test. The t-test is a form of hypothesis testing that examines two sets of data and their means to determine whether the independent variable data and the dependent variable data are statistically significant from one another. The null hypothesis states that the beta is equal to 0, while the alternate states that the beta is statistically different from 0.

There are two methods of t-tests. One is comparing the t-stat to the t-critical value, and the other is comparing the p-value to the alpha level.

Next, I obtained my t-stat. The t-stat can be calculated by dividing the beta by the standard error. Excel regression analysis also outputs a t-stat. Once I obtained my t-stat, I calculated my t-critical values. The t-critical values are calculated using a t distribution table. If the t-stat is within the critical region, then we do not reject the null. However, if the t-stat falls outside the limits of the critical region, we reject the null.

I also compared p-values to the alpha level. This is an alternative to comparing t-stats to t-critical values. The p-value is essentially the chance that the beta could be what was calculated
from the regression if the null were not rejected and the betas were not statistically significant. If the p-value is less than alpha, the null is rejected and the beta is statistically different from 0.

Once I tested for statistical significance between the energy industry subsectors and the SPX and oil price risk factors, I tested for differing levels of exposure to oil price risk between the different subsectors, addressing hypothesis 2.

To begin, I calculated a t-stat for combinations of two subsectors, for of all of the indices.

\[
\frac{\beta_i - \beta_j}{\sqrt{\sigma^2_p}}
\]

where:

- \(\beta_i\) is the beta associated with subsector \(i\)
- \(\beta_j\) is the beta associated with subsector \(j\)
- Subsector \(i\) is either the oilfield services, exploration & production, midstream, downstream, or integrated subsector
- Subsector \(j\) is either the oilfield services, exploration & production, midstream, downstream, or integrated subsector
- \(\sigma^2_p\) is the pooled standard deviation for subsector \(i\) and subsector \(j\)

Once I calculated a t-statistic, I tested the t-stat by comparing p-values to the alpha level of 0.05.
DISCUSSION

Hypothesis 1

After performing regressions, t-tests, and p-tests, the results are as follows for hypothesis 1. Note that the top line of the table denotes the three different scenarios that were tested.

Scenario 1 includes the SPX as x variable 1, and WTI crude as x variable 2; scenario 2 includes the SPX as x variable 1, and Brent crude as x variable 2; scenario 3 includes SPX as x variable 1, and the spread between Brent and WTI crude as x variable 2. Significant betas are bolded in the tables below. Note that oilfield services and exploration and production are abbreviated by OFS and E&P respectively.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Beta</th>
<th>t-stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>OFS (1)</td>
<td>0.96</td>
<td>5.24</td>
<td>0.00</td>
</tr>
<tr>
<td>OFS (2)</td>
<td>0.98</td>
<td>5.25</td>
<td>0.00</td>
</tr>
<tr>
<td>OFS (3)</td>
<td>1.47</td>
<td>7.50</td>
<td>0.00</td>
</tr>
<tr>
<td>E&amp;P (1)</td>
<td>0.92</td>
<td>5.73</td>
<td>0.00</td>
</tr>
<tr>
<td>E&amp;P (2)</td>
<td>0.92</td>
<td>5.73</td>
<td>0.00</td>
</tr>
<tr>
<td>E&amp;P (3)</td>
<td>1.35</td>
<td>7.96</td>
<td>0.00</td>
</tr>
<tr>
<td>Midstream (1)</td>
<td>0.54</td>
<td>3.63</td>
<td>0.00</td>
</tr>
<tr>
<td>Midstream (2)</td>
<td>0.55</td>
<td>3.66</td>
<td>0.00</td>
</tr>
<tr>
<td>Midstream (3)</td>
<td>0.86</td>
<td>5.82</td>
<td>0.00</td>
</tr>
<tr>
<td>Downstream (1)</td>
<td>1.47</td>
<td>6.53</td>
<td>0.00</td>
</tr>
<tr>
<td>Downstream (2)</td>
<td>1.36</td>
<td>6.13</td>
<td>0.00</td>
</tr>
<tr>
<td>Downstream (3)</td>
<td>1.56</td>
<td>8.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Upstream (1)</td>
<td>0.07</td>
<td>0.64</td>
<td>0.52</td>
</tr>
<tr>
<td>Upstream (2)</td>
<td>0.07</td>
<td>0.64</td>
<td>0.52</td>
</tr>
<tr>
<td>Upstream (3)</td>
<td>0.07</td>
<td>0.64</td>
<td>0.52</td>
</tr>
<tr>
<td>FS/PD A</td>
<td>-0.14</td>
<td>-0.74</td>
<td>0.46</td>
</tr>
<tr>
<td>E&amp;P (1)</td>
<td>0.48</td>
<td>5.42</td>
<td>0.00</td>
</tr>
<tr>
<td>E&amp;P (2)</td>
<td>0.48</td>
<td>5.57</td>
<td>0.00</td>
</tr>
<tr>
<td>E&amp;P (3)</td>
<td>0.43</td>
<td>5.57</td>
<td>0.00</td>
</tr>
<tr>
<td>Midstream (1)</td>
<td>0.31</td>
<td>4.58</td>
<td>0.00</td>
</tr>
<tr>
<td>Midstream (2)</td>
<td>0.31</td>
<td>4.43</td>
<td>0.00</td>
</tr>
<tr>
<td>Midstream (3)</td>
<td>0.31</td>
<td>4.34</td>
<td>0.00</td>
</tr>
<tr>
<td>Downstream (1)</td>
<td>0.37</td>
<td>6.53</td>
<td>0.00</td>
</tr>
<tr>
<td>Downstream (2)</td>
<td>0.37</td>
<td>6.13</td>
<td>0.00</td>
</tr>
<tr>
<td>Downstream (3)</td>
<td>0.37</td>
<td>8.07</td>
<td>0.00</td>
</tr>
<tr>
<td>Upstream (1)</td>
<td>0.31</td>
<td>0.64</td>
<td>0.09</td>
</tr>
<tr>
<td>Upstream (2)</td>
<td>0.31</td>
<td>0.64</td>
<td>0.09</td>
</tr>
<tr>
<td>Upstream (3)</td>
<td>0.31</td>
<td>0.64</td>
<td>0.09</td>
</tr>
<tr>
<td>FS/PD A</td>
<td>0.07</td>
<td>-0.50</td>
<td>0.62</td>
</tr>
<tr>
<td>E&amp;P (1)</td>
<td>0.07</td>
<td>1.74</td>
<td>0.09</td>
</tr>
<tr>
<td>E&amp;P (2)</td>
<td>0.07</td>
<td>1.93</td>
<td>0.06</td>
</tr>
<tr>
<td>E&amp;P (3)</td>
<td>0.07</td>
<td>1.93</td>
<td>0.06</td>
</tr>
</tbody>
</table>
For the OFS index, I found that the S&P 500 is a statistically significant risk factor. That means that the SPX has a significant effect on the returns of companies in the OFS subsector. This is also known as “market risk.” In scenarios 1 and 2, the p-values were extremely low: 2.11e-7 and 8.35e-7 respectively. Since these p-values were so much lower than the alpha level of 0.05, we reject the null; WTI and Brent crude are significant risk factors in the OFS subsector.

However, scenario 3 is a different story. The p-value is 0.46, which is greater than the alpha level of 0.05 and yields the inability to reject the null; the spread might not be a systematic risk factor in the OFS subsector.

In the E&P, midstream, and integrated subsectors, my results mirrored those of the OFS subsector. The S&P 500 was a proven systemic risk factor, and the p-values of WTI and Brent returns were lower than the alpha level of 0.05. For scenarios 1 and 2 in the E&P, midstream, and integrated subsectors, we reject the null. The p-value for the spread in scenario 3 resulted in an inability to reject the null for all three aforementioned subsectors.

In the downstream index, only one independent variable I tested was statistically significant: the S&P 500. The p-values for scenarios 1, 2, and 3 were 0.52, 0.09, and 0.06 respectively. All of these values exceed the alpha level of 0.05 and result in an inability to reject the null.
The S&P 500 affects all five indices I tested. This is no surprise, and is somewhat of a strawman hypothesis. Market risk is a widely accepted concept throughout the finance world.

Although the SPX penetrates all five indices, WTI and Brent only statistically affect four of the five: OFS, E&P, midstream, and integrated. The downstream subsector is not affected by the oil independent variables. Finally, the spread is not a statistically significant risk factor in any of the five indices.

**Hypothesis 2**

Hypothesis 2 tested whether or not there is a difference in exposure to oil price risk between the five subsectors. I tested combinations of: OFS and E&P; OFS and midstream; OFS and downstream; OFS and integrated; E&P and midstream; E&P and downstream; E&P and integrated; midstream and downstream; midstream and integrated; and downstream and integrated. I tested these ten combinations for differing exposures to WTI, Brent, and the spread.

The results are explained below, and the significant findings are bolded in the tables.

<table>
<thead>
<tr>
<th>WTI Sector, i</th>
<th>OFS</th>
<th>OFS</th>
<th>OFS</th>
<th>OFS</th>
<th>E&amp;P</th>
<th>E&amp;P</th>
<th>E&amp;P</th>
<th>Midstream</th>
<th>Midstream</th>
<th>Downstream</th>
<th>Integrated</th>
</tr>
</thead>
<tbody>
<tr>
<td>β_i</td>
<td>0.4801</td>
<td>0.4801</td>
<td>0.4801</td>
<td>0.4801</td>
<td>0.4075</td>
<td>0.4075</td>
<td>0.4075</td>
<td>0.3085</td>
<td>0.3085</td>
<td>0.0658</td>
<td></td>
</tr>
<tr>
<td>β_j</td>
<td>0.4075</td>
<td>0.3085</td>
<td>0.0656</td>
<td>0.3519</td>
<td>0.3085</td>
<td>0.0656</td>
<td>0.3519</td>
<td>0.0656</td>
<td>0.3519</td>
<td>0.3519</td>
<td></td>
</tr>
<tr>
<td>β_i - β_j</td>
<td>0.0726</td>
<td>0.1716</td>
<td>0.4143</td>
<td>0.1282</td>
<td>0.0990</td>
<td>0.3418</td>
<td>0.0556</td>
<td>0.2428</td>
<td>-0.0434</td>
<td>-0.2861</td>
<td></td>
</tr>
<tr>
<td>σ_i</td>
<td>0.0833</td>
<td>0.0833</td>
<td>0.0833</td>
<td>0.0833</td>
<td>0.0731</td>
<td>0.0731</td>
<td>0.0731</td>
<td>0.0674</td>
<td>0.0674</td>
<td>0.1023</td>
<td></td>
</tr>
<tr>
<td>σ_j</td>
<td>0.0731</td>
<td>0.0674</td>
<td>0.1023</td>
<td>0.0670</td>
<td>0.0674</td>
<td>0.1023</td>
<td>0.0670</td>
<td>0.1023</td>
<td>0.0670</td>
<td>0.0670</td>
<td></td>
</tr>
<tr>
<td>σ^2 pooled</td>
<td>0.0061</td>
<td>0.0057</td>
<td>0.0087</td>
<td>0.0057</td>
<td>0.0049</td>
<td>0.0079</td>
<td>0.0049</td>
<td>0.0075</td>
<td>0.0045</td>
<td>0.0075</td>
<td></td>
</tr>
<tr>
<td>t-stat</td>
<td>0.9258</td>
<td>2.2652</td>
<td>4.4428</td>
<td>1.6962</td>
<td>1.4089</td>
<td>3.8453</td>
<td>0.7937</td>
<td>2.8037</td>
<td>-0.6460</td>
<td>-3.3106</td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.3562</td>
<td>0.0250</td>
<td>0.0000</td>
<td>0.0921</td>
<td>0.1611</td>
<td>0.0002</td>
<td>0.4287</td>
<td>0.0058</td>
<td>0.5193</td>
<td>0.0012</td>
<td></td>
</tr>
</tbody>
</table>

When comparing the exposures to WTI prices, I did not reject the null for the following combinations: OFS and E&P; OFS and integrated; E&P and midstream; E&P and integrated; and midstream and integrated. These combinations produced a p-value that was greater than the alpha level of 0.05. I rejected the null for the following combinations, because the p-values were
less than the alpha level 0.05: OFS and midstream; OFS and downstream; E&P and downstream; midstream and downstream; and downstream and integrated.

For all combinations involving the downstream subsector, we rejected the null, which means that there is a statistically significant difference between the betas within these combinations. The exposure levels to WTI crude differ between these companies.

For the companies for which we did not reject the null, this means that we cannot state that the exposure levels are not equal; there is a possibility that the exposure to WTI between these combinations of companies is equal. For all combinations involving integrated companies, we did not reject the null. Perhaps the explanation lies in the fact that they are diversified, performing all functions throughout the oil supply chain.

<table>
<thead>
<tr>
<th>Brent Sector</th>
<th>OFS</th>
<th>E&amp;P</th>
<th>Midstream</th>
<th>Downstream</th>
<th>Integrated</th>
</tr>
</thead>
<tbody>
<tr>
<td>β_i</td>
<td>0.4798</td>
<td>0.4251</td>
<td>0.0547</td>
<td>0.0886</td>
<td>0.0763</td>
</tr>
<tr>
<td>β_j</td>
<td>0.4798</td>
<td>0.3138</td>
<td>0.1660</td>
<td>0.0866</td>
<td>0.0708</td>
</tr>
<tr>
<td>β_i - β_j</td>
<td>0.0547</td>
<td>0.1660</td>
<td>0.0948</td>
<td>0.0708</td>
<td>0.0705</td>
</tr>
<tr>
<td>σ_i</td>
<td>0.0886</td>
<td>0.0786</td>
<td>0.0786</td>
<td>0.0736</td>
<td>0.0736</td>
</tr>
<tr>
<td>σ_j</td>
<td>0.0763</td>
<td>0.0708</td>
<td>0.1047</td>
<td>0.0708</td>
<td>0.1047</td>
</tr>
<tr>
<td>σ^2 pooled</td>
<td>0.0065</td>
<td>0.0094</td>
<td>0.0094</td>
<td>0.0094</td>
<td>0.0094</td>
</tr>
<tr>
<td>t-stat</td>
<td>0.6624</td>
<td>2.0702</td>
<td>3.0711</td>
<td>1.7924</td>
<td>1.5120</td>
</tr>
<tr>
<td>p-value</td>
<td>0.5088</td>
<td>0.0403</td>
<td>0.0026</td>
<td>0.1328</td>
<td>0.1089</td>
</tr>
</tbody>
</table>

I was unable to reject the null for most combinations when analyzing differing exposures to Brent. I did not reject the null for the following combinations: OFS and E&P; OFS and integrated; E&P and midstream; E&P and integrated; midstream and downstream; midstream and integrated; and downstream and integrated. I rejected the null for the combinations of: OFS and midstream; OFS and downstream; and E&P and downstream.

Since Brent is more of a global benchmark for oil, and I looked at primarily American companies, this could be a reason that I did not reject the null for more combinations than I did.
for WTI combinations. However, the depth of my testing does not reveal the reason the null was or was not rejected, only whether it was or not.

For testing the spread, my analysis yielded somewhat similar results. The null was rejected for the following combinations: OFS and E&P; OFS and midstream; OFS and integrated; E&P and midstream; E&P and integrated; and midstream and integrated. We rejected the null for the following combinations: OFS and downstream; E&P and downstream; midstream and downstream; and downstream and integrated.

Once again, all downstream combinations rejected the null and proved statistical significance. Although the spread did not prove a significant risk factor in any of the subsectors, the downstream spread p-value was the closest to the alpha level of 0.05, at 0.057. This makes sense that the combinations involving downstream companies saw a significant difference in exposure levels to the spread. Every other combination that did not involve downstream did not reject the null.

Perhaps the most interesting result that my data yielded was the inability to reject the null for the combinations of E&P and midstream. At the beginning of my research, I expected to see differences in levels of exposure due to the way that the businesses operate—they are completely different business models. However, I found that the exposure to oil price risk could be the same
for midstream companies and E&P companies. This could explain why many midstream companies’ stock prices decreased so significantly since the 2014 decline in oil prices.

In summary, hypothesis 2 yielded mixed results. Out of my 30 tests, I did not reject the null for 18 combinations of subsectors. The tables below summarize the results of my tests for hypothesis 2. Note that “do not reject” is abbreviated by DNR.

**IMPLICATIONS**

Although my tests yielded concrete results, there is still room to expand in the future. In order to gain a more clear perspective of the role that oil plays in the economy, more research is needed on the topic of oil price risk.

To expand on this topic, the first change that needs to be addressed is the amount of data used. There are two primary reasons that more data should be incorporated: first, since I only analyzed 72 months of data, I did not capture a lot of market cycles. Second, adding more companies to my indices and adding more sectors (industrials, financials, transportation, etc.) to my analysis would allow for a greater slice of the market represented and analyzed, as opposed to only researching the energy sector.

Regarding hypothesis 1, I found that oil price risk is not a significant risk factor in the downstream subsector. The business model of most downstream companies relies on the “crack spread,” which is the spread between the price of oil and gasoline. Using the crack spread as an
independent variable in regression testing could yield different results for downstream companies.

Analyzing the capital structure of the companies involved would also be helpful for further testing. For example, most midstream companies are structured as a master limited partnership (MLP) which is a tax efficient structure that offers distributions to shareholders. The MLP structure is very popular in the midstream subsector, and this could play a role in the lack of difference in exposure to WTI between E&P and midstream companies.

My findings suggest that oil price risk does play somewhat of a role in the energy industry. This supports Kenealy’s suggestion that risk management will become increasingly more important for energy companies in the future (Kenealy, 2015). Because of its role in the energy industry, this increased energy risk should urge energy professionals to evaluate business decisions more closely.

CONCLUSION

As I watched oil prices fall from my desk at a midstream company during the summer of 2014, I couldn’t help but ask what would happen to the energy sector should they keep falling. In 2016, WTI crude dipped below $27, from its June 2014 high of $108.37. Because of this, many energy companies saw a decline in returns and faced bankruptcy risk.

In order to answer my own questions, I tested my two hypotheses. I found that WTI and Brent are significant risk factors in the exploration and production, oilfield services, midstream, and integrated subsectors. However, the spread between Brent crude and WTI crude is not a significant risk factor. Downstream companies face no exposure to WTI, Brent, or the spread.
My second hypothesis tested the difference in exposures to WTI, Brent, and the spread between the energy subsectors. Some combinations of companies had different levels of exposure, while others did not.

After discussing the underlying financial and economic theories and presenting my results, a final picture will put this research in context. The chart below shows the value of a dollar invested in my E&P, OFS, midstream, downstream, and integrated indices. Also included in the chart is the value of a dollar invested in WTI, Brent, the spread, and the S&P 500 index.

![Chart showing value of $1 invested](chart.png)

By glancing at this chart, one can see that a single subsector has outperformed all of the others: the downstream subsector. With that being said, keep in mind that the downstream sector was the only sector to not be significantly affected by oil price risk.

This means that investors anticipating a return to $100 oil, investing in either an oilfield services, exploration and production, midstream, or integrated company would provide the most value, since these companies are exposed to oil price risk. However, since integrated companies could be exposed to the downstream subsector, which has no oil price risk, then a better investment could be a company in the OFS, E&P, or midstream subsectors. On the contrary, in a
low-oil price environment, investing in a downstream company would be the best alternative as it is not exposed to WTI crude or Brent crude risk.

In conclusion, many of the subsectors are affected by oil price (WTI and Brent) risk. Some of the sectors differ in level of exposure, but determining the underlying reasons will require further research. As oil prices stabilize or recover, companies in the oilfield services, exploration and production, midstream, and integrated sectors will see significant change, and should take into consideration oil price fluctuations when making future business decisions due to the systematic oil risk observed in this study.
REFERENCES


