Effective Hedging Strategy for Investment Trading Firms in Response to US Oil Price Volatility

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***Abstract*— This study examines the use of an algorithmically computed Student T distribution in hedging against losses from oil prices in a Firm'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 exchange traded funds (ETFs) was evaluated based on data from October 8, 2018 through 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 iShares 20 Plus Year Treasury Bond ETF (TLT) as an effective ETF for hedging against oil price losses.**

Keywords—hedging, investment, oil price, volatility, computational finance

I. Introduction

Hedging against fluctuations in oil prices is a critical concern for many investment trading firms, as any large price changes in these prices can have significant impacts on their business and Firm's Portfolio. 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 the effectiveness of hedging. This study aims to explore the use of the algorithmically computed Student T distribution in hedging against losses from oil prices in Firm's stock portfolio. The Student T distribution is known to capture tail values more accurately, which can be important in accurately assessing the 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 losses incurred due to fall in oil price.

II. Methodology

Hedging against oil price fluctuations is important for many investment trading firms, as large price fluctuations can have a significant impact on their business and portfolio. Previous research has examined the relationship between energy prices and stock prices, and the feasibility of hedging stocks with oil. Below listed are earlier research and proposed methods for hedging strategies.

Batten et al examined the relationship between energy and stock prices in the context of Asia, including China and Japan [1]. 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. examined the feasibility of hedging equities with oil using a dynamic conditional correlation (DCC) approach [2]. 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.

Lee and Chiou developed their two-step methodology for studying the impact of oil shocks on stock returns [3]. 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.

Khalfaoui et al used daily data from 2010 to 2016 to analyze volatility spillover between oil and equity markets in oil importing and oil exporting countries [4]. In this study, they used symmetric and asymmetric versions of 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.

The volatility spillover between oil prices and stock sector returns is a crucial consideration for portfolio designs and risk management. Arouri et al conducted a study using a generalized VAR-GARCH approach to examine volatility transmission between oil and stock markets in Europe and the United States at the sector level [5]. Their findings revealed significant volatility spillover between oil and sector stock returns. In Europe, the spillover was primarily unidirectional from oil markets to stock markets, while in the United States, it was bidirectional. Back-testing procedures showed that incorporating cross-market volatility spillovers from VAR-GARCH models improved diversification benefits and hedging effectiveness compared to commonly used multivariate volatility models. This research highlights the importance of considering the relationship between oil prices and stock sector returns in portfolio management and risk mitigation strategies.

In a follow up study, Arouri et al determined that understanding the links between oil price fluctuations and sector stock returns is crucial for effective portfolio management in the presence of oil price risk [6]. Previous studies have also examined volatility spillovers between oil and stock markets. The authors used a VAR-GARCH approach to analyze volatility spillovers between oil and European equity markets at both the aggregate and sector levels. The findings emphasized the significance of considering these spillovers in portfolio management strategies, contributing to the literature on the topic and providing insights for developing effective hedging strategies for investment trading firms in response to US oil price volatility.

Rajgopal and Pincus explored the interaction between accrual management and hedging in oil and gas firms [7]. These firms face earnings volatility due to oil price risk and exploration risk. The study investigated whether firms use abnormal accruals and hedging with derivatives as substitutes to mitigate earnings volatility. The findings suggested that managers of oil and gas firms employ a sequential process, first utilizing derivatives to hedge oil price risk and then employing abnormal accruals, particularly in the fourth quarter. While these mechanisms do not eliminate all volatility and come with costs, they serve as strategies to manage earnings volatility caused by oil price risk, complementing the overall risk management approach of the firms. However, the study's evidence is limited to a specific time period and the oil and gas industry, necessitating further research to generalize the findings to other industries and examine the effectiveness of these strategies in a broader context.

Tansuchat et al conducted a study to investigate the performance of multivariate volatility models in the context of crude oil spot and futures returns for Brent and WTI, two major international crude oil markets [8]. The research aimed to determine optimal portfolio weights, hedge ratios, and propose an effective crude oil hedging strategy. The findings indicated that the optimal portfolio weights suggested holding futures in larger proportions than spot for Brent, while for WTI, the recommendations varied among the multivariate volatility models. Moreover, the calculated optimal hedge ratios offered time-varying hedge ratios, suggesting specific positions in crude oil futures and spot contracts. The study assessed the hedging effectiveness of the models and found that DCC performed the best in reducing portfolio variance, while BEKK performed the worst among the models considered.

Lin et al employed various frameworks, including VAR-GARCH, VAR-AGARCH, and DCC-GARCH, to investigate the dynamic volatility and volatility transmission between oil and Ghanaian stock market returns [9]. The study also computed optimal weights and hedge ratios for oil-stock portfolio holdings. The findings indicated significant volatility spillover and interdependence between oil and the two stock markets, with stronger spillover effects observed in the Nigerian stock market. The study also revealed short-term predictability in oil and stock price changes and highlighted the role of past volatility in driving rapid conditional volatility changes. The results suggested that the DCC-GARCH framework exhibited slightly more effective hedging, particularly in the Ghanaian market. Overall, the findings emphasized the importance of considering volatility links for portfolio management in the presence of oil price risk and challenged assumptions of symmetric effects and constant conditional correlations.

Haigh and Holt conducted a study on crack spread hedging, focusing on the effectiveness of crude oil, heating oil, and unleaded gasoline futures contracts in reducing price volatility for energy traders [10]. The study developed a conceptual model for hedging the crack spread and compared various hedge ratio estimation techniques to a Multivariate GARCH model that accounted for the time to maturity effect observed in futures markets. The Multivariate GARCH methodology, by modeling the time-variation in hedge ratios and considering volatility spillovers between markets, demonstrated significant reductions in uncertainty, even after accounting for trading costs. These findings highlighted the value of incorporating dynamic volatility spillovers in crack spread hedging strategies, providing traders with more effective risk management tools.

Chkili et al explored the time-varying properties of conditional return and volatility for crude oil and US stock markets, as well as their dynamic correlations [11]. Using the DCC-FIAPARCH model, they analyzed data from 1988 to 2013. The findings indicated the presence of long memory and asymmetric behavior in the conditional volatility of both oil and stock market returns. The dynamic conditional correlations between crude oil and US stock markets were influenced by various economic and geopolitical events. The study suggested that investors in the US markets should hold more stocks than crude oil assets to mitigate portfolio risk. The use of the DCC-FIAPARCH model enabled investors to hedge the risk of their stock portfolios more effectively and at lower costs compared to the standard DCC-GARCH model. These findings highlighted the significance of considering long memory and asymmetry in hedging strategies and provided valuable insights for portfolio risk management in the context of crude oil and US stock markets.

Saeed et al conducted a study on the hedging ability of clean/green assets against dirty energy assets, specifically crude oil prices and an energy stock index ETF [12]. The analysis covered the period from January 2012 to November 2019. By employing dynamic conditional correlation models and computing hedge ratios and hedging effectiveness, the authors examined the time-varying nature of the relationships and their portfolio implications. The findings revealed that the hedging effectiveness varied over time, suggesting the importance of adopting a dynamic hedging strategy for investors. Clean energy stocks were found to be more effective hedges than green bonds, particularly against crude oil. Regression analyses further indicated the impact of various factors on hedge portfolio returns. These results provided insights into the dynamics of hedging clean/green assets against dirty energy assets and offered valuable guidance for investors managing portfolio risks in the context of sustainability and energy markets.

Overall, previous research has explored the relationship between energy prices and stock prices, as well as the feasibility of hedging stocks with oil. The findings suggest that hedging equities with oil can provide economic benefits, although its effectiveness varies depending on market conditions. Oil importing countries may be more vulnerable to oil price shocks and could benefit from hedging strategies to mitigate the impact on their stock markets. This study aims to contribute to the existing knowledge by analyzing the performance of different ETFs, including government bonds represented by iShares 20 Plus Year Treasury Bond ETF (TLT), as potential hedges against oil price volatility. The hypothesis is that TLT, with its inverse correlation to yields, could be a suitable option for hedging oil price volatility within an equity portfolio. Through an analysis of ETF performance using log returns, this study seeks to provide insights into the most appropriate strategies for hedging oil price volatility.

III. Experiment

A Correlation Heat Map provides 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. As the United States Oil ETF (USO) decreases, TLT has a trend of increasing which is an observation that can be used for hedging.

A. Normal Distribution

After the data is prepared as shown in Figure 2 and 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 (Figure 4). The data is relatively symmetrical and doesn't have a strong left or right skew. Next a normal distribution bell curve is fitted into

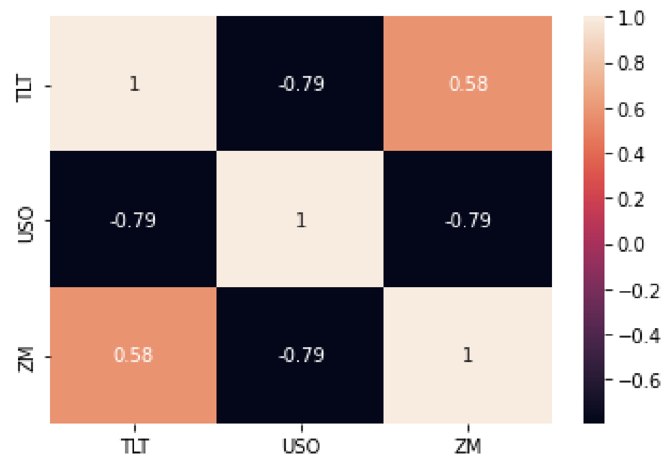

Fig. 1. A heat map showing the correlation between the three assets: TLT, USO, and ZM.

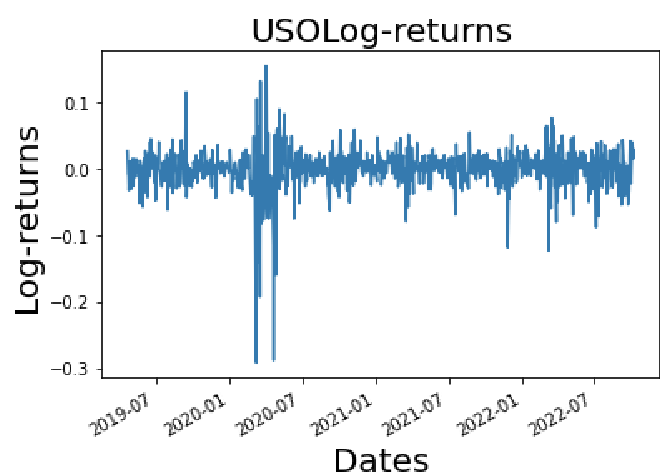

Fig. 2. A line graph with log returns on the y-axis and dates on the x-axis.

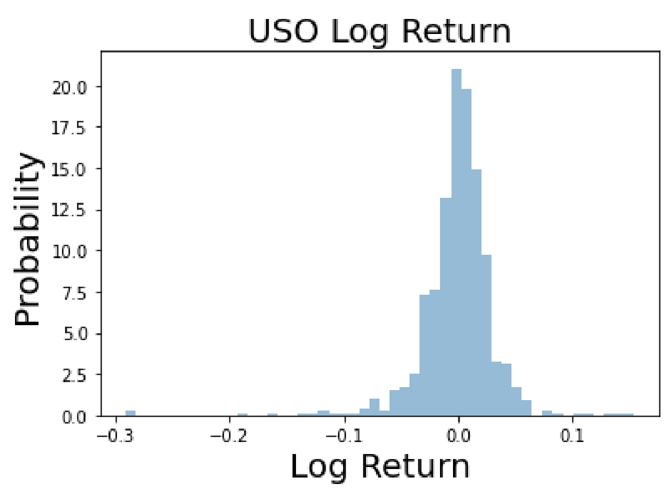

Fig. 3. A histogram of USO stock log returns with probability on the y-axis and log returns on the x-axis.

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.

B. *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.

C. *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.

D. *Model Metrics*

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 VaR from the left tail of the distribution. The VaR would vary based on the time interval and confidence level, so in order to compare the VaR of different assets the time intervals and confidence levels should be equivalent.

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 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.

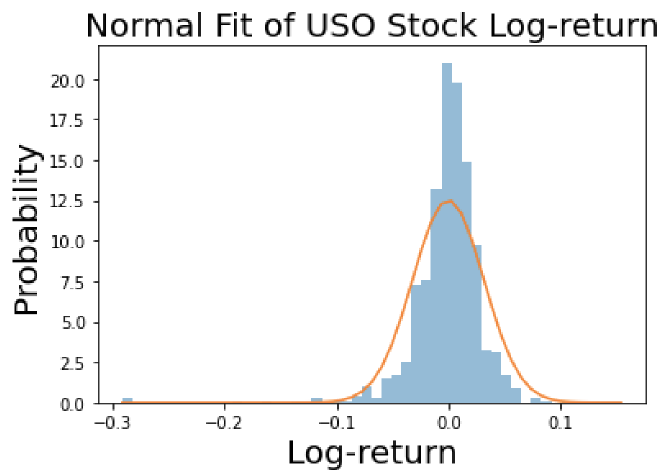

Fig. 4. A histogram of USO stock log returns with a normal distribution fit line, showing probability on the y-axis and log returns on the x-axis.

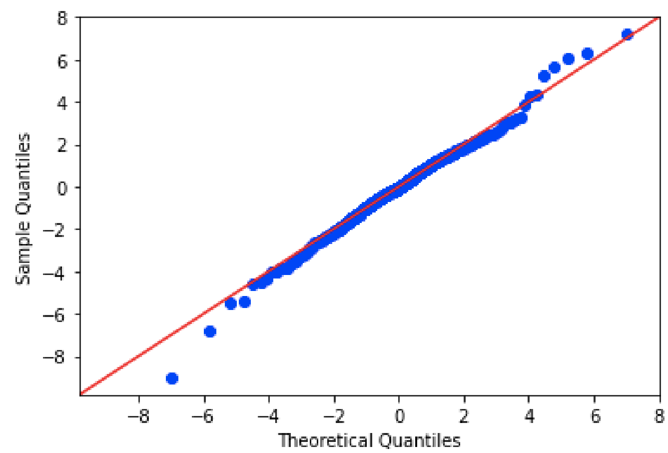

Fig. 5. QQ plot of USO normal distribution.

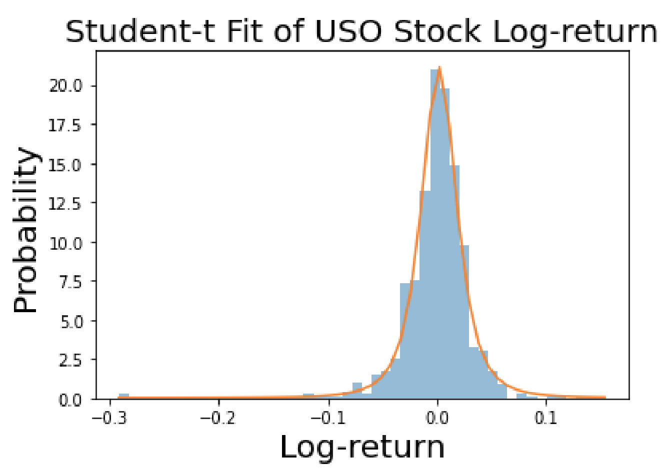

Fig. 6. A graph of a Student-t distribution fit of USO stock log returns.

IV. Results

Based on the results of the 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 Firms to make informed decisions about their capital reserves and better manage the potential risks and losses associated with different ETFs.

TABLE I. 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 II. 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.

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 this analysis highlight the importance of using the Student T-distribution and considering both Value-at-Risk (VaR) and Expected Shortfall (ES) when evaluating hedging strategies for portfolio drawdown. By doing so, Firms Can make more informed decisions about their capital reserves and better manage the potential risks and losses associated with different ETFs.

V. Limitation

There are several limitations to this research that should be considered when interpreting the results. Firstly, the analysis is based on historical data and therefore may not accurately reflect future performance. Although attempts were made 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, the 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 this analysis.

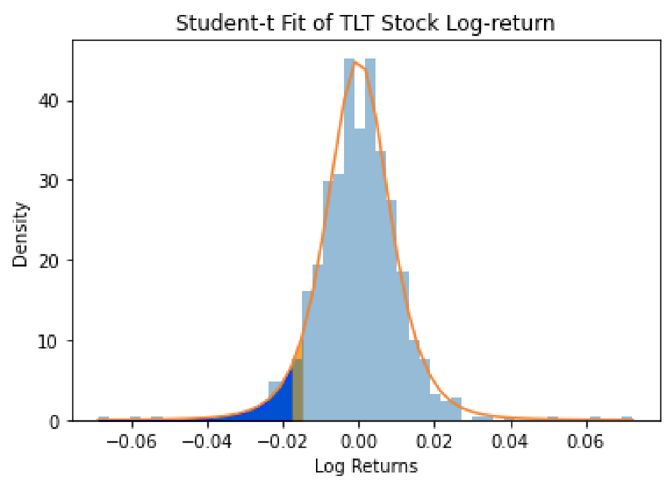

Fig. 7. Student-t Fit of TLT Stock Log return(x-axis:Log Returns, y-axis:Density)

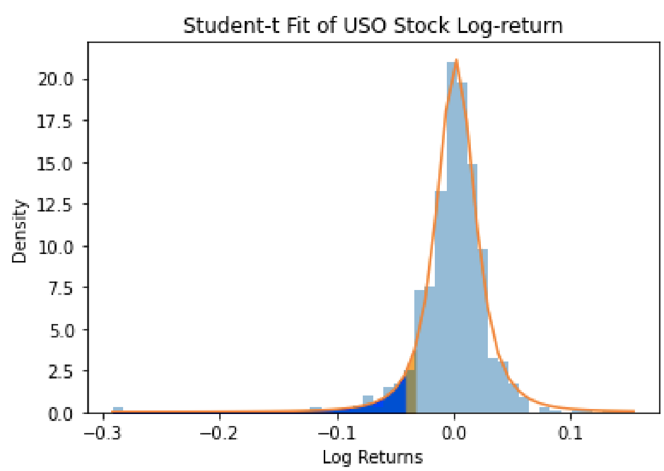

Fig. 8. Student-t Fit of USO Stock Log return(x-axis:Log Returns, y-axis:Density)

Thirdly, the 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, the 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 this 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.

VI. Conclusion

In conclusion, this research examines the feasibility of hedging against oil price losses in a stock portfolio through the use of ETFs. An evaluation of the correlation between oil prices and stock prices, as well as an examination of the effectiveness of different ETFs, led to identification of TLT as the most effective ETF for hedging against oil price losses. This 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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Supplementary Information

The code repository for the project modeling can be found at the following link: https://colab.research.google.com/drive/1sR7pdq8Y9yY6YFVWsZaTmzAYu7wHSdpO?usp=sha ring

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