How Can Oil Suppliers Hedge Against Future Losses From Oil Prices Through Their Stock Portfolios?

by

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Abstract:

This study examines the use of the Student T distribution in hedging against losses from oil prices in a company's stock portfolio. A comprehensive literature review was conducted to examine previous research on the relationship between energy prices and stock prices, and the feasibility of hedging stocks with oil. Using a historical simulation and the Student T distribution, the effectiveness of hedging with various ETFs was evaluated based on data from October 8, 2018 to October 8, 2022. The results of the analysis highlight the importance of the Student T distribution in accurately evaluating the effectiveness of hedging strategies and the usefulness of TLT as an effective ETF for hedging against oil price losses.

Introduction:

Hedging against fluctuations in oil prices is a critical concern for many companies, as large price changes can have significant impacts on their business. Previous research has examined the relationship between energy prices and stock prices, and the feasibility of using oil as a hedge for stock portfolios. However, these studies have primarily used traditional distributions such as the normal distribution to evaluate hedging effectiveness. This study aims to explore the use of the Student T distribution in hedging against losses from oil prices in a company's stock portfolio. The Student T distribution is known to capture tail values more accurately, which can be important in accurately assessing risk in financial markets. By using the Student T distribution, this study aims to provide a more accurate evaluation of the effectiveness of hedging against oil price losses.

Methodology:

Literature Review

Hedging against oil price fluctuations is important for many companies, as large price fluctuations can have a significant impact on their business. Previous research has examined the relationship between energy prices and stock prices, and the feasibility of hedging stocks with oil.

Batten etc. (2017) examined the relationship between energy and stock prices in the context of Asia, including China and Japan. The study found that Asian stock markets tend to follow oil prices, in line with what the international markets are reading. However, the study also identified time-varying consolidations between individual stock market and energy portfolios, which may limit the benefits of diversification in terms of risk mitigation. The study also finds that this relationship can be used to hedge common factors arising from energy risk, providing investors with positive time-varying risk-adjusted returns.

In a follow-up study, Batten et al. (2019) examined the feasibility of hedging equities with oil using a dynamic conditional correlation (DCC) approach. The results of this study showed that there are economic benefits to hedging equities with oil, although hedging effectiveness is dependent on time and market conditions. The study also found that the Global Financial Crisis (GFC) event impacted hedging effectiveness, leading to a positive rise in hedge ratios and increased hedging effectiveness during this period. The study identified the Implied Volatility Index VIX as the most important factor among a set of common financial and macroeconomic factors. The VIX shock will negatively impact equity oil hedge portfolio returns during a time of global financial uncertainty. The study finds that the appreciation of the US dollar against the euro is associated with lower hedge portfolio returns, and that gold prices and maturity spreads are important in explaining hedge portfolio returns after the global financial crisis. also became clear.

Lee and Chiou (2011) developed his two-step methodology for studying the impact of oil shocks on stock returns. Using a regime-switching model to account for jumps, the study found that large fluctuations in oil prices (West Texas Intermediate; WTI) have a negative impact on S&P 500 returns. However, the same result did not hold in a regime with low oil price volatility. The study suggests that a well-diversified portfolio should take into account oil price shocks to improve the accuracy of oil price risk hedging.

Halfawi et al. (2019) used daily data from 2010 to 2016 to analyze volatility spillover between oil and equity markets in oil importing and oil exporting countries. In this study, we used symmetric and asymmetric versions of dynamic conditional correlation (DCC) and modified DCC (cDCC).) Portfolio consideration and hedging implications from the GARCH model. The results show that oil importing countries were severely affected by delayed oil price shocks, with less evidence of equity market interdependence in both oil importing and oil exporting countries. The study also found that delayed oil price shocks negatively affected stock markets in oil importing countries, while stock markets in oil exporting countries were more affected by the current oil price shock. The study concluded that oil importing countries could benefit from hedging strategies to mitigate the impact of oil price shocks on their stock markets.

Overall, previous studies have explored the relationship between energy prices and stock prices, and the feasibility of hedging stocks with oil. The results of these studies suggest that hedging equities with oil may yield economic returns, but the effectiveness of such hedging strategies will vary depending on market conditions and other factors. There are cases. There is also evidence that oil importing countries may be more vulnerable to oil price shocks and could benefit from hedging strategies to reduce the impact of such shocks on their stock markets. Our study builds on this body of knowledge by examining the use of adjusted close price data and log returns to analyze the performance of various ETFs as potential hedges against oil price volatility. Our hypothesis is that government bonds represented by the ticker TLT could be a good option to hedge oil price volatility given their inverse correlation with yields. By analyzing the performance of TLT and other ETFs using log returns, we aim to provide insight into the most appropriate options for hedging oil price volatility using an equity portfolio.

Experiment:

Modeling

Correlation heatmap

A Correlation Heat Map is a graphical representation of the correlation of stock prices across multiple stocks. It is used to analyze the relationships between the stocks, and how their prices move in relation to one another. The heat map shows the correlations between the stocks by coloring each cell according to its correlation coefficient. The correlation coefficient ranges from -1 to 1, where -1 indicates a perfect negative correlation, 0 indicates no correlation, and 1 indicates a perfect positive correlation. White indicates a positive correlation, while black indicates a negative correlation. By analyzing the correlation heat map, investors can identify which stocks move in sync with each other, and which ones move in the opposite direction. This helps them form a better understanding of the stock market and make more informed decisions. An example of a correlation heatmap is shown below(Figure 1). After testing many tickers using a brute force algorithm, TLT was determined to be one of the best tickers to hedge against oil with. As the (United States Oil ETF)USO decreases, (iShares 20 Plus Year Treasury Bond ETF)TLT has a trend of increasing which is an observation that can be used for hedging.

Figure 1. A heat map showing the correlation between the three assets: TLT, USO, and ZM.

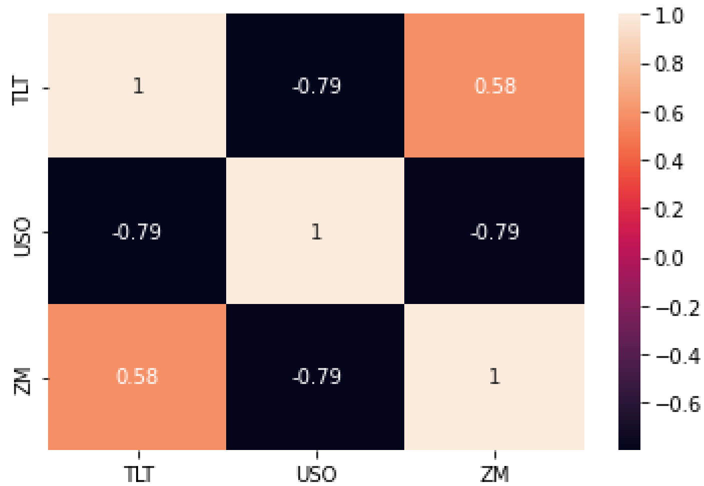


Figure 2. A line graph with log returns on the y-axis and dates on the x-axis.

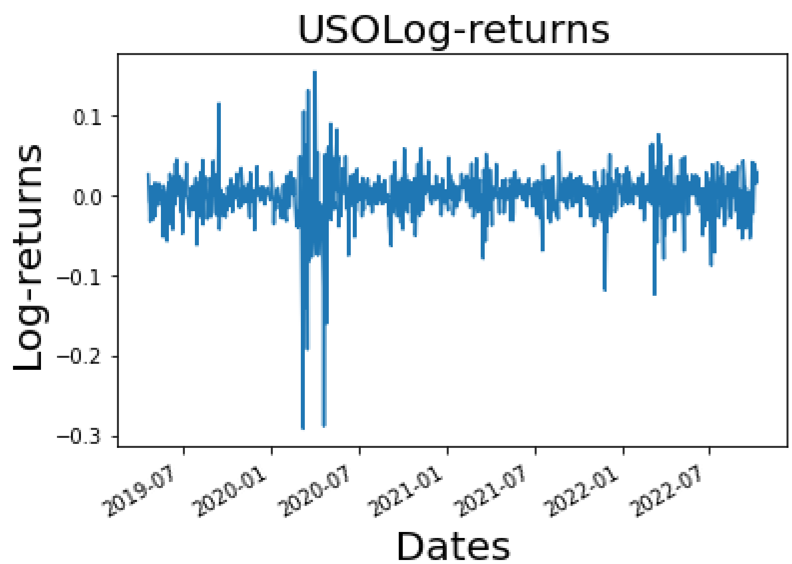
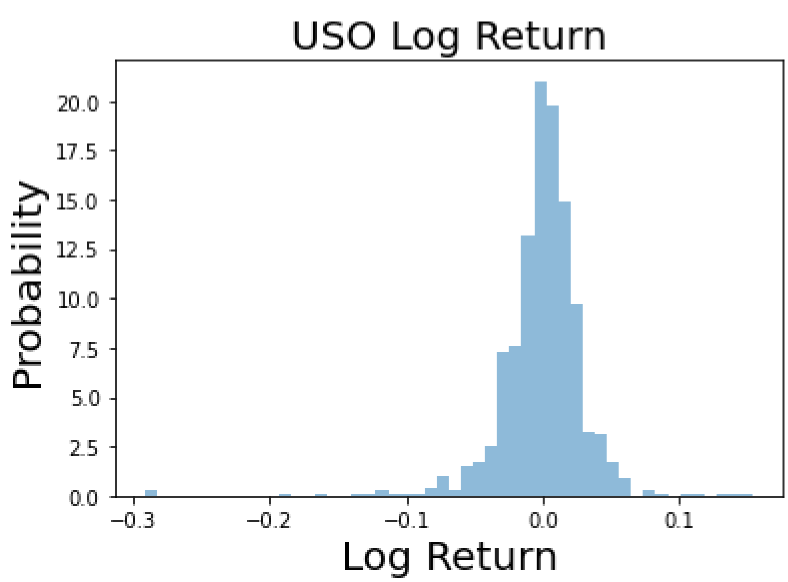


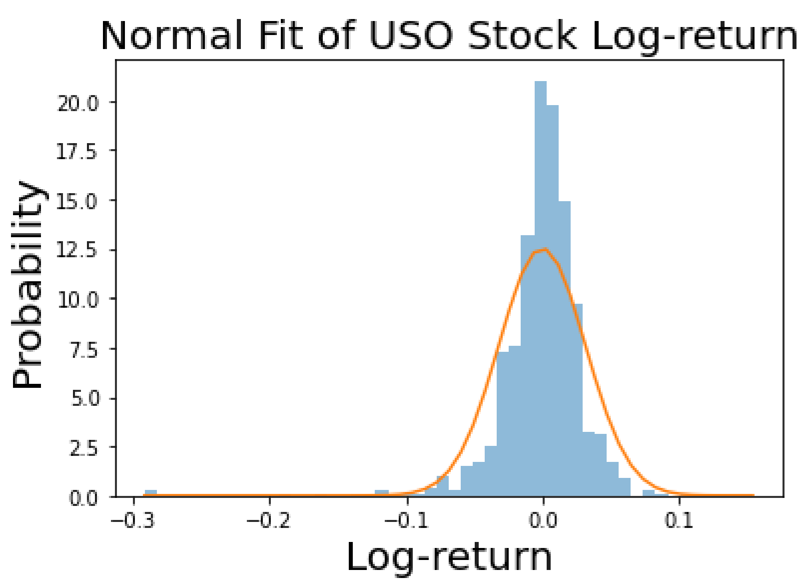
Figure 3. A histogram of USO stock log returns with probability on the y-axis and log returns on the x-axis.



Normal Distribution

After the data is prepared as shown in(Figure 2 & Figure 3) using the log returns from October 8, 2018 to October 8, 2022, it is plotted on a histogram with the x-axis indicating the log return and the y-axis indicating the probability. The data is relatively symmetrical and doesn't have a strong left or right skew. Next a normal distribution bell curve is fitted into the data. The normal distribution bell curve models the data with increasing accuracy as the data is farther from the center. Subsequently, the bell curve does not model the data accurately towards the center of the plot. It is evident that the normal distribution bell curve does not accurately model the data.

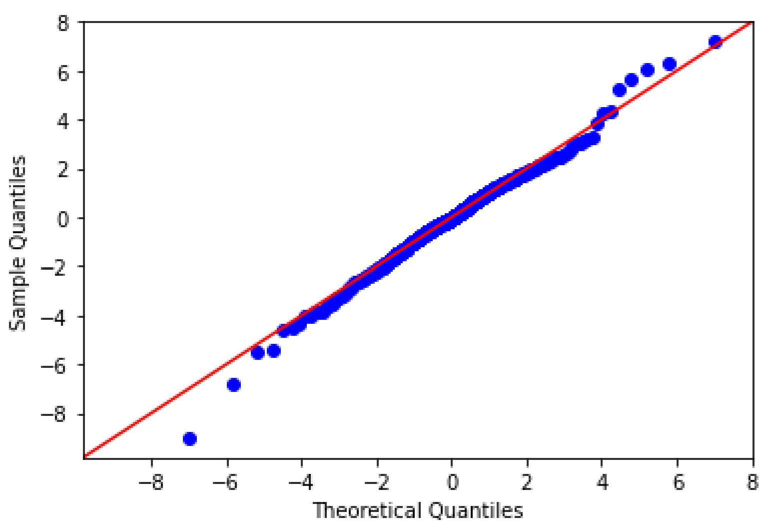
Figure 4. A histogram of USO stock log returns with a normal distribution fit line, showing probability on the y-axis and log returns on the x-axis.



QQ plot

A quantile-quantile plot (or Q-Q plot) is a graphical tool used to compare two probability distributions. In this project we use it to display the sample quantiles of one distribution on the vertical axis and the corresponding theoretical quantiles of a reference distribution on the horizontal axis. A Q-Q plot shows how the two distributions compare in terms of their quantiles by drawing a straight line that indicates how the sample quantiles and theoretical quantiles are related. This line should be approximately linear if the data follows the reference distribution. Since the line is not followed in Figure 5, it indicates that the data deviates from the reference distribution in some way. We wanted to measure the probability of extreme values using QQ Plot, since the probability of extreme values are not represented well on histograms. Based on the QQ plot we can determine that the normal distribution will not be accurate for the tail values of USO, so we would want to use the Student T distribution to accurately capture the tail values.

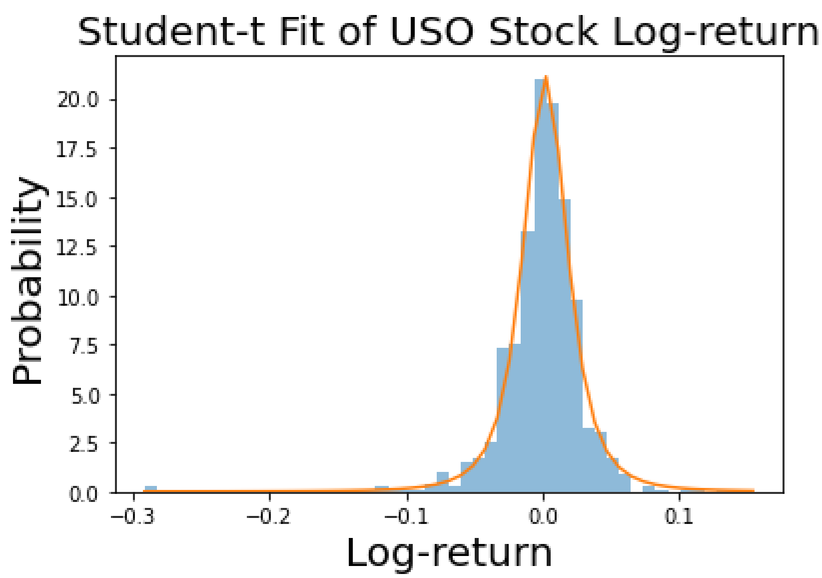
Figure 5. QQ plot of USO normal distribution.



Student-t Distribution

In order to get a more accurate bell curve that models the data without inaccuracy towards the center, we can use a t-fit of the log return data. The t-fit solves the problem of the normal distribution not modeling the data accurately in the center. This bell curve does have data in the histogram that exceeds the probability estimates of the bell curve. The Student-t Distribution captures the tail values of log returns better than the normal distribution.

Figure 6. A graph of a Student-t distribution fit of USO stock log returns.



Model Metrics

Value-at-Risk (VaR)

Value-at-Risk, commonly referred to as VaR measures the maximum loss in value of a given asset at a set time interval and confidence level. We can run a historical simulation and plot the log returns and probability on a histogram. The log returns would be plotted on the x-axis and the probability plotted on the y-axis. After doing so it becomes possible to calculate the Value-at-Risk(VaR) from the left tail of the distribution. The Value-at-Risk(VaR) would vary based on the time interval and confidence level, so in order to compare the Value-at-Risk(VaR) of different assets the time intervals and confidence levels should be equivalent.

Expected Shortfall (ES)

Expected Shortfall (ES) is a risk measure that quantifies the expected loss in value of an asset or portfolio beyond a certain confidence level. It is calculated as the average loss above the Value-at-Risk (VaR) threshold, which is the level at which the maximum loss is expected to occur at a given confidence level. ES is often used in combination with VaR as a more comprehensive measure of risk, as it takes into account not only the maximum expected loss, but also the likelihood and severity of losses beyond that threshold. This allows for a more accurate assessment of the potential risks and losses associated with an asset or portfolio.

Result/Finding:

Based on the results of our analysis, it can be concluded that the use of the Student T-distribution and considering both Value-at-Risk (VaR) and Expected Shortfall (ES) is an important factor in evaluating the effectiveness of hedging strategies. The correlation heat map helps to identify which ETFs are most effective at hedging against a particular risk, such as oil price losses. In this case, TLT was identified as the most effective ETF for hedging against oil price losses, with a strong inverse correlation to oil prices.

The results of the analysis of USO and TLT are presented in Tables 1 and 2, respectively. The tables show the quantile, Value-at-Risk (rVaR) and Expected Shortfall (rES) values for each significance level. At a 5% significance level, the rVaR for USO is 0.039775 and the rES is 0.067709, meaning that an amount equal to 0.039775 times the portfolio value needs to be set aside to prevent losses with a confidence level of 95%. On the other hand, the rVaR and rES for TLT are 0.016915 and 0.024066, respectively, at the same significance level. This suggests that a much smaller amount of capital needs to be set aside to hedge against oil price losses when incorporating TLT into the portfolio. The tables provide valuable information for companies to make informed decisions about their capital reserves and better manage the potential risks and losses associated with different ETFs.

Table 1. TLT Significance Level and corresponding Quantile, rVaR, rES values

Significance Level	Quantile	rVaR	rES
10%	-0.012528	0.012450	0.019270
5%	-0.017059	0.016915	0.024066
1%	-0.028388	0.027988	0.036832

Table 2. USO Significance Level and corresponding Quantile, rVaR, rES values

Significance Level	Quantile	rVaR	rES
10%	-0.027155	0.026790	0.050068
5%	-0.040588	0.039775	0.067709
1%	-0.084115	0.080674	0.124957

In Figure 7, we can see the Student-t fit of TLT stock log returns. The x-axis represents log returns, while the y-axis represents the density of the distribution. This figure shows the distribution of the log returns of TLT and how it fits the Student T-distribution, demonstrating the suitability of using the Student T-distribution to evaluate the risk of portfolio drawdown.

Figure 7. Student-t Fit of TLT Stock Log return(x-axis:Log Returns, y-axis:Density)

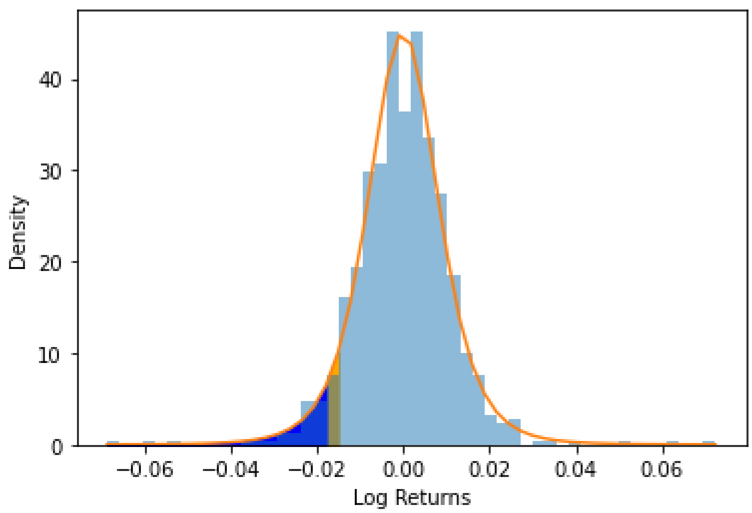
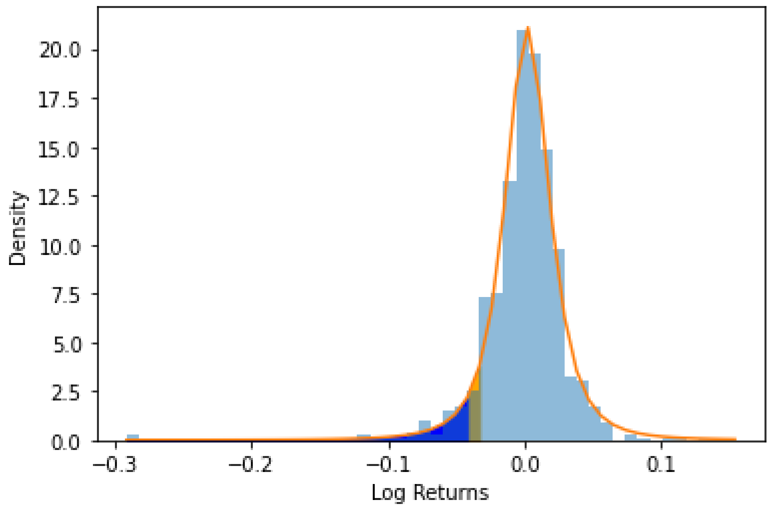


Figure 8. Student-t Fit of USO Stock Log return(x-axis:Log Returns, y-axis:Density)



Similarly, in Figure 8, we see the Student-t fit of USO stock log returns. The x-axis represents log returns, while the y-axis represents the density of the distribution. This figure shows the distribution of the log returns of USO and how it fits the Student T-distribution.

In conclusion, the results of my analysis highlight the importance of using the Student T-distribution and considering both VaR and ES when evaluating hedging strategies for portfolio drawdown. By doing so, companies can make more informed decisions about their capital reserves and better manage the potential risks and losses associated with different ETFs.

Limitation:

There are several limitations to my research that should be considered when interpreting the results. Firstly, my analysis is based on historical data and therefore may not accurately reflect future performance. While I attempted to control for the impact of the Global Financial Crisis and other macroeconomic events, it is possible that future events could have a different impact on the relationship between oil prices and stock prices.

Secondly, my analysis only considered a limited number of ETFs and therefore may not be representative of the entire market. It is possible that there may be other ETFs that are more effective at hedging against oil price losses that were not included in my analysis.

Thirdly, my analysis only looked at a specific time period, from 2018 to 2022. It is possible that the relationship between oil prices and stock prices may differ over other time periods.

Finally, my analysis was based on the use of log returns, which may not accurately reflect the true economic impact of price changes. It is possible that using different measures of returns, such as arithmetic returns, could lead to different conclusions.

Overall, these limitations suggest that the results of my research should be interpreted with caution, and further research may be necessary to fully understand the effectiveness of hedging against oil price losses in a stock portfolio.

Conclusion:

In conclusion, my research examined the feasibility of hedging against oil price losses in a stock portfolio through the use of ETFs. By analyzing the relationship between oil prices and stock prices and evaluating the effectiveness of different ETFs, I was able to identify TLT as the most effective ETF for hedging against oil price losses. My analysis highlighted the importance of considering the use of the Student T-distribution in evaluating the risk of portfolio drawdown, as well as both Value-at-Risk (VaR) and Expected Shortfall (ES) in assessing the potential risks and losses associated with different ETFs.

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