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Hedging crude oil during shocks

Comparison of Hedging Strategies

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Abstract

Crude oil is a valuable commodity that significantly impacts the global economy. Therefore, protecting against the risks associated with its price volatility is necessary. This thesis focuses on regime shift periods and the structural breaks in the oil price. We do this by focusing on seven historical events significantly influencing the oil price's volatility structure. The models we use are naïve 1-to-1 hedge, OLS, standard GARCH, GJR-GARCH, and exponential GARCH. We find the minimum variance hedge ratio of hedge portfolios and that no model outperforms the others. We see that to estimate the volatility accurately, it is crucial to consider the characteristics of the given historical event. Additionally, imposing a perfect correlation between spot and futures diminishes the model's efficacy, emphasizing the significance of precisely measuring their correlation when selecting an appropriate strategy for an oil shock.

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Contents

List of abbreviations

OLS Ordinary Least Squares

GARCH Generalized autoregressive conditional heteroskedasticity

GJR-GARCH Glosten-Jagannathan-Runkle GARCH

E-GARCH Exponential GARCH

GFC Great Financial Crisis

OHR Optimal hedge ratio

MVHR Minimum variance hedge ratio

VR Variance reduction

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1. Introduction

1.1 Motivation

The crude oil market is highly volatile and has suffered several price shocks. Crude oil is one of the world's most essential commodities, significantly impacting global economic growth. However, the price of crude oil can be highly volatile, with sharp fluctuations caused by factors such as changes in supply and demand and geopolitical tensions. For many oil-exporting countries, oil or gas reserves are the single most important national asset, and any change in the price of this asset affects the nation's wealth and the well-being of its citizens. Therefore, hedging crude oil exposure, among exposure to other volatile commodities, is an important aspect of risk management for sovereign wealth funds, oil producers, exporters, and importers. Changes in the price of oil are very volatile, and hedging this exposure during high volatility regimes is increasingly important (Scherer, B, 2010). However, the effectiveness of these hedging strategies can depend on the volatility model used to estimate risk.

This thesis aims to compare the performance of different volatility (GARCH) models in hedging against crude oil price shocks, using empirical data to test their effectiveness in different market conditions. By doing so, this study seeks to provide insights into the best practices for managing crude oil price risk in other contexts and contribute to the ongoing research in the field of risk management. We will add the Covid-19 pandemic and the Ukraine war to the high volatility events we want to cover. By adding events that have had a considerable volatility impact on the crude oil market, we aim to arrive at conclusions that support the existing literature on this field. The number of studies on forecasting oil price volatility has gradually increased, indicating its growing importance in the literature.

1.2 Contribution to existing literature and the industry

We want to examine if there is one universally best solution when determining how to hedge crude oil returns. More specifically, when estimating the hedge ratio in-sample, which statistical model yields the best hedging result measured in variance reduction in the out-sample when the out-sample contains a shock to Brent oil returns. We want to compare the results of using different hedging strategies; these five hedging strategies are:

- Naïve 1-to-1 hedge. One long unit of spot Brent is hedged by shorting 1 unit of Brent futures. This static 1-to-1 hedge ratio is carried out throughout the out-samples.
- Simple OLS hedge. This method runs simple linear regression in-sample, and the resulting static beta (β) coefficient is used as the hedge ratio out-sample.
- Standard GARCH, GJR-GARCH, and E-GARCH. The GARCH model is fitted in-sample, and volatility is forecasted one day ahead. This forecast is then rolled throughout the out-sample and the hedge is adjusted based on the output. Static correlation from the in-sample is used to calculate the time-varying hedge ratio.

With this method, we want to find out which strategy performs best, considering the regime shift due to the shock in oil markets. To the best of our knowledge, this study has yet to be conducted, including the more recent oil shocks resulting from Covid-19 and the Ukraine war.

Chun et al. (2020) compared volatility models, more specifically standard GARCH, SV (stochastic volatility), and diagonal BEKK (named after Baba, Engle, Kraft & Kroner, 1990), in terms of crude oil price shocks and hedging performance. They test the models on five historical events. We aim to build upon this study by extending the number of historical events by including the recent Covid-19 pandemic and Russia-Ukraine war, as these events have significantly impacted the global oil market. We want to see if incorporating models with asymmetric behavior and leverage effects on these historical events using GJR-GARCH and E-GARCH will prove valuable models for crude oil volatility. A study by Hansen et al. (2003) aims to select the superior forecasting models from a more extensive set containing various GARCH models and SV using the MCS (model confidence set) method. Here the superior forecasting model is the one that produces the minimum expected loss. They find that the best-performing models have a leverage effect, which is the asymmetric response in volatility to positive and negative shocks. The leverage effect is vital for understanding stock return dynamics, as it is observed empirically that the volatility tends to rise in response to bad news and tends to fall after good news. It is desirable if the GARCH models prove useful since GARCH models are more computationally convenient than, e.g., SV.

Furthermore, we will consider more simple hedging approaches. This should contribute to academia and industry practitioners by showing if there is a universal best way to hedge Brent oil exposure. If there is one best way in terms of variance reduction, will it also be the best strategy considering transaction costs, simplicity, and practical replication of the hedge.

Using daily data of Brent crude oil prices (both spot and futures) from 1988 to 2022, we use five strategies to find one universal method to hedge crude oil in volatile regimes during this period. Specifically, we employ the naïve 1-to-1 hedge, OLS hedge, and three different GARCH models. We train the models in-sample, which is before the shock has occurred. Then we test it on the out-sample, the volatile period resulting from the oil shock. None of the five strategies we covered significantly outperformed the other. We highlight the importance of correctly estimating the correlation between spot and futures returns to choose the most suitable model. Our findings reveal a trade-off between risk and return, indicating that risk-return preferences and the abovementioned factors must be carefully considered to find an appropriate yet efficient hedging strategy for various oil shocks.

Six sections make up the remainder of this thesis. Section 2 gives some background information on the oil market, a description of the historical events, how to hedge oil price volatility, and the current hedging practices of oil companies. Section 3 is a review of the prior literature that is relevant to this topic. Section 4 outlines the methodology, Section 5 describes the data, and Section 6 discusses the findings. Finally, Section 7 concludes the thesis.

2.0 Background

2.1. Characteristics and risk factors of the oil market

The oil market is a complex and dynamic system influenced by a wide range of factors, including geopolitical tensions, changes in the global economy, and supply and demand dynamics. For many industries, oil is a necessary input and has few substitutes, which means that oil demand is often relatively inelastic in the short term. The Organization of Petroleum Exporting Countries (OPEC) controls a significant portion of global oil production and can influence prices through production quotas. According to the International Energy Agency's Oil Market Report, the global oil market has experienced significant price volatility in recent years. In addition, the report notes that the global oil market is increasingly interconnected, with production levels in one country impacting prices and supply across the entire market. Also, the oil market involves complex supply chains, including drilling, refining, transportation, and storage, making it difficult to predict and manage risks. These characteristics make the oil market challenging and unpredictable for companies and governments. (Oil Market Report, 2021)

The oil market is also influenced by the increasing role of financial markets, where oil prices are driven by financial speculation rather than just supply and demand factors. Using monthly data from January 1990 to May 2019, Chatziantoniou et al. (2021) examined the determinants of oil price volatility. They found that financial indicators have the most significant influence on the oil market. Changes in investor sentiment and speculation can drive oil prices up or down, even without fundamental changes in supply and demand. The financialization of the oil market makes it vulnerable to financial bubbles that can contribute to systemic and non-systemic crises.

Geopolitical events are a crucial risk factor for oil price volatility. According to pioneering research by Hamilton (1983), the fact that a relatively small number of firms produce most of the crude oil is what essentially causes historical oil price shocks. Geopolitical events like the Gulf War and Iraq War have caused disruptions in oil supplies from central global producers. If there are to be supply and demand imbalances for oil, this can lead to price volatility and create risks for producers, consumers, and traders. Meng & Liu (2019) have shown that oil production uncertainty can affect future volatility.

Additionally, weather-related disruptions can lead to oil price fluctuations. Extreme weather events, such as hurricanes, can disrupt oil production. Furthermore, changes in environmental regulations and climate change concerns can affect the oil demand and create new risks for producers and investors. (U.S. Energy Information Administration, 2023)

Overall, the oil market is a complex and dynamic system influenced by various factors, from global economic trends to natural disasters and geopolitical tensions. Understanding these characteristics is essential for companies and governments seeking to manage their oil price risk exposure and navigate this critical market's challenges.

2.2 The historical events

Seven historical events that have influenced the volatility of the oil price are considered in this study. In this subsection, we will go into more detail about the crisis and the type of oil shock it brought about.

During the 1990-1991 Gulf War, oil price volatility increased as prices rose in response to concerns about supply disruptions in the Middle East. In the months after Iraq's invasion of Kuwait in August 1990, oil prices increased more than 100%, according to the US Energy Information Administration. The price spike was driven by concerns that the conflict could spread to other oil-producing regions and disrupt global supplies. In addition to fears of supply disruptions, the Gulf War boosted oil demand as countries built up stockpiles of reserves in anticipation of potential supply shortages. This increased demand further contributed to the upward pressure on prices. The Gulf War price shock significantly impacted the global economy, with rising energy costs leading to inflation and slowing economic growth in many countries. The effect was particularly pronounced in the United States, where high oil prices led to a recession in 1991. (Looney, 2003)

The Asian financial crisis of 1997-1998 caused a significant decline in oil prices. The crisis was triggered by a combination of factors, including substantial capital inflows to Southeast Asia, high levels of debt, and fixed exchange rates that made countries vulnerable to speculative attacks. As a result of the crisis, several Southeast Asian economies experienced severe economic downturns, with a sharp drop in consumer demand and industrial production. The decline in economic activity in Asia led to a significant decrease in oil demand, as the region was a major consumer of oil and petroleum products. The crisis increased uncertainty in the global oil market as investors and traders became more risk-averse and focused on the potential for further economic turmoil in Asia. This increased volatility in the oil market, with daily price swings becoming more pronounced. (Yue, 1998)

The Iraq war in 2003 significantly impacted world oil prices, resulting in the so-called "fear premium" price shock. The fear premium is a term that describes rising oil prices due to fear of potential supply disruptions or geopolitical instability rather than actual supply disruptions. In the case of the Iraq war, concerns about possible damage to Iraq's oil infrastructure and the possibility of broader conflict in the Middle East gave rise to fears of supply disruptions. When tensions between the United States and Iraq grew in the months before the war, oil prices steadily increased. Brent crude oil prices increased from about $25 per barrel in early 2003 to over $40 per barrel by April 2003 after the beginning of the conflict in March 2003. Fears that the conflict would cause interruptions in Middle Eastern oil supplies, which make up a sizable share of the world's oil production, led to the price shock. The fear premium continued to be a factor in oil markets for several years after the war ended, as ongoing conflicts and tensions in the region led to ongoing concerns about potential supply disruptions. (Looney, 2003)

The Great Financial Crisis of 2007–2008 caused individuals and businesses to cut back on spending, which resulted in a significant decline in oil consumption. The collapse of the U.S. housing market set off the crisis, which resulted in a global recession and a sharp decline in demand for oil and other commodities. As a result, there was an excess of oil on the market, and oil prices dropped. For instance, the cost of Brent crude oil dropped from a peak of over $145 per barrel in July 2008 to under $40 per barrel in December of that same year. There was a massive decline in oil demand as the crisis moved from the US to other regions, which pushed oil prices lower. The financial crisis not only affected demand but also significantly affected financial investors, which in turn had a significant impact on oil markets. Several investors withdrew their funds from oil and other commodities as the crisis worsened in favor of safer alternatives like Treasury bonds. This increased the downward pressure on oil prices even more. This crisis demonstrated the interconnectedness of financial markets and the real economy. (Hamilton, 2009)

The shale boom in the early 2010s caused a significant increase in oil production. The development of shale oil production technology led to an increase in oil supply in the US, which disrupted the global oil market and contributed to a period of low oil prices. The shale boom caused a shift in the balance of power in the oil market, with the US becoming a major producer and exporter of oil. However, the rapid expansion of shale oil production also led to an oversupply of oil, which put downward pressure on prices and increased market volatility. As output from shale formations increased, it became more difficult to predict future supply and demand levels, contributing to increased volatility. (Bjørnland & Zhulanova, 2019)

The COVID-19 pandemic led to a global economic downturn and a sharp decrease in oil demand, as travel restrictions and lockdown measures reduced transportation and economic activity. Before and during the COVID-19 pandemic, the paper of Altig et al. (2020) considered several economic uncertainty indicators for the US and UK: implied stock market volatility, newspaper-based policy uncertainty, Twitter chatter about economic uncertainty, subjective uncertainty about business growth, forecaster disagreement about future GDP growth, and a model-based measure of macro uncertainty. In response to the pandemic and its economic impact, all indicators show massive uncertainty rises, with most indicators reaching all-time highs. According to the Current Population Survey, unemployment increased from 3.5% in February 2020, the lowest rate in more than 60 years, to 14.7% in April, the highest rate in 80 years. Between 2019Q4 and 2020Q2, the US

GDP fell 11.2%, the most significant drop since the Great Depression. In the UK, an identical scenario of dramatically declining output emerged, with GDP plunging a record 20.4% in April-June after falling 2.2% in January-March. The COVID-19 contraction surpasses any prior US or UK incident in the modern era in terms of pace and scope. The paper also gathered evidence that the COVID-19 epidemic and its economic consequences have no comparable historical counterparts in at least two ways: The suddenness and magnitude of the significant job losses and the severity of the economic collapse compared to the scale of the mortality shock. The unusual scope and character of the COVID-19 crisis help to understand why it has resulted in such a dramatic increase in economic uncertainty. This economic uncertainty undoubtedly led to increased oil price volatility. As uncertainty about the pandemic and its economic impact grew, oil prices became more volatile, with daily price swings of 10% or more becoming increasingly common (Sharif et al., 2020). In March 2020, the price of Brent crude oil fell to its lowest level in nearly two decades, as concerns about the pandemic and its impact on the global economy led to a collapse in demand for oil. West Texas Intermediate (WTI) crude oil futures dropped to negative prices for the first time in April 2020, indicating that producers were willing to pay buyers to take oil off their hands.

In 2022, Russia invaded Ukraine, disrupting oil and gas markets. The Russia-Ukraine war has been described as the most severe war in Europe after the second world war (Adekoya et al., 2022). Russia is one of the largest producers and exporters of crude oil. Therefore, the war caused a shortage of supply of the commodity and increased prices. It has been eight years since the price of crude oil reached such a high level. Although the war is between Russia and Ukraine, it has caused discussion internationally with economic sanctions against Russia placed by the U.S. and much of the West. One could expect that the supply shock followed by the Russia-Ukraine war will influence European countries and China because they import much oil from Russia. Other non-European countries are industrialized countries that use crude oil in their production activities.

These events underscore the importance of understanding the relationship between the oil market and the global economy and the potential impact of economic and political events on oil price volatility. Most of the circumstances referred to above can be classified as geopolitical shocks, primarily caused by political tensions and conflicts that significantly impacted the global oil market. These events include the Gulf War, the Iraq War, the Russia-Ukraine War, and the COVID-19 pandemic. However, the shale boom in the United States was primarily driven by changes in the domestic oil industry rather than global political events. Similarly, the Great Financial Crisis was caused by financial and economic factors rather than geopolitical tensions, although it significantly impacted the global oil market.

Understanding the source of oil price volatility for various crises can improve the accuracy and reliability of a volatility model. The model can be tailored to better capture and forecast changes in oil volatility by identifying the specific factors that drive oil price fluctuations during various crises. This information can also be helpful in developing hedging strategies better suited to each crisis's specific characteristics. For example, during a crisis caused by geopolitical tensions, such as the Russia-Ukraine war, hedging strategies that focus on political risk may be more effective than those that rely solely on market fundamentals.

2.3 Hedging crude oil price risk

According to Daniel´s (2002) research, hedging strategies can significantly decrease oil price volatility while not affecting returns significantly. Moreover, hedging provides the additional advantage of increased predictability and certainty.

Market participants and investors can hedge against oil price risk using futures contracts. Crude oil futures markets are vital to global commodity trading, allowing producers, traders, and investors to manage their price risk exposure. The primary function of crude oil futures markets is to provide a mechanism for buyers and sellers to hedge against price fluctuations by agreeing to a future price for oil. In the case of crude oil, futures contracts typically involve the delivery of a specified quantity of crude oil at a future date. Hedging through trading futures contracts is a method used to limit or minimize the risk of adverse price movements. The underlying principle is that cash and futures prices for the same commodity typically have a correlated movement. Consequently, the fluctuations in the value of a cash position can be countered by corresponding changes in the value of an opposite futures position (Chang et al., 2011). Futures contracts are a preferred hedging instrument because they offer high liquidity, fast execution, and lower transaction costs.

Salisu & Adediran (2020) investigated gold as a hedge against crude oil price risk during Covid-19. Their results showed that gold could be a safe haven against oil price risk. Other precious metals like silver, platinum, and palladium can also be used as portfolio rebalancing tools to minimize risks associated with volatile oil prices. Adekoya & Oliyide (2020) examined seven industrial metals as a potential hedge against oil price shocks. They found they can provide a partial or complete hedge against oil demand shocks, not supply shocks. Wu et al. (2011) found significant spillovers from crude oil prices to corn crashes and futures prices, and that after the introduction of the Energy Policy Act of 2005, corn markets have become much more connected to the crude oil markets. They tried implementing a cross-hedging strategy for managing corn price risk using oil futures. However, this provided only a slightly better hedging performance than traditional hedging in corn futures markets alone. Yahya et al. (2019) argue that the correlations between oil and agricultural commodities have strengthened since 2006. Consequently, the higher correlations limit the hedging capabilities of commodities against the oil price movements and find that commodities are neither a safe haven nor a hedge against oil volatility.

Mokni et al. (2022) investigated the hedge and safe-haven properties of green bonds against oil price shocks and uncertainty, comparing them to the roles of gold, 3m European government bills, and 3m T-bills in the United States. They separate oil shocks into supply, demand, and risk shocks. The study's findings indicate that green bonds are more appropriate as hedging and safe-haven tools against oil price shocks and uncertainty, depending on whether the oil shocks are supply, demand, or risk shocks. They discover that under bearish green bond market conditions, green bonds act as a powerful hedge and safe haven against structural oil shocks. The findings reveal that green bonds outperform gold and conventional bonds as hedging and safe-haven strategies against oil price shocks and uncertainties. Green bonds fund environmentally friendly projects that should withstand recessions and weak markets. Other assets, such as equities and commodities, suffer during this stage of the business cycle.

Moreover, Dogan et al. (2023) examined the dynamic interdependence and causality of crude oil, green bonds, commodities, geopolitical risks, and policy uncertainty. They confirm the existence of bidirectional causality between green bonds and commodities markets. Their findings support the idea that green bonds are safe havens in times of turmoil. Green bonds' hedging properties suggest that they will be more utilized in investor portfolio distribution in the future.

The primary challenge of futures hedging revolves around identifying the optimal hedge ratio (OHR), which denotes the proportion of exposure to a hedging instrument concerning the value of the hedged asset. The minimum-variance hedge ratio (MVHR) model is one of the most employed hedging techniques, whereby the goal is to minimize the variance of the hedged portfolio. By employing the minimum variance hedge ratio, investors can produce a more efficient and effective hedge against price changes in a specific asset or portfolio. The objective is to reduce the total position's exposure to market volatility while leaving room for potential gains from upward price moves. The minimum variance hedge ratio is crucial in risk management and hedging methods, especially in unpredictable markets and ambiguous economic situations.

2.4. How oil firms hedge in practice

Compared to the intense margin of hedging, fewer studies have explored how corporations effectively hedge, most likely due to a lack of firm-level data on derivatives portfolios. The accounting rules for hedging require entities to disclose the level of an entity´s derivative activity. However, there can be some variances in practice regarding how much information each company discloses about the instrument types, hedging volume, and average hedge price.

Ferriani and Veronese (2022) explore hedging and investment trade-offs in the oil industry in the United States. The research is based on a new firm-level dataset of over 100 E&P US oil producers from 2007 to 2016. They manually collected detailed data on derivative contracts to hedge against oil price risk from the corporations' annual reports (10-K). The corporations' stated hedging instruments are grouped into seven distinct groups. Examples include futures/forward contracts, swaps, collars, and options. They note that roughly one-third of firms do not hedge, with a notable peak around the 2008 oil price slump. Furthermore, hedging activity is concentrated in several derivative instruments, mainly swaps, collars, and three-way collars. According to the survey, swaps are the most employed hedging instrument, accounting for almost 50% of the sample. Collars and three-way collars prove to be attractive since they are less expensive.

Mnasri et al. (2017) investigate the motive for hedging across US oil producers from 1998 to 2010. Their findings highlight the importance of oil market conditions in determining hedging strategies. They show that when oil prices fall, producers utilize stricter linear hedging tactics to lock in predetermined prices and eliminate any deficit in future earnings. On the contrary, when oil prices rise, oil producers prefer nonlinear hedging contracts alone or in combination with linear contracts to profit from the price increase. They also collected information about the nature of hedging instruments in use. Swap contracts, put options, costless collars, forward or futures contracts, and three-way collars are the most common hedging products. Swap contracts are the most often used hedging vehicles, accounting for 45.25% of all oil hedging. With 37.11%, the costless collar is the second most common instrument. Next is put options with 11.85%. Forward or futures contracts, with 2.78%, and three-way collars, with 3.02%, are the least common instruments.

Oil prices experienced major shocks from late 1997 to 2010, including the Asian crisis in late 1997, the Iraq conflict in early 2003, and the global financial crisis that began in 2007. Some of these shocks disturbed oil supply and demand, resulting in short-term price swings, but others had a longer-term impact. For example, the Iraq war increased oil prices from 2003 to early 2006, resulting in a protracted fall in the frequency with which oil companies used pure linear hedging contracts. Regarding uncertainty, firms using linear contracts have higher oil production uncertainty. As predicted, oil producers prefer using nonlinear instruments to profit from upside potential when oil prices are increasing. The median comparison shows that oil producers that use linear hedges have larger firms than users of nonlinear contracts.

It is worth mentioning that integrated firms tend not to hedge. Integrated firms have a combination of midstream and downstream operations that act as a natural hedge against commodity price volatility. As such, integrated firms are less likely to hedge in any particular year, given their ability to partially offset any losses from declining commodity prices through higher margins on refining and retail operations. Also, very few of them report hedging positions. (Mo et al., 2021)

In this study, we are constructing a minimum-variance hedge using futures contracts. Futures contracts are widely recognized as a good risk management tool, and they are regularly utilized to hedge a commodities obligation (Yu et al., 2023). Trading futures contracts is popular among oil market players because it often includes low transaction costs. However, research suggests that oil companies rarely employ futures contracts. Swaps are the most frequently used linear contract, while collars are the most used non-linear contract.

3.0. Literature Review

Since markets are efficient and investors can hedge themselves, according to Modigliani and Miller (1958), hedging cannot create value. Nonetheless, the hedging literature offers theoretical justifications and, to some extent, empirical proof that hedging can increase a firm's value. As McDonald (2014) specified, a hedge is an investment in a derivative whose value is based on an underlying asset, such as oil price. Old corporate finance hedging ideas like Keynes' thesis, which contends that the derivative market is an insurance mechanism, provide the basis for modern hedging theories (Keynes, 1930).

We will compare different models to estimate the optimal minimum-variance hedge ratio (MVHR). MVHR is the most widely used hedging strategy to find the ratio of futures to hedge. Due to the imperfect correlation between spot and future prices, Johnson and Stein (1960) suggested a minimum-variance hedge ratio strategy. This strategy was formally proposed by Ederington (1979), in which the ideal hedging ratio is calculated by regressing spot prices on future prices using ordinary least squares (OLS). Additionally, he put forth a metric for measuring the success of hedging, which compares the variance reduction of a portfolio with hedging to an unhedged spot position.

Given that spot and futures prices vary over time, Ederington (1979) and Baillie & Myers (1991) suggest using a time-varying variance and covariance to measure the volatility of the financial and macroeconomic variables. Floros & Vougas (2004) and Salvador & Aragó (2014) found that a time-varying MVHR outperforms a constant MVHR regarding hedge performance.

Wang et al. (2019) compared the minimum-variance and minimum-risk frameworks for futures hedging in crude oil markets, and they found that the optimal hedge ratio is different for the two frameworks. They used both constant hedge ratio models and dynamic hedge ratio models. They found that constant hedge ratio models, like OLS, performed best when the goal was to minimize the portfolio variance. If the objective is to reduce riskiness, the dynamic hedge models performed best. Byström (2003) claims that while GARCH techniques reduce return volatility, they fall short of the traditional OLS strategy in terms of lowering portfolio variance. They suggest that hedgers use a combination of both constant and dynamic models to obtain the optimal hedge.

Given its simplicity, companies have widely used the naive 1-to-1 hedge as a benchmark. Furthermore, the transaction costs are minimal since there is no need to rebalance the hedge position (Wang et al., 2015). Theoretically, one could expect that the minimum variance framework would outperform the naive strategy. However, several studies have shown that this may not be the case. Complex and more sophisticated strategies do not necessarily provide better hedging performance than simple ones, given that more parameters need to be estimated. Hence it may produce larger estimation errors in the estimates. Nonetheless, Wang et al. (2015) examined the performance of naive and minimum variance hedging strategies for 24 different futures markets, including underlying assets like commodities, currencies, and stock indices. They find that the naive strategy gets outperformed by 18 other hedging strategies, such as OLS and regime-switching models.

One limitation of OLS is the constant variance-covariance matrix, which is difficult to accept for a highly volatile oil market. Therefore, researchers have turned to using time-varying hedge ratios. Engle (1960) proposed the autoregressive conditional heteroscedasticity (ARCH) model to better describe financial time series characteristics. Bollerslev (1986) extended this model to generalized autoregressive conditional heteroscedasticity to suit more general situations. Parametric models, such as GARCH models, assume that the underlying distribution of oil price returns follows a certain statistical form and estimate the parameters of this form using historical data. According to Kroner and Sultan (1993) and Baillie and Myers (1991), bivariate GARCH models produce better hedge performance than the OLS method. The advantage of these models is their simplicity and interpretability, but they may not accurately capture more complex patterns in the data. The paper of Chun et al. (2019) highlights the importance of considering structural breaks in the oil price when measuring its volatility, or else the results may lead to biased or misleading estimates. They found that the GARCH model often fails when this matter occurs. Bina & Vo (2007) showed that the

GARCH model fits crude oil returns well because they are heavy-tailed distributed. Zanotti et al. (2010) found that dynamic GARCH models perform significantly better than other models in the case of high standard deviation of returns and conditional correlations. Hence, many studies have used GARCH models to investigate the volatility of oil returns.

A well-known addition to the basic GARCH model, the GJR-GARCH model, provides for the asymmetric impacts of positive and negative returns on conditional volatility. It has been demonstrated in numerous studies to be effective at capturing the volatility dynamics of financial time series. Glosten et al. (1993) examined the performance of the GJR-GARCH model. They found that the GJR-GARCH model provided a good fit for the volatility dynamics of stock returns and outperformed other models, such as the standard GARCH and exponential GARCH models. In recent years, studies have also shown that the GJR-GARCH model performs well in capturing the volatility dynamics of other financial time series, such as exchange rates, commodities, and interest rates. Engle et al. (1990) found that the GJR-GARCH model outperformed other models in estimating the volatility of exchange rates, while Liu et al. (2015) found that the GJR-GARCH model was the best performer in estimating the volatility of commodity futures.

E-GARCH is a popular extension of the standard GARCH model, allowing for asymmetry and leverage effects in the volatility process. One of the early studies that examined the performance of the EGARCH model is the work of Nelson (1991). He found that the EGARCH model provided a good fit for the volatility dynamics of stock returns and outperformed other models, such as the standard GARCH model. Since then, numerous studies have used the EGARCH model to model the volatility dynamics of various financial time series, such as exchange rates, stock market indices, and commodity prices. Ding et al. (1993) found that the EGARCH model provided a better fit to the volatility of exchange rates than other models, while Baillie and Bollerslev (1990) found that the EGARCH model was the best performer in modeling the volatility of stock market indices. Runfang et al. (2017) estimated the crude oil market volatility using GARCH and EGARCH models and found that EGARCH outperforms GARCH in terms of RMSE (reduced mean squared error). Also, they applied an MSGARCH (Markov-switching) model and found that it could further improve forecasting accuracy.

Wei et al. (2010) used linear and non-linear GARCH class models to forecast crude oil price volatility. Their research concluded that none of the GARCH-class models outperformed the others in all situations. Still, the nonlinear models perform better than the linear ones in long-run volatility forecasting of crude oil prices. Herrera et al. (2018) found that GARCH (1,1) has good forecast accuracies for short forecast horizons, EGARCH (1,1) gives the most accurate forecast for medium horizons, and MSGARCH shows superior forecast predictivity for longer horizons.

Previous studies have argued for using regime-shifting models to capture the changes and volatility shocks in oil prices. Vo (2009) incorporated regime shifting in a stochastic volatility model and found clear evidence of regime shifting in the oil market. Regime-shifting models can be a valuable tool for capturing the structural breaks in the data. Ewing and Malik (2017) modeled asymmetric oil price volatility under structural breaks. They found that both good and bad news has a significant effect on the oil price volatility if structural breaks are accounted for in the model, and to estimate the oil price volatility accurately, it is best to include both asymmetric effects and structural breaks.

Pan et al. (2017) proposed a regime-switching GARCH-MIDAS (Mixed Data Sampling) model to investigate the relationship between oil price volatility and macroeconomic fundamentals and to account for structural breaks in the oil price volatility. One of their findings was that macroeconomic fundamentals could provide helpful information regarding future oil volatility beyond historical volatility. Zhao (2022) used a GARCH-MIDAS model to investigate influencing factors on oil price volatility from four perspectives: macroeconomic factors, commodity attributes, geopolitical events, and alternative energy. His findings were that, in the long run, supply and demand continue to be the most influential factors of oil price volatility. The U.S. dollar exchange rate, inventories, and geopolitical events have roughly the same effect on oil price volatility.

In contrast, alternative energy has a negligible effect and almost no influence on the volatility. Huang et al. (2023) used a rational GARCH-MIDAS model to investigate which uncertainty index is most suitable in terms of forecasting performance for the Chinese crude oil futures markets, and according to their empirical findings, their chosen uncertainty indices most definitely forecast the Chinese crude oil futures volatility. Including the uncertainty index, GPR provides more accurate volatility estimates than other models. Zavadska et al. (2018) analyzed the volatility in the oil market during crises with GARCH models. They found that the series exhibited higher volatility spikes for oil supply and demand shocks like, e.g., the Gulf War. However, for Asia and GFC, the market volatility indirectly impacted the oil market. Supply and demand-related shocks are associated with higher levels of uncertainty, while economic and financial crises exhibit more prolonged levels of persistence.

Fang et al. (2017) found that economic policy uncertainty (EPU) significantly and positively influences the long-run oil-stock correlation. Liu et al. (2018) investigated the role of GPR (geopolitical risk) and GPRS in forecasting oil volatility. They found that serious geopolitical risk (GPRS) contains valuable information for the recent future oil volatility and can provide the best economic gains. Oil market investors and government policymakers should pay more attention to extreme geopolitical events and serious geopolitical risks in the context of risk management and portfolio allocation. Kang et al. (2013) showed that increases in the price of oil are associated with significant increases in economic policy uncertainty if not explained by changes in global oil production or global demand. Also, structural oil price shocks have long-term consequences for EPU.

To conclude, the crude oil market is complex, making it difficult to find an accurate model for the volatility, and there is still an ongoing debate among researchers and practitioners on which model is the most accurate for predicting oil price movements. The various models perform differently in different market conditions. Because of the difficulty with finding an accurate volatility model, it is also challenging to find the optimal hedge ratio, as well as the optimal hedge ratio may change over time as market conditions and other factors evolve.

4.0 Methodology

4.1 Minimum Variance Hedge Ratio

The return of a hedged crude oil portfolio can be expressed as:

$$R_{H,t} = R_{S,t} - \lambda_t R_{F,t}$$

Where $R_{S,t}$ and $R_{F,t}$ are the logarithmic crude oil return of the spot and futures at time t, respectively. λ_t is the hedge ratio at time t. Hedgers should derive the hedge ratio to minimize the conditional variance of the return of the hedged portfolio. This minimum variance hedge ratio (MVHR) can be defined as the hedge ratio that minimizes the conditional variance of the hedged portfolios' return given the information set Ω_{t-1} (Johnson, 1960):

$$\lambda_t^* = argmin\, VAR(R_{H,t}|\Omega_{t-1})$$

Time-varying MVHR can be constructed as the ratio of conditional covariance to conditional variance of futures return:

$$\lambda_t^* = \frac{COV(R_{S,t}, R_{F,t}|\Omega_{t-1})}{VAR(R_{F,t}|\Omega_{t-1})} = \frac{h_{SF,t}}{h_{F,t}} = \rho \sqrt{\frac{h_{S,t}}{h_{F,t}}}$$

Where $h_{S,t}$ and $h_{F,t}$ denote the conditional variance of spot and futures returns, $h_{SF,t}$ and ρ_t are the conditional covariance and correlation of spot and futures returns. We can measure the hedging efficiency with a measure of variance reduction (VR):

$$VR = \frac{VAR(U) - VAR(H)}{VAR(U)}$$

Where $VAR(U)$ and $VAR(H)$ are the variances of unhedged and hedged portfolios, respectively. Higher VR can be interpreted as a better hedging performance than smaller.

4.2 Estimating Hedge Ratios

We estimate the out-sample hedge ratio using the methods described below. With the simple OLS hedge, the hedge ratio is estimated in-sample and used for the whole out-sample without adjusting it. The daily rolling method is used with standard GARCH, GJR-GARCH, and E-GARCH. This means that the model is fitted in the in-sample and estimated for one day ahead for out-sample forecasting. The estimation is then rolled daily throughout the out-sample, resulting in one day ahead forecast. One-day forecast is used as ARCH family models are not tended to use for multi-step ahead forecasts, as the estimated parameters tend to degrade rapidly when the forecast horizon is extended (Figlewski, 1997).

4.2.1 Naive 1-to-1 hedge

The naive 1-to-1 hedge is constructed by shorting futures contracts in the same ratio as we are long the spot. This strategy assumes that covariance between spot and futures returns would equal the variance of futures returns (Brooks, 2019). For example, a long position of 1000 barrels of Brent oil would be hedged by shorting one Brent oil futures contract with a contract size of 1000 barrels (Intercontinental Exchange, 2023).

4.2.2 Simple OLS hedge

The Simple Ordinary Least Squares (OLS) hedge ratio is estimated by running a simple linear regression with spot returns as the dependent variable and futures returns as the independent variable (Brooks, 2019). The slope coefficient β is the static OLS MVHR in the equation below. The intercept α can be interpreted as the mean of the change of the basis of the hedged portfolio (Miffre, 2004).

$$s_t = \alpha + \beta f_t + \varepsilon_t$$

4.2.3 Standard GARCH

Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) process, which recognizes the difference between unconditional and conditional variance. In this process, conditional variance varies based on the function of past errors. A fixed lag structure is generally imposed to avoid negative variance parameter estimates in empirical analysis (Engle, 1983). Due to this, Bollerslev (1986) proposed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) process as a practical extension. The GARCH model is an attractive way to model financial data due to its ability to capture volatility clustering and unconditional return distributions with heavy tails, both being characteristics that commodity returns entail (Morana, 2001). Another advantage of the GARCH formulation is that while all past disturbances can enter the equation, only a few parameters fit, increasing the likelihood that they are well-behaved (Figlewski, 1997). The GARCH can be expressed as:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i h_{t-i}^2 + \sum_{i=1}^{p} \beta_i \varepsilon_{t-i} + , \qquad \varepsilon_t | \psi_{t-1} \sim N(0, h_t)$$

Where α_0, α_i and β_i are the model parameters and h_t is the conditional variance of the vector correction model (VECM) error ε_t.

4.2.4 GJR-GARCH

The extension of the GARCH model, proposed by Glosten, Jagannathan, and Runkle (1993), sometimes also referred to as threshold GARCH (T-GARCH), offers what standard GARCH captures, plus asymmetric behavior by allowing the current conditional variance to respond differently to positive and negative returns. The GJR-GARCH can be expressed as:

$$h_{t+1} = \alpha_0 + \left(\alpha + \gamma \mathbf{1}_{\{r<c\}}\right) r_t^2 + \beta h_t$$

Where **1** is the indicator value, that equals one if the previous return is below threshold c. If negative returns in oil prices cause more volatility than positive returns, then γ should be positive (Brownlees, Engle & Kelly, 2011).

4.2.5 Exponential GARCH

The Exponential Generalized Autoregressive Conditional Heteroskedasticity (E-GARCH) model was first proposed by Nelson (1991) as an extension of standard GARCH to capture the asymmetric effect of positive and negative shocks on volatility. It differs from the standard GARCH model by allowing asymmetric volatility responses to positive and negative shocks, whereas standard GARCH assumes a symmetric response to both. Also, the parameter values are not restricted as they are in standard GARCH. It differs from GJR-GARCH, in which asymmetric response is only allowed to occur above a certain threshold, whereas, in E-GARCH, the impact of negative shocks on volatility is greater than positive shocks of the same magnitude. This is often referred to as the leverage effect, which is captured by the parameter γ. If negative shocks to oil returns cause volatility to rise more than positive, γ should be above 0. Additionally, the E-GARCH model is more flexible in the sense that it can capture both asymmetry and leverage effects simultaneously. In contrast, the GJR-GARCH model only captures asymmetry in the presence of a threshold. The E-GARCH can be expressed as:

$$\ln(\sigma_t^2) = h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \frac{|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \beta_j h_{t-j}$$

5.0. Data

In our thesis, we take the view of a hedger who has a long position in physical Brent crude oil and uses Brent futures contracts to hedge the price risk. In order to do so, we need both spot and futures price data.

5.1. Data description

According to US Energy Information Administration (2023), Brent oil is a blended crude stream that is produced in the North Sea region and serves as a proxy to price many other crude streams. The spot price is defined as the one-time transaction price that you were to pay for immediate delivery at the current market rate.

For Brent futures price data, we use the generic first month daily close price data from Bloomberg with a ticker 'CO1'. The data is collected from the 23rd of June 1988 to the 28th of October 2022. We use the one-month contracts as the hedging instrument because moving further out the curve increases basis risk. This is because the price of the futures contract is not directly tied to the spot price prior to the maturity date. This difference becomes larger when the time until maturity is increased (Byström, 2013). As defined by the U.S Energy Information Agency (2023), the Brent futures price is denominated as $/barrel, and one barrel equals roughly 159 liters.

We use the daily European crude oil spot prices from the Federal Reserve Bank of St. Louis ('DCOILBRENTEU') for Brent spot prices. The data was also collected from the 23rd of June 1988 to the 28th of October 2022 and is also denominated in $/barrel.

5.2. Data transformation

We first match the spot price and futures price based on the date. There are some observations where the spot price is obtained, but the future price is not. This is mainly due to exchange holidays. Thus, those observations have been removed. After this, price data is converted into daily log returns as per the below equation:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$$

Where r_t is the log return at time t, ln is the natural logarithm, and p_t is the underlying price at time t. Log returns are used instead of prices for a few reasons: for one, they exhibit greater stationarity and are less likely to be influenced by non-stationary components like trends or seasonality (Bollerslev, 1986). Also, percentages matter more than price changes for hedgers, and log returns are more likely to be normally distributed, which is our assumption in GARCH modeling (Fama, 1965).

After converting our futures and spot prices to daily log returns and omitting empty cells, we are left with 8672 observations from June 1988 to October 2022 for both spot and futures.

We then split our data into subsamples based on historical events we want to investigate more closely, as seen in Table 1. These events are the Gulf War in the early 1990s that started from the Kuwait Invasion, the Asian Financial Crisis in the late 1990s, the Iraq War in the early 2000s, the Great Financial Crisis from 2008 to 2009, the Shale Oil Boom from 2014 to 2017 that caused the oil prices to drop, Covid-19 Crisis from early 2020 and finally the Russian invasion of Ukraine in early 2022. In addition to these subsamples, we also define a placebo period that acts as a control sample.

The samples are further divided into in-sample periods and out-sample periods to analyze these periods. The in-sample periods are before the oil price shocks and are used to train the models. The out-sample period is the period that contains the high volatility regime. In most cases, the in-sample period starts three years until one day before the event starts, and the out-of-sample is chosen to contain the high volatility regime after the initial shock. Three years are set so that we have enough observations to estimate the models. For example, sample 2 (Asian Financial Crisis) in-sample period starts in 1995 and ends in 1998, one day before the out-sample period begins. Some in-sample periods have been cut smaller to avoid overlapping periods between different crises. Also, since Bloomberg only has CO1 price data from 23rd June 1988, the Gulf War sample in-sample period is less than two years.

Figure 1. Different crises illustrated on a graph.

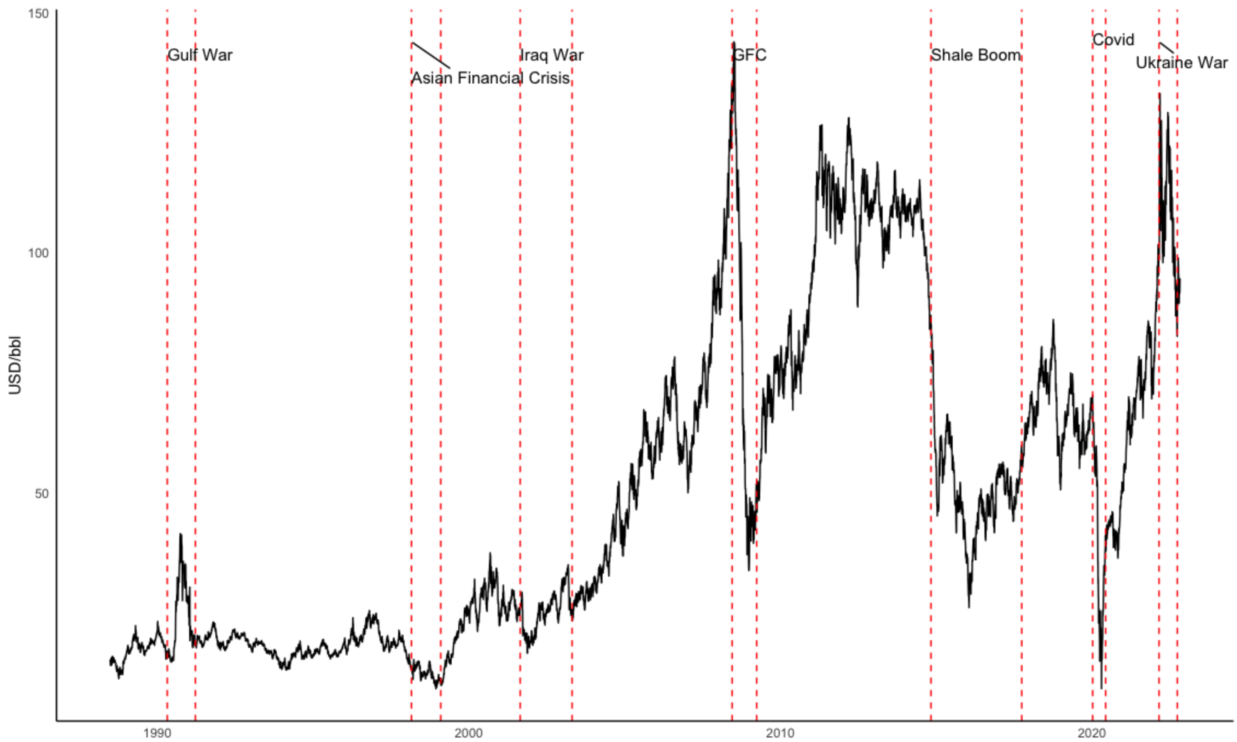

Table 1. Sample periods.

	Main Event	In-Sample period	Out-of-Sample period
S1	Gulf War	06/24/1988–04/26/1990	04/27/1990–03/22/1991
S2	Asian Financial Crisis	02/27/1995–02/26/1998	02/27/1998–02/05/1999
S3	Iraq War	02/08/1999–08/23/2001	08/24/2001–04/25/2003
S4	GFC	06/13/2005–06/12/2008	06/13/2008–03/27/2009
S5	Shale Boom	10/31/2011–10/30/2014	10/31/2014–09/29/2017
S6	Covid Crisis	09/30/2017-01/07/2020	01/08/2020-06/08/2020
S7	Ukraine Invasion	06/09/2020-02/23/2022	02/24/2022-27/09/2022
S8	Placebo Sample	11/30/1992-11/29/1995	11/30/1995-09/27/1998

5.2.1. Placebo Commodities

For comparison, we also use data from commodities that are not considered good hedging tools for exposure in spot Brent crude oil. These commodities are gold, silver, corn, aluminum, natural gas, and copper. We have both their spot and futures price data for all these commodities from the 23rd of July 1997 until the 28th of October 2022. The reason for the shorter data range compared to Brent spot and futures, which we have from June 1988, is that the data is only readily available for some of the commodities that far back. Only from July 1997 can we fetch data for all commodities, making it more accessible in terms of comparison. The price data is also converted into log returns for the mentioned reasons. Another reason for using log returns instead of prices is the different way of quotation between some of the commodity spot prices with their respective future prices. This is not so apparent when looking at Brent spot and futures prices that are both quoted at price per barrel. Still, for some commodities, historical spot prices are readily available in index form, whereas futures are quoted in USD per certain measurements like bushels. This can be seen in Appendix L.2, where aluminum futures are quoted differently than their respective Bloomberg spot index.

5.3. Descriptive statistics

Looking at the correlation matrix (Appendix M.1), it is notable how relatively low the correlation is between the Brent pair (spot to its future) compared to other commodities. With other commodities, the spot correlation with its corresponding future is above 0.90, whereas for the Brent pair, it is merely 0.71. This imperfect correlation will result in lower variance reduction. In fact, in Table 2, it is seen that the correlation between Brent spot and futures log-returns only cross above 0.90 in the Ukraine subsample.

Table 2. Correlations of Brent spot to Brent futures log-returns between subsamples.

	In-Sample	Out-Sample	Whole sample
S1	0,85	0,84	0,84
S2	0,74	0,71	0,73
S3	0,59	0,67	0,63
S4	0,58	0,61	0,60
S5	0,71	0,72	0,72
S6	0,77	0,79	0,77
S7	0,96	0,95	0,95
S8	0,67	0,74	0,72

5.3.1. Tests between in-sample and out-sample

To test for the difference between in-sample and out-sample means, we use the two-sample Welch t-test. It is a hypothesis test introduced by Welch (1947) to compare the means of two samples when we assume that the variances of those two samples are not equal. This should be the assumption in our case as we are comparing the in-sample, where oil returns are more stable, to our out-samples, where a shock has hit the oil markets. The null and alternative hypotheses can be represented as follows:

$$H_0: \mu_1 = \mu_2$$
$$H_1: \mu_1 \neq \mu_2$$

Where μ_1 is the mean of sample 1 and μ_2 is the mean of sample 2.

To test for the difference between the variances of our in-sample and out-sample, we use the F-test. F-test is a hypothesis test used to test if the variances of two populations are not equal (Montgomery et al. 2012). The null and alternative hypotheses can be represented as follows:

$$H_0: \sigma_1^2 = \sigma_2^2$$
$$H_1: \sigma_1^2 \neq \sigma_2^2$$

Where σ_1^2 is the variance of sample 1 and σ_2^2 is the variance of sample 2.

The results of both tests are presented in Table 3. We can see that the null hypothesis is not rejected in any of the Welch t-tests at a significance level of 5%, indicating that none of the crises significantly affected returns. On the other hand, the null hypothesis of F-tests is rejected in every sample at the same significance level. In other words, the structural changes in the oil volatility are evident, and the oil volatility is followed by high volatility regimes after an oil price shock.

Table 3. Tests between mean and variances of samples.

		Mean F	Mean S	Sd. F	Sd. S
S1	In-Sample	0	0	0,019	0,021
	Out-sample	0	0,001	0,051***	0,05***
S2	In-Sample	0	0	0,019	0,019
	Out-sample	-0,001	-0,001	0,027***	0,031***
S3	In-Sample	0,001	0,001	0,024	0,025
	Out-sample	0	0	0,025**	0,028
S4	In-Sample	0,001	0,001	0,018	0,019
	Out-sample	-0,005*	-0,005*	0,043***	0,042***
S5	In-Sample	0	0	0,012	0,012
	Out-sample	-0,001	-0,001	0,025***	0,025***
S6	In-Sample	0	0	0,018	0,019
	Out-sample	-0,005	-0,005	0,065***	0,110***
S7	In-Sample	0	0	0,022	0,020
	Out-sample	-0,001	-0,001	0,034***	0,035***
S8	In-Sample	0	0	0,015	0,015
	Out-sample	0	0	0,022***	0,023***

Superscripts *, **, and *** denote the statistical significance between the difference of means and variance of in -and out-of-sample log returns in Brent spot and futures, with significance levels of 10%, 5%, and 1%, respectively. A two-sided Welch t-test is used to compare the means of the two samples, and a two-sided F-test to test the difference of variances.

5.3.2. Tests for autocorrelation and ARCH-effects

To test for autoregressive conditional heteroskedasticity (ARCH) in our residuals, we use the weighted Ljung-Box test on standardized squared residuals (LB-Squared) and the ARCH-LM test. These are statistical tests used to determine the presence of ARCH effects in the residuals of a time series model (Wooldridge, 1991). It is an extension of the Ljung-Box test on standardized residuals (LB-test), which is used to test if residuals exhibit autocorrelation, meaning that the residuals are not independent of each other (Francq & Zakoian, 2010).

The null hypothesis of the LB-Squared and the ARCH-LM is that there is no autoregressive conditional heteroskedasticity among the squared residuals, while the alternative hypothesis is that ARCH-effects are present. The null hypothesis for LB-Test is that there is no autocorrelation in standardized residuals. The alternative hypothesis states that there is autocorrelation present in the standardized residuals. It is worth mentioning that autocorrelation and ARCH are different, as one can have either or both in time series. (Ljung & Box, 1978)

If the null hypothesis is rejected, it might be better to use a model that does not assume constant variance or, in case of violations in standard GARCH, use different lag orders or modifications of the model like E-GARCH. It is essential that this assumption is satisfied in GARCH models, as the model assumes standardized residuals are independently and identically distributed.

In Appendix B.3, where OLS residuals are tested, we can see that the null hypothesis for the Ljung-Box tests is rejected for most samples at 1% confidence. In Sample 1, the LB-Squared null hypothesis is not rejected. Thus, it does not exhibit ARCH-effects. For the rest, we conclude that the standardized residuals exhibit both autocorrelation and ARCH-effects and a model that does not assume constant variance should be more suitable.

Appendix B.1 shows us the LB-Test results for our standard GARCH model for different lags. It can be concluded from the p-values that the standardized residuals do not exhibit autocorrelation at a 5% confidence level. From Appendix B.2, we can see that only in Sample 2 with lag=1 we may reject the null hypothesis at a 5%

confidence level and conclude that the standardized squared residuals exhibit ARCH-effects. Appendix B.4 shows that Sample 1 exhibits ARCH effects for ARCH lags 3, 5, and 7. In other samples, we fail to reject any null hypotheses.

5.3.3. Tests for normality and stationarity

In addition, tests on the normality and stationarity of Brent spot and futures returns were conducted on the different samples. Jarque-Bera test was used to test if the sample follows a normal distribution, and Augmented Dickey-Fuller (ADF) test was used to test if the time series are stationary.

The Jarque-Bera test is a goodness-of-fit test that evaluates whether a given sample follows a normal distribution based on its skewness and kurtosis. It tests the null hypothesis that the sample comes from a normally distributed population (Jarque & Bera, 1980). The null hypothesis was rejected for all samples (Appendix E.1-E.3) for both spot and futures returns. This indicates that the returns do not follow a normal distribution.

The ADF test is a unit root test used to determine whether a time series is stationary or contains a unit root, which indicates non-stationarity. Stationarity is an important assumption in time series analysis, and the ADF test examines the autoregressive structure of the series to test the null hypothesis of a unit root (Dickey & Fuller, 1979). In all samples, the p-values are less than 0.05 (Appendix F.1-F.3). Therefore, we can conclude that the spot and futures returns are stationary.

6.0. Results

6.1. Hedge effectiveness

The hedge effectiveness, measured by variance reduction, is reported in Table 4. The naïve 1-to-1 hedge is the worst in 4 out of the eight samples, but it performs the best in the Ukraine war sample. Although, outperformance is only 14 basis points better than the OLS hedge. Where the naïve hedge is the worst out of the five methods compared, it tends to underperform the others a lot, making it the worst hedging strategy based on variance reduction. This result is expected, as the strategy assumes covariance between spot and futures returns to equal the variance of futures returns (Brooks, 2019). In fact, it is the best-performing strategy in the Ukraine sample because that sample exhibits by far the highest correlation between spot and futures log returns.

The simple OLS hedge performs relatively well, being the best hedging strategy in three samples and the worst only in one. It is also a relatively simple strategy compared to rolling GARCH hedging to perform and yield good results.

The differences between the three GARCH models are quite tame. Standard GARCH is not the best method in any of the samples, but neither is the worst. E-GARCH is the best in three of the samples but also the worst in two. GJR-GARCH falls between these two being the best strategy in one and the worst in none.

The results from Table 5 illustrate the importance of considering the correlation between the spot and future returns in the hedging process. When ρ is assumed to be 1, which means perfect positive correlation, the hedge effectiveness is significantly lower across most samples and models. This underlines that the correlation between spot and futures prices is usually less than 1, and assuming otherwise could lead to suboptimal hedging outcomes.

Table 4. Hedge effectiveness by variance reduction

Sample	1-to-1	OLS	sGARCH	GJR-GARCH	E-GARCH
Kuwait	66,48 %	67,45 %*	62,51 %	62,32 %	59,84 %†
Asia	48,55 %	50,44 %*	45,43 %†	45,49 %	45,49 %
Iraq	39,33 %†	43,73 %	50,52 %	50,06 %	50,80 %*
GFC	21,68 %†	37,57 %*	29,39 %	35,70 %	34,53 %
Shale	43,09 %†	51,60 %	51,30 %	51,34 %	51,94 %*
Covid	58,56 %	52,81 %†	61,87 %	62,93 %*	60,61 %
Ukraine	89,42 %*	89,28 %	88,23 %	87,36 %	56,34 %†
Placebo	50,19 %†	54,03 %	54,28 %	54,28 %	54,66 %*

Superscript * denotes the best-performing hedging strategy of that subsample. † denotes the worst-performing hedge.

Table 5. Hedge effectiveness with correlation assumption

Sample	sGARCH	sGARCH (ρ=1)	GJR-GARCH	GJR-GARCH (ρ=1)	E-GARCH	E-GARCH (ρ=1)
Kuwait	62,51 %	49,72 %	62,32 %	49,35 %	59,84 %	44,94 %
Asia	45,43 %	34,98 %	45,49 %	31,74 %	45,49 %	33,35 %
Iraq	50,52 %	43,15 %	50,06 %	41,29 %	50,80 %	43,87 %
GFC	29,39 %	35,76 %	35,70 %	28,76 %	34,53 %	32,72 %
Shale	51,30 %	41,03 %	51,34 %	39,98 %	51,94 %	39,56 %
Covid	61,87 %	63,26 %	62,93 %	64,93 %	60,61 %	66,31 %
Ukraine	88,23 %	88,69 %	87,36 %	86,90 %	56,34 %	52,20 %
Placebo	54,28 %	46,99 %	54,28 %	47,39 %	54,66 %	47,97 %

Table 6. Average Rolling Hedge Ratios

Sample	sGARCH	sGARCH (ρ=1)	GJR-GARCH	GJR-GARCH (ρ=1)	E-GARCH	E-GARCH (ρ=1)
Kuwait	0,972	1,146	0,972	1,146	0,978	1,154
Asia	0,648	1,090	0,658	1,107	0,655	1,102
Iraq	0,824	1,108	0,846	1,137	0,818	1,100
GFC	0,382	0,662	0,525	0,910	0,481	0,834
Shale	0,743	1,047	0,749	1,055	0,757	1,068
Covid	1,037	1,344	1,037	1,343	0,912	1,181
Ukraine	0,993	1,35	0,964	1,005	1,006	1,048
Placebo	0,699	1,044	0,698	1,043	0,700	1,046

Table 6 presents the average rolling hedge ratios of different models. The ratios indicate the proportion of the spot position that needs to be hedged to achieve the lowest variance according to the model's estimation. The results show that the hedge ratio is lower than 1 for every model and sample when ρ is not assumed to be 1. In contrast, the hedge ratio is higher than 1 when ρ is assumed to be 1. This again emphasizes the importance of correctly estimating the correlation between spot and futures prices in the hedging process.

Table 7. Portfolio Returns in percentages.

	No Hedge	1-to-1	OLS	S-GARCH	GJR-GARCH	E-GARCH
S1	13,25*	3,50	3,76	7,71	-2,50†	8,27
S2	-20,48†	0,69*	-5,13	-0,89	-0,32	-1,01
S3	-6,24†	-1,34	-3,19	1,48	6,65	7,26*
S4	-60,72†	-0,01*	-30,67	-43,55	-41,72	-38,32
S5	-31,23†	3,31*	-8,57	-8,54	-10,33	-8,96
S6	-40,35†	-3,74*	-12,08	-39,29	-23,14	-39,25
S7	-16,86†	-4,22	-3,99	-8,56	3,33*	-9,22
S8	-15,90†	-0,45*	-5,49	-5,43	-5,80	-5,67

Superscript * denotes hedging strategy of the subsample with the highest return. † denotes the hedging strategy with the lowest return.

Table 8. Portfolio Returns in USD for 10 000 invested.

	No Hedge	1-to-1	OLS	S-GARCH	GJR-GARCH	E-GARCH
S1	1325,30*	350,24	375,85	771,12	-250,17	827,14
S2	-2047,83†	69,40*	-512,84	-89,33	-32,30	-100,98
S3	-623,54†	-134,10	-319,38	148,06	664,76	726,04*
S4	-6072,21†	-1,26*	-3066,52	-4355,13	-4172,46	-3832,46
S5	-3122,81†	330,76*	-857,25	-853,72	-1032,51	-895,79
S6	-4035,50†	-373,60*	-1207,58	-3929,07	-2314,34	-3924,68
S7	-1685,97†	-421,95	-399,02	-856,50	333,27*	-921,88
S8	-1589,60†	-45,07*	-549,24	-543,15	-580,23	-566,72

Superscript * denotes the hedging strategy of the subsample with the highest return.
† denotes the hedging strategy with the lowest return.

Comparing these results of Table 4 to Tables 7 and 8, we notice that the percentage and dollar returns differ significantly from the variance reduction rankings. In some cases, the best-performing strategy based on variance reduction does not necessarily yield the highest percentage return. For instance, in Sample 1, the No Hedge strategy attains the highest return of 13.25%, while the GJR-GARCH method yields a negative return of 2.5%. This shows that although the GJR-GARCH method might have reduced variance effectively in Sample 1, it did not generate the highest returns in the same sample. This should come as no surprise, as the essential goal of hedging is not to generate high returns but to minimize risk. Had the hedged portfolios generated higher positive returns or lower negative returns than the unhedged portfolio, it would have indicated that the hedging strategy or the instrument was flawed.

Table 9. Portfolio Returns in percentages for different hedge horizons.

1-month	No Hedge	1-to-1	OLS	S-GARCH	GJR-GARCH	E-GARCH
S1	-6,75 %	-4,28 %*	-4,35 %	-41,35 %	-41,34 %	-41,47 %†
S2	11,51 %	1,59 %†	4,01 %	45,73 %	45,07 %	52,31 %*
S3	-19,60 %	-6,53 %*	-11,63 %	-91,04 %†	-90,42 %	-90,63 %
S4	7,81 %	1,95 %†	4,21 %	62,23 %*	53,32 %	53,40 %
S5	-17,11 %	-1,46 %*	-6,44 %	-87,11 %†	-86,75 %	-86,35 %
S6	-12,94 %†	-0,38 %	-2,89 %	0,60 %	0,71 %*	-8,64 %
S7	7,19 %*	-0,76 %	-0,89 %	-4,67 %†	-2,21 %	-0,27 %
S8	9,54 %	0,48 %†	3,19 %	175,83 %	176,29 %*	174,27 %
2-months	**No Hedge**	**1-to-1**	**OLS**	**S-GARCH**	**GJR-GARCH**	**E-GARCH**
S1	-7,65 %†	0,46 %*	0,23 %	-4,87 %	-4,84 %	-5,10 %
S2	5,31 %	3,68 %†	4,09 %	20,49 %*	17,54 %	17,26 %
S3	-19,88 %	-2,04 %*	-9,11 %	-57,58 %†	-53,20 %	-54,50 %
S4	-17,51 %	1,00 %*	-6,70 %	-39,25 %†	-31,12 %	-32,18 %
S5	-35,36 %	-2,76 %*	-13,98 %	-90,20 %†	-89,82 %	-89,32 %
S6	-23,59 %†	0,22 %	-4,79 %	0,89 %	1,79 %*	-7,38 %
S7	24,72 %*	1,74 %	1,39 %†	5,41 %	9,13 %	12,89 %
S8	-3,87 %	-0,61 %*	-1,63 %	-21,19 %	-21,98 %	-22,56 %†
3-months	**No Hedge**	**1-to-1**	**OLS**	**S-GARCH**	**GJR-GARCH**	**E-GARCH**
S1	12,83 %*	0,12 %	0,45 %	0,39 %	0,17 %	-4,72 %†
S2	2,09 %	0,66 %†	1,02 %	10,17 %	12,77 %	14,48 %*
S3	-28,14 %	-1,78 %*	-12,57 %	-58,33 %	-58,43 %	-59,19 %†
S4	-27,33 %	1,29 %*	-11,06 %	-44,43 %†	-36,06 %	-38,20 %
S5	-39,49 %	-4,68 %*	-16,83 %	-85,39 %†	-85,15 %	-85,07 %
S6	-67,22 %†	-10,00 %*	-25,67 %	-13,02 %	-12,26 %	-21,31 %
S7	40,55 %*	2,21 %	1,66 %†	2,72 %	4,94 %	8,29 %
S8	8,67 %	4,51 %†	5,78 %	81,71 %*	80,74 %	77,95 %

Superscript * denotes the hedging strategy of the subsample with the highest return.
† denotes the hedging strategy with the lowest return.

Table 10. Variance reduction for different hedge horizons.

1-month	1-to-1	OLS	S-GARCH	GJR-GARCH	E-GARCH
S1	53,41 %*	53,66 %	51,72 %†	51,79 %	52,01 %
S2	84,53 %*	69,60 %†	80,08 %	81,14 %	82,06 %
S3	87,22 %*	74,03 %†	76,25 %	80,66 %	79,78 %
S4	20,85 %†	32,66 %	33,91 %*	33,08 %	31,56 %
S5	35,49 %†	58,01 %	56,78 %	55,59 %	58,72 %*
S6	44,95 %†	50,49 %	51,38 %	51,47 %*	49,04 %
S7	24,67 %†	53,56 %	93,66 %	94,03 %*	65,83 %
S8	96,93 %*	36,01 %	36,38 %	36,55 %	35,98 %†
2-month	1-to-1	OLS	S-GARCH	GJR-GARCH	E-GARCH
S1	40,12 %†	40,97 %	45,45 %*	45,39 %	43,34 %
S2	67,21 %	60,45 %†	69,00 %*	68,67 %	68,76 %
S3	72,30 %*	64,66 %†	65,70 %	68,84 %	68,18 %
S4	0,07 %†	22,87 %	25,28 %*	25,12 %	24,96 %
S5	11,37 %†	42,59 %	42,16 %	40,14 %	44,17 %*
S6	73,21 %*	72,29 %	71,97 %	71,33 %†	72,34 %
S7	58,52 %	35,65 %†	93,98 %	94,27 %*	54,34 %
S8	96,36 %*	59,82 %	60,05 %	59,66 %†	60,08 %
3-month	1-to-1	OLS	S-GARCH	GJR-GARCH	E-GARCH
S1	28,03 %†	29,19 %	32,48 %*	32,38 %	29,60 %
S2	58,75 %	55,64 %†	60,76 %*	60,48 %	60,42 %
S3	67,53 %*	57,67 %†	60,01 %	61,84 %	61,66 %
S4	26,74 %†	35,52 %*	34,53 %	34,63 %	34,44 %
S5	6,00 %†	33,05 %	30,78 %	29,89 %	33,68 %*
S6	72,68 %†	73,00 %	73,10 %	73,02 %	73,65 %*
S7	54,83 %	34,26 %	81,13 %*	81,08 %	32,79 %†
S8	83,13 %*	62,65 %	62,83 %	62,59 %†	62,91 %

Superscript * denotes the best-performing hedging strategy of that subsample measured by variance reduction. † denotes the worst-performing hedge.

Table 9 presents the portfolio return for the subsamples and six different hedge strategies across three different horizons (1 month, 2 months, and 3 months). In this context, the hedge horizon refers to the period during which the hedging strategy is implemented. For example, the 1-month horizon result shows the return of the strategy for the first 21 days after the initial shock. The table shows that the returns vary widely across the different samples and hedge strategies. Table 10, on the other hand, shows the variance reduction of five different hedge strategies across the same three horizons. Similarly, with Tables 4 and 7, when comparing Tables 9 and 10 together, it becomes evident that the best-performing strategies in terms of returns do not necessarily correspond to the best strategies in terms of variance reduction. Thus, it should be noted that a strategy yielding higher returns often comes with a higher risk, which is reflected in the negative returns of the no-hedge strategy in other samples. These results highlight the inherent trade-off between risk and return in portfolio management. Therefore, the choice of a hedging strategy depends on the risk-return preferences of the hedger.

In conclusion, our analysis shows that there is no universally optimal hedging strategy. The effectiveness of different strategies varies depending on the characteristics of the specific sample, including the correlation between spot and futures returns, as well as the risk-return preferences of the investor. Therefore, it is recommended to consider both variance reduction and return performance when evaluating different hedging strategies.

6.2. Volatility estimation

Table 11, Table 12, and Table 13 present the estimates for standard GARCH, GJR-GARCH, and E-GARCH parameters. All standard GARCH (β_1) coefficients are significant at the 1% level for both spot and futures returns, and most of the ARCH (α_1) coefficients are significant. The GARCH coefficients are relatively high, ranging from 0.73 to 0.99, indicating high persistence of shocks. The samples also exhibit significant volatility clustering, given by the high persistence of volatility.

Table 12 gives the estimates of the GJR-GARCH model. When $\gamma > 0$, we observe asymmetrical effects in the volatility process, leading us to the conclusion that negative return shocks cause larger variance. For spot and futures, some estimates are significant at the 1% and 5% levels, while some estimates are not. Sample 5, Sample 6, and Sample 7 all have positive and significant leverage effect coefficients, implying positive leverage effects. The coefficient for leverage effect in Sample 3 for spot and futures is negative and significant, indicating that positive shocks have a greater effect on the returns than bad shocks.

The E-GARCH estimates are presented in Table 13. If $\gamma < 0$, good news creates less volatility than bad news, and $\gamma > 0$ indicates that negative news is less disruptive. For Sample 4, the coefficient is negative for spot and positive for futures. The gamma estimates for the other samples, both spot and futures, are positive and significant. Thus, positive shocks impact oil returns more than negative shocks.

Table 11. S-GARCH estimates for spot and futures.

	μ	Ω	α_1	β_1
Spot				
S1	0,0000	0,0000	0,142***	0,8409***
S2	0,0019*	0,0000	0,0473**	0,898***
S3	-0,0001	0,0000	0,0464***	0,9442***
S4	0,0013*	0***	0,0000	0,999***
S5	-0,0004	0,0000	0,0461	0,9402***
S6	0,0010	0***	0,0634***	0,9009***
S7	0,0025**	0**	0,0791**	0,8255***
S8	-0,0002	0,0000	0,0378	0,9517***
Futures				
S1	0,0003	0**	0,2304	0,7254***
S2	0,0014	0***	0,0199***	0,9664***
S3	-0,0005	0	0,0586**	0,9353***
S4	0,0013**	0	0,0416**	0,9028***
S5	-0,0002	0	0,045***	0,9345***
S6	0,001	0***	0,0529***	0,9246***
S7	0,0022**	0**	0,0793***	0,8266***
S8	-0,0004	0	0,0483**	0,9377***

Superscripts *, **, and *** denote the statistical significance of sGARCH parameter estimates for log returns in Brent spot and futures, with significance levels of 10%, 5%, and 1%, respectively.

Table 12. GJR-GARCH estimates.

	μ	Ω	α_1	β_1	γ
Spot					
S1	0	0	0,1395***	0,8394***	0,0069
S2	0,0019*	0,0001	0,0057	0,839***	0,0915
S3	0,0001	0	0,0671**	0,9531***	-0,0495**
S4	0,0014	0,0001	0	0,7643***	0,1119
S5	-0,0006	0	0	0,9647***	0,0575***
S6	0,0005	0***	0,0051	0,9226***	0,0776***
S7	0,0022**	0**	0	0,8329***	0,1348**
S8	-0,0002	0	0,0317	0,9532***	0,0102
Futures					
S1	0.0003	0.0000**	0.2233***	0.7245***	0.0145
S2	0.0014	0***	0.0205**	0.9663***	-0.0007
S3	0.0001	0.0000	0.1002***	0.9419***	-0.0862***
S4	0.0013**	0.0000	0.0412*	0.902***	0.0009
S5	-0.0005	0.0000	0.0000	0.9589***	0.0557***
S6	0.0005	0.0000***	0.0043	0.9392***	0.0702***
S7	0.0018**	0.0000***	0	0.8410***	0.1470**
S8	-0.0004	0.0000	0.0504**	0.9369***	-0.0029

Superscripts *, **, and *** denote the statistical significance of GJR-GARCH parameter estimates for log returns in Brent spot and futures, with significance levels of 10%, 5%, and 1%, respectively.

Table 13. E-GARCH estimates.

	μ	Ω	α_1	β_1	γ
Spot					
S1	-0,0003	-0,3417**	0,0038	0,9535***	0,3265***
S2	0,0018*	-1,0197**	-0,0918**	0,862***	0,1255**
S3	0,0003	-0,0739***	0,0444***	0,9902***	0,1088***
S4	0,0012**	-1,4805***	-0,1615***	0,8142***	-0,0511*
S5	-0,0007*	-0,0137***	-0,0571***	0,9983***	0,0399***
S6	0,0007	-0,2806***	-0,0847***	0,9647***	0,0762***
S7	0,0019***	-0,7453***	-0,1622***	0,9039***	0,0998***
S8	-0,0003	-0,1005***	-0,0109	0,9879***	0,0897***
Futures					
S1	0,0007*	-0,5748**	0,0009	0,928***	0,3968***
S2	0,0013	-0,1006***	-0,0017	0,9865***	0,0461***
S3	0,0003	-0,0878***	0,0731***	0,9877***	0,1377***
S4	0,0013*	-0,3413***	-0,009	0,9576***	0,0762***
S5	-0,0006	-0,0503***	-0,0537***	0,9941***	0,0436***
S6	0,0003	-0,1873***	-0,1031***	0,9765***	0,0433***
S7	-0,0016***	-0,7591***	-0,1955***	0,9038***	0,0407**
S8	-0,0003	-0,1336***	0,0079	0,9836***	0,1138***

Superscripts *, **, and *** denote the statistical significance of E-GARCH parameter estimates for log returns in Brent spot and futures, with significance levels of 10%, 5%, and 1%, respectively.

7. Conclusion

The oil market is characterized by high volatility and susceptibility to various shocks. This study examined the effectiveness of different hedging strategies and volatility models in the context of various oil shocks. The findings highlight the importance of considering both variance reduction and return performance when evaluating hedging strategies.

The analysis of hedge effectiveness by variance reduction, as presented in Table 4, showed that there is no universally optimal hedging strategy. The simple OLS hedge performed well in three samples, while the naïve hedge consistently underperformed the others. Table 5 emphasizes the significance of considering the correlation between spot and futures returns in the hedging process, highlighting the suboptimal outcomes when assuming a perfect positive correlation. Additionally, the average rolling hedge ratios in Table 6 underscored the importance of accurately estimating the correlation between spot and futures prices.

The comparison of hedge effectiveness from a return perspective to variance minimization, as shown in Tables 7 and 8, revealed a trade-off between risk reduction and return maximization. The strategy that minimized variance did not always yield the highest returns. This should be obvious, as the goal of hedging is not to maximize returns but to cover losses. Had the hedged portfolios generated higher positive returns or lower negative returns than the unhedged portfolio, it would have indicated that the hedging strategy or the instrument was flawed.

These findings emphasize the different needs and risk tolerance of different types of oil market participants. Consider company A, which is active in drilling and selling oil, and company B, a large consumer of oil (or oil-based products) such as an airline. In some situations, it might make sense to fully or partially hedge the price risk for A and not for B and vice versa. This is because the different nature of their business gives them opposite-side exposure to oil prices. Naturally, company A has long exposure since the higher oil price increases their profit margins. For B, higher fuel costs lower their profit margins. Thus, they have short exposure. For example, in March and April 2020, when the price of oil was plummeting, it might not make sense for A to lock in the near-zero prices by fully hedging their oil price exposure. However, at least in hindsight, perhaps they should lower the hedge ratio to increase the long-exposure to the price of oil. For B, locking in the historically low oil prices would make more sense than for A. Then consider February of 2022 when Russia invaded Ukraine and oil prices shot up. For A, locking in the high prices by selling futures might make sense if they believe the price movement is temporary. For B, the situation is likely less fortunate, and they must consider if hedging more heavily at these levels makes sense or if they should even sell some of their futures and hope that prices go down. However, the above examples all depend on their current hedge and position before the shock and their risk tolerance.

Furthermore, the estimation of GARCH model parameters in Tables 11, 12, and 13 provided insights into the persistence of shocks, volatility clustering, and asymmetrical effects. The results of the autocorrelation and ARCH-effect tests indicated the presence of autocorrelation and volatility clustering in the oil market. These findings suggest the inadequacy of assuming constant variance and highlight the importance of models that can capture time-varying volatility.

In conclusion, there is no universally best hedging strategy. This study contributes to the understanding of hedging strategies and volatility modeling in the oil market. The findings highlight the need to consider the specific characteristics of each sample, such as correlation and risk-return preferences when selecting a hedging strategy. Moreover, the results emphasize the importance of accurately estimating volatility using appropriate models that capture the oil market dynamics. By considering these findings, market participants can improve risk management and develop more effective hedging strategies tailored to the oil market's unique characteristics.

Future research can further explore additional factors and refine models to enhance hedging effectiveness and risk management in the dynamic and complex oil market. By addressing these research gaps, we can contribute to the development of more robust and accurate models for effective risk mitigation in the oil market.

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Appendices

Appendix A.1: In-Sample statistics.

		Min	Max	Mean	Sd.	Kurtosis	Skew
S1	Future	-0,089	0,126	0,000	0,019	5,758	0,385
	Spot	-0,100	0,124	0,000	0,021	4,643	0,365
S2	Future	-0,112	0,068	0,000	0,019	4,208	-0,624
	Spot	-0,067	0,075	0,000	0,019	1,091	-0,002
S3	Future	-0,102	0,084	0,001	0,024	1,367	-0,430
	Spot	-0,102	0,072	0,001	0,025	0,975	-0,307
S4	Future	-0,055	0,077	0,001	0,018	0,172	0,020
	Spot	-0,056	0,082	0,001	0,019	0,398	0,017
S5	Future	-0,044	0,068	0,000	0,012	2,085	-0,037
	Spot	-0,052	0,047	0,000	0,012	1,253	-0,153
S6	Future	-0,074	0,136	0,000	0,018	6,749	-0,020
	Spot	-0,064	0,111	0,000	0,019	2,597	0,060
S7	Future	-0,123	0,072	0,000	0,020	4,104	-0,893
	Spot	-0,126	0,053	0,000	0,022	8,489	-1,882
S8	Future	-0,080	0,083	0,000	0,015	3,447	-0,264
	Spot	-0,069	0,078	0,000	0,015	2,098	-0,074

Appendix A.2: Out-Sample statistics.

		Min	Max	Mean	Sd.	Kurtosis	Skew
S1	Future	-0,427	0,132	0,000	0,051	21,458	-2,719
	Spot	-0,361	0,173	0,001	0,050	13,211	-1,826
S2	Future	-0,086	0,129	-0,001	0,027	2,274	0,585
	Spot	-0,091	0,163	-0,001	0,031	3,536	0,778
S3	Future	-0,144	0,084	0,000	0,025	3,107	-0,567
	Spot	-0,199	0,129	0,000	0,028	7,839	-1,085
S4	Future	-0,109	0,127	-0,005	0,043	0,260	0,125
	Spot	-0,168	0,181	-0,005	0,042	2,543	0,326
S5	Future	-0,103	0,104	-0,001	0,025	1,461	0,245
	Spot	-0,081	0,099	-0,001	0,025	1,518	0,399
S6	Future	-0,280	0,191	-0,005	0,065	5,508	-1,001
	Spot	-0,644	0,412	-0,005	0,110	12,290	-1,427
S7	Future	-0,141	0,084	-0,001	0,034	1,574	-0,687
	Spot	-0,133	0,082	-0,001	0,035	0,897	-0,492
S8	Future	-0,112	0,129	0,000	0,022	3,887	0,046
	Spot	-0,076	0,163	0,000	0,023	4,302	0,658

Appendix A.3: Whole sample statistics.

		Min	Max	Mean	Sd.	Kurtosis	Skew
S1	Future	-0,427	0,132	0,000	0,033	43,195	-3,233
	Spot	-0,361	0,173	0,000	0,033	23,663	-1,887
S2	Future	-0,112	0,129	-0,000	0,021	3,893	-0,024
	Spot	-0,091	0,163	0,000	0,023	4,557	0,506
S3	Future	-0,144	0,084	0,001	0,024	2,184	-0,496
	Spot	-0,199	0,129	0,001	0,026	4,548	-0,687
S4	Future	-0,109	0,127	0,000	0,025	3,185	-0,145
	Spot	-0,168	0,181	0,000	0,026	6,101	0,059
S5	Future	-0,103	0,104	-0,000	0,020	3,192	0,236
	Spot	-0,081	0,099	0,000	0,019	3,209	0,383
S6	Future	-0,280	0,191	-0,000	0,030	25,355	-1,727
	Spot	-0,644	0,412	0,000	0,041	84,066	-3,294
S7	Future	-0,141	0,084	0,000	0,025	3,910	-0,924
	Spot	-0,133	0,082	0,000	0,029	2,776	-0,815
S8	Future	-0,112	0,129	-0,000	0,018	4,789	-0,036
	Spot	-0,076	0,163	0,000	0,019	4,990	0,507

Appendix B.1: Ljung-Box test on standardized residuals for standard GARCH.

Ljung-Box test on standardized residuals			
S1	p-value	S5	p-value
Lag=1	0,07	Lag=1	0,15
Lag=5	0,11	Lag=5	0,26
Lag=9	0,19	Lag=9	0,58
S2		S6	
Lag=1	0,96	Lag=1	0,68
Lag=5	0,42	Lag=5	0,48
Lag=9	0,60	Lag=9	0,50
S3		S7	
Lag=1	0,66	Lag=1	0,48
Lag=5	0,44	Lag=5	0,43
Lag=9	0,60	Lag=9	0,40
S4		S8	
Lag=1	0,10	Lag=1	0,49
Lag=5	0,16	Lag=5	0,29
Lag=9	0,33	Lag=9	0,03

Appendix B.2: Ljung-Box test on standardized squared residuals for standard GARCH.

Ljung-Box test standardized squared residuals			
S1	p-value	S5	p-value
Lag=1	0,18	Lag=1	0,31
Lag=5	0,06	Lag=5	0,51
Lag=9	0,09	Lag=9	0,65
S2		S6	
Lag=1	0,04	Lag=1	0,90
Lag=5	0,09	Lag=5	0,99
Lag=9	0,09	Lag=9	0,98
S3		S7	
Lag=1	0,88	Lag=1	0,46
Lag=5	0,96	Lag=5	0,65
Lag=9	0,88	Lag=9	0,85
S4		S8	
Lag=1	0,70	Lag=1	0,66
Lag=5	0,26	Lag=5	0,43
Lag=9	0,37	Lag=9	0,41

Appendix B.3: Ljung-Box and Ljung-Box on squared residuals for simple OLS.

OLS with lag = 20

Sample	LB p-value	LB squared p-value
S1	0.003	0.423
S2	0.000	0.000
S3	0.000	0.006
S4	0.000	0.000
S5	0.000	0.000
S6	0.000	0.000
S7	0.006	0.004
S8	0.000	0.000

Appendix B.4: LM-ARCH test for standard GARCH.

ARCH LM-test			
S1	p-value	S5	p-value
ARCH Lag=3	0,01	ARCH Lag=3	0,28
ARCH Lag=5	0,02	ARCH Lag=5	0,36
ARCH Lag=7	0,04	ARCH Lag=7	0,53
S2		S6	
ARCH Lag=3	0,10	ARCH Lag=3	0,37
ARCH Lag=5	0,19	ARCH Lag=5	0,65
ARCH Lag=7	0,16	ARCH Lag=7	0,85
S3		S7	
ARCH Lag=3	0,80	ARCH Lag=3	0,66
ARCH Lag=5	0,83	ARCH Lag=5	0,95
ARCH Lag=7	0,68	ARCH Lag=7	0,99
S4		S8	
ARCH Lag=3	0,92	ARCH Lag=3	0,37
ARCH Lag=5	0,65	ARCH Lag=5	0,11
ARCH Lag=7	0,81	ARCH Lag=7	0,18

Appendix D.1: Percentage returns of all commodities during out-samples.

	Corn	Gold	Silver	Aluminum	Natural Gas	Copper	Brent
Asia	-31,7	-1,1	-6,7	-21,3	-51,4	-20,9	-19,9
Iraq	-17,8	11,1	-1,9	-9,3	24,5	-7,4	-22,3
GFC	-46,9	7,3	-26,5	-52,4	-67,3	-41,7	-53,6
Shale	-28,8	10,5	4,6	0,6	-59,6	5,3	-15,5
Covid	-15,5	3,7	-10,1	-17,7	-32,1	-13,1	-36,4
Ukraine	0,9	-13,0	-22,7	-27,9	45,7	-24,3	-6,2
Placebo	-22,7	-8,4	23,1	-22,0	-16,3	-27,4	-10,8

Appendix E.1: Jarque-Bera on out-samples.

	Spot		Future	
	Test Statistic	P-value	Test Statistic	P-value
S1	1792,5	0,00	4675,30	0,00
S2	155,4	0,00	68,10	0,00
S3	1157,7	0,00	191,40	0,00
S4	56,9	0,00	1,10	0,60
S5	91,2	0,00	73,60	0,00
S6	29457,7	0,00	4714,00	0,00
S7	32,0	0,00	69,30	0,00
S8	593,5	0,00	443,50	0,00

Appendix E.2: Jarque-Bera on in-samples.

	Spot		Future	
	Test Statistic	P-value	Test Statistic	P-value
S1	428,0	0,00	653,80	0,00
S2	37,2	0,00	602,10	0,00
S3	35,4	0,00	69,50	0,00
S4	5,0	0,08	1,00	0,60
S5	52,3	0,00	136,80	0,00
S6	162,4	0,00	1123,60	0,00
S7	388,0	0,00	429,60	0,00
S8	139,5	0,00	383,60	0,00

Appendix E.3: Jarque-Bera on the whole sample.

	Spot		Future	
	Test Statistic	P-value	Test Statistic	P-value
S1	16627,1	0,00	55242,40	0,00
S2	908,9	0,00	632,20	0,00
S3	997,1	0,00	254,20	0,00
S4	1485,0	0,00	407,70	0,00
S5	679,8	0,00	650,50	0,00
S6	280867,0	0,00	26867,40	0,00
S7	136,4	0,00	224,70	0,00
S8	1579,2	0,00	1397,10	0,00

Appendix F.1: ADF on out-sample.

	Spot				Future		
	Statistic	p-value	Lag		Statistic	p-value	Lag
S1	-6,45	0,01	6	S1	-6,32	0,01	6
S2	-6,31	0,01	6	S2	-6,42	0,01	6
S3	-7,58	0,01	7	S3	-7,36	0,01	7
S4	-7,03	0,01	5	S4	-6,38	0,01	5
S5	-8,05	0,01	9	S5	-7,84	0,01	9
S6	-5,94	0,01	7	S6	-6,61	0,01	7
S7	-7,84	0,01	5	S7	-7,70	0,01	5
S8	-9,10	0,01	8	S8	-9,35	0,01	8

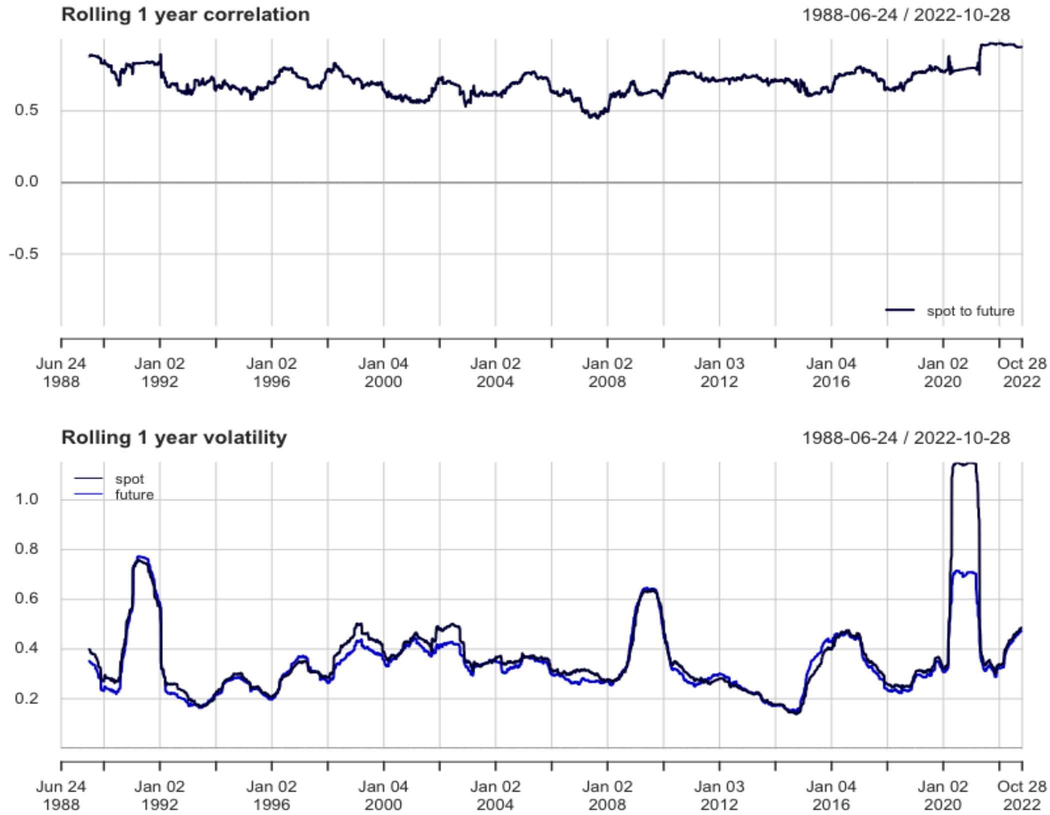
Appendix F.2: ADF on in-sample.

	Spot				Future		
	Statistic	p-value	Lag		Statistic	p-value	Lag
S1	-8,47	0,01	7	S1	-8,61	0,01	7
S2	-7,72	0,01	9	S2	-8,13	0,01	9
S3	-7,24	0,01	8	S3	-7,99	0,01	8
S4	-8,42	0,01	9	S4	-8,37	0,01	9
S5	-8,16	0,01	9	S5	-8,20	0,01	9
S6	-7,72	0,01	8	S6	-7,82	0,01	8
S7	-4,05	0,01	4	S7	-4,32	0,01	4
S8	-9,46	0,01	9	S8	-8,51	0,01	9

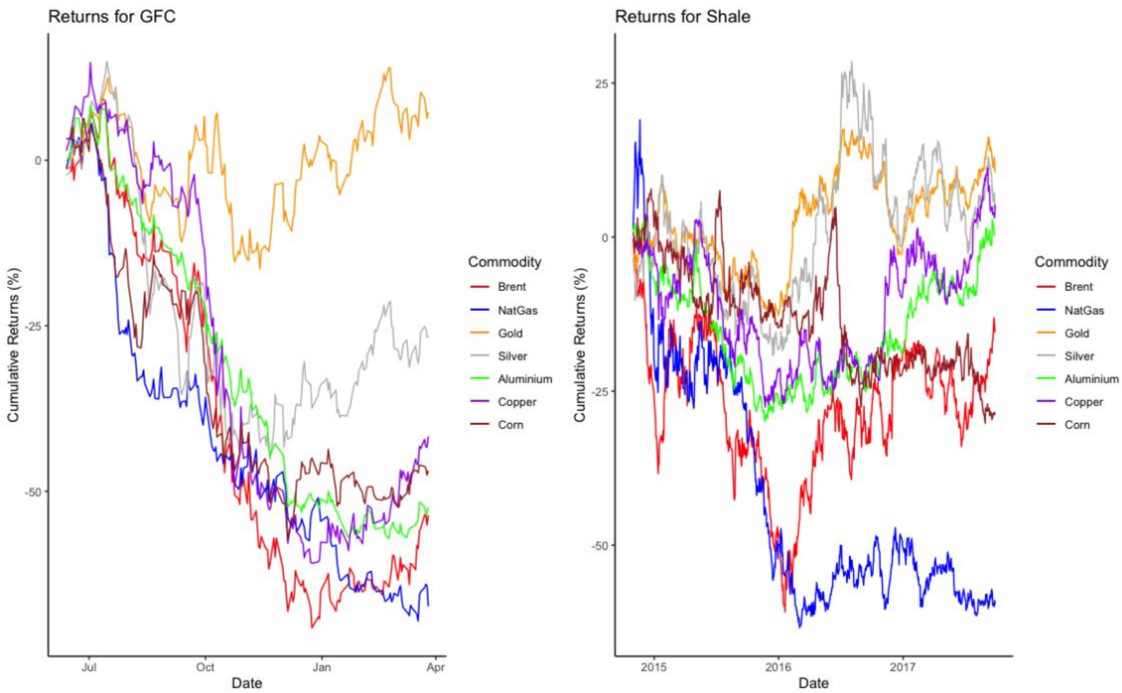
Appendix F.3: ADF on whole sample.

	Spot				Future		
	Statistic	p-value	Lag		Statistic	p-value	Lag
S1	-10,02	0,01	8	S1	-10,18	0,01	8
S2	-9,80	0,01	9	S2	-10,17	0,01	9
S3	-9,04	0,01	10	S3	-9,41	0,01	10
S4	-9,48	0,01	9	S4	-9,17	0,01	9
S5	-10,88	0,01	11	S5	-10,85	0,01	11
S6	-9,05	0,01	9	S6	-9,39	0,01	9
S7	-7,86	0,01	6	S7	-8,13	0,01	6
S8	-12,29	0,01	11	S8	-11,93	0,01	11

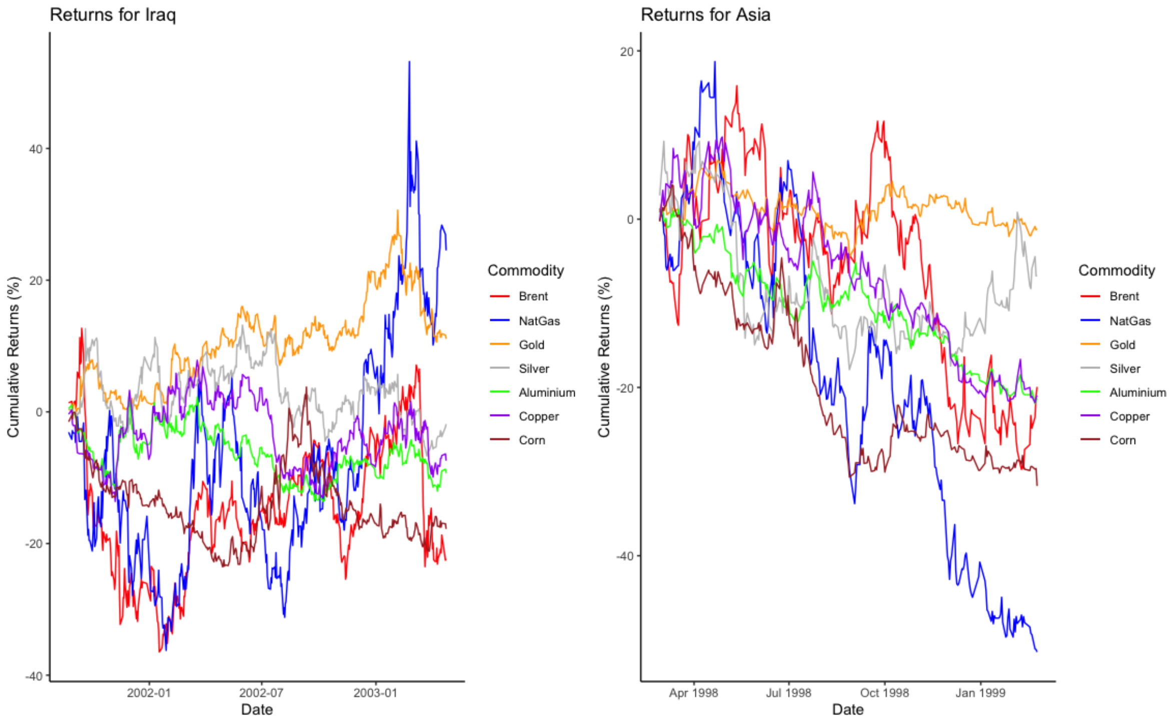
Appendix G.1: Rolling 1-year correlation and volatility of spot and futures prices.



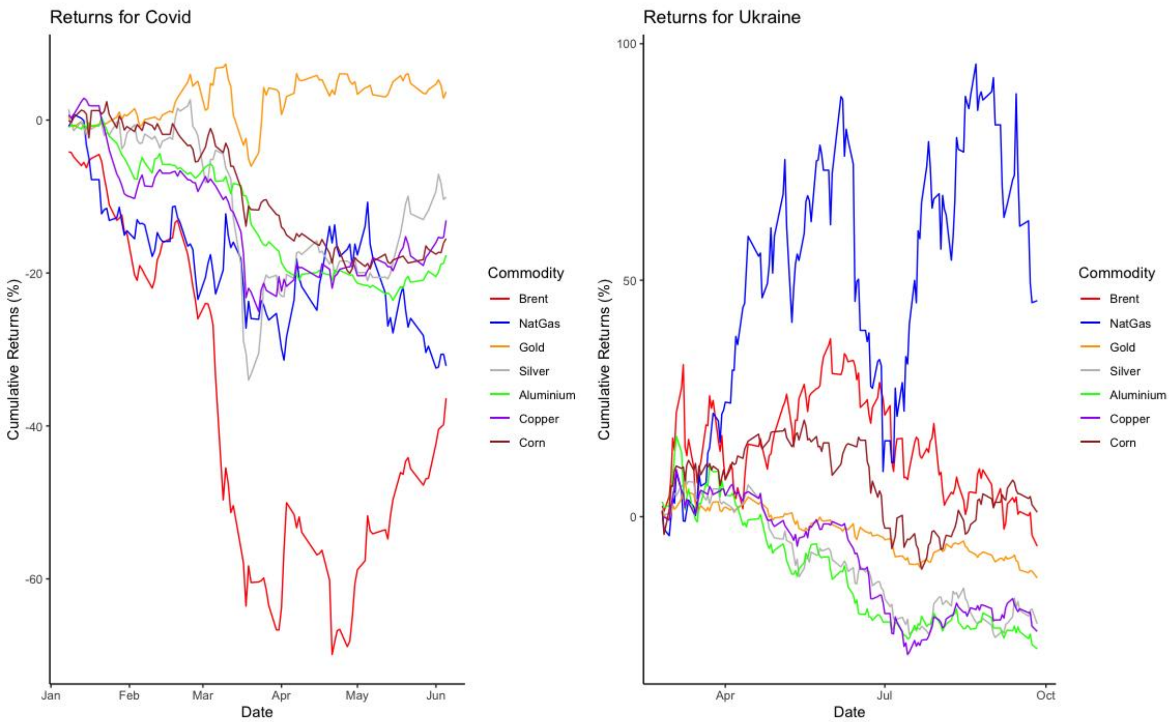
Appendix H.1: Commodity returns for GFC and Shale.



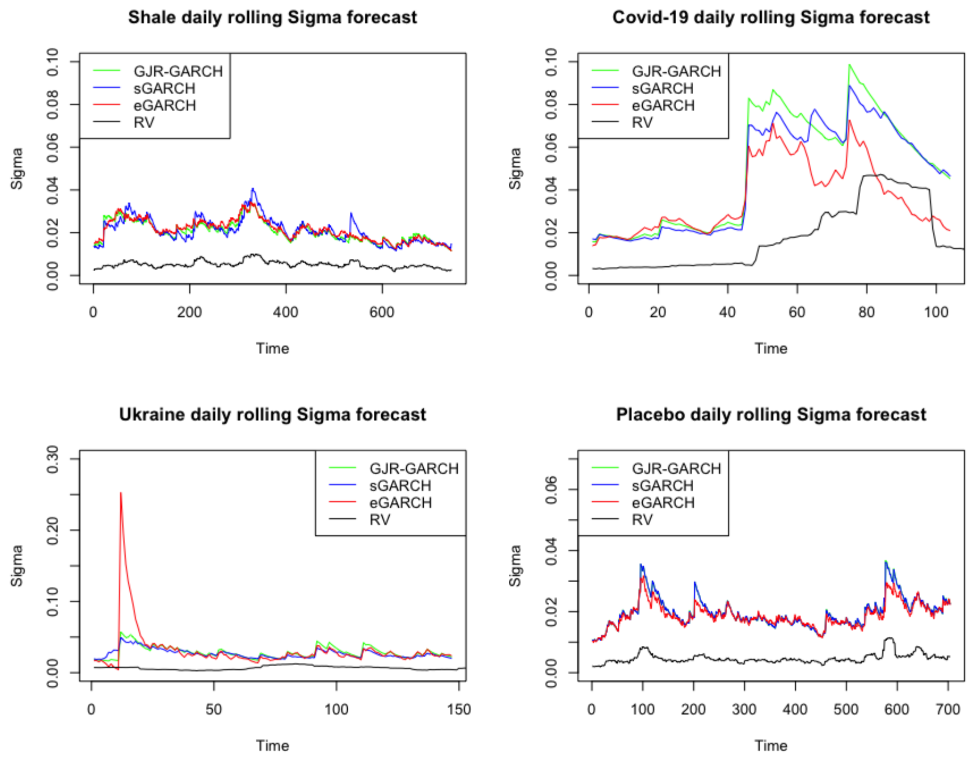
Appendix H.2: Commodity returns for Covid and Ukraine.



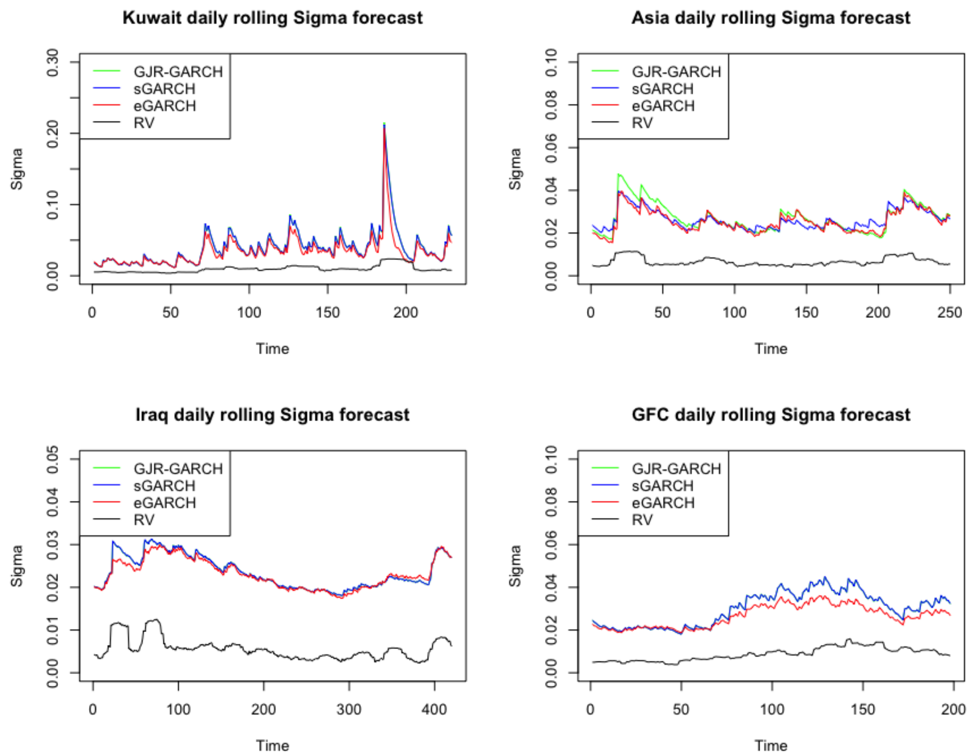
Appendix H.3: Commodity returns for Iraq and Asia.



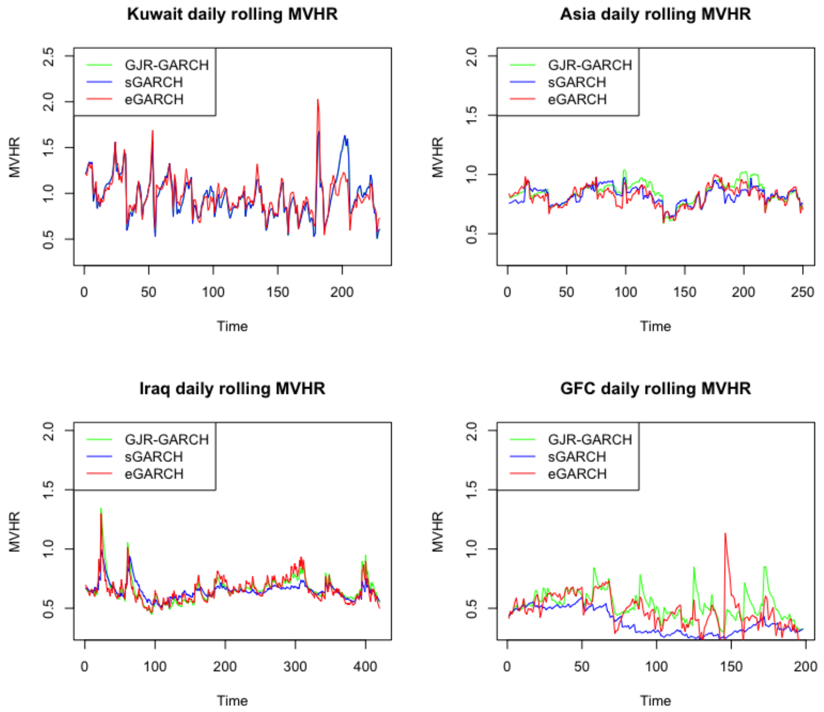
Appendix I.1: Daily rolling volatility forecast for Kuwait (Gulf War), the Asian Financial Crisis, the Iraq war, and the Great Financial Crisis.



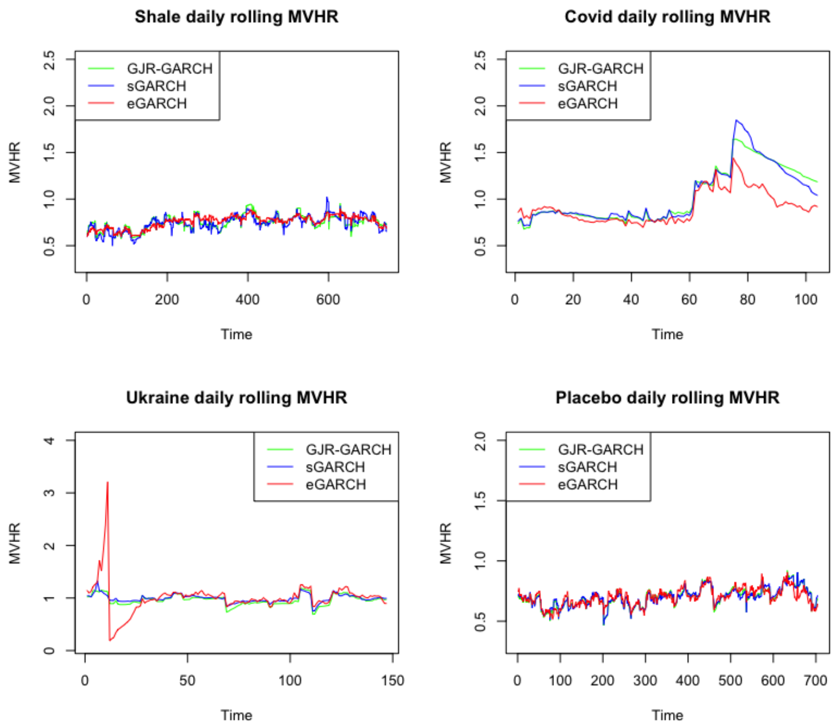
Appendix I.2: Daily rolling volatility forecast for the Shale boom, Covid-19, the Russia-Ukraine war, and the Placebo sample.



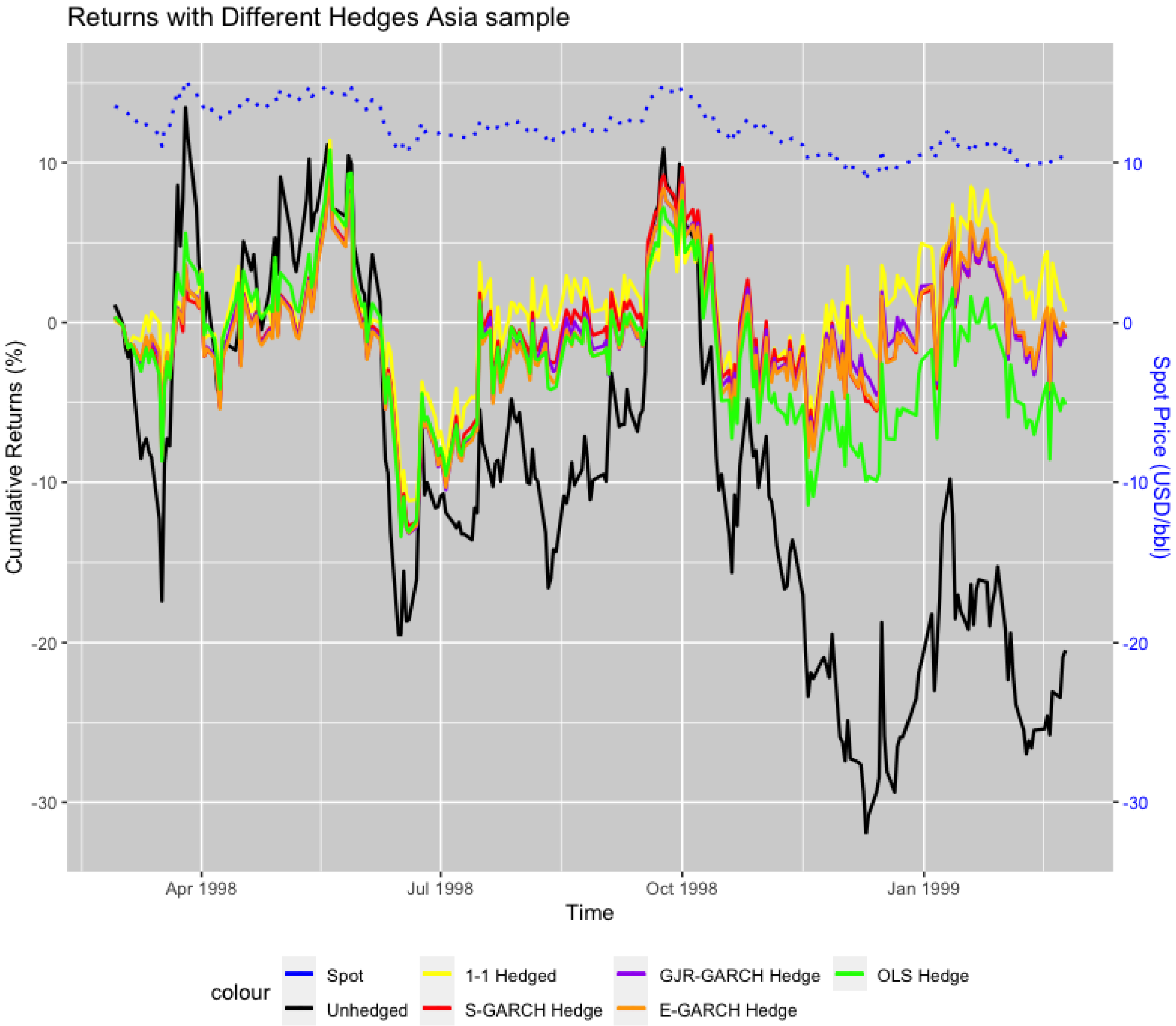
Appendix J.1: Daily rolling minimum variance hedge ratio for Kuwait (Gulf War), the Asian Financial Crisis, the Iraq war, and the Great Financial Crisis



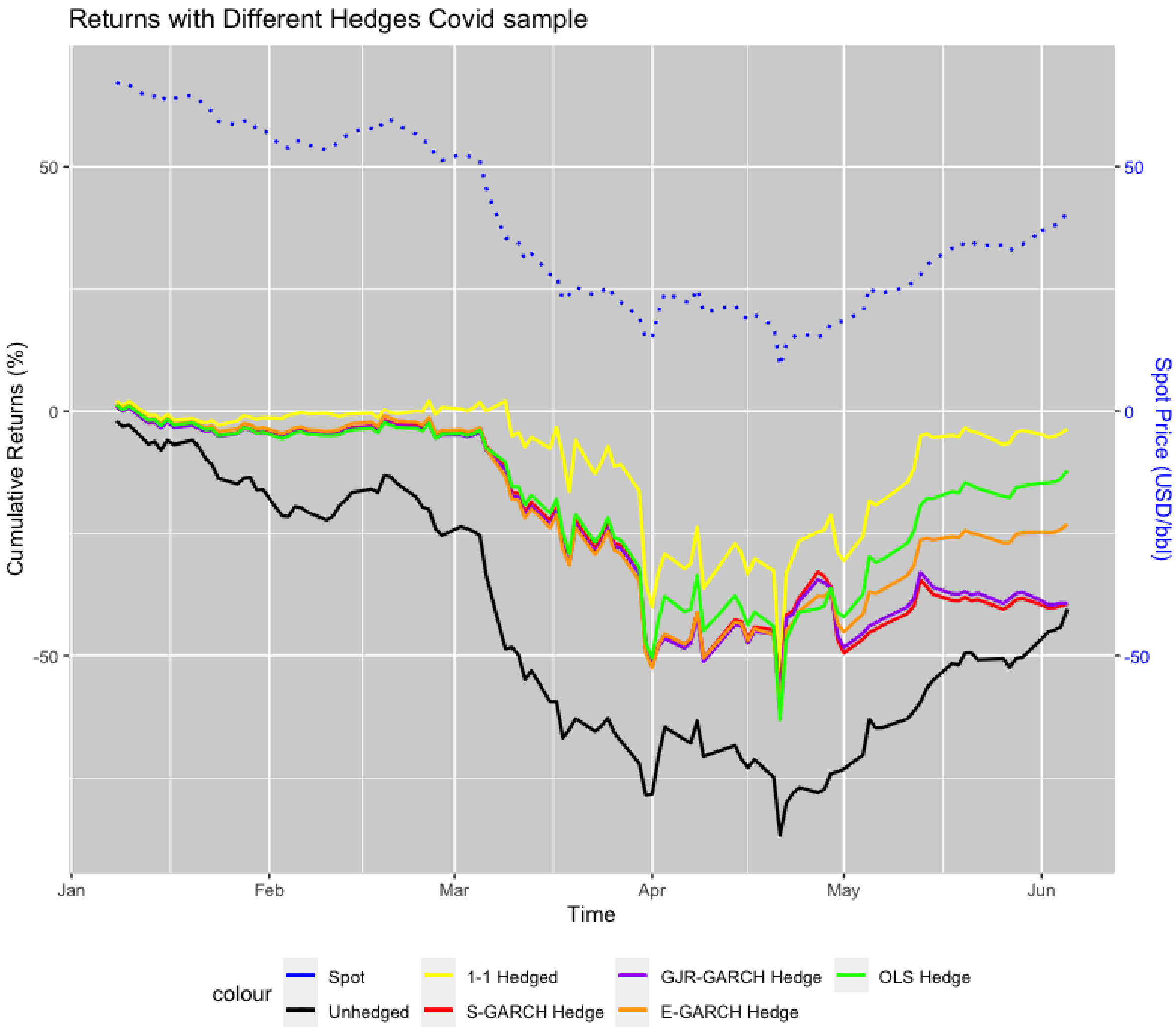
Appendix J.2: Daily rolling minimum variance hedge ratio for the Shale boom, Covid-19, the Russia-Ukraine war, and the Placebo sample.



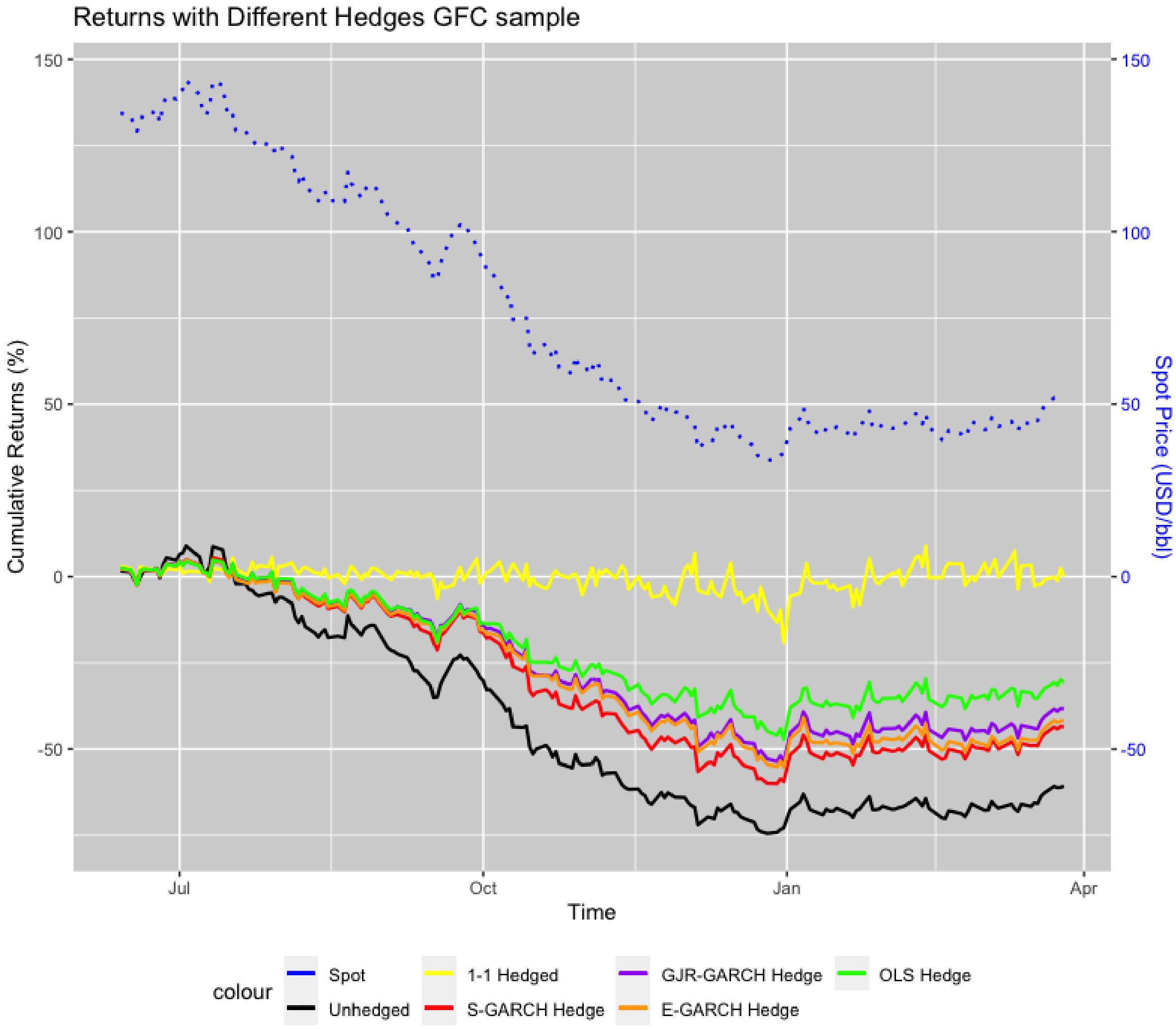
Appendix K.1: Returns with different hedges for the Asian Financial Crisis.



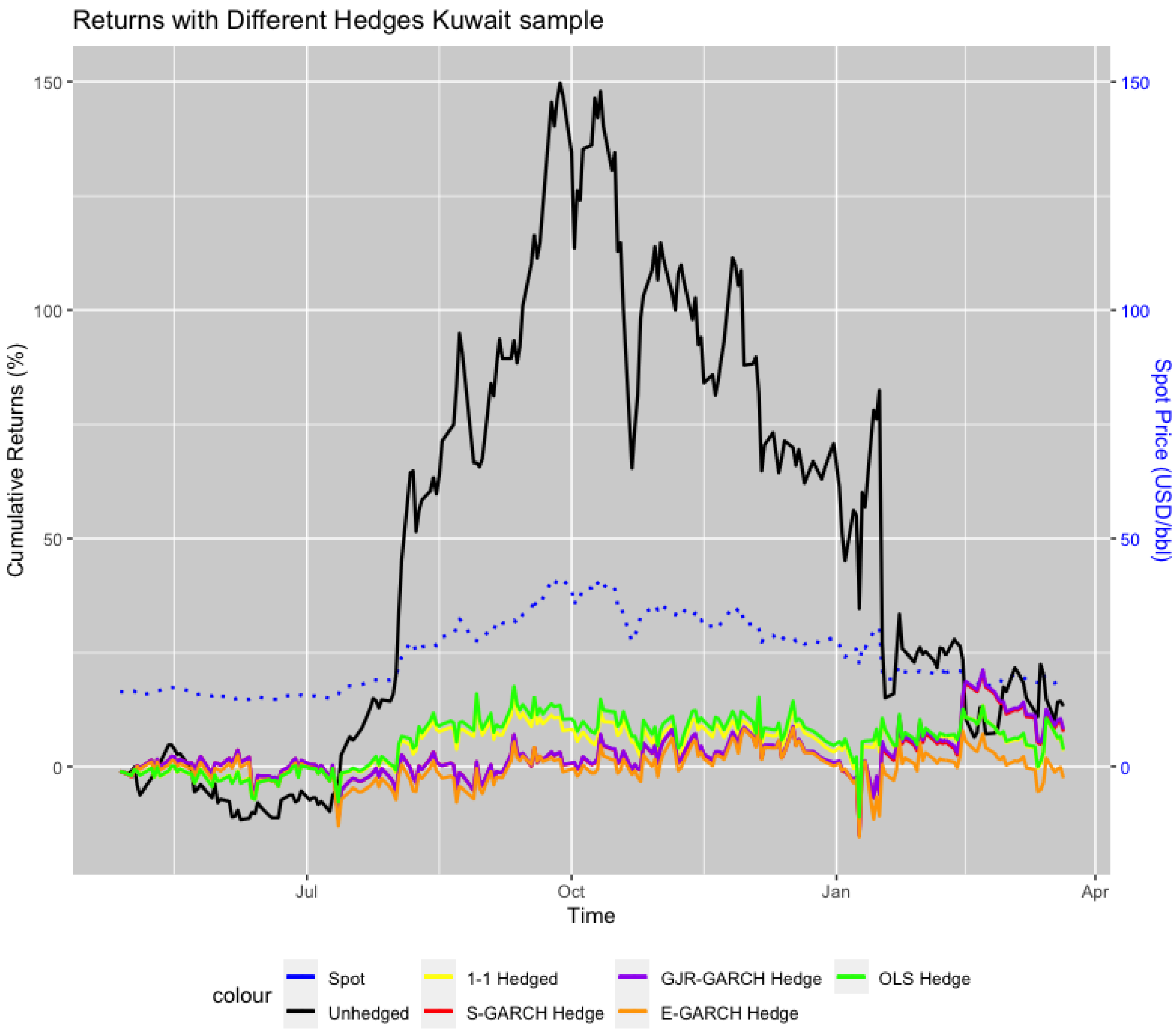
Appendix K.2: Returns with different hedges for Covid-19.



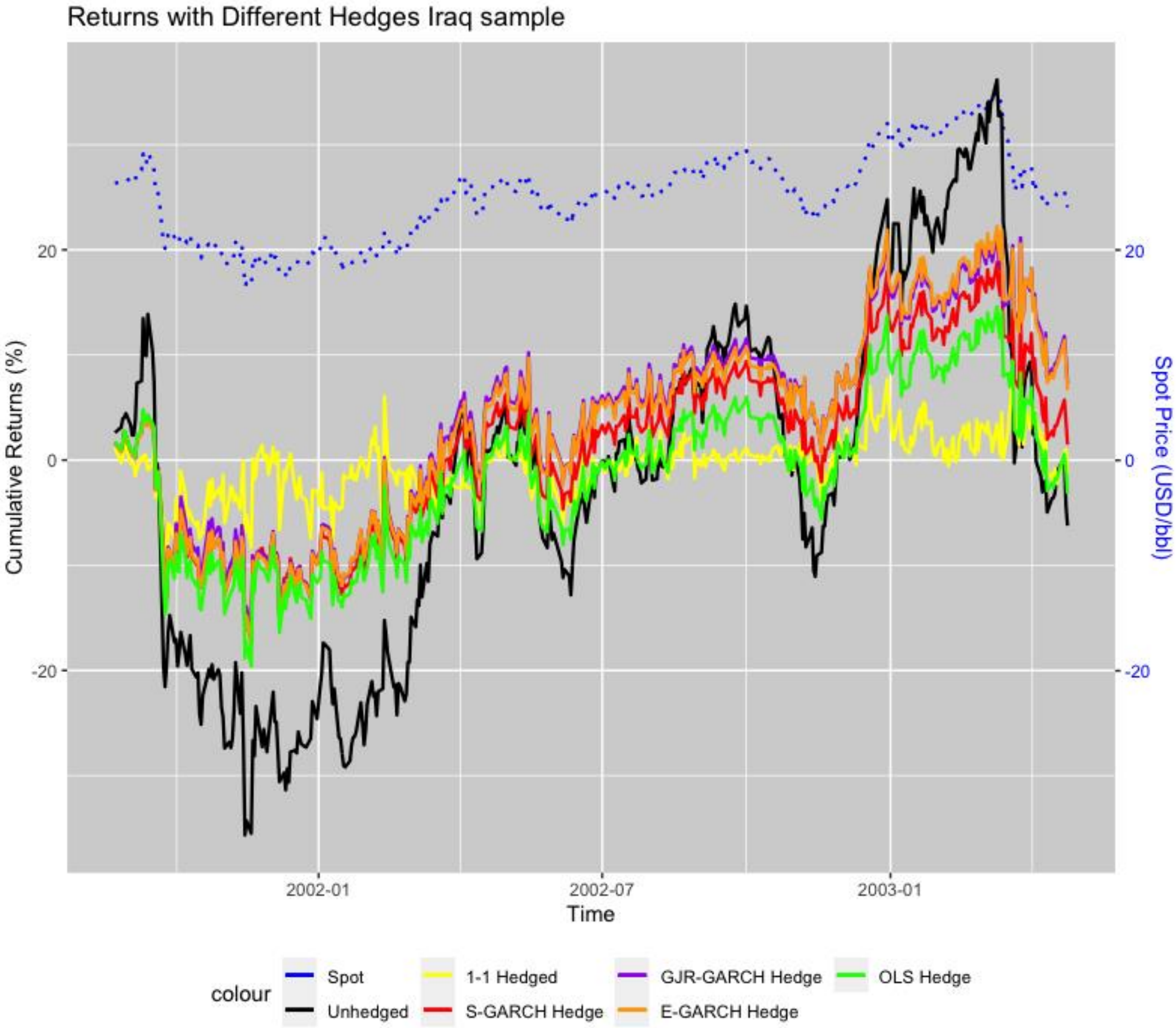
Appendix K.3: Returns with different hedges for GFC.



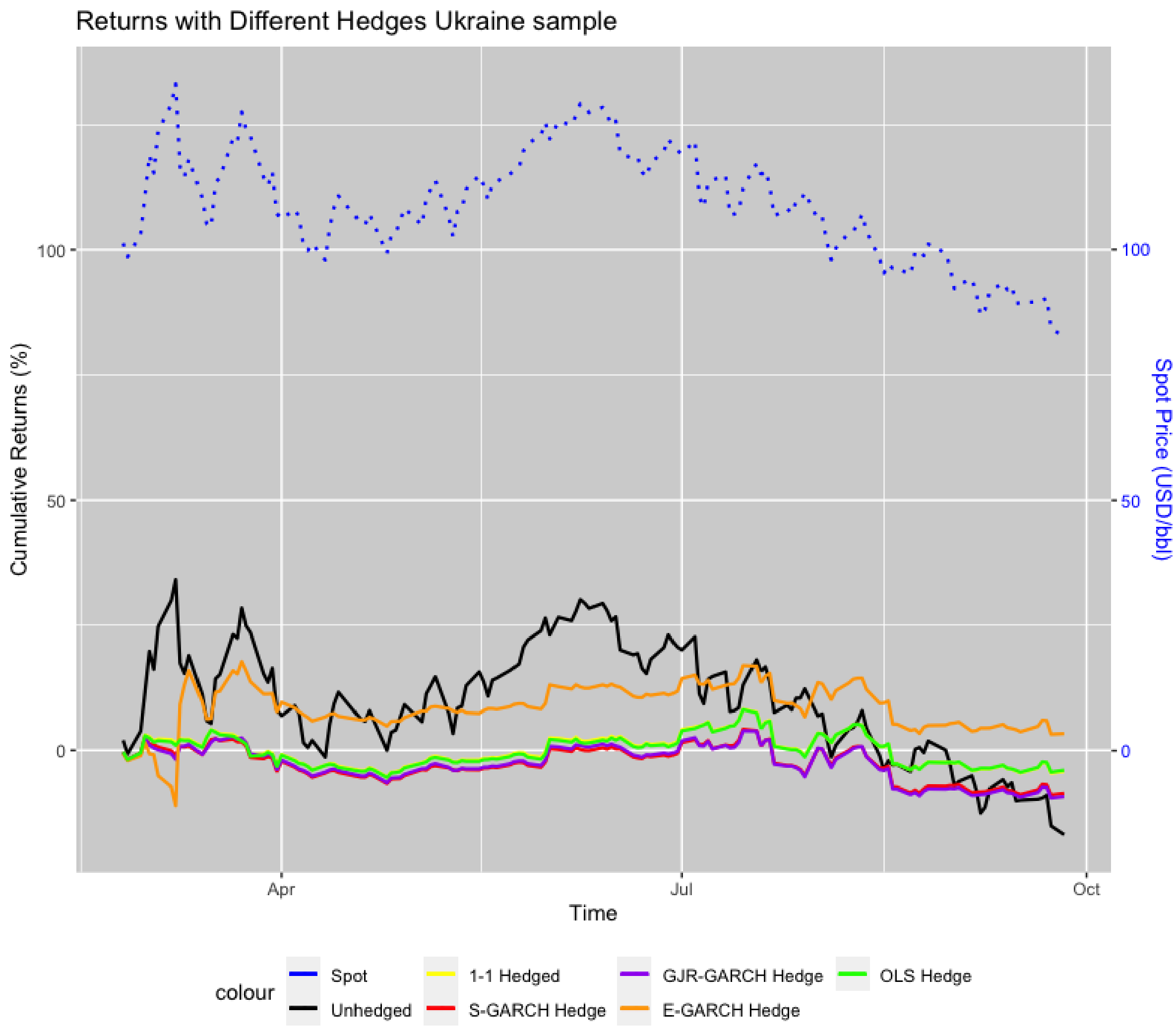
Appendix K.4: Returns with different hedges for Kuwait (Gulf War).



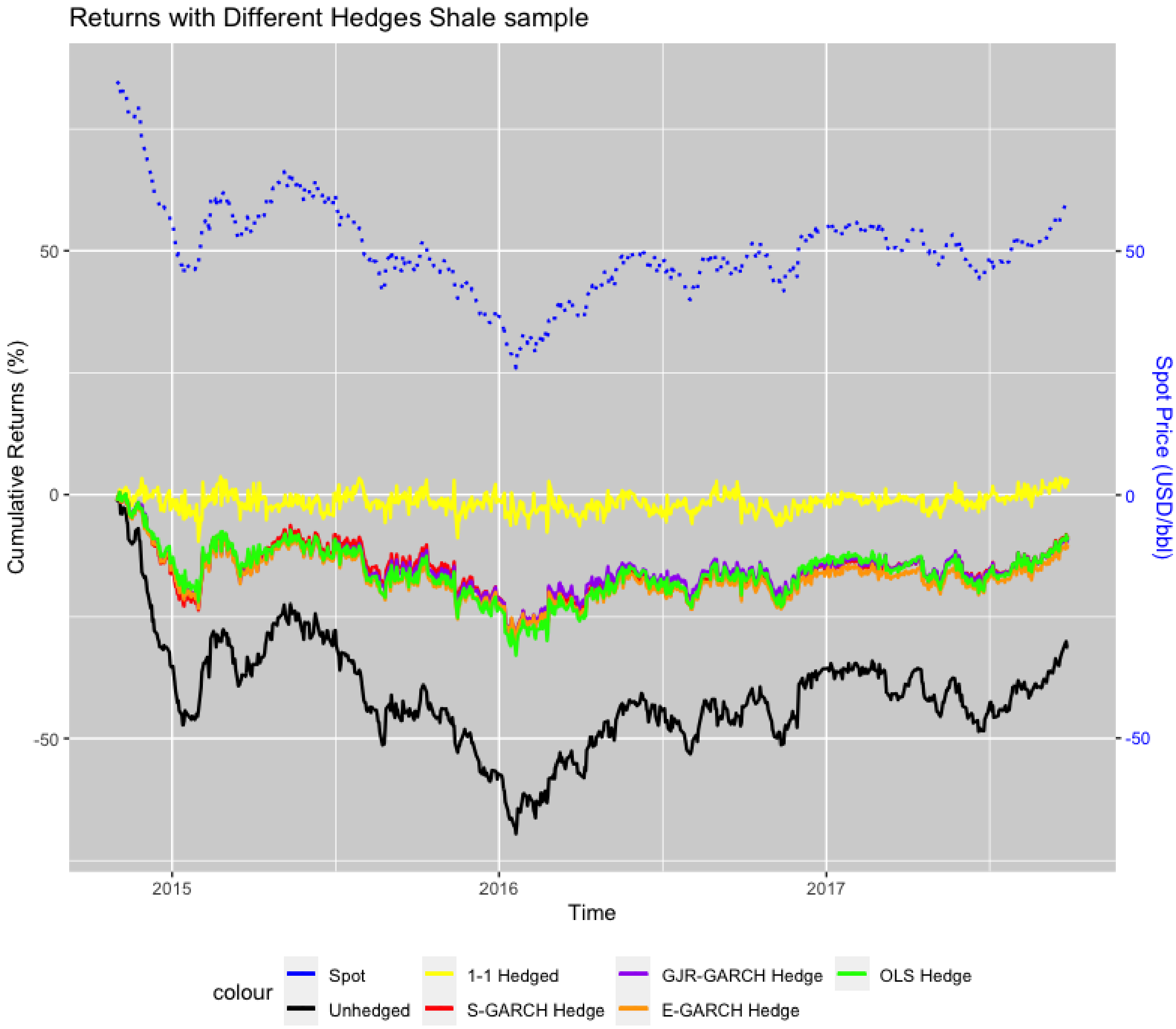
Appendix K.5: Returns with different hedges for Iraq.



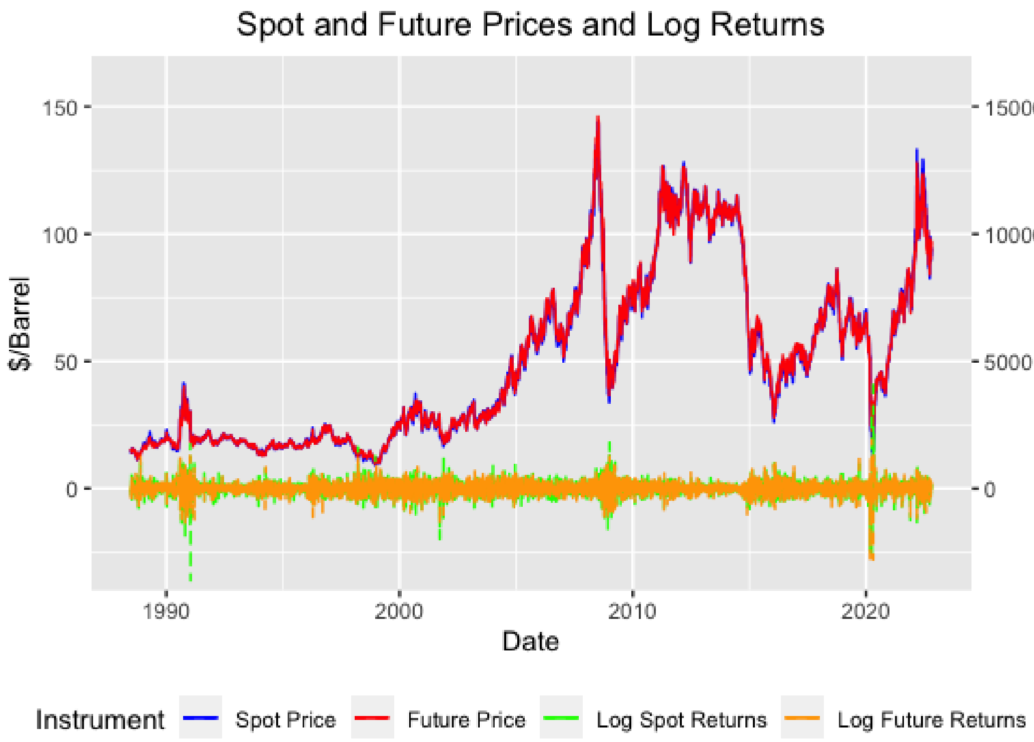
Appendix K.6: Returns with different hedges for Ukraine



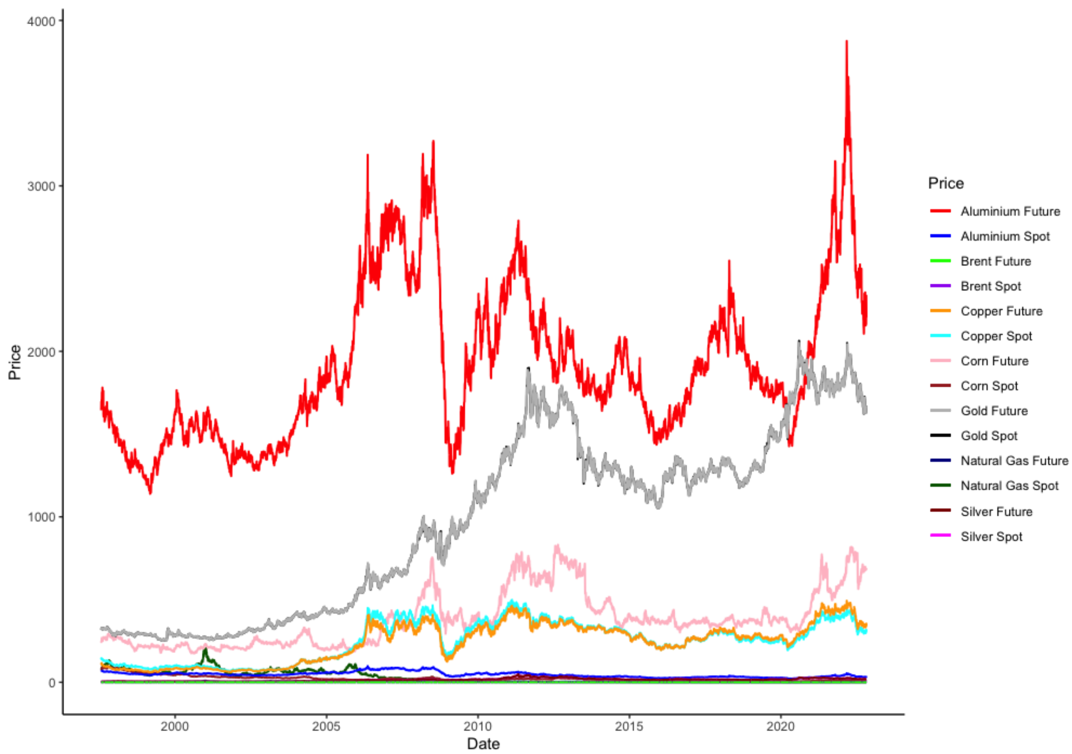
Appendix K.7: Returns with different hedges for Shale.



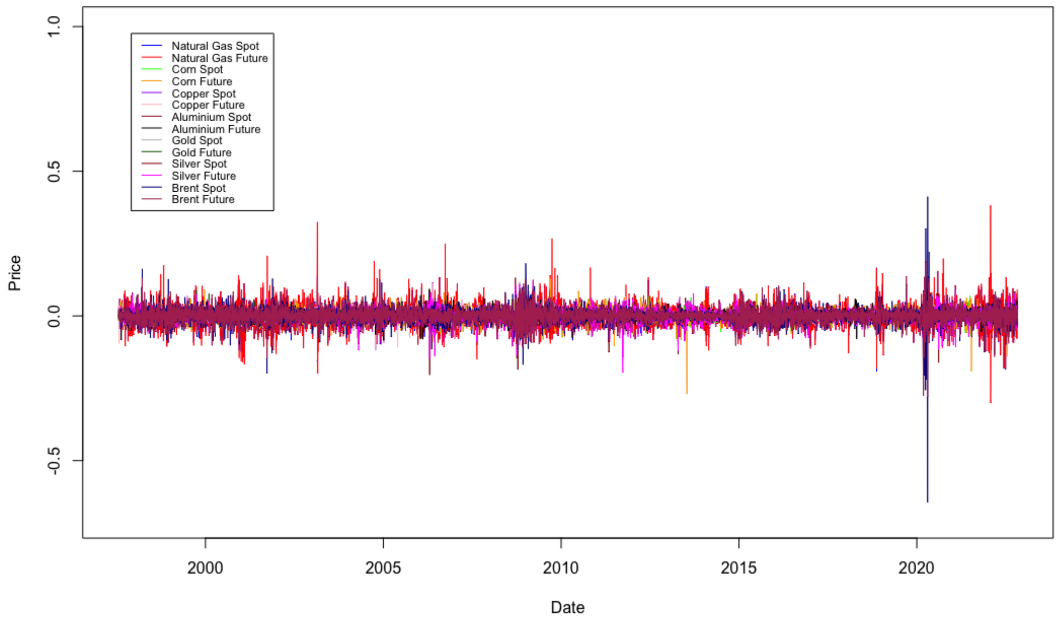
Appendix L.1: Spot and Futures prices and log returns.



Appendix L.2: Placebo sample prices.



Appendix L.3: Placebo sample log returns.



Appendix M.1: Correlation matrix.